Accounting for Investments in Intangible Assets: A Market Perspective

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Abstract

We examine the relevance of capitalizing intangible assets by separating the effects of capitalization from those of subsequent depreciation and amortization (D&A). Using a novel non-linear, firm- and time-specific approach consistent with theoretical models of the earnings–price relationship, we show that bottom-line earnings provide a poor measure of current performance: operating earnings measures—EBIT, EBITDA, and gross profit—are consistently more aligned with stock prices. Adjusting EBITDA to remove the non-capitalized investment component in operating expenses further strengthens this association. These results indicate that adjusting for intangible investment improves performance measurement, whereas subsequent amortization reduces alignment between earnings and prices.

We also revisit claims that earnings are more informative for tangible-intensive firms and that losses convey different information across firm types. For earnings measures higher up the income statement, we find no significant differences between tangible- and intangible-intensive firms. Across all earnings measures and loss definitions, earnings remain significantly more informative for profitable firms than for loss-making firms. Finally, simple capitalization models perform at least as well as more complex alternatives.

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JEL classification: G10, G30, M41

1. Introduction

A substantial literature argues that the non-capitalization of internally developed intangible assets reduces the usefulness of net income (Lev and Zarowin, 1999; Srivastava, 2014; Green et al., 2022). Previous research further shows that adjusting net income by capitalizing assumed investments in intangibles and amortizing them over an assumed useful life improves the quality of earnings according to several standard metrics (e.g., Banker et al., 2019; Gulen et al., 2025; Iqbal et al., 2025; Lev and Sougiannis, 1996). This literature implicitly treats net income as the benchmark measure of current performance and views capitalization followed by depreciation accruals as the appropriate way to enhance its informativeness. In this paper, we relax both premises and treat them as empirical questions.

Using a nonlinear, firm- and time-specific methodology to examine how a broad set of commonly used income-statement measures are reflected in stock prices, we show that relaxing these assumptions is informative. We find that earnings measures reported higher up in the income statement are more

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closely aligned with prices than bottom-line net income, that depreciation and amortization accruals tend to reduce earnings usefulness, and that performance measures excluding the effects of long-term investment provide the most informative summary of current performance as reflected in stock prices. We find no significant differences in the performance of these most informative profitability measures between tangible- and intangible-intensive firms.

The central role of earnings, and profitability more broadly, in equity valuation is well documented in both the accounting and asset pricing literature (Dechow et al., 2010; Graham et al., 2005).[1] In asset pricing, incorporating profitability into multifactor models substantially improves their explanatory power and helps resolve several previously documented anomalies (Novy-Marx, 2013; Hou et al., 2014; Fama and French, 2015). These findings underscore the economic importance of identifying measures that best capture information about current performance as reflected in stock prices, and motivate the use of market prices as a benchmark for evaluating earnings informativeness.

From an accounting perspective, concerns about whether earnings provide a reliable summary of current performance have grown as intangible assets have become a larger component of firm value. For intangible-intensive firms, net income may not reflect the underlying economic performance because investments in internally developed intangible assets are expensed rather than capitalized, weakening the matching between revenues and expenses incurred to generate them (Lev and Zarowin, 1999; Srivastava, 2023; Iqbal et al., 2025; Rajgopal et al., 2025). As intangible assets represent an increasing share of firm value, the consequences of these limitations of net income as a measure of current performance have become more pronounced. Reflecting these concerns, standard setters have recently renewed their focus on the accounting treatment of intangible assets, with the Financial Accounting Standards Board initiating a project to reassess their recognition (FASB, 2024b).[2]

Much of the literature argues that the accounting treatment of intangible assets should mirror that of tangible assets. For tangible assets, capitalization followed by depreciation is intended to align asset consumption with the revenues it helps generate, providing a clearer representation of current financial performance in the income statement (Green et al., 2022); see also the FASB Conceptual Framework for Financial Reporting (OB17). The standard-setting rationale for treating intangible assets differently is that future cash flows from intangibles are subject to greater uncertainty than those from tangible assets. However, Rajgopal et al. (2025) show that investments in tangible assets are also characterized by substantial payoff uncertainty, calling this distinction into question. This evidence suggests that there

[1] The accounting literature typically refers to earnings, whereas the asset pricing literature refers to profitability, defined as earnings scaled by a measure of capital or assets. In this study, we use the two terms interchangeably.

[2] The International Accounting Standards Board has recently launched a similar initiative.

may be economic reasons for treating tangible and intangible assets more symmetrically (cf. Barker et al., 2022). Consistent with this view, several studies find that estimating the capitalization and subsequent amortization of intangible investments improves the quality of bottom-line earnings in multiple dimensions, including their association with market prices, persistence and volatility, matching, and the relationship between accruals and cash flows (e.g., Lev and Sougiannis, 1996; Green et al., 2022; Gu et al., 2023; Rajgopal et al., 2025).

A second empirical development that reinforces concerns about the usefulness of net income is the steady increase in the proportion of U.S. listed firms reporting losses, which now accounts for approximately 30-40 percent of all firms. Because the relationship between earnings and stock prices differs systematically between profitable and loss-making firms (Hayn, 1995; Lipe et al., 1998; Hiemann, 2020; Starica and Marton, 2025), this shift further complicates the use of net income as the predominant measure of current performance.[3] Reported losses may reflect economic distress, temporary investment-related losses, or accounting conservatism, including immediate expensing of intangible investments (Srivastava, 2014; Klein and Marquardt, 2006; Rajan and Zingales, 2003). Recent studies also show that the information conveyed by losses and the valuation implications investors draw from them systematically differ between tangible and intangible-intensive firms (Gu et al., 2023; Rajgopal et al., 2025). Together, these developments raise the question of which earnings measures best capture current performance between firms with different asset structures and profitability.

The literature on the capitalization of intangible investments is based on two implicit assumptions. The first is that bottom-line earnings provide the appropriate measure of current performance. The second is that capitalizing and amortizing intangible investments—so as to mimic the accounting treatment of tangible assets—improves the usefulness of earnings. Consistent with these assumptions, most studies apply capitalization adjustments directly to net income (Lev and Sougiannis, 1996; Green et al., 2022; Gu et al., 2023; Rajgopal et al., 2025).[4] The centrality of bottom-line earnings is also evident in the non-GAAP literature, where net income typically serves as the benchmark for defining non-GAAP exclusions (e.g., Bradshaw and Sloan, 2002; Dechow et al., 2024).

Both prior research and reporting practice provide reasons to question these assumptions. Ball and Nikolaev (2022) show that operating earnings that contain only short-term accruals are more useful than net income to predict next-period cash flows. In asset pricing, operating earnings before investments

[3] Leung and Veenman (2018) suggest that the increase in non-GAAP reporting may reflect firms' responses to the increasing incidence of negative net income.

[4] Iqbal et al. (2025) focus on adjusted book value of equity, while Banker et al. (2019) analyze the incorporation of estimated SG&A investment components into market prices.

outperform bottom-line earnings in predicting stock returns (Fama and French, 2015; Jagannathan et al., 2026; Novy-Marx, 2013). Consistent with these findings, EBITDA—a closely related operating measure—is the most commonly reported non-GAAP metric (Dechow et al., 2024; FASB, 2024a), and previous work shows that non-GAAP earnings, including EBITDA, are more useful to investors than reported net income (Black et al., 2018).

The second assumption—that replicating the accounting treatment of tangible assets yields more useful earnings—has also been questioned. Richardson et al. (2005) show that long-term asset capitalization generates less reliable accruals, reducing the persistence of earnings. Larson et al. (2018) document that long-term operating accruals exhibit substantially higher variance than short-term accruals, making them difficult to estimate accurately. Lewellen and Resutek (2016) further decompose capitalization into two distinct accruals: an initial capitalization accrual recorded at the transaction date and a subsequent amortization accrual based on managerial judgment. They show that the former is informative to investors, whereas the latter is not. This distinction is consistent with the widespread use of EBITDA, which retains information from the initial investment decision while excluding subsequent depreciation and amortization.

In this study, we treat the two central assumptions in the intangible capitalization literature as empirical questions: whether bottom-line earnings provide the most informative summary of current performance, and whether mimicking the accounting treatment of tangible assets enhances earnings usefulness for intangible-intensive firms. We address these questions by departing from the prior literature in two respects: by expanding the set of earnings measures under consideration and by adopting a market-based, nonlinear approach to evaluating their informativeness.

Our first extension of the literature concerns the choice of earnings variables. Rather than focusing on a single benchmark, we broaden the set of performance measures under consideration by comparing earnings defined at different levels of the income statement. Our second extension is methodological and concerns how the relative usefulness of these alternative performance measures is evaluated. Studies in this literature typically rely on one of two benchmarks. One stream uses next-period operating cash flows (or operating earnings) as a proxy for long-term cash-flow prediction (e.g., Finger, 1994; Barth et al., 2001; Kolev et al., 2008; Leung and Veenman, 2018; Black et al., 2021; Ball and Nikolaev, 2022). The other relies on market-based benchmarks, such as prices or returns (e.g., Ball and Brown, 1968; Dechow, 1994; Francis et al., 2003; Barton et al., 2010; Starica and Marton, 2025). Each approach has limitations. Cash-flow benchmarks are econometrically convenient but rely on short horizons and require assumptions about which cash-flow measure investors forecast. Moreover, because performance

measures are highly persistent, measures that more closely resemble the chosen benchmark are mechanically favored. Market-based benchmarks avoid these assumptions and reflect a longer valuation horizon, but pose substantial econometric challenges due to the nonlinearity and heterogeneity of the earnings–price relationship (Lipe et al., 1998; Holthausen and Watts, 2001; Kothari and Shanken, 2003; Hiemann, 2020; Starica and Marton, 2025).

Our method contributes to the market-based literature by modeling the earnings–price relationship as nonlinear and firm- and time-specific (Starica and Marton, 2025). This approach allows us to use a conceptually complete long-horizon benchmark while addressing the mentioned estimation challenges. As a result, we can evaluate the information content of alternative earnings measures without imposing *ex ante* assumptions about which measures should perform better.

These two departures enable us to answer the empirical questions through two complementary comparisons. Specifically, the first comparison evaluates alternative earnings measures relative to bottom-line earnings in terms of how well they summarize current performance as reflected in prices.[5] The second comparison examines how the informativeness of each measure varies between firms with different characteristics, including intangible intensity and profitability.

The results of the first comparison show that bottom-line earnings are not the most informative measure of current performance. All operating earnings measures (those excluding taxes, financial items, and other non-operating components) consistently and significantly outperform net income, across tangible- and intangible-intensive firms and across profit and loss firms. These findings contradict the validity of the assumption that bottom-line earnings should be the preferred performance measure.

Within operating earnings, measures that remove the effects of long-term assets, such as EBITDA, provide the most informative summaries of current performance. For tangible-intensive firms, this pattern implies that initial capitalization improves informativeness, whereas depreciation reduces it. For intangible-intensive firms, where investments are expensed rather than capitalized, we construct an adjusted earnings measure that treats R&D and a portion of SG&A as investment. The results mirror those of tangible firms: removing the initial investment improves the informativeness, while subsequent amortization reduces it. Applying recent capitalization methodologies (Green et al., 2022; Rajgopal et al., 2025) does not improve the usefulness of earnings. Additional tests based on revenue–expense matching (Dichev and Tang, 2008) yield patterns that closely parallel the price-based results. These findings contradict the view that the ideal treatment of intangibles is to replicate the capitalization-and-depreciation

[5]This analysis includes individual income-statement line items and common non-GAAP measures. In addition, we examine capitalized earnings constructed using the methodology of Rajgopal et al. (2025).

model used for tangible assets.

Overall, our evidence indicates that bottom-line earnings are a poor summary of current performance, regardless of firms' asset structure or profitability. Earnings measures that exclude the effects of long-term investments provide the most informative view of current performance, while depreciation and amortization materially reduce informativeness—consistent with their low reliability and high managerial discretion (e.g., Richardson et al., 2005; Lewellen and Resutek, 2016).

The second comparison examines whether the informativeness of earnings varies across firms with different characteristics, in particular tangible versus intangible intensity and profitability. Regarding the claim in the literature that earnings provide a better measure of current performance for tangible firms than for intangible firms, our results confirm that this pattern holds for bottom-line earnings (cf. Srivastava, 2014). In contrast, for the more informative earnings measures higher up in the income statement, we find no statistically significant differences in price informativeness between tangible- and intangible-intensive firms in recent decades. Moreover, the extent to which the best current-performance earnings measure outperforms bottom-line earnings is significantly greater for intangible-intensive firms than for tangible-intensive firms, regardless of profitability. In other words, moving up the income statement yields substantially larger gains in informativeness for intangible-intensive firms.

For loss firms, we show that, regardless of asset structure (tangible or intangible) and definition of loss (losses at different line items of the income statement), the earnings measures most aligned with prices are at the top of the income statement (e.g., gross profit and sales). This suggests that, when considering the most informative measure of current performance, losses do not exhibit systematic differences between intangible-intensive and tangible-intensive firms. Moreover, our evidence indicates that earnings are significantly more informative for profitable firms than for loss-making firms, a pattern that holds across all definitions of losses and all earnings measures considered.

Extending the analysis to earnings adjusted for imputed capitalization of intangibles (Gu et al., 2023; Rajgopal et al., 2025), we document, contrary to claims in the literature (Gu et al., 2023) that earnings adjusted for capitalization and amortization of intangible outlays are significantly better measures of firm performance for profitable firms than for firms whose reported losses are turned into profits by the capitalization and amortization adjustment (referred to as "GAAP losers" by Gu et al., 2023).[6]

[6]Gu et al. (2023) base their conclusions on the magnitudes of earnings response coefficients (ERCs) from regressions of returns on earnings levels and changes, using both reported bottom-line earnings and earnings adjusted for intangible capitalization. However, ERC magnitudes confound two distinct features of the independent variables—their variability and their association with returns—and therefore do not provide a valid basis for comparing informativeness across different earnings measures. When focusing on the regression's R^2 values reported in the paper—which provide a meaningful basis for comparing associations across specifications—the evidence indicates that earnings (both adjusted and unadjusted) are substantially more informative for profitable firms than for GAAP losers (see Section 5.3).

We make several contributions to central debates in the accounting literature. First, we contribute to the literature on the informativeness of *non-GAAP* earnings. Whereas prior research emphasizes the exclusion of non-recurring items from GAAP earnings as the primary source of improved earnings quality (e.g., Rouen et al., 2021; Dechow et al., 2024; Gardner et al., 2024; McClure and Zakolyukina, 2024), we show that the largest gains in informativeness relative to net income arise from excluding recurring items—specifically non-operating components and, most importantly, depreciation and amortization (D&A).[7] Our results are consistent with evidence that recurring negative accruals materially reduce earnings informativeness (Leung and Veenman, 2018; Whipple, 2015).

Second, we identify a central distinction within operating earnings between current expenses and the accounting treatment of long-term investments. Earnings measures that remove all effects of long-term assets, both the initial investment and subsequent D&A, as well as the estimated investment component of SG&A, provide the most informative summary of current performance. These measures are strictly more informative than total operating earnings. This result informs the long-standing debate on the capitalization of intangibles. While prior studies argue that capitalizing and amortizing internally developed intangibles improves earnings usefulness (e.g., Lev and Sougiannis, 1996; Green et al., 2022; Gu et al., 2023; Iqbal et al., 2025; Rajgopal et al., 2025), we show that only the adjustment for the initial investment improves informativeness, whereas subsequent imputed amortization reduces it. Importantly, we find no distinction in the optimal treatment of capitalized (tangible) and non-capitalized (intangible) long-term assets: in both cases, removing both the initial outlay and subsequent D&A from earnings maximizes alignment with prices. Consistent with this result, the differences in earnings relevance between tangible and intangible-intensive firms largely disappear when more informative earnings measures are used.

Third, we contribute to the literature on loss firms. Although prior research suggests that capitalization adjustments can offset the lower relevance of negative earnings (Gu et al., 2023), we show that earnings of loss-making firms remain systematically less informative than those of profitable firms in all earnings measures and loss definitions. Although capitalization-based measures outperform reported net income for loss firms, they do not eliminate this relevance gap. This finding reinforces our broader conclusion that refinements to bottom-line earnings provide limited gains in informativeness.

These findings are enabled by a novel empirical framework that addresses the non-linearity and firm-specific heterogeneity of the earnings–price relationship. By allowing for credible price-based inference over long horizons, our method supports a unified evaluation of earnings measures across

[7] These items correspond closely to the non-transactional accruals identified by Lewellen and Resutek (2016) and to the low-reliability accruals documented by Richardson et al. (2005).

multiple research domains.

Because our analysis focuses on contemporaneous price associations, our conclusions regarding the capitalization and amortization of intangibles are confined to that criterion. We therefore do not assess other dimensions of earnings quality examined in prior work. Nevertheless, similar patterns emerge when applying alternative approaches, including revenue–expense matching (Section 5.5), cash-flow prediction (Ball and Nikolaev, 2022; Jagannathan et al., 2026), and return prediction (Jagannathan et al., 2026).

The remainder of the paper proceeds as follows. Section 2 reviews the literature, Section 3 describes the methodology, Section 4 presents the data, Section 5 reports the empirical results and Section 6 concludes.

2. Literature

In this section, we draw on the literature and financial reporting standards to develop expectations and predictions. To frame the effects of non-capitalization of intangible assets, we first discuss the expected usefulness of different earnings measures, including earnings defined in regulation, alternative non-GAAP measures, and adjusted earnings. Next, we review the literature on the direct effects of non-capitalization of intangibles on earnings measures. Finally, we discuss the role of losses in relation to different earnings measures and intangible assets.

