Intangible Measurement Matters: Price Informativeness and Opaque Signals

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Abstract

We investigate the effect of off-balance sheet (OBS) intangibles, defined as internally generated knowledge and organizational capital, on stock price informativeness. We build on the q-theory framework of Bai et al. (2016) by incorporating both book and OBS intangible assets, allowing us to derive testable predictions about the firm's information environment. Our analysis shows that OBS intangibles provide incremental predictive power beyond the book value of assets for future fundamentals, including cash flows, R&D expenditures, patents, and stock returns. Forecast encompassing tests and principal component analysis indicate that no single proxy fully captures the information content of OBS intangible capital. Consistent with the valuation uncertainty associated with OBS intangibles, firms with higher intangible intensity exhibit significantly lower price informativeness. In contrast, firms with high physical capital intensity exhibit greater price informativeness, reflecting the relative transparency of tangible assets. Overall, our results demonstrate that asset composition, specifically the balance between tangible and intangible capital, significantly affects how effectively stock prices reflect information about future firm fundamentals.

JEL Codes: G11, G12, G17, M41

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1 Introduction

Well-functioning financial markets produce stock prices that "provide accurate signals for resource allocation" (Fama, 1970, p. 383), implying that prices are informative about future firm fundamentals. Bai et al. (2016) develop a theoretical and empirical framework to derive and test a welfare-based measure of price informativeness (PI). Using this framework, Carpenter et al. (2021) examine PI changes in China, Kacperczyk et al. (2021) show that foreign institutional ownership improves PI, and Koijen et al. (2024) investigate how capital flows and regulatory changes affect PI. These papers apply q-theory and measure PI using the coefficient of the log of market capitalization deflated by total assets. However, the book values of assets exclude internally generated intangible capital, which has grown substantially as the economy has shifted toward knowledge-intensive production.[1]

Belo et al. (2022), Crouzet et al. (2022), and Eisfeldt et al. (2022) establish intangible capital as a central driver of firm value, highlighting the limitations of traditional, tangibles-focused measures in valuation and performance metrics. Furthermore, the rapid growth of intangibles has occurred largely off-balance sheet (OBS), as accounting standards prohibit the capitalization of internally generated intangible assets such as knowledge and organizational capital. Crouzet et al. (2022) note that intangible assets are inherently difficult to quantify and interpret, complicating valuation by external investors. Eberly (2022) documents that intangible capital is less transparent, more scalable, harder to measure, and arguably more forward-looking than physical capital.

This raises a central question: does the absence of a widely accepted valuation framework for OBS intangibles obscure their information content and reduce the informativeness of stock prices? Using four prominent approaches to measuring OBS intangibles, we investigate whether these assets possess the same informational content as the book values of intangibles and physical capital. Peters and Taylor (2017) estimate internally generated intangible capital as the sum of knowledge and organizational capital. These estimates are derived using the perpetual inventory method and capitalizing SG&A and R&D expenditures. Eisfeldt et al. (2022) propose an alternative measure using different assumptions to capitalize only SG&A. By contrast, Woeppel (2022) values intangible capital using patents as a direct measure of corporate innovation. Finally, Ewens et al. (2025) estimate knowledge capital and organizational capital using capitalization parameters based on market-based exit prices. These papers

[1] Following Ewens et al. (2025) and Gulen et al. (2025), the book values of assets and intangibles refer to the values of total assets and intangibles recognized on the balance sheet. Physical capital is the tangible capital recognized on the balance sheet as Net Property, Plant, and Equipment. Off-balance sheet intangibles are internally created intangible capital that is not recognized on the balance sheet.

highlight both the challenge of measuring intangibles and the value relevance of internally generated intangible assets.

Measurement of intangible capital is critical for financial decision-making, as the transition to an intangible-intensive economy reshapes financial systems and asset valuations (Li, 2025b). Correctly accounting for intangibles helps resolve several empirical anomalies, including the investment puzzle (Crouzet and Eberly, 2019), corporate cash policies (Falato et al., 2022), the profitability of star firms (Ayyagari et al., 2024), and the declining relevance of book-to-market ratios (Park, 2022; Gulen et al., 2025; Li, 2025a). We contribute to this literature by examining how OBS intangibles affect price informativeness. Our focus is the extent to which scaled market prices anticipate future fundamentals: cash flows, innovation output, and returns.

We begin by documenting fundamental differences between the book values of intangibles and four prominent OBS intangible capital metrics. Our analysis shows that these five metrics exhibit distinct statistical properties and distributions, indicating that OBS measures differ materially in both magnitude and dispersion. We further document that OBS intangible capital is economically large, averaging between 189% and 356% of the book value of intangibles Moreover, the gap between OBS intangibles and both book values and physical capital has widened over time. For instance, Ewens et al. (2025) show that incorporating their intangible measure into the market-to-book ratio reduces its upward trend by 68% and document that OBS intangibles now exceed physical capital. This growing divergence demonstrates the importance of accurate intangible-capital measurement.

To examine how OBS intangible measures affect price informativeness, we build on the q-theory framework of Bai et al. (2016) to develop four testable predictions. The first prediction is that OBS intangibles provide incremental information beyond the book values of assets and therefore influence forecasting price efficiency (FPE).[2] Results show that all four measures of OBS intangible assets significantly predict firm fundamentals, including cash flow, R&D, patents, and returns. In addition, we construct an incremental measure of OBS intangibles and show its significance in forecasting firm fundamentals. These results indicate that traditional book value measures omit relevant information, and forecast encompassing tests confirm that OBS intangibles possess significant explanatory power beyond book value.

Second, we investigate the degree of informational overlap among alternative measures of intangibles and hypothesize that a single measure is insufficient to fully capture the information embedded in

[2]Forecasting price efficiency and price informativeness are used interchangeably in the present paper.

intangible assets. Forecast encompassing tests reveal that the informational content of OBS intangibles is multidimensional. We also find that multiple principal components, rather than a single aggregate, offer incremental predictive power for future firm fundamentals, including cash flows, R&D, and patent activity. These findings indicate that the information embedded in OBS intangible measures is statistically distinct; because alternative proxies capture different facets of firm value, no single measure fully encapsulates the underlying complexity of intangible capital.

Our third prediction is that price informativeness is negatively related to intangible intensity. The opacity inherent in intangible-intensive firms obscures asset values for investors, thereby weakening the ability of market prices to aggregate information and signal future firm fundamentals. We test this prediction by examining how price informativeness varies across levels of intangible intensity. Consistent with our hypothesis, we find that firms in the top 30% of intangible intensity exhibit significantly lower price informativeness for future cash flows than those in the bottom 30%.

Our fourth prediction evaluates differences in PI between physical capital and total intangible capital, where the latter comprises the book value of intangibles and OBS intangibles. Firms with higher levels of physical capital relative to intangible capital are hypothesized to exhibit greater price informativeness than firms with lower physical-to-intangible capital ratios. Regression analysis supports this relationship, consistent with the prediction that more transparent forms of capital facilitate more accurate market pricing. These results indicate that the transition toward an intangible-intensive economy has significant implications for price informativeness and that measures omitting OBS intangibles are subject to substantial bias.

A potentially confounding issue is whether measurement error arises solely from omitting OBS intangibles from the deflator or whether the book values of assets fail to capture value-relevant knowledge and organizational capital that drive future cash flows. We find that the results are jointly driven by the choice of deflator, the gap between BV and OBS intangibles, and the level of intangible intensity. Principal component analysis and forecast encompassing tests provide robust evidence that balance-sheet intangibles exclude relevant information for predicting firm fundamentals. The findings hold when cash flows are deflated by the book value of assets, by assets inclusive of OBS intangibles, or by sales. The sales deflator, notably, is not subject to measurement error.

Our findings have important implications beyond price informativeness. The results highlight that no single measure captures the true value of assets, as estimates of OBS intangibles vary significantly

across methodologies and differ materially from book values; for example, the Eisfeldt et al. (2022) measure of OBS intangibles is three times the book value of intangibles. We demonstrate that the book values of intangibles are incomplete proxies for forecasting future firm fundamentals, and furthermore, a single OBS metric fails to fully capture the omitted information. The inherent complexity and opacity of intangible assets warrant consideration of multiple deflator specifications in financial ratios. For investment analysts, our findings indicate that incorporating OBS intangibles into asset measures yields superior insights into future corporate performance.[3]

The remainder of the paper proceeds as follows. Section 2 describes the challenges and approaches to measuring intangible capital. Section 3 presents a conceptual framework based on q-theory that incorporates OBS intangible assets and testable predictions regarding OBS intangibles, intangible intensity, physical capital intensity, and price informativeness. Section 4 describes our data and methodology for evaluating intangible assets and price informativeness. Sections 5 and 6 discuss our main empirical results and the robustness of our findings. Section 7 concludes.

2 Measuring Intangibles

Our investigation is motivated by the growing dominance of OBS intangible assets and the consequent mismeasurement of corporate capital. Belo et al. (2022) show that knowledge capital is an increasingly important driver of firm value, a finding that holds across industries. Nevertheless, Lev (2018, 2019) and Gulen et al. (2025) argue that balance sheets substantially underestimate intangible capital. Crouzet et al. (2022) and Ewens et al. (2025) find that intangible assets now comprise roughly half of total corporate capital. Eisfeldt et al. (2022) identify a growing measurement gap, noting that because investments in employees, brands, and knowledge capital are expensed, they are absent from corporate balance sheets and harder for investors to price.

The impact of this mismeasurement is amplified as intangible assets possess attributes distinct from physical capital, and these characteristics likely influence price informativeness. Crouzet et al. (2022) identify two fundamental properties of intangible assets: non-rivalry in use and limited excludability. Each of these properties has implications for returns on corporate investment in intangibles. Non-rivalry in use indicates that intangibles are scalable. For firms with a broad scope, intangibles can be deployed across a larger range of operations at a lower marginal cost than tangible capital. Limited excludability

[3] Lev (2001) argues that the "risk assessment of firms containing intangibles is (or should be) at the core of investment analysis, particularly given the deficient public information about intangibles."

implies that intangibles are subject to spillovers to competitors that inhibit firms from capturing profits from innovation. Consistent with the riskiness of intangibles, Hou et al. (2022) find that R&D intensity is associated with increased return volatility and a higher probability of default.

Anderson et al. (2025) document that intangible assets share fewer common characteristics than other balance-sheet categories and elicit greater behavioral bias, even from professional analysts. Intangibles are associated with greater information asymmetry, lower liquidity, lower pledgeability as collateral, and greater investment indivisibility than tangible assets. Because intangibles are inherently difficult for external stakeholders to value (Eberly, 2022), investment in such capital fundamentally alters the firm's information environment. Whereas physical capital has more homogeneous and transparent value across firms within an industry, Aboody and Lev (2000) argue that intangible assets exacerbate information asymmetry due to their firm-specific nature, facilitating larger insider trading profits in R&D-intensive firms.

Gu and Wang (2005) and Barron et al. (2002) demonstrate that the complexity of intangible assets contributes to analyst forecast errors and disagreement. Similarly, Chan et al. (2001) and Cohen et al. (2013) document investor difficulties in pricing intangible assets, leading to systematic underreaction, mispricing, and anomalies related to past R&D performance. More recently, Wu and Lai (2020) document a positive association between intangible intensity and information asymmetry, arguing that the opacity of intangibles facilitates managerial concealment of negative news, resulting in higher crash risk and return volatility. Such informational frictions are structurally reinforced by the exclusion of internally generated knowledge and organizational capital from the book values of assets (total assets). We next discuss the limitations of total assets as a measure of corporate capital and how OBS intangible measures address these deficiencies.

2.1 Total Assets (BV)

Total assets are traditionally measured using Compustat item *at*. This book value of total assets (A_{BV}) includes the book values of tangible assets (*ppent*) and intangible assets (*intan*), which is the sum of goodwill (*gdwl*) and other intangible assets (*intano*). The measure of intangible assets on the balance sheet has several limitations. First, the definition of goodwill has evolved over time, leading to imprecise measurement of externally acquired intangible assets across firms.[4] When a business is

[4] Appendix 1 defines the variables used in our study, and the description of *gdwl* explains the change in accounting rules in 2001 for business combinations.

acquired, goodwill is recognized as the excess of the purchase price over the net identifiable book assets. Although classified as an intangible asset on the acquirer's balance sheet, goodwill may reflect a premium paid for tangible assets.

Second, accounting rules treat externally and internally created intangible assets differently. Other intangible assets (*intano*), such as copyrights, patents, and trademarks, represent externally created intangible capital recognized on the balance sheet during business combinations. However, most intangible capital created internally is expensed rather than capitalized. As a result, investments in knowledge and organizational capital – such as R&D, advertising, employee development, and IT/data – are not reflected in the book values of assets.[5]

The limitations of book-value-based total assets hinder meaningful longitudinal and cross-sectional comparisons across firms that differ in their accounting treatment and mix of internal versus external investment. Yet, studies on PI typically use total assets as a deflator, even as intangible capital has become an increasingly important component of corporate value in a knowledge-based economy. To address this issue, Sections 2.2–2.5 introduce methods of estimating OBS intangible assets that we use to construct comprehensive measures of corporate assets. Our contribution lies in highlighting the significant effect of these estimates on price informativeness.

2.2 Peters and Taylor, 2017 (PT)

Peters and Taylor (2017) address the challenge of valuing intangible capital by developing estimates of internally generated knowledge and organizational capital. Their results indicate that, on average, firms acquire less than 20% of their intangible capital from external sources, implying that most intangible assets are not reported on the balance sheet. They estimate knowledge capital ($G_{i,t}$) by capitalizing R&D expenditures using the perpetual inventory method:

$$G_{i,t} = (1 - \delta_{R\&D})\, G_{i,t-1} + \text{R\&D}_{i,t}, \tag{1}$$

where $\delta_{R\&D}$ is the R&D depreciation rate from the BEA industry guidelines (Li and Hall, 2020). A

[5]The complexity of corporate expenditures on intangible capital is illustrated by the inconsistent accounting treatment of R&D expenditures and advertising expenses. While firms have been required to disclose R&D expenditures since 1975, they are also required to separately report advertising expenses (an investment in brand value) when these expenses are material. Yet, Liang (2024) finds that almost 70% of firm-years in Compustat lack this data. In an analysis of 2023 financial filings, Eisfeldt et al. (2026) find that 30% of companies fail to separately report R&D expenditures, while 60% omit advertising expenses.

depreciation rate of 15% is applied to firms in industries without specific guidelines.

Peters and Taylor (2017) also estimate organizational capital ($S_{i,t}$) using a similar approach:

$$S_{i,t} = (1 - \delta_{SG\&A})S_{i,t-1} + \gamma_S(\text{SG\&A}_{i,t} - \text{R\&D}_{i,t}), \tag{2}$$

where the depreciation rate ($\delta_{SG\&A}$) = 20% and the portion of the expense being capitalized (γ_S) = 30%.[6] Compustat typically includes R&D expenditures in SG&A. Accordingly, R&D is excluded from this formulation, as it is already captured in the measure of knowledge capital. Finally, total assets (A_{PT}) are defined as the sum of book assets, knowledge capital, and organizational capital.

2.3 Eisfeldt et al., 2022 (EKP)

Based on work by Eisfeldt and Papanikolaou (2013) and Eisfeldt and Papanikolaou (2014), Eisfeldt et al. (2022) develop an alternative method of estimating OBS intangible capital (INT). Their estimate is similar to Equation (2) but differs in two key respects. First, they use $\gamma_S = 100\%$ because some industries rely heavily on intangible capital, and the assumption that $\gamma_S = 30\%$ is based on dated studies with small sample sizes. Second, they treat R&D expenditures the same as advertising expenses, and therefore do not subtract them from SG&A in Equation (2). When computing intangible capital, goodwill ($gdwl$) is subtracted to exclude merger activity and avoid double-counting intangibles. Therefore, total assets using this approach (A_{EKP}) are defined as book assets plus OBS intangible capital minus goodwill.

2.4 Woeppel, 2022 (W)

To address underreporting of patent market value, Woeppel (2022) estimates intangible capital using patents as a direct measure of corporate innovation. While this represents a narrower measure than knowledge and organizational capital, patents can be directly valued using the market reaction to the patent announcement. Furthermore, patent capital may be more durable; unlike organizational capital, which is often contingent upon employee retention, patents remain with the firm regardless of labor turnover. Woeppel shows that a modified Tobin's Q, reflecting patent capital, explains more variation in investment than the standard Tobin's Q and the Peters and Taylor (2017) version of Q.

Using this approach, total assets (A_W) are defined as book assets plus patent capital. Patent capital

[6] These assumptions follow the literature. The depreciation rate of 20% is used by Eisfeldt and Papanikolaou (2013) and Falato et al. (2022), and $\gamma_S = 30\%$ is used by Hulten and Hao (2008) and Eisfeldt and Papanikolaou (2014).

is measured using the three-day idiosyncratic return following the announcement of a newly granted patent. The firm-level patent capital is determined using the perpetual inventory approach, which includes the value of new patents and depreciates old patents at the industry depreciation rate for capitalized R&D. This approach does not incorporate an explicit proxy for organizational capital or knowledge capital beyond patents.

2.5 Ewens, Peters, and Wang, 2025 (EPW)

Ewens et al. (2025) build on prior research by using market prices to estimate the parameters of the intangible capitalization model. Like Peters and Taylor (2017), they view OBS intangible capital as composed of knowledge capital and organizational capital. Their approach estimates these items using Equations (1) and (2) with $\delta_{R\&D}$ and γ_S derived using market-based exit prices. This allows their intangible capital estimates to reflect different industry parameters.[7] Using this methodology, total assets (A_{EPW}) equal the sum of book assets, knowledge capital, and organizational capital.

In summary, Sections 2.2–2.5 describe the four methods used in our study to value OBS intangible assets, denoted $OBS_{j,i,t}$ where $j \in \{\text{PT, EKP, W, EPW}\}$:

$$\begin{aligned} OBS_{PT} &= KnowledgeCapital_{PT} + OrganizationalCapital_{PT} \\ OBS_{EKP} &= INT - gdwl \\ OBS_{W} &= PatentCapital \\ OBS_{EPW} &= KnowledgeCapital_{EPW} + OrganizationalCapital_{EPW}. \end{aligned} \tag{3}$$

2.6 The (Non)Equivalence of Intangible Measures

Table 1 presents summary statistics for the intangible asset measures, highlighting material differences across methodologies. The mean (median) BV of intangible assets is \$2,463.7 million (\$299.2 million), whereas the four OBS estimates are 1.9 to 3.6 (2.4 to 9.1) times larger. Tests reject the equality of both means and variances between each OBS measure and BV, indicating that OBS intangibles are significantly greater in both magnitude and dispersion.

For comparison, the final column reports that average Net Property, Plant, & Equipment (NPPE) is \$2,962.9 million, which is below all four OBS intangible measures. Across the full sample period, the

[7] Some research suggests low depreciation rates for certain intangible assets. Emphasizing the long-term advantages gained by first movers in a product category, Bronnenberg et al. (2012) estimate a 2.5% depreciation rate for brand capital associated with consumer packaged goods.

NPPE is 20% greater than the BV intangibles; however, this relationship reverses by the end of the period, with BV intangibles exceeding NPPE by 15% in 2022. The change in mean ($\Delta\mu$) indicates that growth in OBS intangibles substantially outpaced growth in both the BV intangibles and NPPE. The differences in $\Delta\mu$ between the OBS measures and BV are significant at the 99% confidence level; the $\Delta\mu$ of BV is less than half of three of four OBS measures.

Panel B presents summary statistics for the five measures of total assets. Tests of mean and variance reject the equality between BV and each total asset measure incorporating OBS intangibles at the 99% confidence level. On average, including OBS intangibles increases total assets by 48% relative to book values, with the magnitude of the adjustment ranging from 21% to 80%, depending on the valuation methodology.

Table 2 reports pairwise t-tests comparing the five alternative measures of intangible assets. Panel A reports tests for the equality of means, and all t-statistics are highly significant, rejecting the null hypothesis of equal means at the 1% level across all comparisons. Column (1) shows that each OBS intangible measure differs statistically from the BV measure, while Columns (2)–(4) indicate the OBS measures are also statistically distinct from one another. Panel B reports the ratios of standard deviations for each pair of measures, and reveals substantial differences in dispersion. For example, the standard deviation of PT is 2.6 times greater than that of BV. All associated tests reject the null hypothesis that the standard deviation ratio equals one at the 1% significance level, confirming significant differences across methods. Panel C evaluates the mean change ($\Delta\mu$) in each intangible measure over the sample period. Except for the comparison between PT and EKP, t-tests reject equality of mean changes, implying that most metrics experience significantly different growth rates over the sample.

Collectively, Table 2 supports three conclusions. First, book values consistently and significantly understate the value of intangible assets. Second, the five intangible asset measures exhibit statistically distinct distributions, differing in both magnitude (Panel A) and dispersion (Panel B). Third, this mismeasurement relative to BV increases over time (Panel C). Taken together, these findings indicate that the five approaches yield substantially and statistically different estimates of intangible assets.

Figures 1 and 2 present box plots illustrating that the mean, standard deviation, and skewness differ considerably across the various intangible asset measures. Figure 1 deflates the metrics by BV, whereas Figure 2 uses the corresponding total assets measure for each approach, A_j (e.g., PT intangible assets are deflated by total assets that include PT intangible assets). The plots confirm that all four OBS metrics

exhibit significantly higher means and wider interquartile ranges compared to BV. These comparisons also highlight the importance of the deflator, as outliers are less extreme in Figure 2, since large values influence both the numerator (intangibles) and the denominator (total assets). Figure 3 presents a violin plot that further confirms the distinct distributions across measures. The BV distribution is tightly concentrated near zero, reflecting its omission of internally generated intangibles. In contrast, PT shows a relatively uniform distribution, EKP's central mass is positive, and W exhibits a large mass at zero (similar to BV) but with a thicker positive tail.

Finally, Figure 4 presents overlapping histograms of different intangible measures. The top panel contrasts BV's concentration of near-zero values, consistent with its assumption of no internally generated intangible capital, with the PT metric. Because PT estimates internally generated intangibles using SG&A and R&D, its distribution is more dispersed with fewer zeros. The middle panel compares distributions of EKP and EPW, while the bottom panel contrasts BV and W, showing that although many firms report no patent capital, others report substantial intangible values. In summary, the figures and Tables 1 and 2 demonstrate that intangible asset metrics differ significantly in both magnitude and distributional properties.

2.7 Illustrative Examples

Analysts compare firms using financial ratios, which often include the book values of assets. Because these ratios omit OBS intangible assets, they increasingly fail to capture variations in corporate strategies and investment decisions. To illustrate this deficiency, Appendix 2 compares measures of intangible intensity for Best Buy and Ross Stores, which both operate within the Consumer Discretionary Distribution and Retail Industry. From an accounting perspective, both firms appear to have relatively stable intangible capital utilization. Best Buy maintains an intangible intensity of approximately 10%, while Ross Stores has negligible intangible book assets throughout the 2001–2023 period.

However, these firms employ fundamentally different business models concerning intangible capital, which are not reflected in their financial statements. As detailed in Appendix 3, Best Buy made substantial investments in brand equity and human capital, whereas Ross Stores pursued a low-cost strategy with minimal advertising and brand development. While the book value of intangibles fails to reflect these divergent strategies, measures including OBS intangibles (PT, EKP, and EPW) indicate increased investment by Best Buy and a relative decline in intangible focus for Ross Stores.

A second comparison examines Astronics and Oshkosh to further underscore the differences in the intangible capital measurements. Both of these industrial firms operate in the Capital Goods Industry and make significant sales to government and military clients. Astronics' business strategy involves manufacturing highly engineered electronic systems with a skilled workforce, while Oshkosh's model is oriented toward tangible capital and its significant manufacturing scale. Appendix 4 plots the intangible intensity measures. All measures indicate an increasing intangible intensity for Astronics and a declining intensity for Oshkosh.

The comparison of these firms supports two conclusions. First, relying solely on book values to measure intangible intensity can be misleading. For example, BV intangibles in 2023 indicate that Astronics and Oshkosh have similar intangible intensity (approximately 20% each). In contrast, OBS measures reveal a significant disparity, showing that Astronics' intangible intensity is substantially higher than Oshkosh's (e.g., 62% versus 31%, using the PT methodology). Second, the five measures of intangible assets are not equivalent. The measures exhibit significant differences in both variation and magnitude, as shown in Appendix 5.

3 Conceptual Framework

This section introduces the conceptual basis for incorporating OBS intangible capital measures that provide incremental information beyond the book values of assets. We examine how the inclusion of OBS intangibles affects the extent to which market prices reflect or aggregate firm information.

Based on the framework of Bai et al. (2016), we focus on forecasting price efficiency (FPE), also referred to as price informativeness (PI), which quantifies the amount of information about future firm fundamentals embedded in market prices. Specifically, FPE is defined as the variance of the predictable component of firm value $v/\bar{k}$, given the market-to-book ratio $q = p/\bar{k}$, where $v/\bar{k} \approx 1 + z$, z is the firm's production shock, p is the stock price, and $\bar{k}$ is the current assets. That is

$$\mathcal{V}_{FPE} = Var(E[z|q]). \tag{4}$$

Bai et al. (2016) empirically implement this measure by regressing cash flow ($EBIT$), scaled by the book value of total assets (A), on the log market-to-assets ratio (LMA), which also uses the book values of assets. However, as Gulen et al. (2025) emphasize, failing to incorporate OBS intangible capital into

asset measures introduces significant measurement errors. To address this, a firm's current assets can be defined as $\bar{k}=\bar{k}^B+\bar{k}^O$, where $\bar{k}^B$ refers to balance-sheet assets and $\bar{k}^O$ captures OBS intangible capital (e.g., Gulen et al., 2025). To more accurately estimate the latter, we employ several established OBS measures from the literature, each designed to capture distinct dimensions of intangible capital. For instance, Peters and Taylor (2017) define intangible capital as the sum of knowledge and organizational capital. Eisfeldt et al. (2022) propose an alternative capitalization approach with a distinct treatment of R&D and goodwill, while Woeppel (2022) uses patent-based proxies to represent innovation directly. Similarly, Ewens et al. (2025) extend Peters and Taylor (2017) by incorporating market-based exit prices and industry-specific depreciation rates to refine their estimation.

Since price informativeness is measured as the variation in future cash flows explained by market prices (both deflated by assets), the composition of the deflator may be critical. Relying solely on the book values of assets underestimates firm values by ignoring the significant contribution of OBS intangibles. Incorporating these measures enhances the informativeness of the deflator, thereby improving the explanatory power beyond what the book values alone can offer.

Importantly, both cash flows (capturing the firm value component, $v/\bar{k}$) and market prices (capturing the firm's market-to-assets ratio, $p/\bar{k}$) in Equation (4) are influenced by changes in the asset deflator $\bar{k}$, as in the empirical implementation in Bai et al. (2016). When OBS intangibles are included, the composition and scale of the deflator change, which influences forecasting efficiency.

Incorporating OBS intangibles has two opposing effects on FPE. On one hand, it may increase the precision of insider information (i.e., a lower σ_η^2) by capturing a broader set of firm-specific information that is not reflected in book value of assets. By incorporating knowledge and organizational capital, OBS measures provide a more complete representation of the firm's productive capacity, thereby improving the information environment for informed agents. On the other hand, due to the complexity and opacity of intangible valuation, incorporating OBS intangibles may reduce trader signal precision (i.e., a higher σ_s^2), as information acquisition and processing become more costly and noisy (Crouzet et al., 2022). Unlike tangible assets, intangible capital lacks standardized valuation frameworks and is often firm-specific, making it difficult for outside investors to interpret publicly available information. This increases disagreement and noise in signals extracted from prices. According to Bai et al. (2016), a decrease in σ_η^2 raises FPE, while an increase in σ_s^2 reduces it. Thus, the net effect of incorporating OBS intangible capital on price informativeness is theoretically ambiguous.

Prediction 1. *OBS measures of intangibles provide incremental information beyond the book values of assets and therefore influence price informativeness.*

As discussed above, the various approaches to measuring intangible assets differ substantially in construction, reflecting their complex and multidimensional nature. This variation is empirically evident in the summary statistics and t-tests in Tables 1-2, as well as in the box plots, violin plots, and histograms in Figures 1-4, all of which show substantial differences between book value measures and OBS intangible measures.

Given this heterogeneity, how OBS intangibles are incorporated into asset proxies influences both the type and quantity of information produced by traders. Since each proxy captures different dimensions of intangibles, no single measure is likely to fully reflect the underlying firm value. As a result, relying on a single OBS metric may introduce measurement error and limit the explanatory power. This motivates the following prediction:

Prediction 2. *A single measure fails to fully capture the multifaceted nature of intangible assets; therefore, combining multiple measures enhances the explanatory power for price informativeness.*

As noted by Crouzet et al. (2022), intangible assets are inherently difficult to quantify and interpret, posing significant challenges for external investors. This complexity reduces the transparency and precision of financial information, particularly for firms with high intangible intensity. Such firms are therefore more likely to produce opaque information compared to those with predominantly tangible assets. Farboodi et al. (2022) show that when average investors have less precise or accessible information, market prices become less informative. Similarly, as suggested by Prediction 1 in Bai et al. (2016), when traders produce less precise information, the efficiency of market prices in forecasting future fundamentals declines. Firms with high intangible intensity operate in more opaque informational environments, making it harder for prices to fully reflect their underlying fundamentals. Accordingly, higher intangible intensity reduces the ability of market prices to accurately reflect firm fundamentals, motivating our third prediction.

Prediction 3. *Firms with higher intangible intensity exhibit lower price informativeness than firms with lower intangible intensity.*

Extending this logic, we also consider the relative composition of physical versus intangible capital. A high physical-to-intangible asset ratio indicates a greater reliance on tangible assets, which are generally

easier for investors to observe, verify, and value. This transparency reduces information asymmetry and improves investors' ability to interpret firm-specific information, thereby enhancing the informativeness of market prices. In contrast, when firms rely more heavily on intangible capital, information becomes more opaque and harder to process. As a result, the relative mix of physical and intangible assets likely affects how efficiently markets incorporate information into prices, consistent with the framework proposed by Farboodi et al. (2022).

Prediction 4. *Firms with higher physical-to-intangible capital ratios exhibit greater price informativeness than firms with lower ratios.*

4 Data and Methodology

4.1 Data

Our sample period spans 1980–2022, allowing for the analysis of subsamples with comparable lengths before and after the 2001 accounting standard that eliminated goodwill amortization. The starting year of 1980 is broadly consistent with prior studies on intangible assets (Peters and Taylor, 2017; Eisfeldt et al., 2022; Ewens et al., 2025). These studies focus on the period following 1975, when the FASB mandated the expensing of R&D costs. Each year, we construct a sample of large- and mid-capitalization firms by including constituents of the S&P 500 Index and the 400 largest firms outside the S&P 500. Although the S&P MidCap 400 Index, established in June 1991, is a commonly used benchmark for U.S. mid-cap equities, its later inception precludes its direct use over our full sample period.

Following Bai et al. (2016) and Carpenter et al. (2021), our methodology calculates stock returns starting at the end of March and utilizes financial statement data from the prior calendar year, ensuring sufficient time for investors to incorporate publicly available information. Following the methodology of Peters and Taylor (2017), we exclude financials, regulated utilities, and non-operating establishments. We also adopt their assumption that missing values of the Compustat item *intan* are set to zero. Similarly, missing SG&A expenses are treated as zero, following Eisfeldt and Papanikolaou (2013).

We employ intangible capital estimates provided by the authors of each methodology. The PT estimates of knowledge capital and organizational capital are available on WRDS. Kim provides the EKP estimates of OBS intangible capital, Woeppel supplies the patent capital estimates (W), and Ewens

provides intangible capital estimates for the EPW methodology.

Market prices are retrieved from the Center for Research in Security Prices (CRSP), and market capitalization is calculated at the end of March for each year. This date is the starting point for the subsequent one-year stock return. Financial statement data are obtained from Compustat for the prior fiscal year, and Appendix 1 provides variable definitions. The natural logarithm of share turnover (number of shares traded divided by the number of shares outstanding) is calculated over the 12-month period corresponding to the fiscal year. Idiosyncratic volatility is measured as the standard deviation of daily abnormal returns over the 252 calendar days prior to March 31, requiring a minimum of 21 trading days (approximately one month) of return data for each stock (permno). Analyst coverage is measured as the natural logarithm of the number of analysts, scaled by total assets. Finally, all variables are winsorized at the 1% level to mitigate the influence of outliers.

4.2 Methodology

Following Bai et al. (2016), we estimate the informativeness of market prices in forecasting firm i's future cash flow using EBIT as a proxy for cash flow. Specifically, we examine the extent to which market prices at time t incorporate information about cash flows realized in the subsequent year ($CF_{i,t+1}$). The empirical specification is given by:

$$\frac{CF_{i,t+1}}{A_{j,i,t}} = \alpha + \beta_1 \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right) + \rho\left(\frac{CF_{i,t}}{A_{j,i,t}}\right) + \gamma X_{i,t} + \psi \mathbf{1} + \epsilon_{i,t+1}, \tag{5}$$

where $M_{i,t}$ denotes firm i's market capitalization at time t, and $A_{j,i,t}$ represents total assets measured using five alternative asset definitions indexed by j: BV, PT, EKP, W, and EPW. Our measure of price informativeness (PI) is the coefficient on the log of the market-to-assets ratio, $\ln(M_{i,t}/A_{j,i,t})$, which we refer to as LMA in the subsequent analyses. The vector $X_{i,t}$ includes firm-level control variables, and $\mathbf{1}$ denotes year and industry dummy variables.[8]

To account for dynamic firm behavior and unobserved heterogeneity, we include a lagged dependent variable and fixed effects. To address the Nickell bias documented in dynamic panel models (Nickell, 1981), we follow Kacperczyk et al. (2021) and employ the system GMM estimator developed by Blundell and Bond (1998), which extends the difference GMM approach of Arellano and Bond (1991). The GMM estimator applies lagged levels as instruments for the differenced equation and lagged differences

[8] We adopt the industry classification modifications used by Ewens et al. (2025).

as instruments for the level equation.

Because both dependent and independent variables differ across asset definitions, all variables are standardized to have zero mean and unit variance. As a result, conventional model comparison metrics such as adjusted R^2 or information criteria are not directly applicable. Instead, we assess the informativeness of market prices by evaluating the magnitude and statistical significance of the PI coefficient across asset definitions, with particular emphasis on the incremental role of intangible capital measures.