2.1 Earnings numbers and disaggregation

Different earnings numbers capture distinct components of revenues and expenses that may differ in relevance to investors. Still, much of the literature focuses on bottom-line earnings (net income) or applies adjustments (such as those related to the non-capitalization of intangibles) directly to this measure. The role of net income is to capture all changes in firm value attributable to shareholders[8] and, therefore, it has a central role in accounting standards. For example, net income is the basis for calculating earnings per share under ASC 260-10-55.

Although net income is a key financial performance indicator, it is not necessarily the most relevant measure of current firm performance. Regulatory actions by the FASB and the SEC, firms' reporting practices, and recent research point to a growing emphasis on alternative earnings measures alongside bottom-line earnings.

[8] In addition to net income, the FASB refers to some changes in wealth as 'Other comprehensive income' (OCI). We do not further discuss the role of OCI, as the literature suggests it has limited usefulness (Jones and Smith, 2011).

In 2024, the FASB issued Accounting Standards Update No. 2024-03, which requires enhanced disclosures related to the disaggregation of income statement expenses.[9] In motivating this update, the FASB notes:

> *Investors specifically indicated that more granular information on the cost of sales and on selling, general, and administrative expenses (SG&A) would assist them in better understanding an entity's cost structure and forecasting future cash flows.* (Page 1)

The shift toward a broader set of earnings measures is also evident in firms' communication practices. Many firms emphasize alternative non-GAAP earnings measures in their disclosures to investors. The use of non-GAAP earnings has expanded substantially among listed firms. Currently, most S&P 500 firms report at least one non-GAAP earnings measure in their periodic filings (Guggenmos et al., 2022). This growing focus on non-GAAP earnings has, in turn, prompted regulatory responses. Over the past two decades, the SEC has issued regulations governing non-GAAP disclosures (as summarized in Chen et al., 2021), and the FASB has issued an *Invitation to Comment* on the potential regulation of non-GAAP earnings (FASB, 2024a).[10]

The relevance of this growing emphasis on alternative performance measures is supported by recent research. In a study that examines a comprehensive set of accounting variables that span a broad range of financial reporting items, Barth et al. (2023) document a decline in the value relevance of bottom-line earnings during the 1962–2018 period, accompanied by a rising relevance of other performance items, such as operating cash flows before investments and R&D expenditures.

In a related field, the asset pricing literature identifies profitability as a distinct priced factor in linear multi-factor asset pricing models for expected returns. Fama and French (2006) argue, based on the dividend discount model, that current profitability forecasts future returns because it proxies for expected future profitability, an important driver of expected returns. Motivated by this argument, Fama and French (2015) and Hou et al. (2014) present linear asset-pricing models that include a profitability factor and show that these models explain previously noted return anomalies. Several studies argue, explicitly or implicitly, that earnings higher up in the income statement are a better proxy for profitability than bottom-line earnings. Fama and French (2015) use earnings before taxes, depreciation, and amortization (EBTDA) as their proxy for profitability. Novy-Marx (2013) argues that gross profit is the cleanest

[9] While disaggregated information is not identical to alternative earnings numbers, the additional granularity in disclosures allows investors to construct additional earnings numbers.

[10] Internationally, the IASB requires reconciliation between IFRS and alternative performance measures in IFRS 18 *Presentation and Disclosure in Financial Statements*, which becomes mandatory in 2027.

accounting proxy for true current economic profitability.[11] Ball et al. (2015) compare different profitability measures and find that EBITDA adjusted for R&D expenditures provides the strongest results for predicting stock returns.

In a recent paper, Jagannathan et al. (2026) evaluate the ability of a wide range of current profitability measures—including bottom-line earnings, earnings before extraordinary items, earnings before tax (EBT), EBTDA, gross profit, and revenue—to predict future operating cash flows over horizons of up to ten years. They find that predictive power increases for measures higher up in the income statement, peaks at EBTDA, and declines for measures above this, such as gross profit and revenue. Across all time horizons, gross profit predicts future operating cash flows better than bottom-line earnings. Based on these results, Jagannathan et al. (2026) select EBTDA as the reference profitability factor in their comparison of mispricing across multi-factor linear asset-pricing models. These findings suggest that profitability measures higher up in the income statement may better capture the economic performance relevant for valuation.

As non-GAAP earnings have become more prevalent in practice, the literature increasingly focuses on such measures. The evidence generally shows that non-GAAP earnings are more useful to investors than GAAP earnings (see, e.g., Brown and Sivakumar, 2003; Black et al., 2018). In this literature, non-GAAP earnings are often constructed by applying adjustments to reported bottom-line earnings. Research typically attributes the higher usefulness of non-GAAP earnings to the exclusion of non-recurring items, as the adjustments inform investors about items not expected to persist (e.g., Leung and Veenman, 2018; Dechow et al., 2024; McClure and Zakolyukina, 2024). Meanwhile, in practice, the most widely used non-GAAP metric is EBITDA (Dechow et al., 2024; FASB, 2024a), where the main adjustments from GAAP operating income are recurring items such as depreciation and amortization.

The discrepancy between the transitory adjustments emphasized in academic research and the recurring adjustments commonly made by practitioners is largely unexplained in the non-GAAP earnings literature Leung and Veenman (2018). However, other studies suggest reasons for excluding items such as depreciation and amortization. First, profitability measures higher up in the income statement may better align with the cash flows that investors forecast when valuing firms. Ball and Nikolaev (2022) show that focusing on earnings that reflect only short-term accruals—by removing items such as depreciation and amortization—substantially improves the ability of earnings to predict next-period operating cash flows.[12] This improved alignment likely explains why, in linear asset-pricing models, profitability

[11] Novy-Marx (2013) contends that profitability measures become increasingly "polluted" the further down the income statement one moves and therefore are poorer reflections of underlying economic profitability.

[12] Through their method, Ball and Nikolaev (2022) implicitly assume that investors forecast operating cash flows as defined

measures based on earnings higher up in the income statement generate factors that explain the cross-section of returns better than those based on bottom-line earnings or other measures further down the income statement.

A second explanation is that some accruals that are theoretically relevant are difficult to quantify reliably in practice, thereby adding noise to earnings. Richardson et al. (2005) argue that both capitalization of investments in long-term assets and subsequent depreciation and amortization have low reliability because they are based on subjective managerial estimates. Consistent with this view, Larson et al. (2018) shows that long-term accruals—defined as the difference between operating and working-capital accruals and including depreciation and amortization—exhibit the highest variance and the slowest mean reversion among all accrual categories, making them particularly difficult to estimate. Lewellen and Resutek (2016) distinguish between transactional accruals, which are directly linked to transactions such as the acquisition of assets, and non-transactional accruals (NTAs), which capture changes in the value of existing assets and liabilities rather than new expenditures. NTAs include accruals unrelated to working-capital or long-term asset investments, such as depreciation and amortization.[13] Because NTAs are not based on actual transactions, they involve substantial managerial discretion. Lewellen and Resutek (2016) argue that this limited reliability reduces the usefulness of NTAs to investors.

Based on accounting standard setting, reporting practice, and prior research discussed above, we develop several expectations about how well different earnings measures capture firm performance as reflected in stock prices. These arguments suggest that informativeness can vary systematically between earnings measures defined at different levels of the income statement. First, we expect operating income (e.g., EBIT) to be more informative than bottom-line earnings (Ball and Nikolaev, 2022). Second, prior research provides conflicting predictions regarding the usefulness of EBITDA (EBIT adjusted for depreciation and amortization). The non-GAAP earnings literature suggests that EBITDA should not outperform EBIT because it excludes important recurring items (Dechow et al., 2024). Evidence that EBITDA performs better among income statement profitability measures comes from linear asset-pricing models (Jagannathan et al., 2026), the documented low reliability of depreciation and amortization accruals (Richardson et al., 2005; Lewellen and Resutek, 2016; Larson et al., 2018), and the widespread reliance on EBITDA in practice. Therefore, we expect to observe the pattern documented in Jagannathan et al. (2026): alignment with prices increases when moving up the income statement, peaks at EBITDA, and

in ASC 230-10-42-2. This excludes the effects of long-term assets, which are included in investing activities (ASC 230-10-45-13).

[13] Notably, the NTAs identified by Lewellen and Resutek (2016) correspond to the components excluded by Ball and Nikolaev (2022) to improve the ability of earnings to predict next-period cash flows.

then declines for measures higher up, i.e., gross profit and sales. In the empirical analysis, we evaluate these predictions by comparing the alignment between alternative earnings measures and stock prices between firms with different asset structures and profitability.

2.2 Earnings adjusted for intangibles

Most investments in intangible assets are included as current expenses in the income statement, primarily as part of R&D and SG&A. The finance literature shows that investors attribute value to assets created through R&D and SG&A expenditures (Crouzet and Eberly, 2023; Eisfeldt and Papanikolaou, 2013; Peters and Taylor, 2017). Furthermore, the literature shows that the profitability measures adjusted for assumed investments in intangibles outperform the unadjusted measures in explaining the cross-section of stock returns in linear asset pricing models (Ball et al., 2015; Fama and French, 2015, 2018; Gulen et al., 2025; Jagannathan et al., 2026). Many studies assume industry- and firm-constant investment proportions, such as 100% of R&D (RD, Crouzet and Eberly, 2023), 100% of R&D and 30% of SG&A (RD+.3SGA, Crouzet and Eberly, 2023; Eisfeldt and Papanikolaou, 2013; Peters and Taylor, 2017), or 100% of both R&D and SG&A (RD+SGA, Eisfeldt et al., 2022).

Jagannathan et al. (2026) compare several profitability measures, both unadjusted and adjusted for different assumed investment proportions. Assessing the ability of adjusted earnings to predict future operating cash flows over horizons of up to ten years, they find that intangible-adjusted measures exhibit lower predictive power than EBTDA—the strongest-performing unadjusted measure—for horizons of up to three years but outperform EBTDA for horizons of four to ten years. This pattern is consistent with the idea that intangible investments require time before translating into cash flows. In linear asset pricing models, the intangible-adjusted profitability measures generate statistically and economically significant alphas relative to a broad set of benchmark models, with the RD and RD+.3SGA specifications performing best. The resulting model also reduces several asset pricing anomalies, such as price momentum.

The accounting literature on intangibles (see, e.g., Lev and Sougiannis, 1996; Lev and Zarowin, 1999; Lev and Gu, 2016) argues that the immediate expensing of investments in internally developed intangible assets leads to poor matching between investment outflows and cash inflows generated by these assets in subsequent periods (Green et al., 2022). According to this literature, the lack of matching has become increasingly consequential as intangible assets grow in economic importance (Srivastava, 2023). A proposed solution is to mimic the accounting treatment of tangible investments based on the view that matching works well for such assets. Consequently, several studies estimate firms' intangible

investments and amortize them over an assumed useful life. Some accounting studies apply an approach similar to that used in the asset pricing literature, imputing a fixed investment share of R&D or SG&A and using a single amortization period for all imputed assets (e.g. Green et al., 2022). Others estimate industry-specific capitalization and amortization rates based on their association with subsequent earnings (Banker et al., 2019; Gu et al., 2023; Lev and Sougiannis, 1996) or revenues (Iqbal et al., 2025). The standardized approach offers objectivity (Banker et al., 2019) and broad data availability (Peters and Taylor, 2017), but does not capture important industry-level differences (Banker et al., 2019; Iqbal et al., 2025).

Most studies that adjust for non-capitalized investments in intangibles modify both income statement and balance sheet items. However, Jagannathan et al. (2026) find that their profitability measures perform better when only earnings are adjusted and not book value. They argue that estimating the value of intangible assets involves substantial measurement error. Consistent with this view and their focus on EBTDA, they do not include any amortization of assets imputed in previous periods.

Based on previous research in asset pricing and accounting, we formulate several expectations for our empirical findings. First, the asset pricing literature suggests that market prices reflect both R&D expenditures and the investment-related portion of SG&A. Consequently, we expect EBITDA adjusted for investments in intangibles, and possibly gross profit, to provide a better summary of current performance as reflected in prices than unadjusted EBITDA. The improvement should be particularly pronounced for intangible-intensive firms. Second, given their substantial intangible investments, we also expect the difference between adjusted EBITDA and unadjusted EBITDA—as well as the difference between adjusted EBITDA and bottom-line earnings—to be considerably larger for intangible-intensive firms.

Third, drawing on the accounting literature on intangible capitalization, we expect earnings measures that incorporate imputed capitalization and amortization (e.g., adjusted EBIT) to better capture the information reflected in stock prices than unadjusted earnings or earnings adjusted only for capitalization without amortization. Conversely, to the extent that the low reliability of depreciation and amortization accruals makes EBITDA more informative than EBIT for tangible investments, we expect a similar pattern for intangibles. If so, adjusting for the initial investment without imposing a subsequent amortization should instead enhance the usefulness of the earnings (also supported by findings in Jagannathan et al., 2026). Fourth, approaches that apply industry-specific adjustments for intangible investment should outperform more standardized, one-size-fits-all methods.

2.3 Loss-making firms

The proportion of loss-making firms—defined as firms that report negative bottom-line earnings—has increased substantially over the past few decades (Gu et al., 2023, see also Figure 13, Appendix B). This trend is economically significant, and previous research shows that negative earnings are less informative to investors than positive earnings. When firms report losses, investors are less likely to use reported earnings for valuation, which makes earnings less useful for forecasting and valuation (Hayn, 1995; Joos and Plesko, 2005; Konstantinidi and Pope, 2016).

The literature distinguishes between transitory and persistent losses (Joos and Plesko, 2005), where transitory losses have a high probability of reversal. The two types of losses have different implications for the relationship between earnings and stock prices. Early work focused on persistent losses, analyzed within a framework of limited liability and investors' abandonment option (Hayn, 1995; Burgstahler and Dichev, 1997). In this framework, persistent losses signal financial distress, which makes it economically rational for investors to exercise the abandonment option or to curtail loss-making operations (Lawrence et al., 2018; Leung and Veenman, 2018). Consequently, the reported earnings of firms with persistent losses are largely uninformative about future prospects, leading to an earnings–returns relationship with a slope not statistically different from zero (Hayn, 1995). In contrast, transitory losses imply a lower likelihood of abandonment and are therefore potentially informative about future profitability and can exhibit a statistically significant association between earnings and prices.

Although early evidence is broadly consistent with the abandonment option view (Hayn, 1995), the literature quickly documented different empirical patterns. For example, abandonment is unusual in practice, and even firms that report recurring losses for several years remain active (Burgstahler and Dichev, 1997; Darrough and Ye, 2007). In addition, the relationship between losses and prices is on average both significant and negative (Burgstahler and Dichev, 1997; Joos and Plesko, 2005; Starica and Marton, 2025), i.e., higher losses are associated with higher prices. This suggests that the distinction between transitory and persistent losses is not as clear as initially assumed and that losses recurring over several years can signal future profitability (Darrough and Ye, 2007; Hiemann, 2020; Joos and Plesko, 2005; Leung and Veenman, 2018).

Hiemann (2020) theoretically explain the negative relationship through investors' expectations that investments (which may occur over several years) lead to future profitability. Higher current investments – resulting in higher current losses – are expected to lead to higher future profits, which explains the negative relationship. The theoretical model developed by Hiemann (2020) assumes unbiased accounting

and could therefore be applied to both cash flows and earnings. Investment periods often show negative cash flows that, if investments are successful, result in positive cash flows in later periods. Accruals moderate this effect through capitalization of cash outflows on the balance sheet, followed by matching of expenses to future periods when the cash inflows generated by the investments occur. This mechanism is particularly relevant for investments in intangible assets that are expensed rather than capitalized. Therefore, empirical studies of the negative relationship between earnings and prices focus on investments in intangibles that are not capitalized. For intangible-intensive firms, the earnings and cash flow effects are similar, with losses (negative cash flows) in the investment and buildup periods and profits (positive cash flows) in subsequent periods when the intangible assets generate returns. For example, Joos and Plesko (2005) show that investors see value in recurring losses with an R&D component, while Darrough and Ye (2007) find that non-capitalized R&D explains most of the negative association between losses and prices.

Starica and Marton (2025) confirms the theoretical prediction by Hiemann (2020) of a negative slope in the relationship between earnings and prices for the average firm. They also show that the slope is significantly steeper for high-tech firms (intangible-intensive) than for low-tech firms (tangible-intensive). This supports prior research showing that non-capitalized intangibles are an important explanation for the negative relationship. It also indicates that even in firms without significant intangible assets, other items can drive a negative relationship.

The literature suggests that investors can use different approaches to partly overcome difficulties in valuing loss-making firms. When bottom-line earnings do not fully capture the future prospects of firms, adjustments can be made to construct current-performance measures that are informative for valuation (Darrough and Ye, 2007). The literature considers several such adjustments, including non-GAAP earnings measures (Leung and Veenman, 2018) and earnings constructed through capitalization and amortization of intangible outlays (Green et al., 2022; Gu et al., 2023; Rajgopal et al., 2025). As discussed in Section 2.2, these studies assume that net income is the most informative summary measure of performance.

An alternative approach is to rely on earnings measures higher up in the income statement, such as EBITDA (cf., Section 2.1) or revenues (Ertimur et al., 2003; Jegadeesh and Livnat, 2006; Chandra and Ro, 2008; Kama, 2009). The analysis in Chandra and Ro (2008) indicates that revenue is useful as a summary measure for valuation purposes, particularly in extreme earnings situations (such as losses), especially for technology firms. Ertimur et al. (2003) and Kama (2009) document that investor reactions to revenue surprises are stronger than reactions to expense surprises and differ systematically between

growth and value firms, with growth firms responding more strongly. Jegadeesh and Livnat (2006) provide evidence that revenue surprises predict more persistent future earnings growth.