4.3 Intangible Assets and Cash Flow

Previous studies that examine PI using the approach in Equation (5) do not include a separate term for intangible assets and deflate variables using total assets. By failing to isolate the informational role of intangibles, this specification is misspecified in two respects. First, it aggregates physical and intangible assets into a single variable, despite their distinct characteristics (see Section 2) that likely lead to divergent explanatory power regarding firm fundamentals. Second, book value based total assets omit OBS intangible assets, which represent an increasingly important component of overall corporate capital. To assess the impact of these issues, we examine how different measures of intangible assets and intangible intensity affect price informativeness using several approaches. First, we test whether adding a measure that includes OBS intangibles into total assets improves the forecasting power of market prices for cash flows deflated by the book values of assets (BV), as measured by Compustat item *at*. Specifically, we estimate:

$$\frac{CF_{i,t+1}}{A_{BV,i,t}} = \alpha + \beta_1 \ln\left(\frac{M_{i,t}}{A_{BV,i,t}}\right) + \beta_2 \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right) + \rho\left(\frac{CF_{i,t}}{A_{BV,i,t}}\right) + \gamma X_{i,t} + \psi \mathbf{1} + \epsilon_{i,t+1}, \tag{6}$$

This specification includes two LMA ratios: one based on the book values of assets (j = BV), and the other based on total assets including OBS intangibles (j = PT, EKP, W, or EPW). However, because both variables share the same numerator (market capitalization), this specification is susceptible to multicollinearity. To address this, we construct an alternative measure of incremental intangible capital that does not depend on market capitalization. Specifically, we compute the difference between the two LMA terms: $LMA_{BV} - LMA_j = \ln\left(\frac{A_{j,i,t}}{A_{BV,i,t}}\right)$. This expression isolates the contribution of OBS intangibles to total assets.[9] It equals zero for firms without OBS intangibles and increases with the

[9] Appendix 6 explains the derivation.

amount of OBS intangibles. The model specification is:

$$\frac{CF_{i,t+1}}{A_{BV,i,t}} = \alpha + \beta_1 \ln\left(\frac{M_{i,t}}{A_{BV,i,t}}\right) + \beta_2 \ln\left(\frac{A_{j,i,t}}{A_{BV,i,t}}\right) + \rho\left(\frac{CF_{i,t}}{A_{BV,i,t}}\right) + \gamma X_{i,t} + \psi \mathbf{1} + \epsilon_{i,t+1}. \tag{7}$$

A significant, positive β_2 supports Prediction 1, demonstrating that OBS intangibles provide incremental explanatory power for future cash flows beyond what is captured by the book value of assets.

Second, to evaluate the role of intangible intensity and test Prediction 3, we sort firms within each Fama-French 5 Industry classification based on their intangibles-to-assets ratio. We identify firms in the top 30% and bottom 30% of intangible intensity and construct the corresponding dummy variables.[10] These dummies are then interacted with LMA_{BV} to examine whether the informativeness of market prices varies with intangible intensity, both in the full sample and across the two subgroups:

$$\frac{CF_{i,t+1}}{A_{BV,i,t}} = \alpha + \beta_1 \ln\left(\frac{M_{i,t}}{A_{BV,i,t}}\right) + \beta_2 \ln\left(\frac{A_{j,i,t}}{A_{BV,i,t}}\right) + \beta_H \mathcal{I}_H \times \ln\left(\frac{M_{i,t}}{A_{BV,i,t}}\right) + \beta_L \mathcal{I}_L \times \ln\left(\frac{M_{i,t}}{A_{BV,i,t}}\right) + \gamma Z_{i,t} + \epsilon_{i,t+1}, \tag{8}$$

where $\mathcal{I}_H$ and $\mathcal{I}_L$ equal 1 for firms in the top and bottom 30% of intangible intensity, respectively, and 0 otherwise. The vector $Z_{i,t}$ includes the lagged dependent variable, firm-level controls, and year and industry fixed effects, for brevity.

5 Results

5.1 Summary Statistics

Table 3 presents summary statistics for ratios. Panel A uses a common denominator (book values of assets, A_{BV}), and confirms that the four ratios incorporating OBS intangible assets are substantially and statistically different from the ratio based only on the book values (BV) of assets. The OBS ratios exhibit significantly greater means and standard deviations than the BV ratios; specifically, their standard deviations are 1.5 to 4 times larger. Furthermore, the average change over time in the OBS ratios exceeds that of the BV ratio.

Panel B underscores the importance of the deflator choice by presenting ratios where each intangible asset measure is deflated by its corresponding total asset measure (e.g., IN_{PT}/A_{PT}). A comparison between Panels A and B shows that the specification of the asset measure materially influences the

[10] The use of this dummy variable structure is consistent with prior research. Gu and Wang (2005) find that analyst forecast errors increase with intangible intensity that diverges from the industry median. These forecast errors are a proxy for the informational complexity of intangible assets.

magnitude of the ratio. For instance, the mean PT ratio is 0.52 when deflated by book assets (A_{BV}) but declines to 0.37 when deflated by its corresponding assets (A_{PT}), a difference exceeding 40%. Panel C examines the market premium on assets, measured as the log market-to-assets ratio ($\ln(M/A_j)$), which is used in the estimation of PI. The choice of asset measure (A_j) impacts the ratio's sign. Notably, the ratios based on PT and EKP ($\ln(M/A_{BV})$) have a negative mean, indicating that the book values exceed the market capitalization.

Finally, Panel D of Table 3 shows that these differences have a significant effect on the cash-flow-to-assets ratio. The mean and variance of the ratios that incorporate OBS assets are significantly lower than the ratio using BV. This finding has important consequences for corporate performance analysis, which often relies on profitability and efficiency metrics that divide earnings or cash flows by total assets. When total assets omit a significant capital component, performance metrics are upwardly biased. In this case, the average cash flow return is 21%–60% higher when total assets exclude OBS intangibles. For example, CF/A_{BV} equals 11.5%, which is 60% higher than the 7.2% obtained when OBS intangibles (PT) are included in assets. Overall, the evidence highlights that incorporating OBS intangible assets yields economically distinct and statistically significant differences in asset measurement.

5.2 Price Informativeness for Cash Flow

Table 4 presents the estimation results for Equation (5), where the dependent variable is the one-year-ahead cash-flow-to-assets ratio. Columns (1)–(5) report the five different measures of assets. The specifications are built incrementally across the panels. Panel A includes industry fixed effects, Panel B adds year fixed effects, and Panel C incorporates the full specification with firm-level controls for institutional ownership, idiosyncratic volatility, and analyst coverage. Appendix 1 defines these variables. Panel C serves as the baseline specification for all subsequent regression analyses. The final row reports the number of observations; we omit this from later tables for brevity, as the sample size remains consistent.

Results in Table 4 show that the proxy for PI, the coefficient on LMA represented by β_1, is statistically significant across all five asset measures. However, a direct comparison of the coefficient estimates across Models (1)–(5) is problematic, as the dependent variable (CF/A_j) is constructed differently in each specification. Furthermore, interpreting the difference in coefficients is confounded by potential model misspecification if OBS intangible assets and the book value of intangibles differ in their levels

of price informativeness.

To address this issue, we estimate a model using Equation (7) that incorporates an additional term for OBS intangible assets. As described in Section 4.3 and derived in Appendix 6, this is measured as the difference between LMA using the book values of assets (BV) and LMA deflated by assets including OBS intangibles. The top panel of Table 5 reports estimates using book assets as a common deflator. Extending prior research, we find that the coefficient for LMA_{BV}, the measure of PI, is positive and significant across all five metrics. The coefficient for OBS intangible assets (β_2) is large, positive, and statistically significant when using the methodologies of PT, EKP, and EPW, even when controlling for LMA_{BV}. This provides strong support for Prediction 1, indicating that OBS intangible assets are incrementally informative about future cash flows.

We next turn to Prediction 3, which posits that price informativeness is lower among firms with high intangible intensity. Equation (8) specifies the model, incorporating indicator variables for high ($\mathcal{I}_H$) and low ($\mathcal{I}_L$) intangible intensity. $\mathcal{I}_H$ ($\mathcal{I}_L$) takes the value of 1 if a firm ranked in the top (bottom) 30% of intangible intensity, and 0 otherwise. Panel B of Table 5 presents the estimates. In four of the five models, β_H is negative and statistically significant, consistent with the hypothesis that high intangible intensity is associated with reduced price informativeness. The average coefficient for β_H is –0.057 and for β_L is 0.043. F-tests reject the null hypothesis of equality ($\beta_H = \beta_L$) for two of the five metrics at the 10% level. In addition, the joint restriction ($\beta_H = \beta_L = 0$) is rejected for four (five) metrics at the 5% (10%) level. Taken together, the large and significant coefficients on the OBS intangibles variable ($LMA_{BV} - LMA_j$), combined with the findings for intangible intensity, imply that models omitting intangible assets (e.g., Equation 5) are misspecified.

We examine the robustness of our results to different asset metrics (A_j) with:

$$\frac{CF_{i,t+1}}{A_{j,i,t}} = \alpha + \beta_1 \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right) + \beta_2 \ln\left(\frac{A_{j,i,t}}{A_{BV,i,t}}\right) + \beta_H \mathcal{I}_H \times \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right) + \beta_L \mathcal{I}_L \times \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right) + \gamma Z_{i,t} + \epsilon_{i,t+1}. \quad (9)$$

For brevity, the vector $Z_{i,t}$ includes the lagged dependent variable, firm-level controls, and year and industry fixed effects. Table 6 reports the estimation results. The coefficients on the difference term $LMA_{BV} - LMA_j$ are large and statistically significant across all specifications except for W, which uses patent capital as its OBS intangible asset proxy. These findings reinforce the predictive power of intangible capital for one-year-ahead cash flows and provide further support for Prediction 1. As shown in Panel B, F-tests indicate that the price informativeness intensity coefficients are significantly different

for three (four) of the measures at the 5% (10%) level; the average difference between high and low intangible intensity is -0.174, a relatively large magnitude. Moreover, the joint restriction $\beta_H = \beta_L = 0$ is strongly rejected for all five intangible measures, implying that intangible intensity significantly affects price informativeness and providing further support for Prediction 3.

Next, we employ an alternative specification to verify that the results are not driven by the choice of the dependent-variable deflator. Table 7 reports estimates using the cash-flow-to-sales ratio as the dependent variable. Sales serves as an advantageous deflator in this context because, as an income-statement variable, it is insulated from the valuation complexities of intangible assets and is less susceptible to measurement error. Following the structure of Tables 5 and 6, we first assess the incremental impact of the $LMA_{BV} - LMA_j$ term, then interact this term with intangible intensity in Panel B. Consistent with the results in Tables 5 and 6, the estimated β_1 coefficients exhibit notable stability across all specifications in Panels A and B. Furthermore, the large magnitude and significance of the LMA_{BV}–LMA_j coefficients reinforce the hypothesis that OBS intangibles convey distinct informational signals for forecasting cash flows. F-tests reject the null that intangible intensity equals zero for four of the five metrics, confirming that OBS intangibles provide value-relevant information not captured by the book values of assets.

Results across Tables 5, 6, and 7 demonstrate that our price informativeness estimates (β_1) are robust to the choice of cash flow deflator. More importantly, the significant coefficients on the OBS intangible term ($LMA_{BV} - LMA_j$) and the variation across intensity levels suggest these measures capture unique information regarding future cash flows that is absent from reported book values. Our findings are unlikely to be driven solely by measurement error in the denominator arising from the omission of OBS intangibles.

In summary, our results demonstrate that incorporating OBS intangible measures into a q-theory equation provides significant incremental forecasting power, while price informativeness is attenuated for firms with high intangible intensity. These findings suggest that the baseline model in Equation (5), which includes only a single LMA term, is misspecified. This model fails to capture both the contribution of OBS intangibles and the cross-sectional heterogeneity in price informativeness driven by intangible intensity.

5.3 Forecast Encompassing Tests

We next evaluate whether the metrics contain significant, distinct information using the forecast encompassing test proposed by Fair and Shiller (1990). This test statistically evaluates whether the information in one forecast is fully contained in a competing forecast:

$$y_{i,t} = \alpha + \beta_1 \hat{y}_{1,i,t} + \beta_2 \hat{y}_{2,i,t} + u_{i,t}, \tag{10}$$

where $y_{i,t}$ is the realized outcome, regressed on the forecasts from two competing models ($\hat{y}_{1,i,t}$ and $\hat{y}_{2,i,t}$). We first examine future cash flow scaled by the book values of assets ($CF_{i,t+1}/A_{BV,i,t}$). Model 1, shown in Equation (11), serves as the baseline and uses only the book values of assets (BV) to generate forecasts, denoted as $\widehat{CF}^{BV}_{BV}$, where the superscript BV denotes the dependent variable denominator and the subscript BV denotes using BV to deflate the LMA terms on the right-hand side. This represents forecasts of cash flow deflated by BV, generated using the market cap and intangible intensity, both deflated by BV. Model 2, provided in Equation (12), employs an alternative asset measure (j) that incorporates OBS intangible assets to construct forecasts, designated by $\widehat{CF}^{BV}_{j}$, where LMA terms on the right-hand-side are deflated by A_j. It forecasts the same dependent variable as Model 1 but uses Aj to deflate market capitalization and intangible intensity:

$$\frac{CF_{i,t+1}}{A_{BV,i,t}} = \alpha + \beta_1 \ln\left(\frac{M_{i,t}}{A_{BV,i,t}}\right) + \beta_H \mathcal{I}_H \times \ln\left(\frac{M_{i,t}}{A_{BV,i,t}}\right) + \beta_L \mathcal{I}_L \times \ln\left(\frac{M_{i,t}}{A_{BV,i,t}}\right) + \gamma Z_{i,t} + \epsilon_{i,t+1}. \tag{11}$$

$$\frac{CF_{i,t+1}}{A_{BV,i,t}} = \alpha + \beta_1 \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right) + \beta_H \mathcal{I}_H \times \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right) + \beta_L \mathcal{I}_L \times \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right) + \gamma Z_{i,t} + \epsilon_{i,t+1}. \tag{12}$$

The forecast encompassing test of Fair and Shiller (1990) evaluates the significance of the coefficients β_1 and β_2 in the following model:

$$\frac{CF_{i,t+1}}{A_{BV,i,t}} = \alpha + \beta_1 \widehat{CF}^{BV}_{BV} + \beta_2 \widehat{CF}^{BV}_{j} + u_{i,t}. \tag{13}$$

If β_1 is statistically significant and close to one, and $\beta_2 = 0$ is not rejected, the baseline forecast (BV) generated from Equation (11) encompasses the competing forecast (OBS), rendering the latter redundant. However, if β_2 is statistically significant, it indicates the model incorporating OBS intangibles as the deflator provides predictive information incremental to that contained in the model deflated by the book value of assets.

Table 8 reports the forecast encompassing tests. The first column in the top panel presents a Mincer-

Zarnowitz regression based solely on the forecast using the book values (BV) of assets, $\widehat{y}_1$. We find that $\beta_1 \approx 1$, confirming that the forecast is unbiased. This specification serves as the baseline model, and its adjusted R^2 reflects the explanatory power of an information set limited to book values. Columns (2)–(6) of Panel A present the Fair-Shiller encompassing tests for CF/A_{BV}. In Column (2), both β_{BV} (0.52) and β_{PT} (0.57) are statistically significant, consistent with the PT deflator containing relevant incremental information beyond the book value for forecasting future cash flows. Similarly, Columns (4) and (5) reveal that the coefficients for W and EKP are positive and significant at the 1% level. In contrast, Column (3) indicates that the coefficient for EKP is negative and only marginally significant at the 10% level. The last column presents results using principal components derived from the four OBS intangible forecasts. The first two principal components are statistically significant at the 1% level, indicating that multiple OBS intangible deflator metrics provide significant information, consistent with Prediction 2. This incremental information is economically relevant, increasing the adjusted R^2 by 3.5%.

For robustness, we employ the forecast encompassing test of Chong and Hendry (1986). This test determines whether a baseline model (Model 1) omits useful predictive content found in a competing model (Model 2). We implement it by regressing the forecast errors from the baseline model on the difference between the competing forecast and the baseline forecast:

$$e_{BV} = \alpha + \gamma(\widehat{CF_j^{BV}} - \widehat{CF_{BV}^{BV}}) + v_t, \tag{14}$$

where e_{BV} is the forecast error from the baseline model from Equation (11), defined as $CF/A_{BV} - \widehat{CF_{BV}^{BV}}$. The independent variables $\widehat{CF_j^{BV}}$ and $\widehat{CF_{BV}^{BV}}$ are the forecasts from Models 1 and 2 above. Chong and Hendry (1986) tests evaluate the incremental predictive content of alternative intangible metrics, providing a direct test of Predictions 1 and 2. If information in the deflator is similar, $\gamma = 0$. If $\gamma > 0$, it indicates that the baseline model's forecast errors have different information, implying that the baseline model fails to encompass the OBS model. Panel B of Table 8 reports the results, showing that the OBS metrics PT, W, and EPW yield significant γ coefficients. This finding suggests that OBS intangibles contain information that is incremental to book values, consistent with Prediction 1. Furthermore, the results in Column (5) support Prediction 2; both principal components are positive and significant in explaining baseline forecast errors, confirming that OBS measures enhance cash flow forecasting.

While Table 8 demonstrates that OBS metrics offer incremental information for forecasting CF/A_{BV}, Table 9 presents encompassing tests for forecasting CF/A_j. We present both sets of results because

a priori, the appropriate deflator is uncertain and BV may have relevant information for forecasting CF/A_j. This may seem counterintuitive as this measure includes BV. However, BV may be significant if the information in OBS intangibles is noisy due to incorrect model assumptions. We find that LMA_{BV} is insignificant in the PT and EPW specifications. In contrast, in Table 8 we find that LMA_J is significant in forecasting PT, W and EPW. Combined with earlier results, this implies that LMA_{PT} and LMA_{EPW} fully encompass the baseline model. In contrast, LMA_{BV} remains significant for EKP and W, indicating that neither model fully subsumes the other. The continued relevance of LMA_{BV} in these cases may reflect measurement errors, potentially arising from inaccurate assumptions regarding the capitalization or depreciation of OBS intangible assets.

To further evaluate Prediction 2, we test whether any single OBS intangible metric encompasses all relevant information, and Panel B of Table 9 presents the results. To mitigate multicollinearity, we conduct a principal component analysis. When testing a specific metric (e.g., LMA_{PT}), we extract principal components (PCs) from the remaining metrics (e.g., LMA_{BV}, LMA_{EKP}, LMA_W, and LMA_{EPW}). We find that the first two principal components are statistically significant across all specifications, with the sole exception of the first component in Column (3). This evidence suggests that no single OBS metric captures the full spectrum of relevant information, aligning with Prediction 2. Additionally, the Chong-Hendry encompassing tests reported in Panel C serve as a robustness check, showing that BV only contains incremental information beyond that captured by EKP intangibles. The results are broadly consistent with the findings reported in Panel A.

Collectively, the results from the principal component analysis and pairwise encompassing tests indicate that no single intangible metric is informationally complete. Incorporating information from multiple intangible metrics is important for forecasting for both CF/A_{BV} and CF/A_j.

5.4 Physical Capital Intensity

To test Prediction 4, we analyze whether price informativeness varies with physical capital intensity. Firms are ranked within each industry based on the difference between physical capital ($NPPE$) and intangible assets, scaled by total assets (A_j). Equation 15 follows a similar structure to Equation 9, but examines relative physical capital intensity. We define $\mathcal{I}_{HK}$ and $\mathcal{I}_{LK}$ as indicator variables for firms in the top and bottom 30% of this distribution, respectively and estimate:

$$\frac{CF_{i,t+1}}{A_{j,i,t}} = \alpha + \beta_1 \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right) + \beta_2 \ln\left(\frac{A_{j,i,t}}{A_{BV,i,t}}\right) + \beta_{HK}\mathcal{I}_{HK} \times \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right) + \beta_{LK}\mathcal{I}_{LK} \times \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right) + \gamma Z_{i,t} + \epsilon_{i,t+1}. \quad (15)$$

Table 10 presents the regression results. We hypothesize that $\beta_{HK} > 0$ and $\beta_{LK} < 0$. In line with our predictions, β_{HK} is positive in all five specifications and statistically significant in two. Furthermore, β_{LK} is consistently negative and is significant in four cases, providing consistent support for our hypothesis. Statistical tests further validate these differences; F-tests reject the null hypothesis of equality between β_{HK} and β_{LK} in three specifications at the 5% level and in four specifications at the 10% level. Additionally, we reject the joint null hypothesis that $\beta_{HK} = \beta_{LK} = 0$ across all models. These findings collectively indicate that firms with more tangible capital possess greater price informativeness, supporting the view that tangible assets offer higher transparency to the market than intangible assets.

5.5 Price Informativeness for R&D, Patents, and Returns

We test whether the patterns documented for cash flow forecasts extend to R&D expenditures, patent output, and stock returns. Panel A of Table 11 reports regression estimates for one-year-ahead R&D, scaled by A_j. Across all five specifications, we find that $\beta_H < 0$ and $\beta_L > 0$, indicating that firms with high intangible intensity exhibit lower price informativeness, while those with low intensity exhibit higher informativeness. F-tests reject the null hypothesis of coefficient equality in four out of five cases at the 10% level.[11]

These findings bear on the price-feedback channel through which managers extract information from market valuations to guide investment (Bond et al., 2012). Lower price informativeness in intangible-intensive firms attenuates this channel: market signals less fully convey investment-relevant information that managers do not already possess. Our results indicate that intangible-intensive firms operate in a distinct information environment, in which both the level of intangible intensity and the inclusion of OBS intangible measures shape the informativeness of stock prices for R&D-expenditure forecasts.

We next extend our analysis to future patent output, which represents the realized outcome of innovation. This allows us to distinguish between inputs (R&D expenditures) and outputs (patents) of intangible capital investment. Panel B of Table 11 presents model estimates for changes in patents,

[11] We further strengthen these findings by forecasting $R\&D/A_{BV}$, reported in Panel A of Appendix 8. Across all specifications, β_H is significantly negative, while β_L is significantly positive and economically large. The statistically significant difference between these coefficients indicates that models relying solely on book values of assets fail to capture key variation in R&D forecasts.

scaled by A_j. F-tests reject both the equality of coefficients ($\beta_H = \beta_L$) and the joint restriction ($\beta_H = \beta_L = 0$) in four out of five specifications. The coefficient on the OBS intangible proxy ($LMA_{BV} - LMA_{A_j}$) is statistically significant with economically meaningful magnitudes.

As a check for robustness, Panels A and B of Appendix 8 report the results of the specifications using A_{BV} as the denominator. Here, we find even stronger evidence supporting the relevance of OBS intangibles and intangible intensity. Coefficients for $\mathcal{I}_H$ are negative and significant at the 5% level across all specifications in Panels A and B. F-tests strongly reject both equality and joint insignificance in every case in Appendix 8. These findings reinforce the view that intangible assets are highly informative about future innovative outcomes.

We then examine whether intangible assets predict future stock returns, with results presented in Panel C of Table 11. Consistent with Bai et al. (2016), we anticipate negative coefficients on LMA_{BV}, reflecting the value effect where high market-to-book (growth) firms tend to underperform. The first row confirms these expectations: across all specifications, the coefficient on LMA_{BV} is negative and statistically significant at the 1% level.

Crucially, our results indicate that incorporating OBS intangible measures enhances return predictability. In three of the four specifications, OBS intangible proxies exhibit positive and statistically significant coefficients with economic magnitudes that generally exceed those of LMA_{BV}. This suggests that markets may underreact to intangible capital and that OBS measures provide incremental predictive content. This finding aligns with Hirshleifer et al. (2013), who argue that investors underreact to innovation because the inherent complexity of intangible capital makes its valuation difficult to process. However, the interaction between these measures and levels of intangible intensity yields more nuanced results in the return context.

To compare model performance more formally, Table 12 presents forecast encompassing tests across the R&D, patent, and return models. In eleven of twelve cases (Columns (1)–(4)), the competing specifications that include OBS intangible assets produce statistically significant forecasts, implying that the baseline models using only the book values of assets fail to encompass the information in intangibles. The principal components extracted from OBS intangibles in Columns (5) of Panels A and C are also statistically significant, consistent with Prediction 2: no single intangible metric subsumes all price-relevant variation for forecasting R&D, patents, and returns.

6 Robustness

6.1 Alternative Specification of OBS Intangible Assets

Our main specifications measure OBS intangibles through the difference term $LMA_{BV} - LMA_j$, which captures the OBS intangible capital that is incremental to the assets recognized on the balance sheet. An alternative approach directly evaluates the price informativeness of OBS intangible assets by specifying $LMOBS_j = \ln\left(\frac{M_{i,t}}{OBS_{j,i,t}}\right)$, which parallels the log market-to-assets ratio in Bai et al. (2016) but uses OBS intangible capital rather than total assets as the deflator. Specifically, we estimate:

$$\frac{CF_{i,t+1}}{A_{BV,i,t}} = \alpha + \beta_1 \ln\left(\frac{M_{i,t}}{A_{BV,i,t}}\right) + \beta_2 \ln\left(\frac{M_{i,t}}{OBS_{j,i,t}}\right) + \beta_H \mathcal{I}_H \times \ln\left(\frac{M_{i,t}}{A_{BV,i,t}}\right) + \beta_L \mathcal{I}_L \times \ln\left(\frac{M_{i,t}}{A_{BV,i,t}}\right) + \gamma Z_{i,t} + \epsilon_{i,t+1}. \tag{16}$$

The coefficient β_1 captures the price informativeness of market prices scaled by balance-sheet assets, while β_2 captures the incremental informativeness of market prices adjusted by OBS intangible capital. A significant β_2 indicates that OBS intangibles convey information about future cash flows beyond what is reflected in the book value of assets.

Table 13 Panel A presents the results with CF/A_{BV} as the dependent variable. The coefficient on $LMOBS_j$ is negative and statistically significant for PT, EKP, and EPW. This confirms that the standard PI specification relying solely on total balance-sheet assets omits relevant information contained in OBS intangibles. The last column replaces the individual OBS measures with the first three principal components extracted from the four OBS intangible metrics (PT, EKP, W, and EPW). Two principal components are significant at the 1% level, and a third is significant at the 10% level, indicating that information from multiple OBS measures is collectively important and supporting Prediction 2.

Panel B examines CF/A_j and similarly employs principal components to assess the joint information content of OBS intangible measures. The significance of multiple principal components provides further evidence that no single intangible metric fully captures the information relevant for forecasting cash flows. Taken together, the results in Table 13 indicate that the results in our main analysis are robust to an alternative specification of OBS intangible assets and models of price informativeness using only the book values of assets are misspecified. The incremental information in OBS intangible assets is economically large, statistically significant, and provides substantial predictive power for future cash flows.

6.2 Recent Time Period and Forecast Horizon

To examine the temporal stability of our findings, Table 14 reports price informativeness (PI) estimates for the 2002–2022 period, which is approximately half the full sample. We select this subsample to mitigate the confounding effects of the dot-com bubble and to align with the post-SFAS 142 reporting regime regarding goodwill impairment.[12]

Panel A reports price informativeness estimates for cash flow for the subsample and can be compared with the results for the full sample in Table 6. The coefficients of LMA_j and $(LMA_{BV} - LMA_j)$ are higher for the recent subsample. For LMA_j, all five metrics exceed 0.71, and their average is 0.76 compared to an average of 0.52 in Panel B in Table 6. The observed increase in price informativeness is consistent with advancements in financial reporting quality and information technology (Gao and Huang, 2020; Gu et al., 2020; Dessaint et al., 2024). Another difference is that the coefficients for $(\mathcal{I}_L)$ are all positive and significant for recent years, but only one coefficient is positive and significant for the full sample. In summary, our results are robust over the recent subperiod, confirming that OBS intangible assets and intangible intensity affect the price informativeness of cash flows.

Panel B of Table 14 focuses on R&D price informativeness over the most recent two decades. We find that the results within this subsample are largely consistent with the baseline evidence shown in Panel A of Table 11. We observe a similar stability for patents in Panel C of Table 14; these estimates are qualitatively comparable to the full-sample analysis in Panel A of Table 11. Panel D presents the estimates for returns. When compared to the full sample in Table 11, the coefficients on LMA_j (row 1) retain similar sign and significance. However, the results for the difference term, $LMA_{BV} - LMA_j$ (row 2), are sensitive to the sample period; neither the PT nor EKP estimates maintain consistency in sign or significance.

Lastly, we consider a three-year horizon for cash flow in Table 15. Results are relatively similar to Panel A of the prior table. The coefficient for $LMA_{BV} - LMA_j$ is significant for PT, EKP and EPW. Further, there are significant intangible intensity differences for four of the five metrics. Additional results for patents, R&D and returns are available upon request.

[12] Appendix 1 details the accounting treatment of goodwill and the 2001 regulatory change to goodwill recognition and impairment.

7 Conclusion

We examine how the book values of intangibles, OBS intangibles, and physical assets affect price informativeness for future firm fundamentals. Prior literature tests price informativeness using only the book values of assets (total assets), a method that overlooks the significant corporate investment in internally generated intangibles, which are not recognized on the balance sheet. Over the past three decades, OBS intangibles have grown substantially alongside the expansion of the knowledge-based economy. Using four distinct measurement methods, we document that OBS intangibles are statistically significant and economically substantial relative to the book values of intangibles.

This study applies a q-theory conceptual framework incorporating OBS intangibles to derive four predictions, which are tested using cash flow, R&D, patent activity, and returns. We find that OBS intangibles provide incremental information beyond the book value of intangibles for forecasting firm fundamentals. Forecast encompassing tests and principal components analysis document that no single proxy for OBS intangibles fully captures the information content of this capital. We show that firms with higher intangible intensity exhibit lower price informativeness, consistent with greater opacity and increased difficulty for investors in interpreting market signals relative to tangible-intensive firms. In contrast, firms with higher physical-to-intangible capital ratios display greater price informativeness, implying that tangible assets are easier to evaluate, and thus more reliably reflected in stock prices. Consequently, asset composition, specifically the balance between tangible and intangible capital, significantly affects the predictive power of prices for firm fundamentals.

Our findings have direct implications for empirical finance and financial analysis. We caution against the conventional use of book values of assets, given the growing economic importance of OBS intangibles and their distinct predictive content. Furthermore, the heterogeneity of internally generated intangible capital and the lack of a consensus measure indicate that researchers should consider multiple proxies for OBS intangibles in their analyses.

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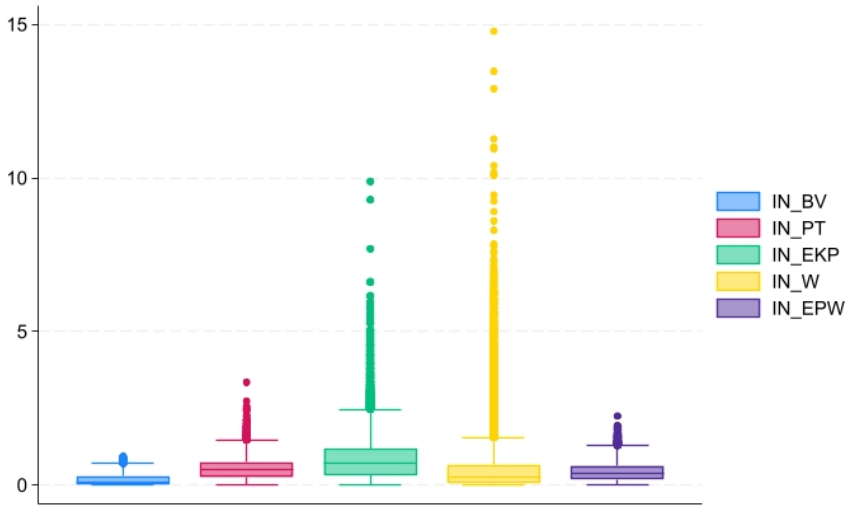


Figure 1: Five Metrics of Intangibles over Book Values of Assets (A_{BV})
The figure presents box plots for five different measures of intangible assets, each scaled by total book assets, A_{BV}. BV is based on the Compustat intangible variable ($intan$), while PT_BV, EKP_BV, W_BV, and EPW_BV correspond to the approaches proposed by Peters and Taylor (2017), Eisfeldt et al. (2022), Woeppel (2022), and Ewens et al. (2025), respectively.

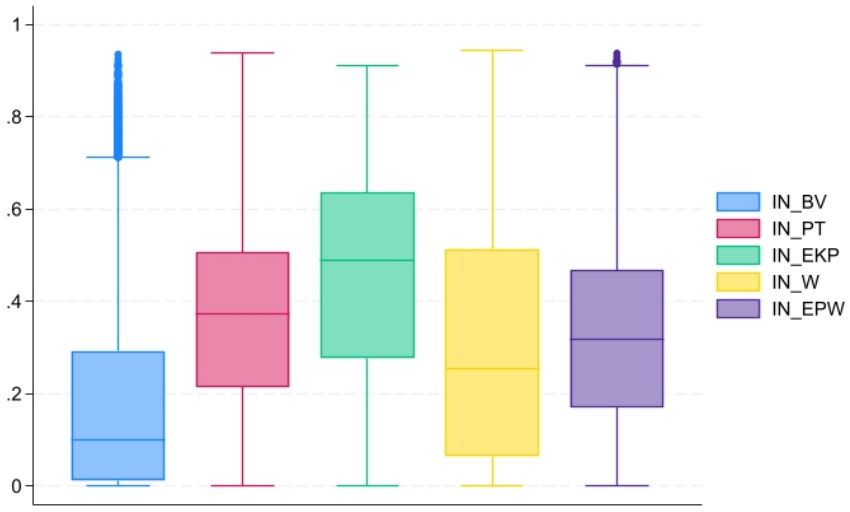


Figure 2: Five Metrics of Intangibles over Their Corresponding Total Assets (A_j)
The figure presents box plots for five different measures of intangible assets, each scaled by the corresponding definition of total assets, A_j. BV is based on the Compustat intangible variable ($intan$) divided by book value of assets (AT). The remaining measures, PT, EKP, W, and EPW, reflect intangible assets estimates following the approaches of Peters and Taylor (2017), Eisfeldt et al. (2022), Woeppel (2022), and Ewens et al. (2025), respectively, each scaled by their corresponding definitions of total assets that include OBS intangibles.