Based on previous research and the discussion above, we develop expectations for loss-making firms, including how losses interact with findings on disaggregation and intangible assets. Overall, we expect profits to reflect performance information in stock prices significantly better than losses. We also expect profits to be more informative than losses regardless of firms' asset structure, i.e., for both tangible- and intangible-intensive firms. The literature focuses on losses and profits in bottom-line earnings, and whether this difference applies to other earnings numbers is an empirical question (which we examine in Section 5.3). It is also unclear from the literature to what extent adjustments of non-capitalized investments in intangibles affect the usefulness of earnings higher up in the income statement. However, an expectation based on existing research is that the top number in the income statement—revenues—may be particularly useful to investors in loss-making firms.

3. Methodology

The objective of this study is to assess the relative pertinence of different earnings numbers for stock market investors. In empirical tests, we use stock prices as the benchmark for comparing different earnings measures. Stock prices are viewed as the most comprehensive benchmark under the assumption that they reflect the information contained in realized earnings about firm performance. Unlike alternative outcome measures, such as next–period operating cash flows, stock prices do not rely on any *ex ante* assumptions about investors' choice of which cash flows to predict or the time horizons in their predictions. Instead, stock prices reflect the aggregate outcome of investors' valuation processes. Thus, we assess the pertinence of earnings numbers by their ability to summarize information about performance, as reflected in stock prices.[14] Although the literature has historically used stock prices to evaluate the relative pertinence of performance measures (e.g., Dechow, 1994; Brown and Sivakumar, 2003), recent studies often use alternative benchmarks, such as next-period cash flows (e.g., Ball and Nikolaev, 2022; Nallareddy et al., 2020).

Using stock prices as a benchmark requires addressing several econometric challenges (Holthausen and Watts, 2001), as previous research shows that the relationship between earnings and stock prices is non-linear and varies between firms and time periods (Starica and Marton, 2025). To address these

[14] A common method in the literature is to relate change in earnings with returns, based on Easton and Harris (1991). However, Starica and Marton (2025) show that the slope of this relationship lacks any linear part, making it difficult to fit. Meanwhile, the relationship between prices and earnings has two largely linear parts, one for positive and one for negative earnings.

issues, we closely follow the research design of Starica and Marton (2025), which we outline step by step in this section.

We assume that stock prices contain multiple types of information, including (but not limited to) a component that reflects current firm performance and another that captures investors' expectations regarding future growth, risk, and the effects of accounting and economic factors. To disentangle these effects, we estimate the price relationship of each earnings measure conditional on the second component, that is, keeping growth, risk, accounting, and economic factors constant. We use these conditional relationships to generate out-of-sample price predictions for each earnings metric. The ability of an earnings number to summarize performance information is measured by the magnitude of its conditional price prediction error, where smaller errors indicate a closer alignment with the performance information reflected in market prices.

3.1 Non-linear, and firm- and time-specific relationships

To reflect the non-linearities in the relationship between earnings and prices[15], the research design in Starica and Marton (2025) models the relationship of the firm i at time t as a non-linear regression:

$$Mktv_{i,t} = f(X_{i,t}) + \epsilon, \tag{1}$$

where $Mktv$ is the price of the stock, X is a measure of earnings and f is a nonlinear regression function that is measure-specific: $f := f^{(X)}$.

The relationship of earnings with prices varies between firms driven by differences in industry, business model, growth rate, operating cycle length, and accounting policies (Ball and Nikolaev, 2022). The relationship also varies over time as the determinants change. The firm- and time-specific nature of the relationship means that it is observation-specific:[16]

$$f := f_{i,t}^{(X)}.$$

Consistent with theoretical models in the literature about the earnings–price relationship (Ohlson, 1995; Fischer and Verrecchia, 1997; Zhang, 2000; Breuer and Windisch, 2019; Hemmer and Labro, 2019; Hiemann, 2020), Starica and Marton (2025) allow the function f in Equation (1) to vary between

[15] It is intuitive that investors respond differently to varying levels of earnings—such as losses, average earnings, or unusually high profits—implying a nonlinear relationship between earnings and stock prices. (Fischer and Verrecchia, 1997; Zhang, 2000; Breuer and Windisch, 2019; Hemmer and Labro, 2019; Hiemann, 2020), and empirical studies confirm these predictions (Hayn, 1995; Burgstahler and Dichev, 1997; Starica and Marton, 2025).

[16] Traditional regression analysis assumes that all observations follow a single underlying functional relationship. When relationships are observation-specific, they do not provide a consistent pattern required for conventional regression modeling. In contrast, the methodological setup in Starica and Marton (2025) is designed to capture relationships that vary with each observation. The solution is to identify firms with similar projections of current-period earnings into future discounted cash flows. Such firms which display the same functional relationship between earnings and prices (peers) provide repeated observations of the relationship that can be used for regression analysis.

firms and over time through the values of proxies for key determinants of the relationship between earnings and prices (**Attributes**) (e.g., growth, risk, accounting policies, and economic determinants):[17]

$$f(y) = f_{i,\,t}^{(X)}(y) = g(y,\, \mathbf{Attributes}_{i,t}).$$

The function $g = g^{(X)}$ is specific to each earnings measure X and is assumed to remain constant over time, reflecting the economic stability of the conditional earnings-to-price relationship. Consistent estimation is achieved through an algorithm that infers the regression:

$$Mktv_j = g(X_j,\ \mathbf{Attributes}_j) + \varepsilon_j, \tag{2}$$

locally,[18] over the firms j in the cross section t with attribute values similar to the firm i. The magnitude of the error for the firm i at time t:

$$|\varepsilon_i| = |Mktv_i - g(X_i,\, \mathbf{Attributes}_i)|\,, \tag{3}$$

is a firm- and year-specific measure of how well earnings X summarize the performance of firm i as reflected in stock prices at time t, conditional on the growth, risk, accounting policies and economic profile of the firm. It is our measure of the usefulness of the earnings number X to investors. A lower error signals a higher ability of earnings to measure performance, as reflected in stock prices.

3.2 Comparison between different earnings measures

To assess the informational value of different earnings measures, we compare their out-of-sample prediction errors, conditional on firm's market-implied growth and risk, as well as accounting policies and economic determinants. For each cross-section t and earnings measure X, we estimate the regression (2) and produce the conditional out-of-sample[19] errors:

$$\varepsilon_{it}^{(X)} = Mktv_i - g^{(X)}(X_i,\, \mathbf{Attributes}_i),$$

where i covers all the firms in the cross-section t.

The size of the absolute error terms $|\varepsilon_i^{(X)}|$ is used to compare how well different earnings numbers summarize the performance of the firm, as reflected in its stock prices. The comparison between different measures is done in two different ways: comparisons between different earnings measures within the same firm, and comparisons of the same earnings number between different types of firms.

[17] Starica and Marton (2025) empirically identify the key variables that shape the functional relationship between earnings and stock prices. Specifically, they examine a wide set of variables identified by previous research as relevant proxies for the determinants of the shape of the relationship. From this set, they select those with the strongest influence on the shape of the relationship: the price-to-book ratio, leverage (long-term debt over the market value of equity) and the Fama-French 48 industry classification (see Section 4.2).

[18] By excluding firms with different attribute values and thus different earnings-to-price relationships, the local inference provides a consistent estimate of the firm i's mapping of earnings into prices at time t.

[19] The function g in the regression (2) is estimated on the cross-section t leaving out firm i. It is then evaluated at the value $(X_i,\, \mathbf{Attributes}_i)$ and subtracted from firm's market value to produce $\varepsilon_{it}^{(X)}$.

Comparison between earnings numbers within the same firm. In this setup, for each firm, we compare the absolute error of each earnings metric (other than the bottom line earnings E) against the absolute error of the bottom line earnings. The comparison is based on the difference between the two *mean absolute errors* (MAE),[20] calculated over the whole sample:

$$MAE(E) - MAE(X) := \sum_{i,t} |\varepsilon_{i,t}^{(E)}|/n - \sum_{i,t} |\varepsilon_{it}^{(X)}|/n = \sum_{i,t} \left(|\varepsilon_{i,t}^{(E)}| - |\varepsilon_{i,t}^{(X)}|\right)/n, \tag{4}$$

where the index i runs over all firms in cross-section t while n is the number of firm-year observations in the sample.

Under the null hypothesis:

> H_0 : *Earnings X and bottom line earnings E summarize a firm's performance (as reflected in prices) equally well.*

the statistic defined in (4) is not significantly different from zero. A strictly positive MAE difference implies that, for most firms, investors need to make smaller adjustments to predictions based on earnings X compared to those based on bottom line earnings E. Therefore, we interpret strictly positive values of the statistic as evidence that earnings X provide a better summary of firm performance, as reflected in stock prices, than E.

Comparison of the same earnings number between different type of firms. In this comparison, we assess the relative usefulness of each earnings measure across two types of firms ($i \in S_1$ and $j \in S_2$), such as tangible-intensive versus intangible-intensive firms or profitable versus loss-making firms. The comparison is performed over the entire sample and is formalized as follows:

$$MAE_{S_2}(X) - MAE_{S_1}(X) := \frac{\sum_{j \in S_2,t} |\varepsilon_{jt}^{(X)}|}{n_2} - \frac{\sum_{i \in S_1,t} |\varepsilon_{it}^{(X)}|}{n_1}, \tag{5}$$

where the index i represents firms of type 1, and j represents firms of type 2 in each cross section t. Here, n_1 is the total number of firm-years for type 1 firms, and n_2 is the corresponding number for the type 2 firms.

A strictly positive value of the statistic (5)[21] indicates that earnings X are a better summary of the performance of the firms, as reflected in stock prices, for type 1 firms compared to type 2 firms.

[20] There are potential alternative measures. The *Mean Absolute Error (MAE)* is one of the most widely used measures of forecast accuracy. Compared to, e.g., the *Root Mean Square Error (RMSE)*, MAE is less sensitive to outliers, making it particularly suitable for our analysis. Unlike an additional alternative measure, the *Mean Absolute Percentage Error (MAPE)*, MAE is more appropriate in our context because the predicted variable is already expressed as a relative price. For robustness and consistency with standard practices, we also performed our analysis using the $MAPE$ metric. The results align closely with those obtained with MAE.

[21] The statistic and its confidence intervals are derived through a robust regression of the absolute errors on an indicator variable representing intangible intensive firms or loss-making firms, while including fixed year effects in the regression model.

3.3 Choice of inference method

As explained above, the estimation method must satisfy two key criteria. First, it should be flexible, that is, adaptable to the data and capable of capturing complex nonlinear relationships without overfitting.[22] Second, it should enable local estimation by deriving the earnings-to-price relationship from a relevant set of peer firms with closely aligned attribute values. A method that meets these requirements will effectively capture the two essential features of the earnings-price relationship emphasized in the literature: (1) nonlinearity and (2) its firm- and time-specific nature.

Starica and Marton (2025) choose the Random Forest (RF) algorithm (Breiman, 2001; Hastie et al., 2009).[23] While several nonlinear regression methods provide consistent estimates of the regression function f in regression (1) (Györfi et al., 2002; James et al., 2013), the RF algorithm aligns with the logic of our research design. RF reliably captures the relationship of interest by first grouping firms with similar attributes and is then used to estimate the regression function within these groups by averaging the responses of peer firms. This approach yields a step-function approximation of the nonlinear, multidimensional regression function. For each observation, we use RF to generate an out-of-sample expectation or prediction of the price based on earnings, which is conditional on the additional predictor variables (PB, Lev, $FF48$, $SG\&A$, TG and $sign(E)$). Absolute errors are obtained by comparing the predicted and actual prices. Note that all variables, including $Mktv$ (price), are compared in the same period, so we do not make any prediction of future prices or returns. Instead, we use price as a measure of investors' predictions of discounted future cash flows.

3.4 Presentation of statistical tests

We substantiate our comparisons between earnings measures with formal statistical tests. Rather than presenting results in tables, as is commonly done in the accounting literature, we present the results in graphs. For statistics (4) and (5), the graphs show the earnings numbers on the x-axis and the statistic on the y-axis. The plots also display the 95% confidence intervals for the difference between the two expected absolute errors. The reason for the choice of presentation is that the statistics themselves are not in focus, and have no significance level. Instead, the statistics only make sense in relation to each other, and are only significant in terms of differences between individual statistics, which is made clear through graphs.

[22] This flexibility allows for identifying the earnings-to-price mapping without relying on *ex ante* assumptions, which makes it particularly useful for descriptive research.

[23] The algorithm has recently been introduced into accounting and finance research, with applications in studies such as Gu et al. (2020) and Barth et al. (2023).

This presentation approach shows results for two types of hypotheses. First, a confidence interval for the earnings measure X completely above (below) zero provides evidence that: (1) X is a superior (inferior) summary performance measure compared to E (bottom line earnings), based on the statistic (4); or (2) X summarizes performance more (less) effectively for type 1 firms compared to type 2 firms, according to the statistic (5).[24]

4. Variable measurement and sample description

In this section, we define the earnings measures and other variables used, provide an econometric specification of the regression (3), and provide descriptive statistics about the sample.

4.1 Variable definitions

This study aims to evaluate various earnings measures that are widely used and readily available to investors. We define these measures in several ways, with all the variable definitions provided in Table 1. First, we consider line items specified under US GAAP (ASC 225 *Income Statement*) and SEC Regulation S-X 5-03, including sales ($SALES$), gross profit (GP), operating income or EBIT ($OIBIT$), and net income or bottom line earnings (E).[25] These line items capture distinct aspects of financial performance: EBIT separates operating from nonoperating income, while gross profit, by excluding Selling, General & Administrative (SG&A) expenses, reflects only expenses directly related to the production or sale of goods and services.

Second, we examine non-GAAP earnings measures that are widely used in practice. In November 2024, the FASB issued an *Invitation to Comment* on non-GAAP performance indicators (FASB, 2024a), stating that the most commonly reported non-GAAP measure among listed firms is $EBITDA$. Bentley et al. (2018) and Dechow et al. (2024) document that the use of non-GAAP earnings has increased over time, with common exclusions including depreciation, amortization, and interest expense. Based on this information, we examine $OIBITDA$ (close to EBITDA), which represents operating income before the effects of recognized long-term assets, primarily capturing current operating performance. We also assess income before interest expense.

$OIBITDA$ removes the earnings effects of recognized tangible and intangible assets. However, a key limitation of this measure is that most internally developed intangible assets are not recognized,

[24] Confidence intervals may overlap even when point estimates are statistically different (e.g., Greenland et al., 2016), indicating that our approach to assessing statistical significance is conservative.

[25] While US GAAP does not explicitly define all line items, they can be easily derived from required disclosures and are typically presented on the face of the income statement.

noted both by standard setters—the FASB recently issued an *Invitation to Comment* on intangible asset recognition (FASB, 2024b)—and the academic literature (e.g., Lev and Zarowin, 1999; Green et al., 2022; Gu et al., 2023). To ensure comparability between recognized and unrecognized investments in long-term assets, previous research suggests adjusting for an assumed investment portion of $SG\&A$ expenses (Banker et al., 2019; Iqbal et al., 2025).

Following this approach, we construct $OIBITDA^+$ starting with $OIBITDA$ and excluding $R\&D$ expenditures and 50% of the remaining $SG\&A$, representing an assumed investment component (cf. Green et al., 2022; Falato et al., 2022; Peters and Taylor, 2017). We also test using industry-specific adjustments of the investment portion of R&D and SG&A, based on the method presented by Iqbal et al. (2025). Conceptually, $OIBITDA^+$ reflects operating income with all investment-related effects removed, regardless whether investments are recognized on the balance sheet or not. The variables used

Variable	Definition
$SALES$	Revenues: *revt*
GP	Gross profit (*gp*): SALES − cost of goods sold (*cogs*)
$OIBITDA^+$	Operating income (OI) adjusted for investment outlays in SG&A: *GP* $- 0.5 \times$ (selling, general & administrative expenses (*xsga*) − research & development (*xrd*))
$OIBITDA$	Operating income before interests, taxes, depreciation and amortization (*oibdp*): *GP* − *xsga*
$OIBIT$	Operating income before interests and taxes (after depreciation and amortization) (*oiadp*): *OIBITDA* − depreciation expenses (*dp*)
$OIAI$	Income after interest (and before nonoperating income): *OIBIT* - interest and related expense (*xint*)
PI	Pretax Income: $OIAI$ + nonoperating income (*nopi*) + special items (*spi*)
E (bottom line)	Income before extraordinary items (*ib*): PI − income taxes (*txt*)
$Mktv$	Price: Number of outstanding common shares (*csho*) × closing price three months after the end of financial year (CRSP *prccm*)
B	Book value of equity (*ceq*)
TA	Total assets (*at*)
Lev	Leverage: Total liabilities (*lt*) / market value of equity (P)
$SG\&A$	$SG\&A$ intensity: $SG\&A$ outlays (*xsga*) / *revt*
TG	Asset tangibility: PPE investments (*ppent*) / *at*

Table 1: **Variable definitions.** All variables are from Compustat's Fundamentals Annual database, except where noted.

in the empirical estimation are shown in Table 1. In addition to different earnings numbers, they include price, obtained three months after the end of the fiscal year, book value of equity (used to calculate price-to-book and for scaling), total assets (used for scaling), and leverage. $SG\&A$ intensity is a measure of the assumed importance of intangible assets, while TG measures the importance of tangible assets. In addition, we use the Fama-French 48 and 5 industry portfolios ($FF48$ and $FF5$).