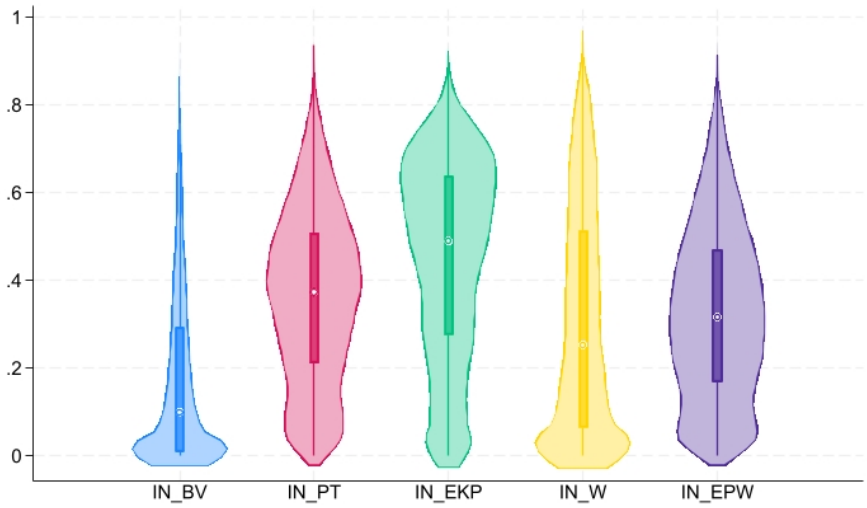


Figure 3: Violin Plots of Intangibles over Assets, A_{BV}
The figure displays violin plots for five different measures of intangible assets, each scaled by total assets, A_j. The BV measure is based on the Compustat intangible variable ($intan$), while PT, EKP, W, and EPW correspond to the approaches proposed by Peters and Taylor (2017), Eisfeldt et al. (2022), Woeppel (2022), and Ewens et al. (2025), respectively.

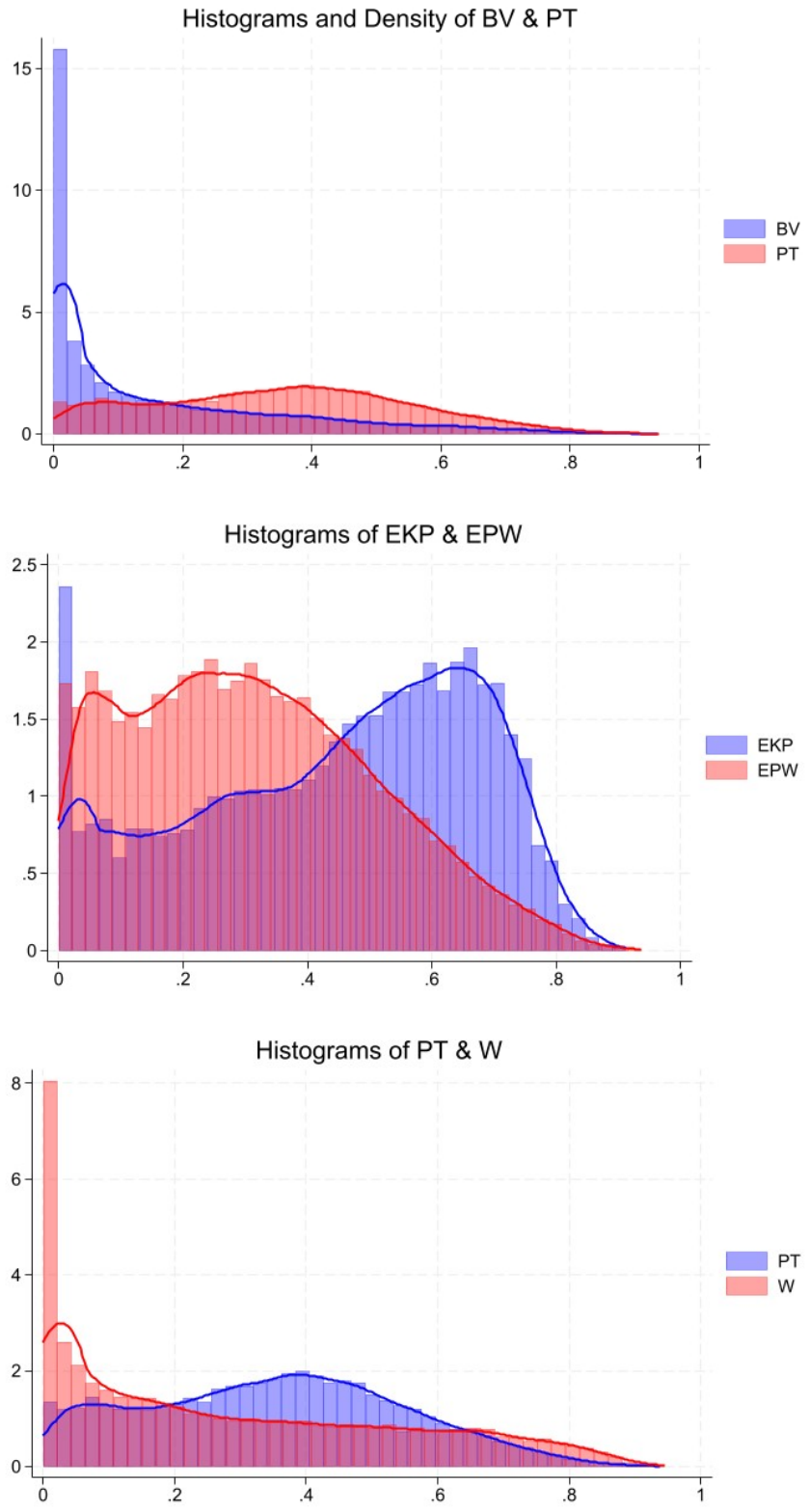


Figure 4: Histograms of Intangibles over Assets
This figure presents overlapping histograms comparing the distribution of intangible assets scaled by total assets across different measurement approaches. The top panel compares the distributions of book value (BV) and PT intangibles. The middle panel compares EKP and EPW, while the bottom panel contrasts PT and W.

Table 1: Summary Statistics for Assets ($)

This table presents summary statistics for intangible and tangible assets in Panel A, and for total assets in Panel B, over the period 1980-2022. Intangible assets (IN_j) and total assets (A_j) are estimated using five different approaches, denoted by j. The BV method uses the book values of assets (Compustat item *at*). The PT approach includes OBS intangibles as measured by Peters and Taylor (2017). The EKP method incorporates OBS intangibles following the method of Eisfeldt et al. (2022). The W approach is based on the estimates from Woeppel (2022), and the EPW method follows Ewens et al. (2025). Tangible assets are measured as Net Property, Plant, & Equipment (Compustat item *ppent*). Reported statistics include the mean (μ), median ($p50$), standard deviation (σ), skewness (γ), and change in mean ($\Delta\mu$), all expressed in millions of U.S. dollars. N denotes the number of observations. t-tests compare the values of μ, $\Delta\mu$, and σ in Column (1) against those in Columns (2) – (5). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Summary Statistics of Intangible (IN_j) and Tangible ($NPPE$) Assets

	IN_{BV}	IN_{PT}	IN_{EKP}	IN_W	IN_{EPW}	$NPPE$
	(1)	(2)	(3)	(4)	(5)	(6)
μ	2,463.73	5,356.98***	8,482.97***	8,763.36***	4,653.05***	2,962.92
$\Delta\mu$	226.99	452.05***	544.00***	887.84***	406.58***	209.28
$p50$	299.16	1,449.94	2,725.71	894.10	1,170.55	711.60
σ	7,639.85	14,222.87***	18,666.36***	30,616.22***	12,796.49***	7,435.54
γ	7.02	6.62	4.95	7.00	6.70	6.46

Panel B: Summary Statistics of Total Assets (A_j)

	A_{BV}	A_{PT}	A_{EKP}	A_W	A_{EPW}
	(1)	(2)	(3)	(4)	(5)
μ	10,035.07	12,778.33***	18,100.12***	16,251.66***	12,096.12***
$\Delta\mu$	756.12	962.61***	1,026.86***	1,391.39***	914.91***
$p50$	3,041.67	4,063.01***	6,426.14***	3,744.59***	3,815.02***
σ	23,966.93	30,241.77***	37,716.11***	46,604.52***	28,717.36***
γ	6.53	6.41	5.21	67.86	6.45
N	27,213	27,183	19,324	27,213	26,967

Table 2: Pairwise Means and Standard Deviations t-tests

This table presents t-statistics for pairwise tests comparing five different measures of intangible assets. The measures include the book value of intangibles (INTAN) and four OBS intangible asset estimates based on Peters and Taylor (2017) (PT), Eisfeldt et al. (2022) (EKP), Woeppel (2022) (W), and Ewens et al. (2025) (EPW). Panel A reports t-statistics testing the equality of means between each pair of intangible measures (e.g., H_0: $\mu_{PT} = \mu_{INTAN}$). Panel B shows the ratio of standard deviations ($\sigma_{\text{row}}/\sigma_{\text{column}}$) for each pair, along with tests of whether the ratio differs significantly from one (e.g., H_0: $\sigma_{PT}/\sigma_{INTAN} = 1$). For instance, $\sigma_{PT}/\sigma_{INTAN} = 2.61$ and $\sigma_{EPW}/\sigma_W = 0.16$, and both ratios are statistically different from one at the 1% significance level (***). Panel C reports t-statistics testing for equality in the change in means across pairs of measures (e.g., H_0: $\Delta\mu_{PT} = \Delta\mu_{INTAN}$). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: t-tests for mean (μ)				
	IN_{BV}	IN_{PT}	IN_{EKP}	IN_W
IN_{PT}	50.78***			
IN_{EKP}	40.11***	25.26***		
IN_W	32.91***	23.47***	11.82***	
IN_{EPW}	49.23***	42.12***	30.76***	26.73***
Panel B: t-tests for standard deviation (σ)				
	IN_{BV}	IN_{PT}	IN_{EKP}	IN_W
IN_{PT}	2.61***			
IN_{EKP}	5.81***	2.22***		
IN_W	13.12***	5.02***	2.25***	
IN_{EPW}	2.05***	0.79***	0.35***	0.16***
Panel C: t-tests for change in mean ($\Delta\mu$)				
	IN_{BV}	IN_{PT}	IN_{EKP}	IN_W
IN_{PT}	21.49***			
IN_{EKP}	14.14***	0.30		
IN_W	20.90***	14.70***	12.59***	
IN_{EPW}	18.85***	8.28***	2.76***	16.00***

Table 3: Summary Statistics using Asset Deflators

This table presents summary statistics for various ratios constructed using five different asset measures as deflators. BV uses the book values of intangibles. PT includes OBS intangibles measured following Peters and Taylor (2017). EKP includes OBS intangibles measured following Eisfeldt et al. (2022). W includes OBS intangibles measured following Woeppel (2022). EPW includes OBS intangibles measured following Ewens et al. (2025). The table reports the mean (μ), median ($p50$), standard deviation (σ), skewness (γ), and change in mean ($\Delta\mu$) for ratios involving intangible assets, market capitalization, and cash flow. t-tests compare the μ, $\Delta\mu$, and σ in Column (1) to each of the values in Columns (2) – (5). N denotes the number of observations. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Intangible Assets$_j$/Assets$_{BV}$					
	IN_{BV}/A_{BV}	IN_{PT}/A_{BV}	IN_{EKP}/A_{BV}	IN_{W}/A_{BV}	IN_{EPW}/A_{BV}
	(1)	(2)	(3)	(4)	(5)
μ	0.178	0.519***	0.864***	0.540***	0.434***
$\Delta\mu$	0.006	0.007**	−0.005***	0.025***	0.007***
$p50$	0.100	0.502	0.707	0.279	0.401
σ	0.200	0.332***	0.740***	0.821***	0.295***
γ	1.184	0.665	1.872	4.166	0.660
N	24,427	24,404	18,385	24,427	24,197
Panel B: Intangible Assets$_j$/Assets$_j$					
	IN_{BV}/A_{BV}	IN_{PT}/A_{PT}	IN_{EKP}/A_{EKP}	IN_{W}/A_{W}	IN_{EPW}/A_{EPW}
	(1)	(2)	(3)	(4)	(5)
μ	0.178	0.366***	0.449***	0.306***	0.328***
$\Delta\mu$	0.006	0.005***	0.001***	0.008***	0.005***
$p50$	0.100	0.490	0.253	0.316	0.198
σ	0.200	0.197	0.226***	0.257***	0.197
γ	1.184	0.060	−0.417	0.487	0.312
N	24,427	24,404	18,385	24,427	24,197
Panel C: ln(Market Cap/Assets$_j$)					
	$\ln(M/A_{BV})$	$\ln(M/A_{PT})$	$\ln(M/A_{EKP})$	$\ln(M/A_{W})$	$\ln(M/A_{EPW})$
	(1)	(2)	(3)	(4)	(5)
μ	0.239	−0.036***	−0.251***	0.020***	0.019***
$\Delta\mu$	−0.021	−0.022**	−0.154***	−0.030***	−0.021**
$p50$	0.207	−0.060	−0.262	−0.029	−0.004
σ	0.908	0.872***	0.915*	0.888	0.860**
γ	0.202	0.212	0.145	0.323	0.194
N	27,196	27,196	27,196	27,196	26,950
Panel D: Cash Flow/Assets$_j$					
	CF/A_{BV}	CF/A_{PT}	CF/A_{EKP}	CF/A_{W}	CF/A_{EPW}
	(1)	(2)	(3)	(4)	(5)
μ	0.115	0.087***	0.072***	0.095***	0.093***
$\Delta\mu$	−0.005	−0.004***	−0.003***	−0.005	−0.004***
$p50$	0.106	0.084	0.069	0.083	0.089
σ	0.130	0.103***	0.082***	0.119***	0.106***
γ	−0.295	−0.186	−0.585	0.302	−0.092
N	18,147	18,147	18,147	18,147	17,997

Table 4: Price Informativeness

This table presents regressions estimating one-year-ahead cash flow using the following specification:

$$\frac{CF_{i,t+1}}{A_{j,i,t}} = \alpha + \beta_1 \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right) + \rho\left(\frac{CF_{i,t}}{A_{j,i,t}}\right) + \gamma X_{i,t} + \psi \mathbf{1} + \epsilon_{i,t+1}.$$

where $M_{i,t}$ is market capitalization, $CF_{i,t}$ is cash flow (EBIT), and $A_{j,i,t}$ denotes total assets measured using alternative definitions indexed by j. The term $\ln(M_{i,t}/A_{j,i,t})$ is the log market-to-asset ratio (LMA). Panel A includes industry fixed effects, and Panel B adds year fixed effects. Panel C incorporates the lagged dependent variable ($CF_{i,t}/A_{j,i,t}$) and firm-level control variables including institutional ownership ratio (IOR), idiosyncratic volatility ($IVOL$), institutional ownership concentration (HHI), and analyst coverage ($COVERAGE$). All regressions include robust standard errors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dep. Vars.	CF/A_{BV}	CF/A_{PT}	CF/A_{EKP}	CF/A_{W}	CF/A_{EPW}
	(1)	(2)	(3)	(4)	(5)
Panel A: Model with industry fixed effects					
LMA	0.389***	0.394***	0.465***	0.333***	0.388***
	(0.052)	(0.051)	(0.044)	(0.053)	(0.050)
Panel B: Model with industry and year fixed effects					
LMA	0.429***	0.426***	0.491***	0.362***	0.423***
	(0.069)	(0.067)	(0.057)	(0.067)	(0.065)
Panel C: Full model with controls and fixed effects					
LMA	0.468***	0.442***	0.514***	0.383***	0.448***
	(0.122)	(0.127)	(0.115)	(0.116)	(0.123)
CF_t/A_t	0.225**	0.223*	0.392**	0.195*	0.218*
	(0.100)	(0.115)	(0.165)	(0.101)	(0.112)
IOR	0.128	0.116	−0.101	0.153	0.160
	(0.210)	(0.204)	(0.225)	(0.178)	(0.207)
$IVOL$	−2.004	−2.267	−2.006	−1.375	−2.201
	(1.837)	(1.964)	(1.983)	(1.733)	(1.960)
HHI	0.153	0.145	−0.030	0.169	0.177
	(0.210)	(0.204)	(0.221)	(0.178)	(0.207)
$COVERAGE$	0.123**	0.102	0.111*	0.112**	0.112
	(0.060)	(0.069)	(0.068)	(0.056)	(0.070)
N	13,701	13,701	13,701	13,701	13,698

Table 5: Price Informativeness of CF/A_{BV} with Intangible Intensity

This table tests price informativeness for CF/A_{BV} with the following equation:

$$\frac{CF_{i,t+1}}{A_{BV,i,t}} = \alpha + \beta_1 \ln\left(\frac{M_{i,t}}{A_{BV,i,t}}\right) + \beta_2 \ln\left(\frac{A_{j,i,t}}{A_{BV,i,t}}\right) + \gamma Z_{i,t} + \epsilon_{i,t+1},$$

where $LMA_{BV} - LMA_j = \ln\left(\frac{A_{j,i,t}}{A_{BV,i,t}}\right)$ and measures OBS intangible assets. $Z_{i,t}$ includes the lagged dependent variable, firm-level controls, and year and industry fixed effects. Panel A reports results for this baseline model. Panel B extends the analysis by interacting the benchmark LMA with firm-level intangible intensity indicators. Firms are classified into high ($\mathcal{I}_H$) and low ($\mathcal{I}_L$) intangible intensity groups based on the top and bottom 30% of the distribution within each industry. The following model is estimated:

$$\frac{CF_{i,t+1}}{A_{BV,i,t}} = \alpha + \beta_1 \ln\left(\frac{M_{i,t}}{A_{BV,i,t}}\right) + \beta_2 \ln\left(\frac{A_{j,i,t}}{A_{BV,i,t}}\right) + \beta_H \mathcal{I}_H \times \ln\left(\frac{M_{i,t}}{A_{BV,i,t}}\right) + \beta_L \mathcal{I}_L \times \ln\left(\frac{M_{i,t}}{A_{BV,i,t}}\right) + \gamma Z_{i,t} + \epsilon_{i,t+1}.$$

All regressions include industry and year fixed effects, as well as the firm-level control variables. Robust standard errors are used in all specifications. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Including $LMA_{BV} - LMA_j$					
Dep. Var.	CF/A_{BV}				
LMA_j Metric	LMA_{BV}	LMA_{PT}	LMA_{EKP}	LMA_W	LMA_{EPW}
	(1)	(2)	(3)	(4)	(5)
LMA_{BV}	0.468***	0.446***	0.366***	0.468***	0.446***
	(0.122)	(0.122)	(0.119)	(0.122)	(0.122)
$LMA_{BV} - LMA_j$		1.145***	0.876***	0.026	1.145***
		(0.174)	(0.097)	(0.104)	(0.174)
Panel B: Including interaction term with intangible intensity dummies					
Dep. Var.	CF/A_{BV}				
LMA_j Metric	LMA_{BV}	LMA_{PT}	LMA_{EKP}	LMA_W	LMA_{EPW}
	(1)	(2)	(3)	(4)	(5)
LMA_{BV}	0.534***	0.459***	0.477***	0.506***	0.508***
	(0.107)	(0.108)	(0.043)	(0.102)	(0.106)
$LMA_{BV} - LMA_j$		1.735***	1.798***	0.595***	2.003***
		(0.227)	(0.156)	(0.102)	(0.251)
$\mathcal{I}_H \times \ln\left(\frac{M_{i,t}}{A_{BV,i,t}}\right)$	-0.129***	-0.065**	0.043	-0.063**	-0.070**
	(0.030)	(0.028)	(0.038)	(0.027)	(0.029)
$\mathcal{I}_L \times \ln\left(\frac{M_{i,t}}{A_{BV,i,t}}\right)$	-0.020	0.066	0.126***	0.017	0.026
	(0.081)	(0.071)	(0.042)	(0.106)	(0.074)
F: $\beta_H = \beta_L$	2.42	2.96	0.59	2.04	2.56
	0.1199	0.0853	0.4429	0.1537	0.0983
F: $\beta_H = \beta_L = 0$	23.37	9.17	5.75	8.14	8.96
	0.0000	0.0102	0.0565	0.0171	0.0092

Table 6: Price Informativeness of CF/A_j with Intangible Intensity

This table tests price informativeness for CF/A_j with the following equation:

$$\frac{CF_{i,t+1}}{A_{j,i,t}} = \alpha + \beta_1 \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right) + \beta_2 \ln\left(\frac{A_{j,i,t}}{A_{BV,i,t}}\right) + \gamma Z_{i,t} + \epsilon_{i,t+1},$$

where the lagged dependent variable, firm-level controls, and year and industry fixed effects are included in $Z_{i,t}$ for brevity. Panel A reports results for this baseline model. Panel B extends the analysis by interacting the benchmark LMA with firm-level intangible intensity indicators. Firms are classified into high ($\mathcal{I}_H$) and low ($\mathcal{I}_L$) intangible intensity groups based on the top and bottom 30% of the distribution within each industry. The following model is estimated:

$$\frac{CF_{i,t+1}}{A_{j,i,t}} = \alpha + \beta_1 \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right) + \beta_2 \ln\left(\frac{A_{j,i,t}}{A_{BV,i,t}}\right) + \beta_H \mathcal{I}_H \times \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right) + \beta_L \mathcal{I}_L \times \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right) + \gamma Z_{i,t} + \epsilon_{i,t+1}.$$

All regressions include industry and year fixed effects, as well as the firm-level control variables. Robust standard errors are used in all specifications. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Including $LMA_{BV} - LMA_j$					
Dep. Var.	CF/A_{BV}	CF/A_{PT}	CF/A_{EKP}	CF/A_W	CF/A_{EPW}
LMA_j Metric	LMA_{BV}	LMA_{PT}	LMA_{EKP}	LMA_W	LMA_{EPW}
	(1)	(2)	(3)	(4)	(5)
LMA_j	0.468***	0.458***	0.514***	0.382***	0.480***
	(0.122)	(0.130)	(0.115)	(0.125)	(0.125)
$LMA_{BV} - LMA_j$		0.842***	0.480***	-0.003	1.064***
		(0.188)	(0.149)	(0.103)	(0.169)
Panel B: Including interaction term with intangible intensity dummies					
Dep. Var.	CF/A_{BV}	CF/A_{PT}	CF/A_{EKP}	CF/A_W	CF/A_{EPW}
LMA_j Metric	LMA_{BV}	LMA_{PT}	LMA_{EKP}	LMA_W	LMA_{EPW}
	(1)	(2)	(3)	(4)	(5)
LMA_j	0.534***	0.459***	0.667***	0.421***	0.500***
	(0.107)	(0.116)	(0.055)	(0.105)	(0.113)
$LMA_{BV} - LMA_j$		1.036***	0.980***	0.025	1.247***
		(0.200)	(0.136)	(0.091)	(0.237)
$\mathcal{I}_H \times \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right)$	-0.129***	-0.095***	-0.023	-0.133***	-0.084***
	(0.030)	(0.027)	(0.036)	(0.025)	(0.028)
$\mathcal{I}_L \times \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right)$	-0.020	0.106	0.199***	0.066	0.053
	(0.081)	(0.071)	(0.051)	(0.109)	(0.075)
F: $\beta_H = \beta_L$	2.42	9.33	14.92	3.72	4.26
	0.1199	0.0023	0.0001	0.0538	0.0389
F: $\beta_H = \beta_L = 0$	23.37	21.86	16.86	34.74	14.17
	0.0000	0.0000	0.0002	0.0000	0.0008

Table 7: Price Informativeness of CF/S with Intangible Intensity

This table tests price informativeness for the cash-flow-to-sales ratio with the following equation:

$$\frac{CF_{i,t+1}}{S_{i,t}} = \alpha + \beta_1 \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right) + \beta_2 \ln\left(\frac{A_{j,i,t}}{A_{BV,i,t}}\right) + \gamma Z_{i,t} + \epsilon_{i,t+1},$$

where S denotes sales, the lagged dependent variable, firm-level controls, and year and industry fixed effects are included in $Z_{i,t}$ for brevity. Panel A reports results for this baseline model. Panel B extends the analysis by interacting the benchmark LMA with firm-level intangible intensity indicators. Firms are classified into high ($\mathcal{I}_H$) and low ($\mathcal{I}_L$) intangible intensity groups based on the top and bottom 30% of the distribution within each industry. The following model is estimated:

$$\frac{CF_{i,t+1}}{S_{i,t}} = \alpha + \beta_1 \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right) + \beta_2 \ln\left(\frac{A_{j,i,t}}{A_{BV,i,t}}\right) + \beta_H \mathcal{I}_H \times \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right) + \beta_L \mathcal{I}_L \times \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right) + \gamma Z_{i,t} + \epsilon_{i,t+1}.$$

All regressions include industry and year fixed effects, as well as the firm-level control variables. Robust standard errors are used in all specifications. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Including $LMA_{BV} - LMA_j$					
Dep. Var.	CF/S				
LMA_j Metric	LMA_{BV}	LMA_{PT}	LMA_{EKP}	LMA_W	LMA_{EPW}
	(1)	(2)	(3)	(4)	(5)
LMA_j	0.264***	0.252***	0.241***	0.268***	0.256***
	(0.050)	(0.052)	(0.055)	(0.052)	(0.049)
$LMA_{BV} - LMA_j$		0.609***	0.339***	0.194***	0.647***
		(0.131)	(0.071)	(0.066)	(0.161)
Panel B: Including interaction term with intangible intensity dummies					
Dep. Var.	CF/S				
LMA_j Metric	LMA_{BV}	LMA_{PT}	LMA_{EKP}	LMA_W	LMA_{EPW}
	(1)	(2)	(3)	(4)	(5)
LMA_j	0.283***	0.230***	0.250***	0.258***	0.232***
	(0.048)	(0.053)	(0.051)	(0.053)	(0.047)
$LMA_{BV} - LMA_j$		0.705***	0.357***	0.229***	0.724***
		(0.158)	(0.082)	(0.075)	(0.181)
$\mathcal{I}_H \times \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right)$	-0.075***	-0.062***	-0.031	-0.034*	-0.047***
	(0.020)	(0.020)	(0.022)	(0.019)	(0.018)
$\mathcal{I}_L \times \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right)$	0.004	0.091**	0.120**	0.063	0.093**
	(0.042)	(0.039)	(0.048)	(0.050)	(0.043)
F: $\beta_H = \beta_L$	2.5	9.5	6.46	2.85	7.46
	0.1138	0.0021	0.011	0.0913	0.0063
F: $\beta_H = \beta_L = 0$	15.24	11.15	6.6	3.94	9.03
	0.0005	0.0038	0.0369	0.1398	0.011

Table 8: Forecast Encompassing Test of CF/A_{BV}

This table presents results for the one-year-ahead forecast encompassing tests of cash flows, CF/A_{BV}. Panel A contains Fair-Shiller regressions. The last column includes the principal component forecast, constructed from the four OBS intangibles. Panel B reports the Chong-Hendry tests, which regress the forecast residual (e_{BV}) on the differences between competing forecasts ($\widehat{CF}_{BV,j} - \widehat{CF}_{BV,BV}$). All regressions include industry and year fixed effects, as well as the firm-level control variables. Robust standard errors are used in all specifications. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Fair-Shiller encompassing test						
Dep. Var.	CF/A_{BV}					
LMA_j Metric	LMA_{BV}	LMA_{PT}	LMA_{EKP}	LMA_W	LMA_{EPW}	LMA_{PC}
	(1)	(2)	(3)	(4)	(5)	(6)
$\hat{y}_{BV}$	1.024***	0.520***	1.189***	0.599***	0.450***	0.159
	(0.012)	(0.141)	(0.057)	(0.104)	(0.145)	(0.170)
$\hat{y}_j$		0.567***	-0.080*	0.490***	0.633***	
		(0.167)	(0.043)	(0.144)	(0.158)	
$PC1$						0.265***
						(0.047)
$PC2$						-0.370***
						(0.048)
$PC3$						-0.093
						(0.118)
R^2	0.4187	0.4579	0.429	0.4582	0.4558	0.4533
Panel B: Chong-Hendry encompassing test						
Dep. Var.	e_{BV}					
LMA_j Metric	LMA_{PT}	LMA_{EKP}	LMA_W	LMA_{EPW}	LMA_{PC}	
	(1)	(2)	(3)	(4)	(5)	
$\widehat{CF}_{BV,j} - \widehat{CF}_{BV,BV}$	-0.407***	0.037	-0.407***	-0.469***		
	(0.134)	(0.044)	(0.101)	(0.151)		
$PC1$					0.028***	
					(0.010)	
$PC2$					0.070***	
					(0.023)	
$PC3$					-0.004	
					(0.033)	
R^2	0.0704	0.0692	0.0731	0.0683	0.0894	

Table 9: Forecast Encompassing Test of CF/A_j

This table presents the one-year ahead forecast encompassing tests for CF/A_j. Unlike the previous table, the dependent variable is cash flow deflated by the alternative j measures of assets. Panel A compares the forecasts based on LMA_j and LMA_{BV}. Panel B then reports results using principal components of the forecasts, excluding information from that asset. Panel C performs the Chong-Hendry test. All regressions include robust standard errors, industry and year fixed effects, and firm-level control variables. Robust standard errors are used in all specifications. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Fair-Shiller encompassing test				
Dep. Var.	CF/A_{PT}	CF/A_{EKP}	CF/A_W	CF/A_{EPW}
	(1)	(2)	(3)	(4)
$\hat{y}_j$	1.123***	0.085	0.664***	0.890***
	(0.142)	(0.057)	(0.225)	(0.248)
$\hat{y}_{BV}$	-0.063	0.910***	0.430**	0.169
	(0.097)	(0.067)	(0.171)	(0.199)
R^2	0.4083	0.3171	0.5027	0.4166
Panel B: Fair-Shiller encompassing test using PC				
Dep. Var.	CF/A_{PT}	CF/A_{EKP}	CF/A_W	CF/A_{EPW}
	(1)	(2)	(3)	(4)
$\hat{y}_j$	0.837***	0.190***	1.049***	1.740***
	(0.153)	(0.057)	(0.144)	(0.282)
PC_{j1}	0.072*	0.223***	-0.007	-0.121**
	(0.081)	(0.016)	(0.028)	(0.058)
PC_{j2}	-0.181*	-0.181*	-0.206***	0.161***
	(0.081)	(0.078)	(0.078)	(0.031)
R^2	0.399	0.3271	0.4892	0.506
Panel C: Chong-Hendry encompassing test				
Dep. Var.	e_{PT}	e_{EKP}	e_W	e_{EPW}
	(1)	(2)	(3)	(4)
$\widehat{CF}_{BV,BV} - \widehat{CF}_{BV,j}$	0.047	-0.919***	-0.334	-0.189
	(0.115)	(0.064)	(0.227)	(0.184)
R^2	0.0594	0.2219	0.0354	0.0597

Table 10: Price Informativeness with Physical Capital Intensity

This table presents estimates for the following model of one-year-ahead forecasts of CF/A_j:

$$\frac{CF_{i,t+1}}{A_{j,i,t}} = \alpha + \beta_1 \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right) + \beta_2 \ln\left(\frac{A_{j,i,t}}{A_{BV,i,t}}\right) + \beta_{HK}\mathcal{I}_{HK} \times \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right) + \beta_{LK}\mathcal{I}_{LK} \times \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right) + \gamma Z_{i,t} + \epsilon_{i,t+1},$$

where $\mathcal{I}_{HK}$ and $\mathcal{I}_{LK}$ are indicator variables denoting firms with high (top 30%) and low (bottom 30%) relative physical capital intensity. Intensity is calculated as the difference between physical capital ($NPPE$) and intangible assets (IN_j), scaled by total assets A_j. All regressions include industry and year fixed effects, as well as the firm-level control variables. Robust standard errors are used in all specifications. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dep. Var.	CF/A_{BV}	CF/A_{PT}	CF/A_{EKP}	CF/A_{W}	CF/A_{EPW}
LMA_j Metric	LMA_{BV}	LMA_{PT}	LMA_{EKP}	LMA_{W}	LMA_{EPW}
	(1)	(2)	(3)	(4)	(5)
LMA_j	0.450***	0.479***	0.655***	0.404***	0.511***
	(0.154)	(0.111)	(0.059)	(0.110)	(0.099)
$LMA_{BV} - LMA_j$		0.996***	0.957***	0.021	1.205***
		(0.192)	(0.138)	(0.085)	(0.231)
$\mathcal{I}_{HK} \times \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right)$	0.192***	0.056	0.210***	0.076	0.016
	(0.073)	(0.085)	(0.057)	(0.091)	(0.112)
$\mathcal{I}_{LK} \times \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right)$	-0.065**	-0.102***	-0.006	-0.098***	-0.088**
	(0.031)	(0.032)	(0.036)	(0.027)	(0.035)
F: $\beta_{HK} = \beta_{LK}$	18.53	4.35	12.37	3.26	1.21
	0.0000	0.037	0.0004	0.0711	0.2719
F: $\beta_{HK} = \beta_{LK} = 0$	23.96	15.32	14.48	14.63	11.27
	0.0000	0.0005	0.0007	0.0007	0.0036