4.2 Econometric specification of the earnings–price regression

The main attributes determining the shape of the relationship between earnings and prices include growth, risk, accounting policies, and economic determinants (e.g., capital investment typology or industry characteristics). Following Starica and Marton (2025), we include the price-to-book ratio (PB), leverage (long-term debt over the market value of equity, Lev), and the Fama-French 48 industry classification ($FF48$) as proxies for these attributes in our empirical application.[26] The price-to-book ratio is a proxy for growth and risk, and unconditional accounting conservatism.[27] Industry is as a proxy for growth, risk and accounting determinants such as conservatism and accrual quality, as well as economic determinants (types of productive capital, capital intensity, barriers to entry, concentration, etc.). Leverage reflects financial risk and indirectly accounts for economic risk and the type of firm capital investments.[28]

Our empirical analysis seeks to capture systematic variation in the earnings–price relationship based on the firm's capital investment profile (intangible vs. tangible intensive) and profitability status. To better account for this variation, we include three additional independent variables: SG&A intensity ($SG\&A$) and asset tangibility (TG), which proxy for the type of productive capital, and an indicator for the sign of bottom line earnings ($sign(E)$). SG&A intensity ($SG\&A$) is measured as the ratio of SG&A expenses (Compustat $xsga$) to revenue ($revt$), while asset tangibility (TG) is defined as the ratio of property, plant and equipment (PPE) (Compustat $ppent$) to total assets (at).

To address scale[29] and enhance comparability among firms, we use the market value of the prior period as a size proxy and deflate both the current prices and the earnings numbers with this variable (cf. Dechow, 1994; Starica and Marton, 2025).[30] This results in the following cross-sectional regression specification:

$$Mktv_i/Mktv_{i,-1} = g\Big(X_i/Mktv_{i,-1};\ PB_i,\ Lev_i,\ FF48_i, SG\&A_i, TG_i, sign(E)_i\Big) + \varepsilon_i, \qquad (6)$$

[26] These three variables act as proxies for well-established determinants of the earnings–price relationship recognized in the accounting and finance literature.

[27] Variation in the price-to-book (PB) ratio can also be attributed to differences in firm-specific economic rents. In our econometric specification of the regression (2) in equation (6), earnings are scaled by a measure of firm size, which effectively controls for differences in economic rents. As a result, in our setup, the remaining variation in the PB ratio captures mainly differences in expected growth and risk (and conservatism.

[28] Companies with low leverage are frequently small, have high levels of intangible investments, large investment opportunities, high volatility, or develop unique products (Harris and Raviv, 1991; Rajan and Zingales, 1995).

[29] Scale, a core concept in accounting research (e.g., Barth and Kallapur, 1996; Barth and Clinch, 2009; Brown et al., 1999; Christie, 1987; Easton, 1998; Easton and Sommers, 2003; Lev and Sunder, 1979; Penman et al., 2018; Stigler, 1968), refers to the size of variables within an observation. Although scale may not always be the central focus, it can have a substantial impact on the interpretation of relationships. For further discussion on the importance of considering scale, see Starica and Marton (2025).

[30] As robustness we scale with alternative measures proposed in the literature—book value and total assets—and results are unaffected by the choice of scaling variable.

where X denotes the earnings number, $sign(E)$, the sign of bottom line earnings, the index -1 identifies the prior period, the cross-section ranges from 1988 to 2023, and $g = g^{(X)}$ is a multivariate non-linear earnings-specific function estimated using the Random Forest algorithm. This approach enables us to account for firm-specific characteristics, thus achieving a more accurate estimation of the earnings-to-price relationship.

4.3 Sample description

The sample, drawn from Compustat (accounting data) and CRSP (stock prices), spans 36 years from 1988 to 2023[31] and includes all firm-year observations (excluding financial firms) with available data for the required earnings measures and additional variables needed to calculate the statistic in Equation (6). Following Dechow (1994), we exclude firm observations that fall within the most extreme one percent (0.5 percent in each tail) of the deflated price and earnings measures. The final sample comprises 87,165 firm-year observations, representing 10,601 distinct firms, with an average of 2,421 firm observations per year.

Table 2 displays the summary statistics of the price and independent variables other than earnings in the regression (6) (Panel A) and the different earnings measures (Panel B).

Variable	Mean	SD	10%	25%	50%	75%	90%
Panel A: Variables in regression (6) (other than earnings)							
$MKTV$	1.20	0.83	0.49	0.74	1.04	1.40	1.99
PB	2.91	7.02	0.61	1.13	1.97	3.52	6.46
LEV	1.03	1.79	0.09	0.20	0.48	1.09	2.31
$SG\&A$	0.40	0.72	0.08	0.14	0.25	0.41	0.68
TG	0.26	0.22	0.04	0.09	0.20	0.37	0.60
Panel B: Earnings measures							
E	-0.03	0.23	-0.22	-0.04	0.04	0.07	0.11
PI	-0.01	0.26	-0.24	-0.04	0.05	0.10	0.17
$OIAI$	0.01	0.20	-0.18	-0.03	0.05	0.10	0.15
$OIBIT$	0.05	0.20	-0.14	-0.00	0.07	0.13	0.21
$OIBITDA$	0.12	0.23	-0.08	0.04	0.11	0.20	0.33
$OIBITDA+$	0.35	0.37	0.05	0.14	0.25	0.44	0.74
GP	0.54	0.60	0.10	0.20	0.36	0.65	1.16
$SALES$	1.89	2.47	0.22	0.48	1.06	2.26	4.40

Table 2: **Descriptive statistics.** *Panel A:* Variables (other than earnings) used to estimate the regression (6). *Panel B:* Firms' earnings measures.

It shows the substantial proportion of loss-making firms (measured by bottom line earnings E) in

[31] As shown in Appendix A, the stock market has been relatively stable both in terms of SG&A intensity and earnings for this sample period.

the sample, as the 25th percentile and the average firm exhibit negative earnings.[32] The PB shows that price is, on average, almost three times higher than book value of equity. Many variables display skewness, with means that are notably higher or lower than medians. Table 3 presents the Spearman

	$MKTV$	PB	LEV	SGA	TG	E	PI	$OI-AI$	$OI-BIT$	$OI-BITDA$	$OI-BITDA^+$	GP	$SALE$
$MKTV$	1.00	0.16	-0.22	-0.01	-0.03	0.06	0.07	0.07	0.11	0.16	0.21	0.19	0.13
PB	0.39	1.00	-0.13	0.06	-0.06	0.04	0.03	0.02	-0.02	-0.06	-0.11	-0.11	-0.12
LEV	-0.31	-0.54	1.00	-0.09	0.13	-0.30	-0.29	-0.26	0.01	0.22	0.38	0.39	0.45
$SG\&A$	-0.08	0.14	-0.34	1.00	-0.15	-0.24	-0.25	-0.31	-0.35	-0.36	-0.19	-0.13	-0.18
TG	-0.01	-0.10	0.23	-0.38	1.00	0.02	0.02	0.01	0.08	0.24	0.06	0.00	0.03
E	0.31	0.09	-0.07	-0.39	0.09	1.00	0.97	0.82	0.73	0.52	0.10	-0.04	-0.07
PI	0.31	0.08	-0.07	-0.40	0.10	0.97	1.00	0.84	0.75	0.55	0.13	-0.01	-0.04
$OIAI$	0.30	0.09	-0.03	-0.43	0.09	0.87	0.90	1.00	0.91	0.69	0.22	0.05	0.00
$OIBIT$	0.29	-0.02	0.20	-0.50	0.17	0.79	0.82	0.91	1.00	0.89	0.47	0.28	0.22
$OIBITDA$	0.28	-0.16	0.38	-0.54	0.32	0.66	0.68	0.76	0.91	1.00	0.68	0.49	0.41
$OIBITDA+$	0.24	-0.31	0.49	-0.22	0.14	0.38	0.40	0.46	0.61	0.75	1.00	0.97	0.74
GP	0.20	-0.35	0.51	-0.12	0.08	0.26	0.28	0.33	0.48	0.61	0.96	1.00	0.77
$SALES$	0.14	-0.42	0.62	-0.46	0.16	0.22	0.24	0.28	0.44	0.57	0.81	0.85	1.00

Table 3: **Correlation between variables in the analysis.** The list includes variables used in the regression (6), including earnings measures. *Upper triangle:* Pearson correlation, *Lower triangle:* Spearman correlation. Earnings measures and price ($MKTV$) are scaled by beginning of period market value. All correlations bigger than 0.02 in absolute value are statistically significant.

(lower triangle) and Pearson (upper triangle) correlations among the variables used in the regression (6) and earnings measures.[33] Although both Pearson and Spearman correlations are reported for consistency with the existing literature, Pearson correlations may be less reliable due to skewness in the distributions of many variables, as shown by the descriptive statistics in Table 2.

As expected, prices show a positive Spearman correlation with earnings measures and the price-to-book ratio, while they are negatively correlated with leverage. The price-to-book ratio and leverage are also negatively correlated, reflecting that firms with high price-to-book ratios are typically intangible intensive and thus have low leverage due to limited collateral for borrowing (Harris and Raviv, 1991; Rajan and Zingales, 1995).

5. Empirical results

In this section, we present results from two different types of tests. First, we compare the usefulness of different earnings numbers, keeping the sample of firms constant (Section 5.1). Second, we present a

[32] Such firms exhibit a statistically distinct relationship between earnings and price (Burgstahler and Dichev, 1997; Hayn, 1995; Hiemann, 2020), which introduces significant nonlinearity in the overall mapping of earnings to prices. Therefore, the simplifying assumption of linearity, which is fundamental to the research design in Dechow (1994), is open to question.

[33] The correlations in Table 3 should be interpreted with caution, as they may not fully capture the relationships between variables. Although correlation summarizes linear dependence well, some variables are related nonlinearly

comparison between different types of firms, keeping the earnings numbers constant (Section 5.2). We also report results on additional tests related to recognition of intangible assets (Section 5.3).

5.1 Comparison of earnings numbers within firms

The graphs in this section display the mean gain in price-prediction accuracy (Equation 4) of various earnings measures (both those reported in the income statement and adjusted measures such as $OIBITDA$ and $OIBITDA^{+}$) relative to bottom-line earnings. Each statistic is shown as a circle, accompanied by 95% confidence intervals represented by vertical lines.

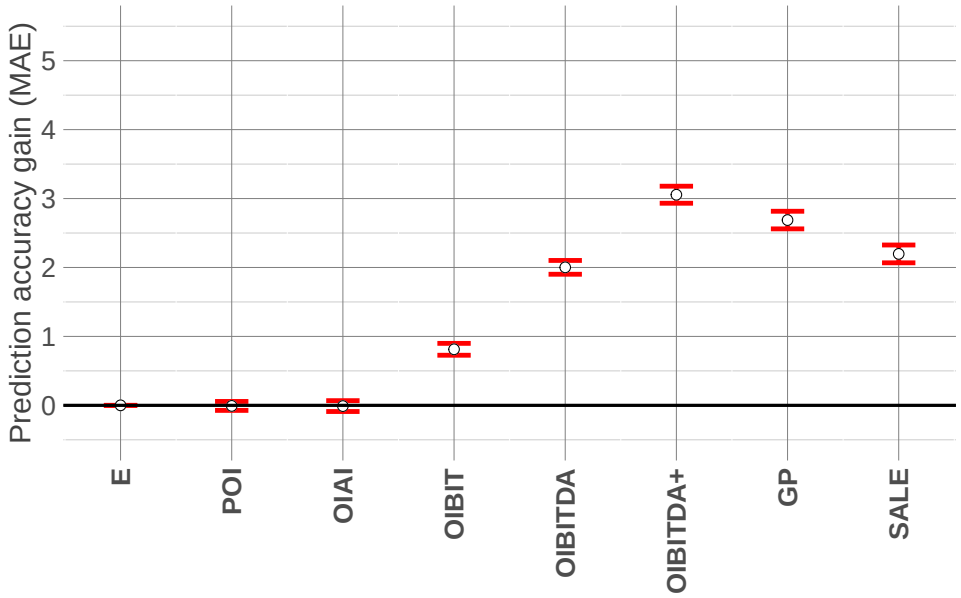


Figure 1: **Relative difference in price prediction accuracy of income statement and adjusted earnings compared to bottom line earnings.** The plot displays the sample mean gain in price prediction accuracy (Equation (4)) for income statement and adjusted earnings numbers relative to bottom line earnings E. The mean gain is represented by circles, while the corresponding 95% confidence intervals are shown as vertical segments centered around the statistic. A confidence interval entirely above 0 indicates that the earnings number is significantly better at summarizing performance compared to bottom line earnings.

Figure 1 presents the results for the full-sample analysis of the usefulness of different earnings measures. Earnings measures located near the bottom of the income statement (PI, $OIAI$, and $OIBIT$) exhibit little to no improvement over bottom-line earnings. In contrast, measures higher up the income statement ($OIBITDA$, $OIBITDA^{+}$, GP, and $SALE$) provide substantially more informative summaries of firm performance. In particular, $OIBITDA^{+}$, which reflects operating earnings while excluding both actual and imputed effects of long-term assets, provides the best summary of firm performance as reflected in prices.

These findings are consistent with our first prediction in Section 2.1, i.e., that operating income

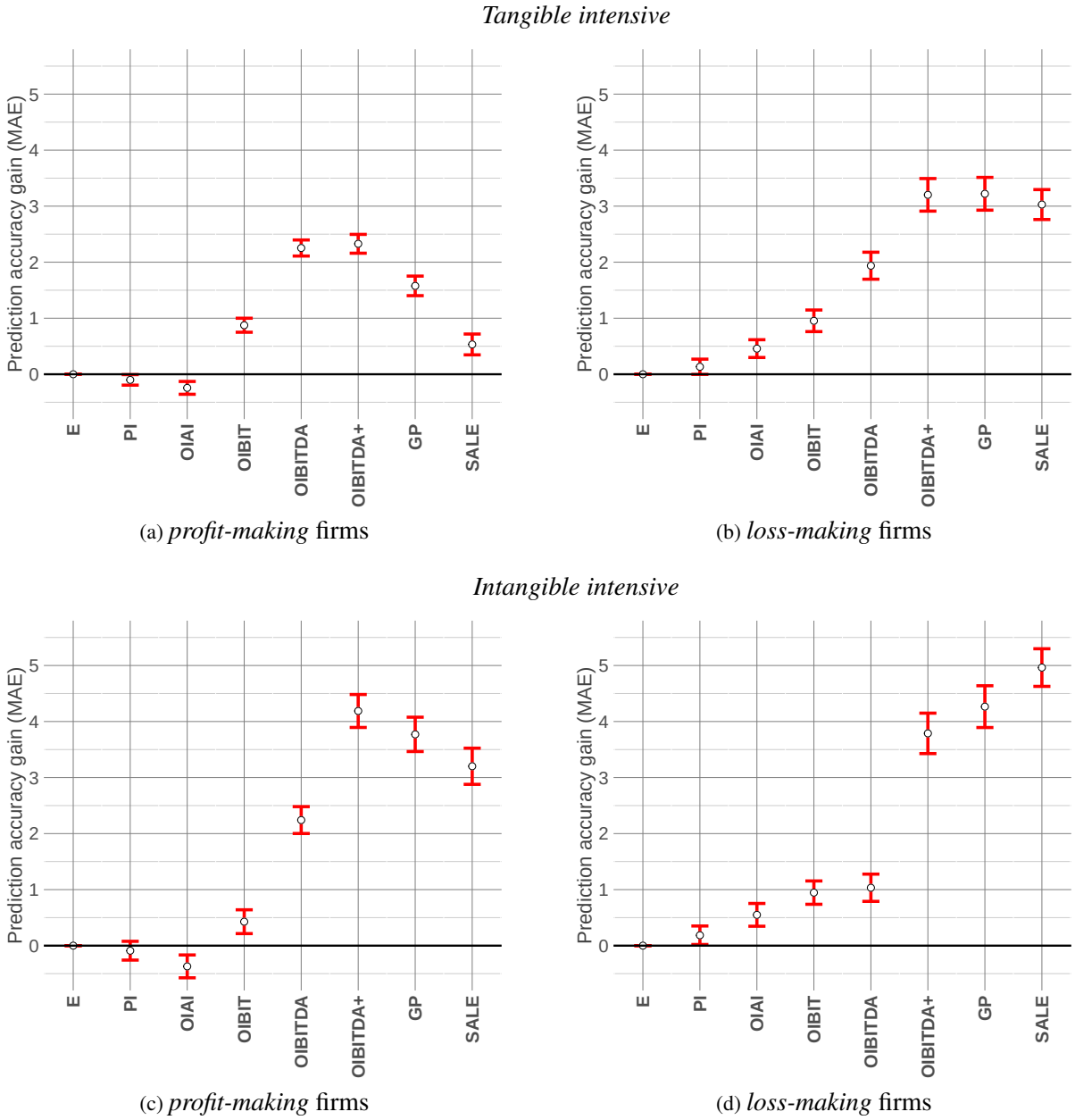
is a better summary of firm performance than bottom line earnings. Section 2.1 also discusses that the literature points in different directions regarding adjustments for recurring vs. non-recurring items. The finding that $OIBITDA$ is more useful than $OIBIT$ shows that adjustment for recurring items—depreciation and amortization—is helpful to investors. This is consistent with the argument by Lewellen and Resutek (2016) that non-transactional accruals—such as depreciation—are less reliable than transactional accruals—such as initial recognition of the investment in long-term assets. Richardson et al. (2005) show that accruals with lower reliability are associated with lower earnings persistence, potentially making such accruals less useful for valuation. Meanwhile, the findings appear to contradict a basic assumption in much of the non-GAAP literature that only non-recurring items should be adjusted for (Dechow et al., 2024; Laurion and Sloan, 2022). Furthermore, findings in Figure 1 are consistent with the third expectation in Section 2.2, as $OIBITDA^+$ (which is $OIBITDA$ adjusted for investments in unrecognized intangible assets) is more informative than $OIBITDA$

The literature distinguishes between intangible and tangible intensive firms (Lev and Zarowin, 1999; Lev and Gu, 2016), as well as between loss-making and profit-making firms (Hayn, 1995; Starica and Marton, 2025), when analyzing the relationship between prices and earnings. To explore these distinctions, Figure 2 shows the results of an analysis of how well various earnings numbers summarize firm's performance (compared to bottom line earnings) conditional jointly on tangibility and profitability.[34] We classify observations into four different groups: tangible intensive and profitable (graph (a)), tangible intensive and loss-making (graph (b)), intangible intensive and profitable (graph (c)), and intangible intensive and loss-making (graph (d)).