Table 11: Price Informativeness of R&D, Patents, and Returns

This table reports regression estimates of three forward-looking outcomes using alternative asset definitions ($A_{j,i,t}$) as scaling variables. Panel A presents regressions of one-year-ahead R&D expenditures scaled by assets, specified as $\frac{R\&D_{i,t+1}}{A_{j,i,t}}$. Panel B displays regressions for the one-year-ahead change in patents, scaled similarly as $\frac{\Delta PAT_{i,t+1}}{A_{j,i,t}}$. Panel C reports regressions of one-year-ahead stock returns, measured as $\ln(RET_{i,t+1})$. All panels employ the following regression specification:

$$Y = \alpha + \beta_1 \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right) + \beta_2 \ln\left(\frac{A_{j,i,t}}{A_{BV,i,t}}\right) + \beta_H \mathcal{I}_H \times \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right) + \beta_L \mathcal{I}_L \times \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right) + \gamma Z_{i,t} + \epsilon_{i,t+1},$$

where Y corresponds to the outcome variable of interest in each respective panel. All regressions include industry and year fixed effects, as well as the firm-level control variables. Robust standard errors are used in all specifications. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Forecasts of $R\&D/A_j$					
Dep. Var	$R\&D/A_{BV}$	$R\&D/A_{PT}$	$R\&D/A_{EKP}$	$R\&D/A_W$	$R\&D/A_{EPW}$
LMA_j Metric	LMA_{BV}	LMA_{PT}	LMA_{EKP}	LMA_W	LMA_{EPW}
	(1)	(2)	(3)	(4)	(5)
LMA_j	0.396***	0.406***	0.553***	0.299***	0.432***
	(0.053)	(0.050)	(0.077)	(0.041)	(0.052)
$LMA_{BV} - LMA_j$		1.310***	-0.012	0.080	1.166***
		(0.227)	(0.124)	(0.081)	(0.352)
$\mathcal{I}_H \times \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right)$	-0.105***	-0.032	-0.033	-0.031	-0.023
	(0.031)	(0.030)	(0.032)	(0.022)	(0.026)
$\mathcal{I}_L \times \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right)$	0.162***	0.029	0.085*	0.225***	0.089
	(0.054)	(0.052)	(0.051)	(0.073)	(0.057)
F: $\beta_H = \beta_L$	16.56	1.19	3.79	9.63	3.08
	0.0001	0.2758	0.0515	0.0019	0.0793
F: $\beta_H = \beta_L = 0$	18.18	1.67	3.8	9.7	3.1
	0.0001	0.4334	0.1499	0.0078	0.2124
Panel B: Forecasts of $\Delta PAT/A_j$					
Dep. Var	$\Delta PAT/A_{BV}$	$\Delta PAT/A_{PT}$	$\Delta PAT/A_{EKP}$	$\Delta PAT/A_W$	$\Delta PAT/A_{EPW}$
LMA_j Metric	LMA_{BV}	LMA_{PT}	LMA_{EKP}	LMA_W	LMA_{EPW}
	(1)	(2)	(3)	(4)	(5)
LMA_j	0.446***	0.386***	0.374***	0.408***	0.415***
	(0.040)	(0.037)	(0.040)	(0.041)	(0.039)
$LMA_{BV} - LMA_j$		1.438***	0.391***	0.878***	1.973***
		(0.110)	(0.071)	(0.067)	(0.169)
$\mathcal{I}_H \times \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right)$	-0.092***	-0.056***	-0.026	0.015	-0.068***
	(0.022)	(0.021)	(0.021)	(0.029)	(0.022)
$\mathcal{I}_L \times \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right)$	0.018	0.032	-0.041*	-0.097***	0.040
	(0.033)	(0.026)	(0.024)	(0.037)	(0.029)
F: $\beta_H = \beta_L$	8.05	6.33	0.28	6.52	8.63
	0.0046	0.0119	0.5965	0.0107	0.0033
F: $\beta_H = \beta_L = 0$	17.3	8.12	3.76	7.71	11.27
	0.0002	0.0173	0.1523	0.0212	0.0036

Table 11 continued

Panel C: Forecasts of $\ln(RET)$					
Dep. Var	$\ln(RET)$				
LMA_j Metric	LMA_{BV}	LMA_{PT}	LMA_{EKP}	LMA_W	LMA_{EPW}
	(1)	(2)	(3)	(4)	(5)
LMA_j	-0.644***	-0.701***	-0.786***	-0.621***	-0.659***
	(0.049)	(0.051)	(0.062)	(0.051)	(0.051)
$LMA_{BV} - LMA_j$		0.915***	0.398***	-1.118***	1.321***
		(0.210)	(0.120)	(0.123)	(0.270)
$\mathcal{I}_H \times \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right)$	-0.050	-0.077	0.062	-0.106**	-0.053
	(0.051)	(0.051)	(0.054)	(0.054)	(0.051)
$\mathcal{I}_L \times \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right)$	0.032	0.112**	0.042	0.150***	0.087
	(0.061)	(0.050)	(0.055)	(0.056)	(0.055)
F: $\beta_H = \beta_L$	0.92	6.15	0.08	9.57	3.13
	0.3378	0.0132	0.7822	0.002	0.0767
F: $\beta_H = \beta_L = 0$	1.11	6.51	1.78	9.8	3.26
	0.5745	0.0385	0.4116	0.0075	0.1961

Table 12: Forecast Encompassing Tests: R&D, Patents, and Returns

This table reports the one-year-ahead forecast encompassing tests for R&D (Panel A), Patents (Panel B), and Returns (Panel C) using Fair-Shiller regressions. The last column includes the principal component forecast, constructed from the four OBS intangibles. All regressions include industry and year fixed effects, as well as the firm-level control variables. Robust standard errors are used in all specifications. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: $R\&D/A_{BV}$					
Dep. Var.	$R\&D/A_{BV}$				
	(1)	(2)	(3)	(4)	(5)
$\hat{y}_{BV}$	0.372***	0.608***	0.151*	0.426***	0.671***
	(0.121)	(0.121)	(0.088)	(0.123)	(0.126)
$\hat{y}_j$	0.567***	0.388***	0.873***	0.495***	
	(0.127)	(0.127)	(0.102)	(0.124)	
$PC1$					0.166***
					(0.054)
$PC2$					0.197
					(0.168)
$PC3$					1.043***
					(0.168)
R^2	0.7126	0.7286	0.7281	0.7109	0.7434
Panel B: $\Delta PAT/A_{BV}$					
Dep. Var.	$\Delta PAT/A_{BV}$				
	(1)	(2)	(3)	(4)	(5)
$\hat{y}_{BV}$	0.453***	0.564***	0.876***	0.321*	0.575**
	(0.155)	(0.082)	(0.040)	(0.178)	(0.245)
$\hat{y}_j$	0.524***	0.424***	0.141***	0.652***	
	(0.160)	(0.084)	(0.051)	(0.183)	
$PC1$					0.249
					(0.155)
$PC2$					0.042
					(0.072)
$PC3$					0.863***
					(0.234)
R^2	0.7439	0.7554	0.7313	0.7463	0.7308
Panel C: $\ln(RET)$					
Dep. Var.	$\ln(RET)$				
	(1)	(2)	(3)	(4)	(5)
$\hat{y}_{BV}$	-0.040	-0.011	0.159***	-0.063**	-0.115
	(0.029)	(0.026)	(0.046)	(0.029)	(0.127)
$\hat{y}_j$	0.166***	0.153***	-0.040	0.187***	
	(0.029)	(0.026)	(0.043)	(0.029)	
$PC1$					0.038***
					(0.003)
$PC2$					-0.044***
					(0.014)
$PC3$					0.045
					(0.039)
R^2	0.2851	0.3026	0.2841	0.2856	0.3033

Table 13: Robustness: PI of CF with LMA_{BV} and OBS intangible assets ($LMOBS_j$)

This table examines the price informativeness of incremental intangible assets using two model specifications. Panel A estimates forecasts $CF_{i,t+1}/A_{BV,i,t}$, using the standard PI measure (LMA_{BV}) and the log of market capitalization/OBS assets, $LMOBS_j = \ln\left(\frac{M_{i,t}}{OBS_{j,i,t}}\right)$:

$$\frac{CF_{i,t+1}}{A_{BV,i,t}} = \alpha + \beta_1 \ln\left(\frac{M_{i,t}}{A_{BV,i,t}}\right) + \beta_2 \ln\left(\frac{M_{i,t}}{OBS_{j,i,t}}\right) + \beta_H \mathcal{I}_H \times \ln\left(\frac{M_{i,t}}{A_{BV,i,t}}\right) + \beta_L \mathcal{I}_L \times \ln\left(\frac{M_{i,t}}{A_{BV,i,t}}\right) + \gamma Z_{i,t} + \epsilon_{i,t+1}.$$

The last column of Panel A uses the three principal components of the OBS intangibles measures. Panel B evaluates $CF_{i,t+1}/A_{j,i,t}$ using these principal components. All regressions include industry and year fixed effects, and the firm-level control variables. F-statistics are omitted for brevity. Robust standard errors are used in all specifications. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Forecasts of CF/A_{BV}

$LMOBS_j$ Metric	$LMOBS_{PT}$	$LMOBS_{EKP}$	$LMOBS_W$	$LMOBS_{EPW}$	$LMOBS_{PC}$
	(1)	(2)	(3)	(4)	(5)
LMA_{BV}	0.610***	0.768***	0.605***	0.593***	0.821***
	(0.138)	(0.058)	(0.045)	(0.131)	(0.070)
$LMOBS_j$	-0.123**	-0.191***	-0.006	-0.102**	
	(0.059)	(0.032)	(0.019)	(0.051)	
$\mathcal{I}_H \times \ln\left(\frac{M_{i,t}}{A_{BV,i,t}}\right)$	-0.135***	-0.069**	-0.077**	-0.134***	-0.034
	(0.031)	(0.028)	(0.031)	(0.031)	(0.031)
$\mathcal{I}_L \times \ln\left(\frac{M_{i,t}}{A_{BV,i,t}}\right)$	-0.009	0.079	0.031	-0.010	0.056
	(0.097)	(0.051)	(0.049)	(0.097)	(0.056)
OBS_{PC1}					-0.211***
					(0.038)
OBS_{PC2}					0.250***
					(0.064)
OBS_{PC3}					0.115*
					(0.059)

Panel B: Forecasts of CF/A_j

CF_j Metric	CF/A_{PT}	CF/A_{EKP}	CF/A_W	CF/A_{EPW}
LMA_{BV}	0.716***	0.601***	0.568***	0.734***
	(0.061)	(0.060)	(0.056)	(0.067)
$\mathcal{I}_H \times \ln\left(\frac{M_{i,t}}{A_{BV,i,t}}\right)$	-0.097***	-0.049	-0.073**	-0.049
	(0.032)	(0.035)	(0.029)	(0.033)
$\mathcal{I}_L \times \ln\left(\frac{M_{i,t}}{A_{BV,i,t}}\right)$	0.143***	0.219***	0.240***	0.156***
	(0.046)	(0.064)	(0.046)	(0.049)
OBS_{PC1}	-0.145***	-0.079**	-0.128***	-0.171***
	(0.033)	(0.034)	(0.029)	(0.032)
OBS_{PC2}	0.152***	0.144**	0.268***	0.150***
	(0.054)	(0.062)	(0.053)	(0.056)
OBS_{PC3}	-0.034	0.084	0.030	-0.008
	(0.049)	(0.053)	(0.046)	(0.051)

Table 14: Robustness: Recent Time Period

This table presents regression estimates for four forward-looking firm outcomes, using alternative asset definitions ($A_{j,i,t}$) as scaling variables, over the sample period from 2002 to 2022. Panel A reports estimates for one-year-ahead cash flow scaled by assets, specified as $\frac{CF_{i,t+1}}{A_{j,i,t}}$. Panel B presents regressions of one-year-ahead R&D expenditures scaled by assets, specified as $\frac{R\&D_{i,t+1}}{A_{j,i,t}}$. Panel C displays regressions for the one-year-ahead change in patents, scaled similarly as $\frac{\Delta PAT_{i,t+1}}{A_{j,i,t}}$. Panel D reports regressions of one-year-ahead stock returns, measured as $\ln(RET_{i,t+1})$. All panels employ the following regression specification:

$$Y = \alpha + \beta_1 \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right) + \beta_2 \ln\left(\frac{A_{j,i,t}}{A_{BV,i,t}}\right) + \beta_H \mathcal{I}_H \times \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right) + \beta_L \mathcal{I}_L \times \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right) + \gamma Z_{i,t} + \epsilon_{i,t+1},$$

where Y corresponds to the outcome variable of interest in each respective panel. All regressions include industry and year fixed effects, as well as the firm-level control variables. Robust standard errors are used in all specifications. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Price Informativeness of CF 2002–2022					
Dep. Var.	CF/A_{BV}	CF/A_{PT}	CF/A_{EKP}	CF/A_{W}	CF/A_{EPW}
LMA_j Metric	LMA_{BV}	LMA_{PT}	LMA_{EKP}	LMA_{W}	LMA_{EPW}
	(1)	(2)	(3)	(4)	(5)
LMA_j	0.766***	0.767***	0.784***	0.712***	0.760***
	(0.059)	(0.066)	(0.071)	(0.063)	(0.063)
$LMA_{BV} - LMA_j$		1.665***	1.019***	0.323***	1.872***
		(0.274)	(0.158)	(0.092)	(0.309)
$\mathcal{I}_H \times \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right)$	-0.078**	-0.104***	-0.008	-0.118***	-0.066*
	(0.031)	(0.035)	(0.042)	(0.039)	(0.035)
$\mathcal{I}_L \times \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right)$	0.110*	0.219***	0.208***	0.177***	0.197***
	(0.064)	(0.055)	(0.060)	(0.053)	(0.054)
F: $\beta_H = \beta_L$	6.93	25.28	10.09	24.26	19.22
	0.0085	0.0000	0.0015	0.0000	0.0000
F: $\beta_H = \beta_L = 0$	9.32	25.52	12.52	24.82	19.24
	0.0095	0.0000	0.0019	0.0000	0.0001
Panel B: Price Informativeness of R&D 2002–2022					
Dep. Var.	$R\&D/A_{BV}$	$R\&D/A_{PT}$	$R\&D/A_{EKP}$	$R\&D/A_{W}$	$R\&D/A_{EPW}$
LMA_j Metric	LMA_{BV}	LMA_{PT}	LMA_{EKP}	LMA_{W}	LMA_{EPW}
	(1)	(2)	(3)	(4)	(5)
LMA_j	0.469***	0.479***	0.604***	0.307***	0.472***
	(0.066)	(0.077)	(0.096)	(0.046)	(0.064)
$LMA_{BV} - LMA_j$		2.825***	0.048	0.061	1.535***
		(0.353)	(0.160)	(0.087)	(0.530)
$\mathcal{I}_H \times \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right)$	-0.086***	0.011	-0.028	-0.031	0.017
	(0.030)	(0.044)	(0.039)	(0.026)	(0.030)
$\mathcal{I}_L \times \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right)$	0.138***	-0.057	0.080	0.075*	0.032
	(0.050)	(0.066)	(0.055)	(0.039)	(0.046)
F: $\beta_H = \beta_L$	19.11	1.58	2.34	6.63	0.12
	0	0.2809	0.1265	0.01	0.7339
F: $\beta_H = \beta_L = 0$	21.39	1.6	2.44	6.65	0.6
	0	0.5494	0.2953	0.0359	0.7423

Table 14 continued

Panel C: Price Informativeness of Patents 2002–2022					
Dep. Var.	$\Delta PAT/A_{BV}$	$\Delta PAT/A_{PT}$	$\Delta PAT/A_{EKP}$	$\Delta PAT/A_{W}$	$\Delta PAT/A_{EPW}$
LMA_j Metric	LMA_{BV}	LMA_{PT}	LMA_{EKP}	LMA_{W}	LMA_{EPW}
	(1)	(2)	(3)	(4)	(5)
LMA_j	0.517***	0.409***	0.438***	0.340***	0.446***
	(0.046)	(0.037)	(0.047)	(0.023)	(0.039)
$LMA_{BV} - LMA_j$		1.565***	0.408***	0.682***	2.092***
		(0.146)	(0.086)	(0.070)	(0.221)
$\mathcal{I}_H \times \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right)$	-0.097***	-0.041*	-0.011	-0.003	-0.061***
	(0.026)	(0.022)	(0.021)	(0.018)	
$\mathcal{I}_L \times \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right)$	-0.013	0.014	-0.077***	-0.070***	0.011
	(0.037)	(0.020)	(0.025)	(0.024)	(0.027)
F: $\beta_H = \beta_L$	3.98	3.77	5.41	6.09	4.74
	0.0461	0.0521	0.02	0.0136	0.0294
F: $\beta_H = \beta_L = 0$	13.61	4.32	9.23	8.76	9.02
	0.0011	0.1155	0.0099	0.0125	0.011
Panel D: Price Informativeness of RET 2002–2022					
Dep. Var.	$\ln(RET)$				
LMA_j Metric	LMA_{BV}	LMA_{PT}	LMA_{EKP}	LMA_{W}	LMA_{EPW}
	(1)	(2)	(3)	(4)	(5)
LMA_j	-0.491***	-0.493***	-0.515***	-0.502***	-0.483***
	(0.034)	(0.037)	(0.036)	(0.035)	(0.033)
$LMA_{BV} - LMA_j$		0.035	-0.177**	-0.359***	0.491***
		(0.103)	(0.070)	(0.068)	(0.169)
$\mathcal{I}_H \times \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right)$	0.023	-0.009	0.045*	0.006	0.009
	(0.028)	(0.026)	(0.027)	(0.028)	
$\mathcal{I}_L \times \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right)$	0.058	0.033	-0.012	0.093**	0.037
	(0.038)	(0.032)	(0.031)	(0.038)	(0.032)
F: $\beta_H = \beta_L$	1.53	2.31	3.73	0.51	1.25
	0.2157	0.1285	0.0536	0.4759	0.2631
F: $\beta_H = \beta_L = 0$	1.77	3.29	6.12	1.32	1.36
	0.4123	0.1926	0.047	0.5157	0.5065

Table 15: Robustness to Alternative Horizon, CF_3/A_j

This table presents regressions estimating three-year-ahead cash flow from 2002–2022. The model specification is:

$$\frac{CF_{i,t+3}}{A_{j,i,t}} = \alpha + \beta_1 \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right) + \beta_2 \ln\left(\frac{A_{j,i,t}}{A_{BV,i,t}}\right) + \beta_H \mathcal{I}_H \times \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right) + \beta_L \mathcal{I}_L \times \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right) + \gamma Z_{i,t} + \epsilon_{i,t+1},$$