To analyze the difference between tangible- and intangible-intensive firms, we compare the pair of graphs (a) and (b) with the pair of graphs (c) and (d) in Figure 2. The comparisons indicate substantial similarities between the two types of firms. The main distinction related to tangibility among profit-making firms is that $OIBITDA$ matches $OIBITDA^+$ in usefulness for tangible intensive firms, whereas it is strictly less effective for intangible intensive firms. Among loss-making firms, $OIBITDA$ performs significantly better for tangible intensive firms.

We analyze the difference between profitable and loss-making firms by comparing the pair of graphs (a) and (c) with the pair of graphs (b) and (d) in Figure 2. For profitable firms, the ability of the earnings numbers to summarize firm performance as reflected in stock prices improves monotonically as we move "up" the income statement until $OIBITDA^+$, after which it declines for GP and $SALE$.

[34] We use the Fama-French five-industry classification ($FF5$) to identify tangible and intangible intensive firms, Appendix B indicates that our use of $FF5$ is reasonable. Profitability is based on the sign of bottom line earnings.



(a) *profit-making* firms (b) *loss-making* firms

(c) *profit-making* firms (d) *loss-making* firms

Figure 2: **Relative difference in price prediction accuracy of income statement and adjusted earnings over bottom line earnings, jointly conditional on the firm's profitability and tangibility.** The plots display the sample mean gain in price prediction accuracy (Equation 4) for income statement and adjusted earnings numbers relative to bottom line earnings E. The mean gain is represented by circles, while the corresponding 95% confidence intervals are shown as vertical segments centered around the statistic. A confidence interval entirely above 0 indicates that the earnings number is significantly better at summarizing performance compared to bottom line earnings. Based on the Fama-French five-industry classification, firms in industries 1, 2, and 5 are classified as tangible intensive, while those in industries 3 and 4 are classified as intangible intensive. Profitability is based on the sign of bottom line earning (E).

For loss-making firms, there is a monotonic pattern, with the top three measures summarizing performance significantly better than those closer to bottom line earnings. Figure 2 shows that the most informative current-performance measures for loss-making firms do not vary systematically across intangible- and tangible-intensive firms. Regardless of asset structure, $OIBITDA^{+}$, gross profit, and

revenues align most closely with the prices of loss-making firms.

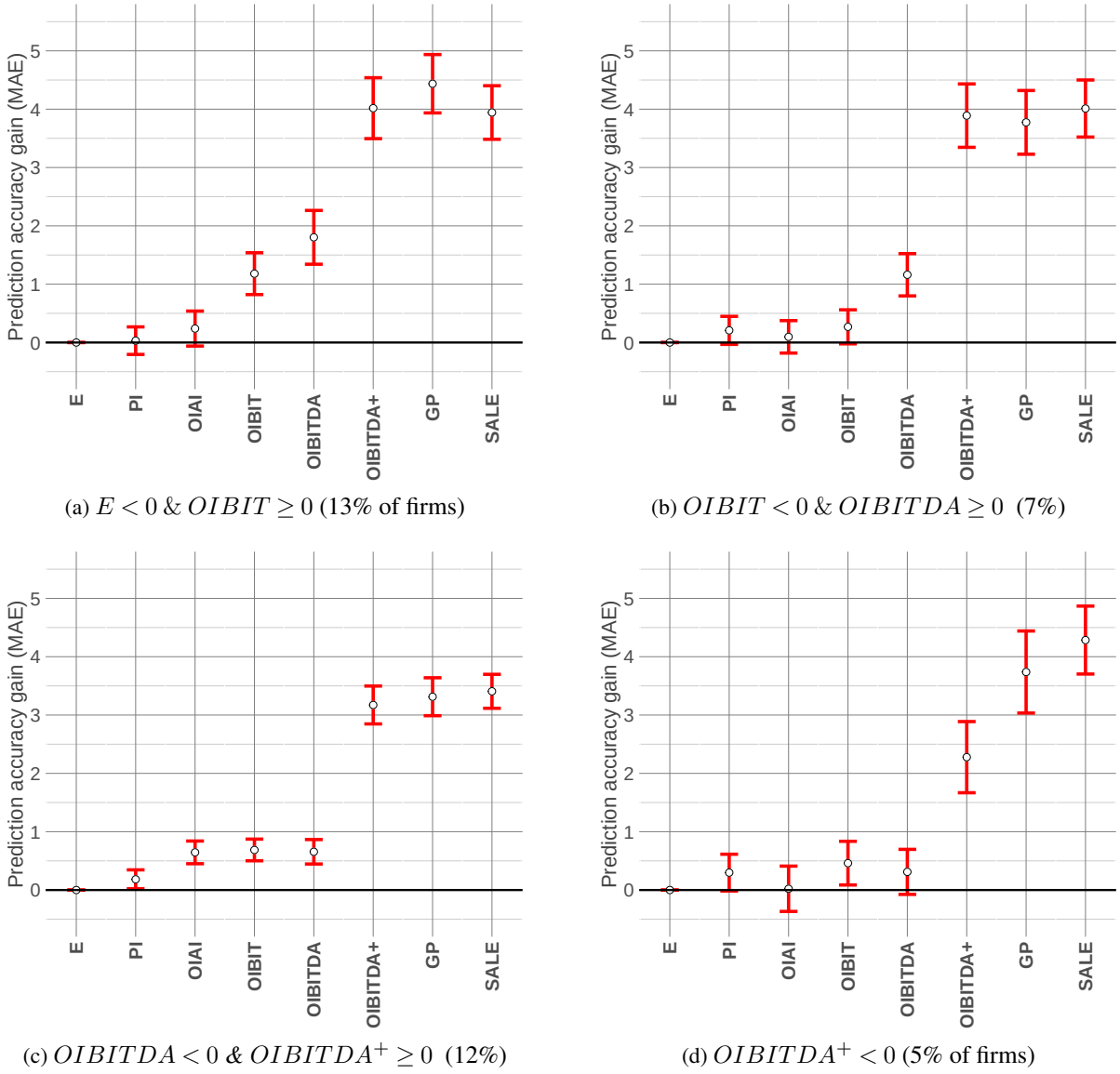
Finally, the pattern for profitable firms is similar to the pattern for all firms, shown in Figure 1, while the pattern for loss-making firms is not. This pattern reflects the cross-sectional composition of the data, where profitable firms outnumber loss-making firms, causing the results to be driven largely by the behavior of profit-making firms.

Figure 2 shows three main results. First, for both profit-making and loss-making firms, the patterns are broadly similar across tangible-intensive and intangible-intensive firms. Second, the patterns for profit-making and loss-making firms differ significantly (additional analyses conditioning solely on profitability or solely on asset type are reported in the Appendix). Third, the improvement of the most informative current-performance measures over bottom-line earnings is significantly larger for intangible-intensive than for tangible-intensive firms, regardless of profitability, and significantly larger for loss-making than for profit-making firms, regardless of asset type. This pattern is consistent with evidence from the non-GAAP literature, which finds that non-GAAP earnings provide relatively more incremental information about future performance for loss-making firms than for profitable firms (Leung and Veenman, 2018).

In Figure 3, we examine the usefulness of earnings measures for intangible-intensive firms that report bottom-line losses but positive earnings at higher levels of the income statement. For these firms, reported losses can reflect the immediate expensing of intangible investments that are not recognized on the balance sheet, thereby affecting which components of the income statement remain positive. For example, Gu et al. (2023) argue that when reported losses arise from the expensing of intangible investments, earnings adjusted to capitalize and amortize those investments are as informative as the earnings of profitable firms.

To assess how the source of the loss affects the informativeness, we divide loss-making firms ($E < 0$) into four categories based on the income statement item at which the earnings first become negative. The first group includes firms with positive $OIBIT$, where losses are driven by special items or nonoperating components. The second group comprises firms with negative $OIBIT$ but positive $OIBITDA$, indicating that losses arise from the depreciation and amortization accrual. The third group includes firms with negative $OIBITDA$ but positive $OIBITDA^{+}$, where losses are attributable to the expensing of intangible investments. The final group consists of firms with negative $OIBITDA^{+}$, indicating that losses arise after expensing the operational component of SG&A.

The results indicate that the pattern documented in panel (d) of Figure 2 holds in all four groups. For firms reporting bottom-line losses, the pricing behavior of earnings measures does not vary with



(a) $E < 0$ & $OIBIT \geq 0$ (13% of firms)

(b) $OIBIT < 0$ & $OIBITDA \geq 0$ (7%)

(c) $OIBITDA < 0$ & $OIBITDA^{+} \geq 0$ (12%)

(d) $OIBITDA^{+} < 0$ (5% of firms)

Figure 3: **Relative difference in price prediction accuracy of income statement and adjusted earnings over bottom line earnings for loss-making intangible intensive firms.** The plots display the sample mean gain in price prediction accuracy (Equation 4) for income statement line items, $OIBITDA$ and $OIBITDA^{+}$ relative to bottom line earnings E. The mean gain is represented by circles, while the corresponding 95% confidence intervals are shown as vertical segments centered around the statistic. A confidence interval entirely above 0 indicates that the earnings number is significantly better at summarizing performance compared to bottom line earnings. Based on the Fama-French five-industry classification, firms in industries 1, 2, and 5 are classified as tangible intensive, while those in industries 3 and 4 are classified as intangible intensive. Firms are classified by losses at different earnings measures, as indicated by graph captions.

profitability at higher levels of the income statement. In particular, the expensing of intangible investments drives losses for firms with $OIBITDA < 0$ but $OIBITDA^{+} \geq 0$, whereas it is unlikely to be the source of losses for firms with $OIBITDA^{+} < 0$. Nevertheless, in both cases, stock prices are more closely aligned with profitability measures higher up in the income statement. This finding suggests that, from the market's perspective, losses attributable to the expensing of intangible investments (accounting

losses) do not differ in informational content from losses reflecting underlying operating weakness (real losses), which contrasts with the interpretation in Gu et al. (2023).[35]

In summary, the analysis in this section shows that bottom line earnings are the least effective earnings measure of firm performance, as reflected in stock prices. The earnings numbers at the bottom of the income statement (PI, $OIAI$, and $OIBIT$) have little or no improvement over the bottom line earnings. In contrast, the earnings numbers higher on the income statement ($OIBITDA$, $OIBITDA^+$, GP, and $SALE$) provide significantly better summaries of firm performance. Among these, $OIBITDA^+$ stands out as the most effective summary measure when considering all firms.

The results reveal two distinct patterns in how effectively earnings measures summarize firm performance, as reflected in stock prices, and these patterns are independent of firms' tangibility (as proxied by the Fama–French five-industry classification). For profitable firms, effectiveness peaks at $OIBITDA^+$. This finding reinforces prior evidence that investors try to disentangle the investment component of operating expenses—particularly SG&A—from current-period performance (Banker et al., 2019; Iqbal et al., 2025). For loss-making firms, gross profit and sales are statistically indistinguishable in their alignment with prices. This pattern is intuitive: when firms report losses, investors appear to place greater weight on revenues than on negative bottom-line earnings when assessing current performance.

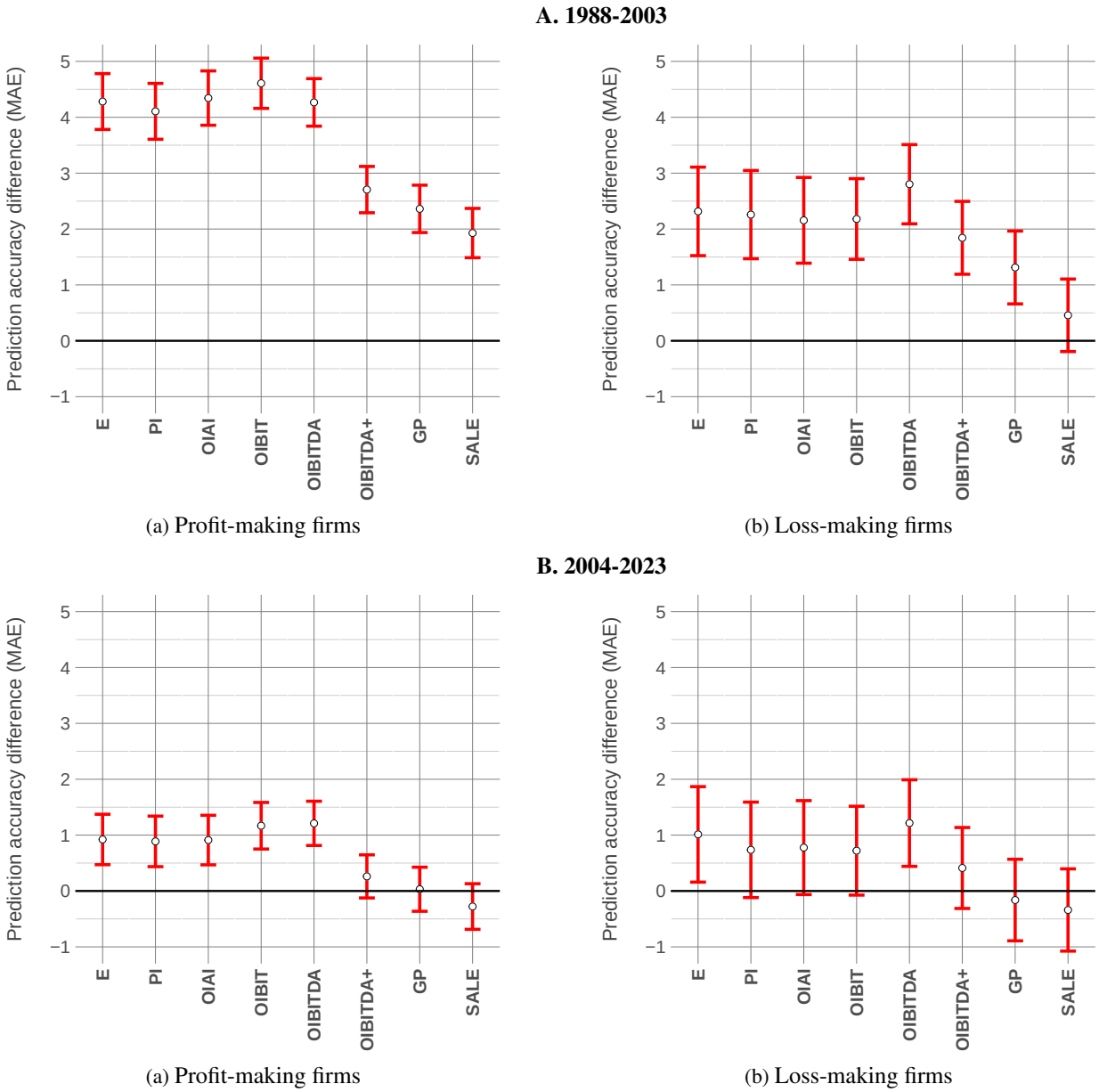
5.2 Comparison of the same earnings measures between different types of firms

The analysis in Section 5.1 documents how various earnings measures align with prices relative to bottom-line earnings, both for the full sample and within specific types of firms. In this section, we shift focus and compare the usefulness of a given earnings measure between different types of firms.

In Figure 4, we compare the usefulness of earnings measures for tangible and intangible intensive firms, conditional on profitability. For the early years of the sample (Panel A), earnings from tangible intensive firms provide significantly more informative summaries of performance than those from intangible intensive firms, particularly among profit-making firms. Over the past two decades, however, this difference has narrowed substantially (Panel B).[36] For the most informative measures ($OIBITDA^+$ among profitable firms and $OIBITDA^+$, GP and $SALE$ among loss-making firms, see Figure 2) there are no significant differences in usefulness between the two types of firms. These findings lead us to conclude that, in recent years, the earnings measures most relevant to investors have become equally

[35] For a detailed discussion reconciling our findings with those of Gu et al. (2023), see Section **??**.

[36] The break in the sample was determined empirically. It is intuitively plausible that the improvement in earnings usefulness for intangible intensive firms relative to tangible intensive for the most recent period reflects broader changes in market dynamics following the dot-com bubble in the early 2000's.



(a) Profit-making firms

(b) Loss-making firms

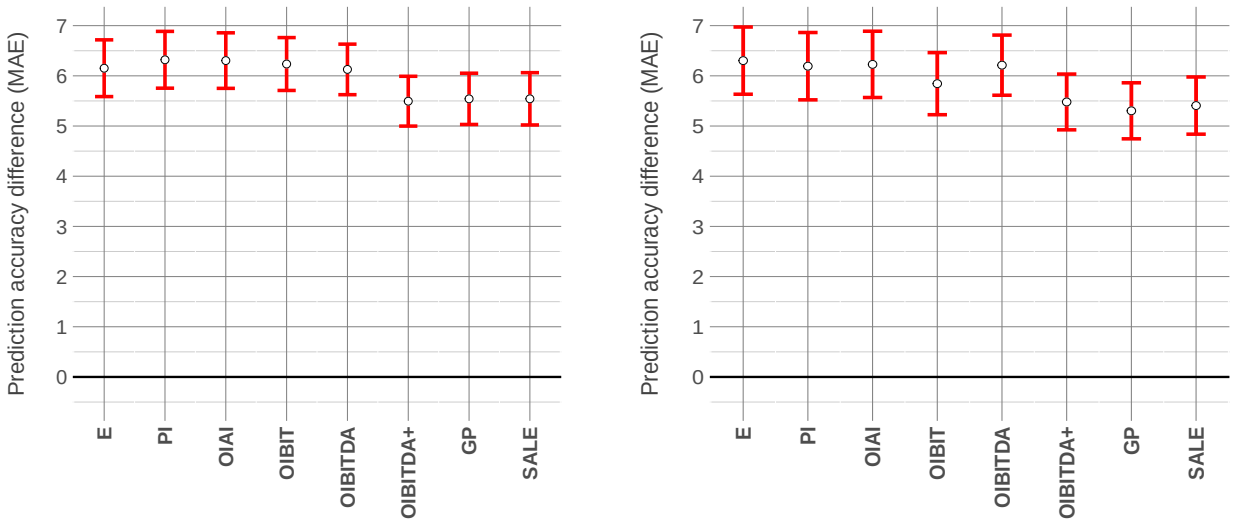
(a) Profit-making firms

(b) Loss-making firms

Figure 4: **Comparison of the same earnings numbers for tangible intensive vs. intangible intensive firms.** The plots display the sample mean gain in price prediction accuracy (Equation (5)) for different earnings numbers in tangible intensive firms relative to earnings in intangible intensive firms, divided into profit-making (graphs (a)) and loss-making (graphs (b)). The mean gain is represented by circles, while the corresponding 95% confidence intervals are shown as vertical segments centered around the statistic. A confidence interval entirely above 0 indicates that the earnings number is significantly better at summarizing performance in tangible intensive firms compared to intangible intensive firms. Based on the Fama-French five-industry classification, firms in industries 1, 2, and 5 are classified as tangible intensive, while those in industries 3 and 4 are classified as intangible intensive. Observations are classified by periods, as indicated by panel captions.

effective in summarizing firm profitability for both tangible and intangible intensive firms. We also observe that bottom line earnings, the primary focus of much of the prior literature, more effectively reflect the information embedded in stock prices for tangible intensive firms, consistent with existing findings in the literature.

In Figure 5, we compare the effectiveness of individual earnings measures in summarizing perfor-



(a) Tangible intensive firms

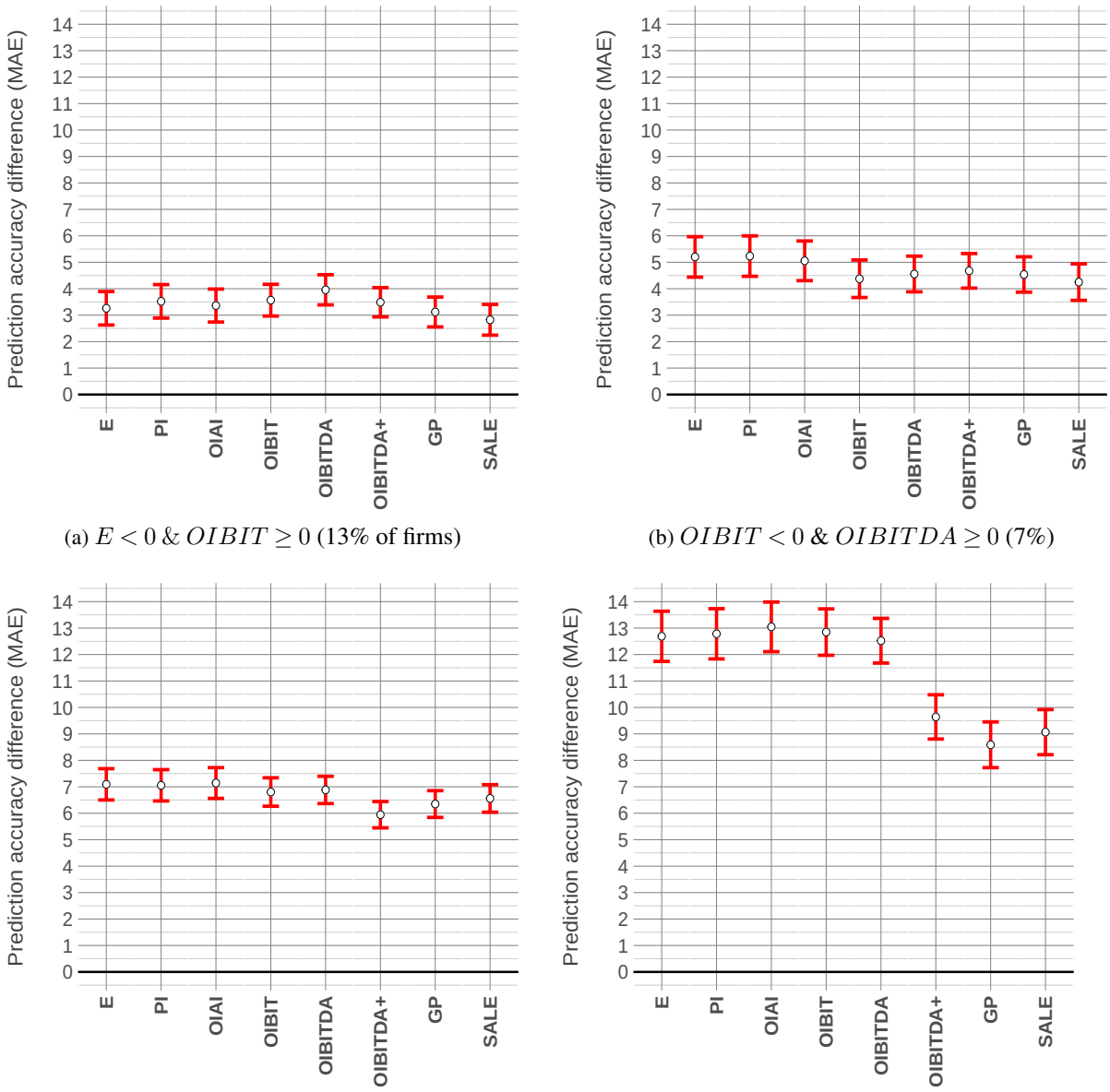
(b) Intangible intensive firms

Figure 5: **Comparison of the same earnings numbers for profit-making vs. loss-making firms.** The plots display the sample mean gain in price prediction accuracy (Equation (5)) for different earnings numbers in profit-making firms relative to earnings in loss-making firms, divided into tangible intensive (graph (a)) and intangible intensive (graphs (b)). The mean gain is represented by circles, while the corresponding 95% confidence intervals are shown as vertical segments centered around the statistic. A confidence interval entirely above 0 indicates that the earnings number is significantly better at summarizing performance in profit-making firms compared to loss-making firms. Based on the Fama-French five-industry classification, firms in industries 1, 2, and 5 are classified as tangible intensive, while those in industries 3 and 4 are classified as intangible intensive. Profitability is based on the sign of bottom line earning (E).

mance between profit-making and loss-making firms. The pattern is independent of the asset structure of the firm. For each measure, the earnings of profit-making firms more accurately reflect the underlying performance than those of loss-making firms. This is consistent with the first expectation in Section 2.3.

Figure 6 compares the same set of earnings measures for profit-making firms ($E \geq 0$) and for several categories of loss-making firms, where losses are defined with respect to different earnings measures. We find that the advantage of earnings measures for profitable firms increases the higher up the income statement the losses arise: the earlier the losses appear, the larger the performance gap between profit and loss firms. The pattern is independent of the asset structure of the firm.

In summary, our findings support the existing results in the literature that losses are less useful for valuation than positive earnings (Hayn, 1995; Gu et al., 2023). However, our findings both refine and, in part, contradict the common belief that earnings are less useful for intangible intensive firms (e.g. Srivastava, 2014; Lev and Gu, 2016; Green et al., 2022; Gu et al., 2023). In particular, the results suggest that investors can rely on earnings adjusted for investments in all long-term assets (both tangible and intangible) ($OIBITDA^{+}$) to offset the potentially adverse effects of unrecognized intangible assets. These adjusted earnings measures are equally informative regardless of the underlying asset structure of



(a) $E < 0$ & $OIBIT \geq 0$ (13% of firms)

(b) $OIBIT < 0$ & $OIBITDA \geq 0$ (7%)

(c) $OIBITDA < 0$ & $OIBITDA^{+} \geq 0$ (12%)

(d) $OIBITDA^{+} < 0$ (5% of firms)

Figure 6: **Comparison of the Same Earnings Numbers for Profit-Making Firms** ($E \geq 0$) **vs. Different Types of Loss-Making Firms.** The plot illustrates the difference in MAE (5) (circles) between loss-making firms of the specified type indicated in the graph's caption and profit-making firms, based on valuations informed by the earnings measure labeled on the x-axis. Vertical segments represent the 95% confidence intervals around the statistic. A confidence interval entirely above 0 indicates that the corresponding earnings number provides a better summary of firm performance for profit-making firms.

the firm. This evidence aligns with the second expectation outlined in Section 2.3.

5.3 Additional testing of recognition of intangible assets

One of the main findings in Sections 5.1 and 5.2 is that earnings measures perform similarly in summarizing performance (as reflected in stock prices) for both tangible and intangible intensive firms. This result holds particularly for the earnings metrics most relevant to investors, which focus on short-term operating performance, that is, before the effects of long-term assets. Therefore, the recognition and subsequent amortization of intangibles does not necessarily provide relevant information to investors.

A feature of our study is the use of a simplifying assumption regarding intangible investments: we assume that 50% of SG&A and 100% of the R&D expenses represent investment across all firms and industries. To ensure comparability with the literature, we also implement the approach of Iqbal et al. (2025), which models industry-specific investment assumptions about SG&A and R&D outlays and constructs earnings measures that incorporate capitalization and subsequent amortization of intangibles (see also Rajgopal et al., 2025). This allows us to test the ability of earnings to reflect information in stock prices under both generalized and industry-specific assumptions of intangible investments in the SG&A. We construct a bottom line earnings number, $E.I$, based on the recognition and amortization of intangible investments embedded in SG&A and R&D, following the methodology outlined in Iqbal et al. (2025). In addition, we construct an adjusted version of $OIBIT$, denoted $OIBIT.I$[37] and an adjusted version of $OIBITDA^{+}$, denoted $OIBITDA.I^{+}$, both reflecting the industry-specific proportions of SG&A and R&D expenses based on the approach in Iqbal et al. (2025). We evaluate the performance of these earnings numbers relative to unadjusted bottom line earnings using the methodology presented in Section 3. The results of the comparison are reported in Figures 7 and 8.

Figure 7 indicates that bottom line earnings that capitalize and amortize the industry-specific investment portion of $SG\&A$ and R&D ($E.I$) are a better performance measure than E. Moreover, it supports the findings in Section 5.1. First, the earnings measure that excludes the effects of long-term assets, $OIBITDA.I^{+}$, provides a better summary of performance than bottom line earnings ($E.I$). Second, depreciation and amortization do not improve the ability of earnings to summarize firm performance. The earnings measure based on recognition and amortization of intangible investments embedded in SG&A and R&D and before interest, taxes, special items, and nonoperating income ($OIBIT.I$) performs significantly worse[38] as a summary measure of performance than the earnings number before amortization ($OIBITDA.I^{+}$). This finding is consistent with the third expectation in Section 2.2, conditional on the findings in Section 2.1 that ($OIBITDA$) is more useful than ($OIBIT$).

[37] $OIBIT.I$ adds back to $E.I$ interest and taxes and removes special items and nonoperational income.

[38] It gives, however, a small but significant improvement over the adjusted bottom line earnings ($E.I$).

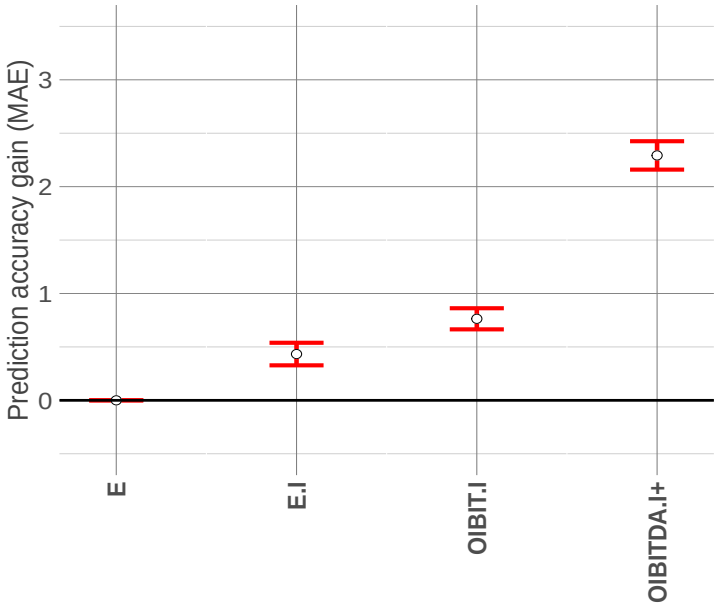


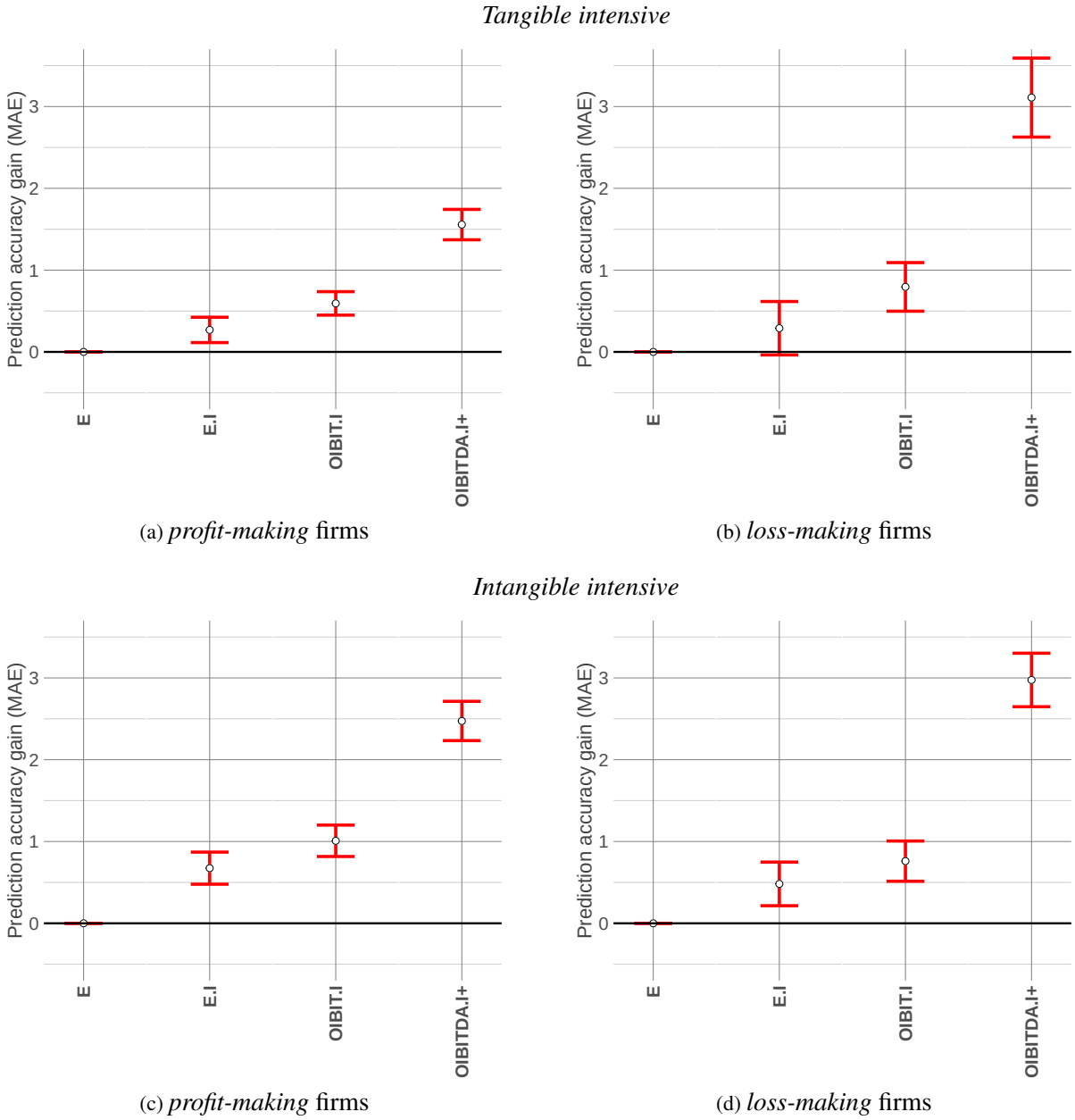
Figure 7: **Relative difference in price prediction accuracy of earnings with industry-specific capitalized and amortized intangible investments within SG&A and R&D compared to unadjusted bottom line earnings.** The plot illustrates the sample mean gain in price prediction accuracy (Equation (4)) for earnings numbers based on recognition and subsequent amortization of the investment portion of SG&A and R&D expenses as defined in Iqbal et al. (2025), relative to unadjusted bottom line earnings E. $E.I$ denotes bottom-line earnings adjusted for the recognition and amortization of intangible investments. $OIBIT.I$ is the corresponding adjustment to $OIBIT$ and $OIBITDA.I^+$ is the adjusted counterpart of $OIBITDA^+$. The mean gain is represented by circles, while the corresponding 95% confidence intervals are shown as vertical segments centered around the statistic. A confidence interval entirely above 0 indicates that the earnings number has a statistically significant improvement in summarizing firms' performance compared to bottom line earnings.

We note that $OIBITDA^+$ is a better profitability measure than $OIBITDA.I^+$. The improvement in prediction accuracy from using $OIBITDA^+$ over bottom line earnings is around 3%, significantly exceeding the gain from the earnings measure constructed using the method of Iqbal et al. (2025), which is below 2.5%.[39] This contradicts the second expectation in Section 2.2.

The results presented in Figure 8 provide more details on the performance of $E.I$. The earnings measure based on recognition and amortization of intangible investments embedded in SG&A and R&D outperforms bottom line earnings slightly more for intangible intensive firms than for tangible intensive firms. Although the improvement in prediction accuracy from using $OIBITDA.I^+$ over bottom line earnings (or $OIBIT.I$) is similar in pattern to that of $OIBITDA^+$ (Figure 2), it is consistently smaller in magnitude.

We conclude that our results based on the simplified assumption that approximately half of SG&A expenses and all R&D expenditures represent intangible investments are qualitatively consistent with those obtained under the more elaborate design of Iqbal et al. (2025). Furthermore, adjusting for in-

[39] The y-axis in Figure 7 is identically scaled to that of Figure 1, allowing for direct comparison.



(a) *profit-making* firms

(b) *loss-making* firms

(c) *profit-making* firms

(d) *loss-making* firms

Figure 8: **Relative difference in price prediction accuracy of earnings with industry-specific capitalized and amortized intangible investments within SG&A and R&D relative to bottom line earnings, conditional on profitability and tangibility jointly.** The plots illustrate the sample mean gain in price prediction accuracy (Equation (4)) for earnings numbers based on recognition and subsequent amortization of the investment portion of SG&A and R&D expenses as defined in Iqbal et al. (2025), relative to unadjusted bottom line earnings E (circles) together with its 95%-confidence intervals (the vertical segments centered at the statistic). A confidence interval entirely above 0 indicates that the corresponding earnings number is strictly more price pertinent than bottom line earnings. $E.I$ denotes bottom-line earnings adjusted for the recognition and amortization of intangible investments. $OIBIT.I$ is the corresponding adjustment to $OIBIT$ and $OIBITDA.I^+$ is the adjusted counterpart of $OIBITDA^+$. Following the Fama-French five-industry classification, firms in industries 1, 2, and 5 are classified as tangible intensive, while those in industries 3 and 4 are classified as intangible intensive.

vestment outlays within SG&A improves the informativeness of earnings as a summary performance measure, while incorporating depreciation and amortization does not. In particular, our adjusted earnings measure that excludes the effects of long-term assets, $OIBITDA^+$, outperforms its counterpart

under the more complex specification. These findings suggest that relatively straightforward adjustments to earnings can lead to substantial gains in price prediction accuracy, offering a potentially more transparent and accessible alternative to complex recognition approaches.

5.4 Other aspects of the relation to recent literature

How our findings relate to Gu et al. (2023). Gu et al. (2023) argue that the well-established result that losses are less informative than profits (Hayn, 1995; Hiemann, 2020; Starica and Marton, 2025) applies only to firms with real economic losses. For firms whose reported losses arise from the expensing of intangible investments, they contend that *adjusted earnings*—after capitalizing and amortizing these investments—*are as informative as the earnings of profitable firms*. This claim is highlighted as a principal contribution in their abstract. Our evidence does not support this conclusion, and the remainder of this section details the basis for this disagreement.

Figure 9 compares the same earnings numbers for profit-making firms ($E > 0$) with GAAP-loser firms ($E < 0$ and $E.I \geq 0$) and suggests that all earnings measures considered in the previous section are significantly better summarizing measures of firm performance for profitable firms than for GAAP-losers. A similar unreported analysis shows that the superiority extends to all loss-making firms.

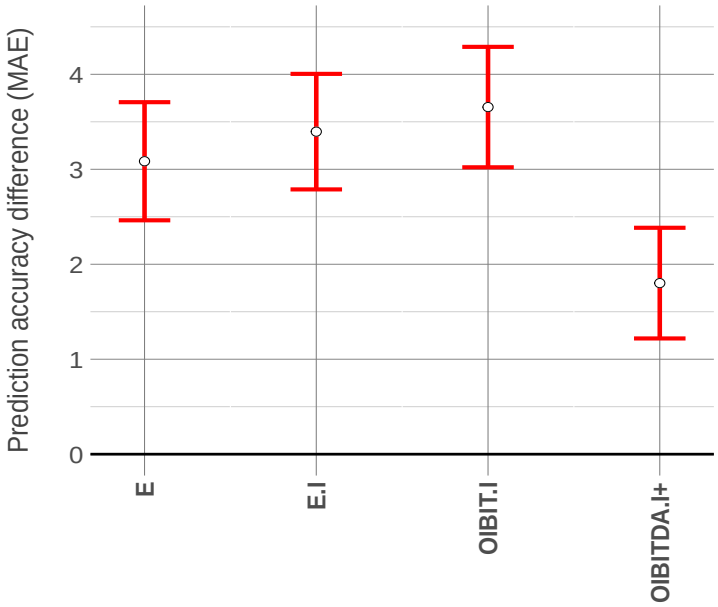


Figure 9: **Comparison of the Same Earnings Numbers for Profit-Making Firms ($E \geq 0$) vs. GAAP-loser Firms ($E < 0$ and $E.I \geq 0$).** The plot illustrates the difference in MAE (5) (circles) between GAAP loser firms and profit-making firms, based on valuations informed by the earnings measure X. Vertical segments represent the 95% confidence intervals around the statistic. A confidence interval entirely above 0 indicates that the corresponding earnings number provides a better summary of firm performance for profit-making firms.

The analysis in Gu et al. (2023) estimates separate regressions of returns on earnings and changes in

earnings following Easton and Harris (1991),[40] using both reported bottom-line earnings and earnings adjusted for intangible outlays, and partitioning firms into profit- and loss-making groups, as well as GAAP-losers and Real-losers.[41]

When the independent variables whose informativeness is compared in earnings-return regressions differ between specifications,[42] the established practice is to assess the explanatory power using the regression's R^2 (Easton and Harris, 1991; Dechow, 1994; Francis and Schipper, 1999; Ali and Hwang, 2000; Francis et al., 2003; Srivastava, 2014). In such settings, comparing regression coefficients is inappropriate. Although the regressions share the same dependent variable, they use different sets of regressors. In such cases, the magnitudes of the coefficients depend jointly on the variability of the regressors and their association with the dependent variable. As a result, differences in coefficient sizes can reflect scale differences rather than differences in informational content. In contrast, the R^2 statistic provides a valid basis for comparing the association in regressions with distinct independent variables. Despite this, Gu et al. (2023) rely on the sum of two regression coefficients as their measure of informativeness and interpret larger sums as indicating greater explanatory power. Given the issues noted above, this metric is not appropriate for the comparisons they draw, and the inferences based on it should therefore be treated with caution. Beyond the fact that the magnitude of the sum of coefficients confounds two distinct properties of the independent variables (their variability and their association with the dependent variable), the statistical treatment of this measure in Gu et al. (2023) is questionable. To support their claim that adjusted earnings are more informative for GAAP-loss firms than for profitable firms, the authors assert that the sum of the regression coefficients on adjusted earnings for GAAP-loss firms, 0.314, is significantly larger than the corresponding sum for profitable firms, 0.268. However, a closer inspection of Table 2 in Gu et al. (2023) indicates that no statistical test is performed to assess the significance of this difference. In addition, the coefficient on bottom-line earnings for profitable firms is 0.305, a value that is almost certainly statistically indistinguishable from 0.314.

More importantly, the R^2 statistics, which only measure the strength of association between earnings and returns, points to very different conclusions. The R^2 from the regression of returns on adjusted (unadjusted) earnings is 6.9% (6.72%) for GAAP-loss firms but 15.3% (15.52%) for profitable firms. This suggests that earnings (both adjusted and unadjusted) are substantially more informative for profitable

[40] These regressions do not account for firm-specific heterogeneity or for the nonlinear relation between returns and earnings. Starica and Marton (2025) show that the linear specification provides a poor approximation to the relationship of interest.

[41] GAAP-losers are firms with negative reported earnings but positive adjusted earnings, whereas Real-losers are firms for which both measures are negative.

[42] Examples include comparisons between alternative earnings measures (Francis et al., 2003), or between cash flows and earnings (Dechow, 1994), among others.

firms than for GAAP-loss firms, which plainly contradicts the conclusion of the authors.

Moreover, Table 2 in Gu et al. (2023) shows no statistically significant differences in R^2 between regressions using bottom-line earnings and those using adjusted earnings, across all firm categories examined (all firms, profit-makers, loss-makers, GAAP-losers, and Real-losers). Thus, the R^2 statistics provide no evidence that adjusted earnings are more closely associated with returns than GAAP earnings.

Even more puzzling, the reported R^2 for Real-losers (8.01%) exceeds that for GAAP-losers (6.90%). If taken at face value, these results would imply that adjusted earnings for Real-losers are at least as informative, if not more so, than those for GAAP-losers, a strong argument against adjusted earnings.

How our findings further relate to Rajgopal et al. (2025). In Rajgopal et al. (2025), the only analysis directly comparable to our focus on the contemporaneous price–earnings association is their regression of prices on P/E ratios constructed from alternative earnings measures. They document "a significant improvement in the adjusted R-squared of a regression of price on earnings". Specifically, the adjusted R^2 increases from 18% when using the reported EPS to 19% when using their adjusted earnings measure, indicating a very modest gain in explanatory power.

Rajgopal et al. (2025) motivate their investigation by highlighting the decline in the matching of expenses with revenues, which they attribute to the growing prevalence of intangible-intensive business models. They emphasize that a central contribution of their study is the examination of the matching property of earnings, an aspect that, they argue, has not been fully addressed in prior research. Comparing the matching of as-reported expenses with expenses calculated under intangibles capitalization, their key finding is that the matching measure, as defined by Dichev and Tang (2008), improves from 0.823 to 0.867. In the Appendix, we extend the analysis to a broader set of earnings measures. The results show that the pattern of revenue–expense matching closely parallels the association results, indicating that earnings obtained through capitalization and amortization do not necessarily constitute the most relevant measure of firm profitability according to the matching criterion either.

In summary, our findings show that several alternative earnings measures summarize firm profitability, as reflected in market prices, more effectively than earnings adjusted for the capitalization and amortization of intangibles. This calls into question the emphasis on adjusted earnings in recent literature.

As noted in the introduction, our analysis is restricted to two dimensions of earnings quality: contemporaneous association with market prices and, to a much lesser extent, the matching of revenues and expenses. Although these criteria do not encompass all the measures used to support the benefits of capitalization and amortization of intangible outlays, the evidence we present raises doubts about their

purported superiority.

5.5 Matching of revenues and operating expenses

In this section we document that Following Dichev and Tang (2008), we estimate the following panel regression with industry (Fama-French 48-industry classification) and year fixed effects:

$$Revenues_{i,t} = \beta_0 + \beta_1 \times TotalExpenses_{i,t-1} + \beta_2 \times TotalExpenses_{i,t} \tag{7}$$
$$+ \beta_3 \times TotalExpenses_{i,t+1} + \epsilon_{i,t}.$$

We compute the total expenses ($TotalExpenses$) corresponding to a given earnings measure by subtracting the earnings value from revenues (Compustat *revt*). We scale all variables by the average total assets. The matching is measured by the regression coefficient on contemporaneous expenses (β_2), which represents the contemporaneous revenue–expense correlation.

We examine how matching varies with firm characteristics, such as profitability and asset composition, by estimating the following panel regressions:

$$Revenues_{i,t} = \beta_0 + \gamma_0 \times I_{i,t} + \beta_1 \times TotalExpenses_{i,t-1} + \beta_2 \times TotalExpenses_{i,t} \tag{8}$$
$$+ \gamma_1 \times TotalExpenses_{i,t} \times I_{i,t} + \beta_3 \times TotalExpenses_{i,t+1} + \epsilon_{i,t},$$

where I is equal to one if the firm is profitable (matching conditional on profitability) or it belongs to the intangible-intensive industries (3 and 4) in the Fama-French five-industries classification (matching conditional on intangible intensity) and zero otherwise.

The results in Figures 10 and 11 display a pattern consistent with the analysis in Section 5.1, which examined how effectively earnings numbers summarize profitability information embedded in prices. The alignment of revenues and expenses improves as one moves "up" the income statement, peaking at $OIBITDA^+$. By excluding the effects of long-term assets, $OIBITDA^+$ achieves the best matching of revenues and expenses across all earnings measures, regardless of firm type: profit- or loss-making, tangible- or intangible-intensive.

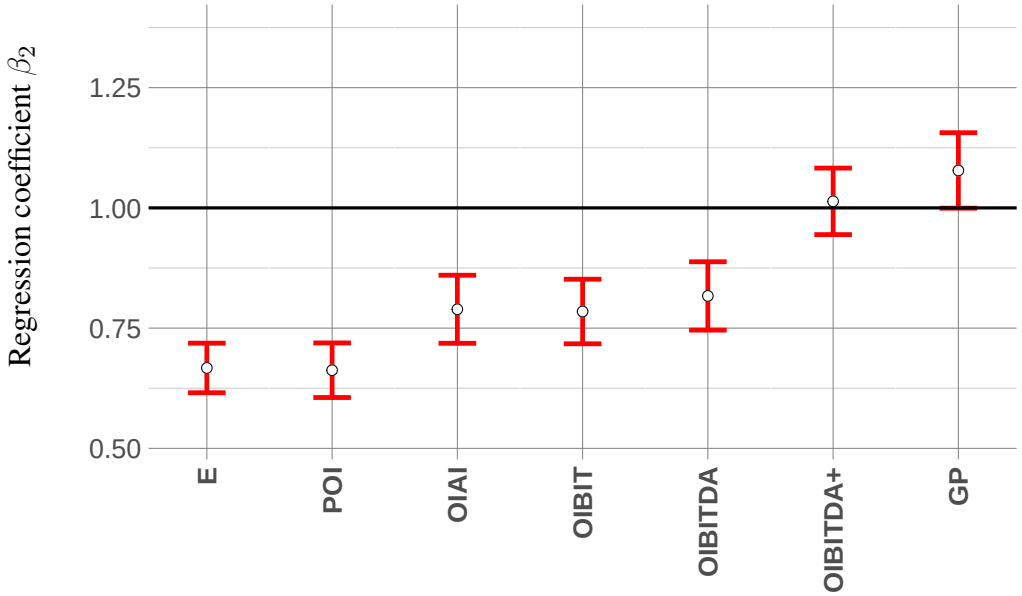
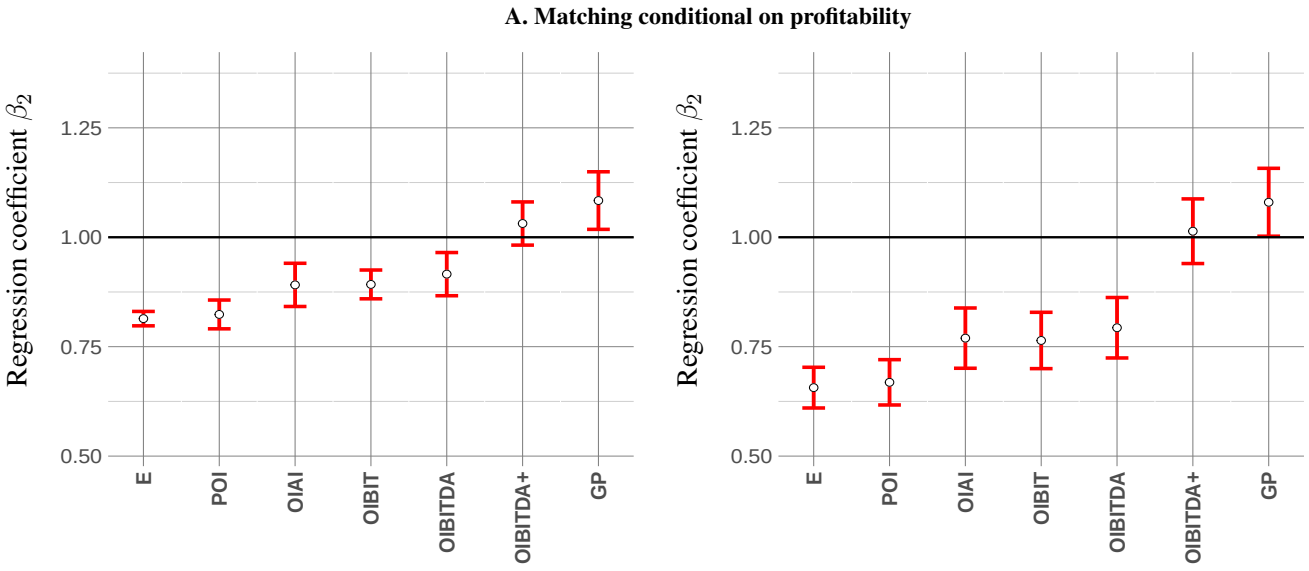
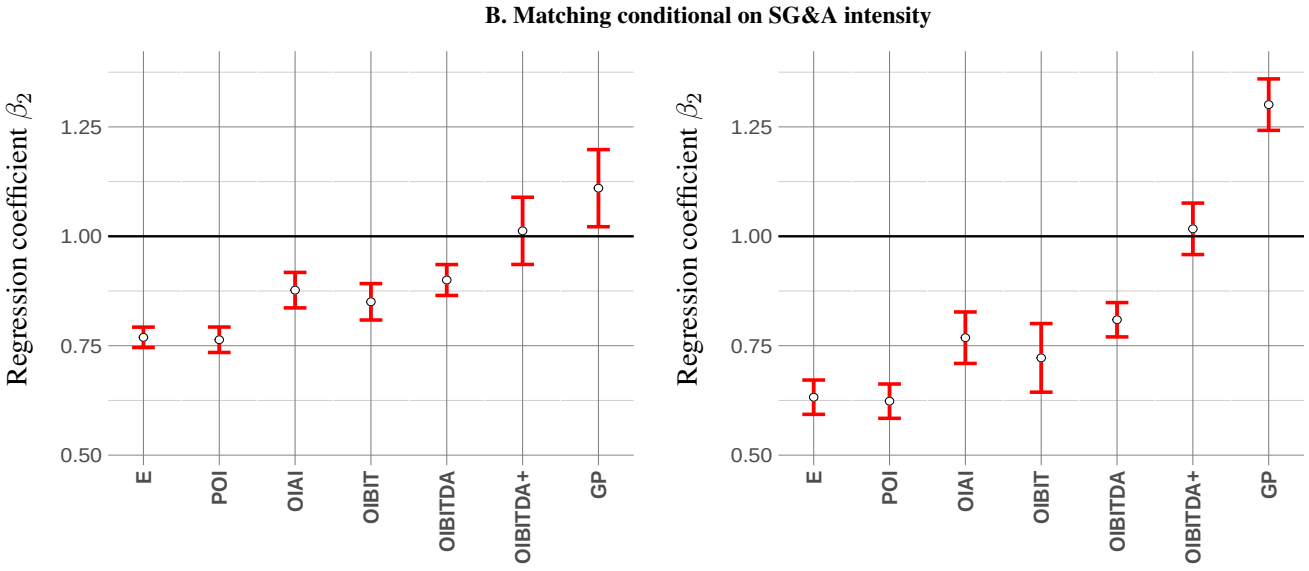


Figure 10: **Matching of revenues with operating expenses implied by different earnings numbers from the Income Statement.** The plot displays the value of the coefficient β_2 from regression (7) measuring the association between revenues and the contemporaneous operating expenses corresponding to the earnings numbers (depicted by circles). The vertical segments represent 95% confidence intervals for β_2. A confidence interval entirely above or below 1 suggests that the operating expenses tied to the profitability measure do not align with the firm's revenues. Conversely, if the confidence interval includes 1, the null hypothesis of matching revenues and expenses cannot be rejected at the 5% significance level.



(a) Profitable firms: $E \geq 0$

(b) Nonprofitable firms: $E < 0$



(a) Tangible-intensive firms

(b) Intangible-intensive firms

Figure 11: **Matching of revenues with operating expenses implied by different earnings numbers from the Income Statement conditional on firm's caracteristics.** The plot illustrates the relationship between revenues and the contemporaneous operating expenses associated with the earnings numbers as measured by the coefficient β_2 from regression (7) (depicted by circles) conditional on firm's profitability (Panel A) and firm's intangible intensity (Panel B). The vertical segments represent 95% confidence intervals for β_2. A confidence interval entirely above or below 1 suggests that the operating expenses tied to the profitability measure do not align with the firm's revenues. Conversely, if the confidence interval includes 1, the null hypothesis of matching revenues and expenses cannot be rejected at the 5% significance level.

6. Conclusions

We focus on the potential relevance of capitalization of investments in intangible assets that are currently expensed in GAAP financial statements. We start by empirically studying which line item in the income statement aligns the most with information reflected in stock prices. It turns out to be EBITDA and this finding is robust for different types of firm, including tangible- and intangible-intensive, and profitable and loss-making firms. The findings question the common method in research to adjust bottom-line earnings for the estimated capitalization and amortization. Net income is unlikely to be the focus of investors and, while adjustment for the initial investment may be relevant, adding subsequent amortization may not be.

We further find that losses do not reflect information in stock prices as well as profits and that this is true for losses at all levels of the income statement. This questions recent research on the relationship between losses and non-capitalization of intangibles, which defines losses only in terms of bottom-line earnings.

We also compare a simple, standardized method for identifying the investment portion of current expenses (100% of R&D and 50% of SG&A) with a substantially more complex method aimed at capturing industry differences in investment rates and useful life of intangibles. We find no improvement in using the more complex method. This finding points to the difficulty of specifying investment rates using publicly available data through financial statements.

The findings have relevance for both research and standard setting practice. Researchers should reflect on which line item of the income statement they use in studying the effects of accounting policies. Furthermore, complex models to estimate unobservable phenomena require robust validation. In addition, we propose a novel method for studying the relationship between earnings and prices. The method is fully flexible, allowing for full non-linearity in all variables and interactions, it allows for firm- and time-specific relationships, and it provides out-of-sample tests.

The findings also have implications for standard setters that currently work to improve the accounting of intangible assets. For example, this study points to the importance of firms providing information on the portion of current expenses that represent investments in intangible assets. Given that subsequent amortization (or impairment) is less important, the information might not need to be provided through capitalization. Instead, it could be disclosed in the notes.

APPENDICES

A Sample selection

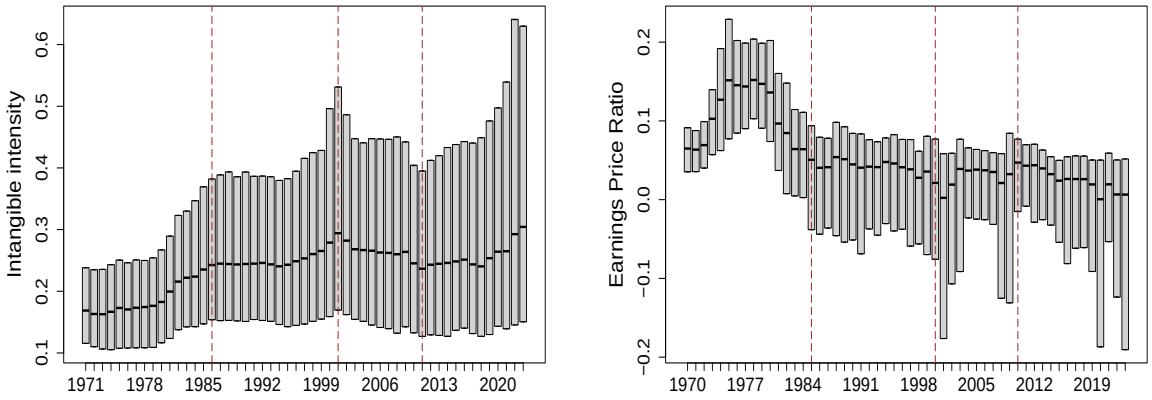


Figure 12: **Changes over time in the distribution of SG&A intensity and the earnings–price ratio.** The horizontal line shows the median by year. $SG\&A$ intensity (intangible intensity) is defined in Table 1.

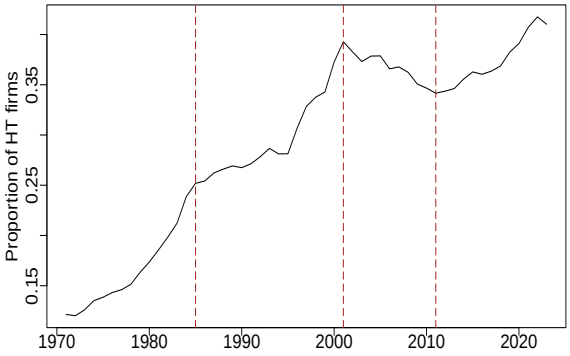
Figure 12 displays the cross-sectional variability of the SG&A intensity (left) and earnings (scaled by the prices of the previous period) (right). It shows that both the median intangible intensity and the earnings-to-price ratio have remained relatively stable since the middle of the 1980s.

Figure 13 displays the cross-sectional proportion of intangible intensive firms (graph a) and the proportion of loss-making firms (graph b), by cross-section. The figure also shows the proportion of firms making losses at different levels of earnings, among tangible intensive firms (graph c) and intangible intensive firms (graph d). The proportion of intangible intensive firms is increasing over time. Furthermore, such firms are more likely to be loss-making than tangible intensive firms. Only for losses higher up in the income statement, that is, for $OIBITDA^{+}$, is there a smaller difference in the proportion of loss-making firms between those that are intangible and tangible intensive.

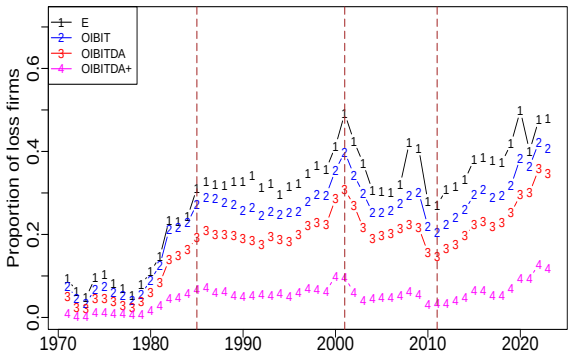
B Fama-French industry classification and intangible/tangible intensive

In this study, we refer to firms in industries 3 and 4 of the Fama-French five-industry classification ($FF5$) as intangible intensive, and firms in industries 1, 2 and 5 as tangible intensive. This appendix provides evidence supporting the use of this terminology.

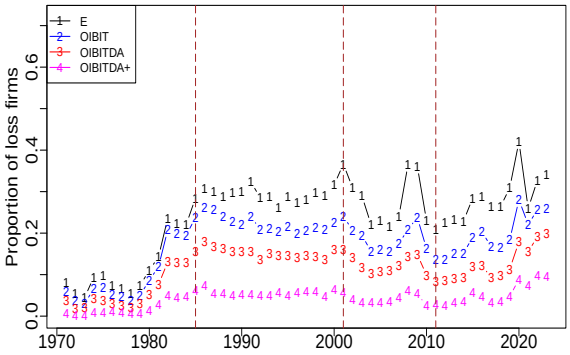
Figure 14 presents boxplots of the SG&A intensity ($SG\&A$) and asset tangibility (TG) (defined in Table 1) conditional on the Fama-French five-industry classification. The graph shows that firms in intangible intensive industries (3 and 4) exhibit significantly higher SG&A intensity and lower asset tangibility. In contrast, firms in tangible intensive industries (1, 2, and 5) display the opposite pattern—higher asset tangibility and lower SG&A intensity. These findings support the assumption that firms in industries 3 and 4 are more intangible intensive and less tangible intensive compared to firms in industries 1, 2 and 5.



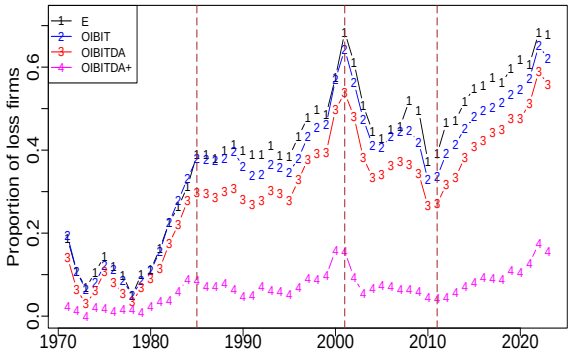
(a) Cross-sectional proportion of intangible intensive firms



(b) Cross-sectional proportion of loss firms: All firms in cross-section



(c) Cross-sectional proportion of loss firms: tangible intensive firms



(d) Cross-sectional proportion of loss firms: intangible intensive firms

Figure 13: **Changes in the cross-sectional proportion of intangible intensive firms and of loss-making firms.** Loss-making firms are classified as those reporting negative earnings at different levels of the income statement, as indicated in the figures. Based on the Fama-French five-industry classification, firms in industries 1, 2, and 5 are classified as tangible intensive, while those in industries 3 and 4 are classified as intangible intensive.

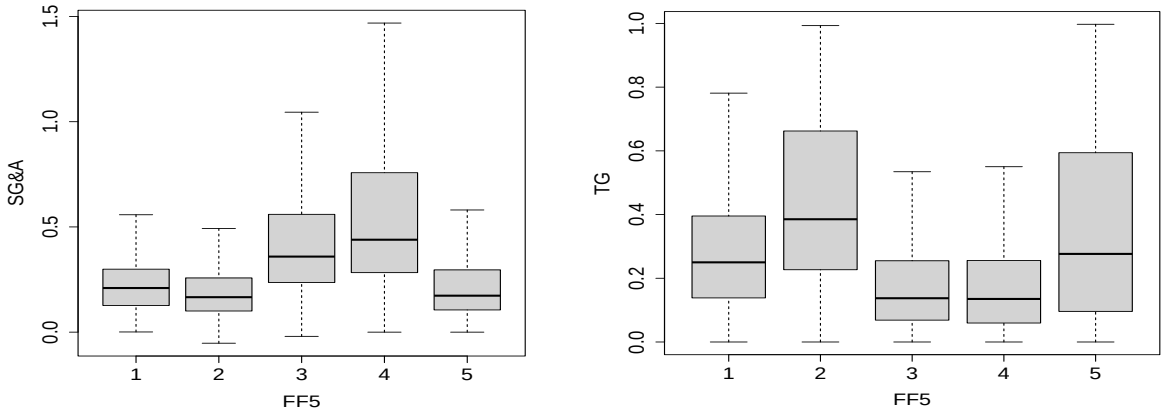
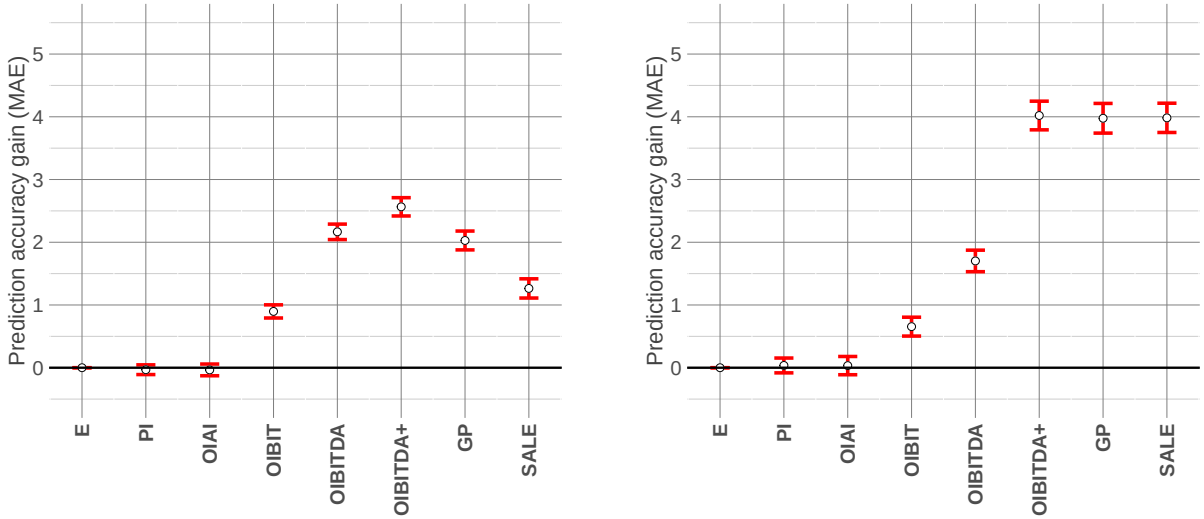


Figure 14: **The distribution of SG&A intensity ($SG\&A$) and asset tangibility (TG) conditional on industry classification.** The graphs display boxplots of the variables $SG\&A$ and TG (defined in Table 1) across the industries in the Fama-French five-industry classification. Based on this classification, firms in industries 1, 2, and 5 are defined as tangible intensive, and firms in industries 3 and 4 as intangible intensive.

C Why asset structure might look important when it is not

This section presents the results of an analysis that conditions only on investment type. Such an analysis highlights the role of the cross-sectional composition, in particular the share of firms reporting losses. Figure 2 documents a common pattern in the relative performance of the earnings measures for profitable and loss-making firms, independent of their primary type of investment. For profitable firms, relative performance peaks at $EBITDA^{+}$ and declines thereafter, with sales providing a significantly smaller improvement over bottom-line earnings than $EBITDA^{+}$. In contrast, for loss-making firms, the strongest relative performance is obtained from sales for both tangible and tangible intensive firms. An analysis that conditions only on asset type would combine these two patterns, with weights proportional to the share of loss-making firms within each type of firm (tangible- or intangible-intensive). Figure 15 presents the results of such an analysis and appears to indicate a structural difference between the two types of firms, as the earnings measures for tangible-intensive firms (graph (a)) summarize performance in a significantly different way from those for intangible-intensive firms (graph (b)).



(a) Tangible intensive firms

(b) Intangible intensive firms

Figure 15: **Relative difference in price prediction accuracy of income statement and adjusted earnings over bottom line earnings conditional only on tangibility.** The plots display the sample mean gain in price prediction accuracy (Equation 4) for income statement and adjusted earnings numbers relative to bottom line earnings E. The mean gain is represented by circles, while the corresponding 95 confidence intervals are shown as vertical segments centered around the statistic. A confidence interval entirely above 0 indicates that the earnings number is significantly better at summarizing performance compared to bottom line earnings. Based on the Fama-French five-industry classification, firms in industries 1, 2, and 5 are classified as tangible intensive, while those in industries 3 and 4 are classified as intangible intensive.

It is worth noting that the pattern for tangible-intensive firms resembles that of profit-making firms, whereas the pattern for intangible-intensive firms resembles that of loss-making firms. The similarity between intangible-intensive and loss-making firms, together with the information in Figure 13 in Appendix A (which shows that 40–70% of intangible-intensive firms are loss-making, compared with only 20–30% of tangible-intensive firms), suggests a possible interaction between the two classification criteria of tangibility and profitability.

Our interpretation of the patterns in Figure 15 is that the apparent differences between tangible-intensive

and intangible-intensive firms are largely driven by the higher incidence of losses among intangible-intensive firms. Because the patterns for loss-making and profitable firms differ substantially, and because most intangible-intensive (tangible-intensive) firms are loss-making (profit-making), removing the conditioning on profitability, i.e., conditioning only on tangibility, preserves the patterns observed for loss-making (profit-making) firms in Figure 2.

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