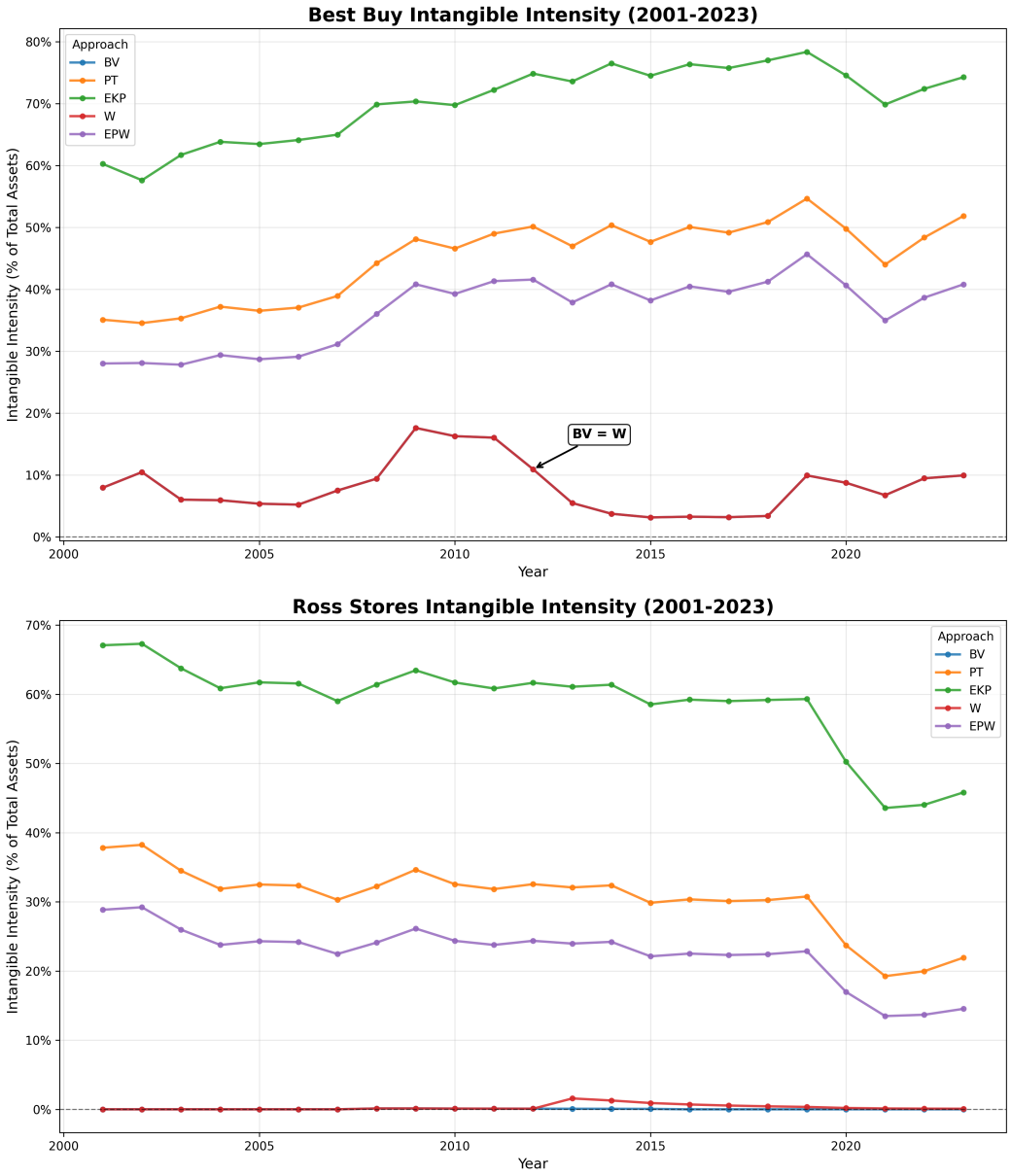
where $M_{i,t}$ is market capitalization, $CF_{i,t}$ is cash flow (EBIT), and $A_{j,i,t}$ denotes total assets measured using alternative definitions indexed by j. The term $\ln(M_{i,t}/A_{j,i,t})$ is referred to as the log market-to-assets ratio (LMA). All regressions include industry and year fixed effects, as well as the firm-level control variables. Robust standard errors are used in all specifications. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dep. Var.	CF/A_{BV}	CF/A_{PT}	CF/A_{EKP}	CF/A_{W}	CF/A_{EPW}
LMA_j Metric	LMA_{BV}	LMA_{PT}	LMA_{EKP}	LMA_{W}	LMA_{EPW}
	(1)	(2)	(3)	(4)	(5)
LMA_j	0.269***	0.207***	0.240***	0.146***	0.191***
	(0.052)	(0.048)	(0.061)	(0.050)	(0.051)
$LMA_{BV} - LMA_j$		1.005***	0.521***	0.047	1.230***
		(0.194)	(0.136)	(0.066)	(0.240)
$\mathcal{I}_H \times \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right)$	-0.065	0.044*	-0.007	0.091***	0.108***
	(0.046)	(0.027)	(0.039)	(0.028)	(0.030)
$\mathcal{I}_L \times \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right)$	0.171***	0.006	-0.022	0.079	0.065
	(0.047)	(0.039)	(0.040)	(0.051)	(0.041)
F: $\beta_H = \beta_L$	0.95	0.07	0.07	1.14	10.85
	0.3308	0.7847	0.7949	0.2851	0.001
F: $\beta_H = \beta_L = 0$	2.89	0.33	0.49	12.98	13.95
	0.2352	0.8500	0.0053	0.0015	0.0009

Appendix 1 Variable Definitions

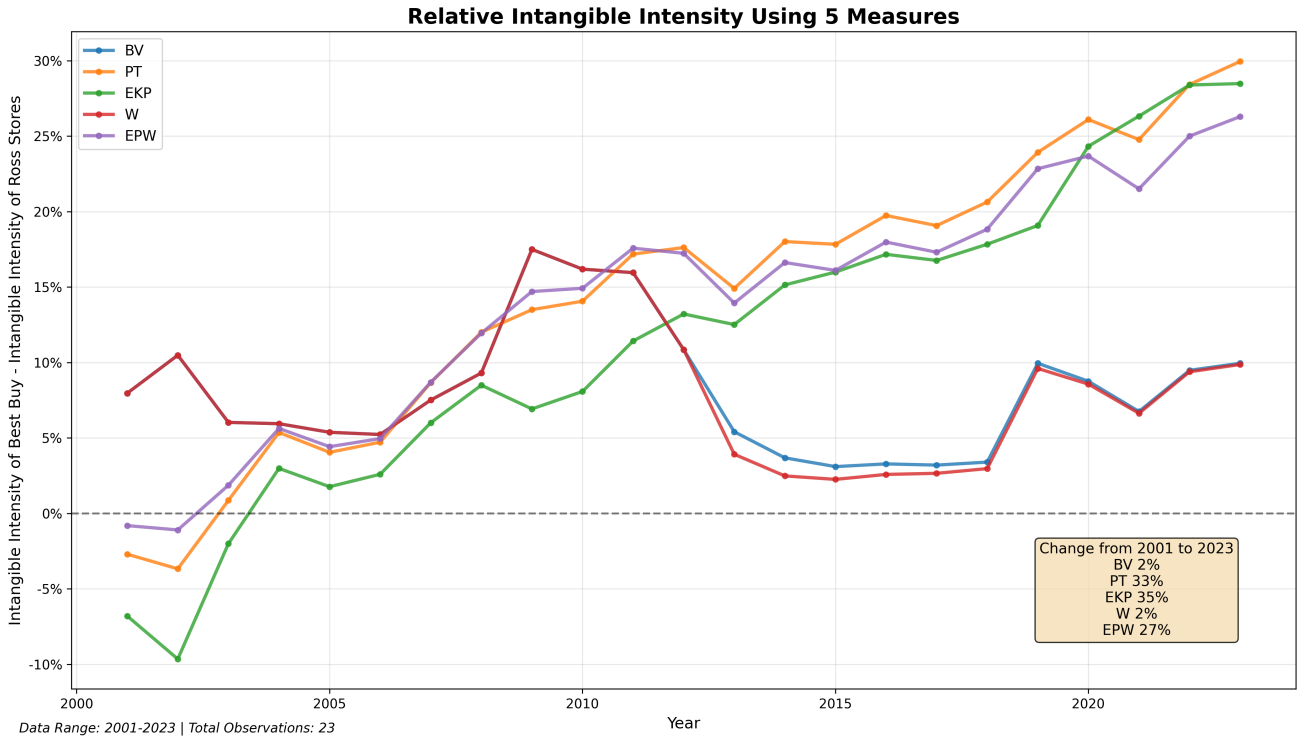
Variable	Description
TOTAL ASSETS	$A_{j,i,t}$ is total assets using approach j for firm i at time t. $j \in$ {BV, PT, EKP, W, EPW}. $A_{BV,i,t} = at$, where Compustat item at is total assets on the balance sheet. $A_{PT,i,t} = at + KnowledgeCapital_{PT} + OrganizationalCapital_{PT}$, Peters and Taylor (2017). $A_{EKP,i,t} = at + INT - gdwl$, Eisfeldt et al. (2022). $A_{W,i,t} = at + PatentCapital$, Woeppel (2022). $A_{EPW,i,t} = at + KnowledgeCapital_{EPW} + OrganizationalCapital_{EPW}$, Ewens et al. (2025).
LMA	The log of market capitalization ($M_{i,t}$) for firm i at time t, divided by total assets ($A_{j,i,t}$), where approach j is used to incorporate OBS intangible assets into total assets. Bai et al. (2016) calculate LMA using the market capitalization measured on March 31 and Compustat item at for total assets. The regression coefficient on LMA serves as the primary measure of price informativeness (PI).
CASH FLOW	$CF_{i,t+1}$ is next year's firm i cash flow measured as EBIT following Bai et al. (2016). Compustat item *ebit* equals Net Sales (*sale*) minus Cost of Goods Sold (*cogs*) minus Selling, General & Administrative Expense (*xsga*) minus Depreciation/Amortization (*dp*).
SG&A	Compustat variable *xsga* is the selling, general, and administrative expense. This generally includes all operating expenses not directly assigned to COGS. While Compustat has a separate variable for R&D and most companies report this expenditure separately, *xsga* includes R&D expenditure as well as marketing, advertising, employee training and IT.
R&D	Compustat item *xrd* is the research and development expenditure.
RET	The return is calculated over the one-year period starting in April using CRSP data.
NPPE	Compustat item *ppent* is Net Property, Plant and Equipment. It represents the cost of tangible fixed assets used to generate revenue (*ppegt*) minus Accumulated Depreciation and Amortization (*dpact*)
INTAN	Compustat item *intan* is the value of intangible assets on the balance sheet. We refer to this as the book value (BV) of intangible assets. *Intan* is the sum of Compustat items *ggdwl* and *intano*.
GDWL	Compustat item *gdwl* reflects the excess cost of equity of an acquired company. Under Accounting Principles Board (APB) Opinion No. 17, companies amortize goodwill on a straight-line basis over a period not exceeding 40 years. This approach was superseded in 2001 when FASB issued SFAS 141 and SFAS 142. SFAS 141 eliminated the pooling of interests method of accounting for business combinations. SFAS 142, which applies to mergers and acquisitions completed after June 30, 2001, requires goodwill to be capitalized and subject to an annual impairment test.
INTANO	Compustat item *intano* represents all intangible assets other than goodwill. These include assets such as copyrights, patent costs, client lists, subscription lists, technology know-how intellectual property, and trademarks/tradenames.
TURNOVER	Share turnover is measured as the natural log of the number of shares traded divided by the number of shares outstanding. Calculated over the 12-month period corresponding to the fiscal year.
IVOL	Idiosyncratic volatility is the standard deviation of daily abnormal returns over the 252 calendar days before (and including) March 31. At least 21 return observations (one-month trading days) over that 252-day period for a permno are required to calculate its stock return volatility. This approach follows Bai et al. (2016).
IOR	Institutional ownership ratio calculated using 13F filings.
HHI	Herfindahl-Hirschman index of institutional ownership concentration.
COVERAGE	The natural log of 1 plus the number of equity analysts covering the stock.

Appendix 2 Intangible Intensity: Best Buy & Ross Stores



Note. The plots show the intangible intensity for Best Buy and Ross Stores from 2001 to 2023. Intangible intensity is the ratio of intangible assets to total assets. Intangible assets are measured using the following approaches: BV, PT, EKP, W, and EPW. The intangible intensity measured using BV and W are the same for Best Buy during this time period.

Appendix 3 Relative Intangible Intensity: Best Buy & Ross Stores



Note. The plot shows the difference in intangible intensity for Best Buy and Ross Stores from 2001 to 2023. Best Buy and Ross Stores have distinct business models and competitive positioning in the retail industry. This results in fundamentally different strategies with respect to intangible capital investments.

Best Buy: Significant Investments in Brand and Employee Capital

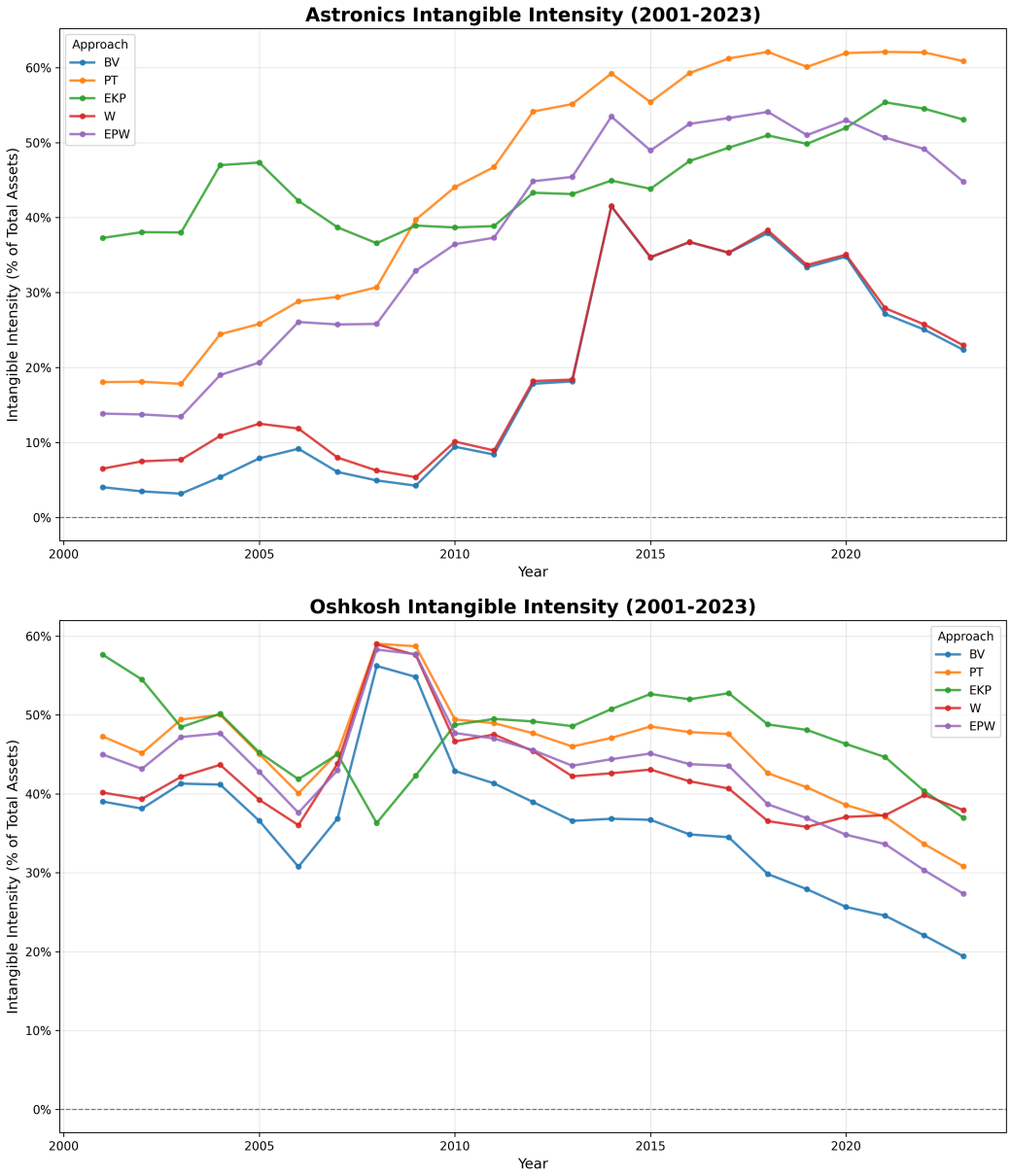
- Geek Squad: distinctive service brand relying on employee expertise,
- Advertising: high spending to promote brand awareness and customer retention,
- Omnichannel Experiences: e-commerce and mobile apps.

Ross Stores: Operational Efficiency with Low Expenses

- Organic Growth: minimal acquisitions and word-of-mouth marketing,
- Advertising: low spending relative to other retailers,
- In-Store Experiences: no e-commerce platform.

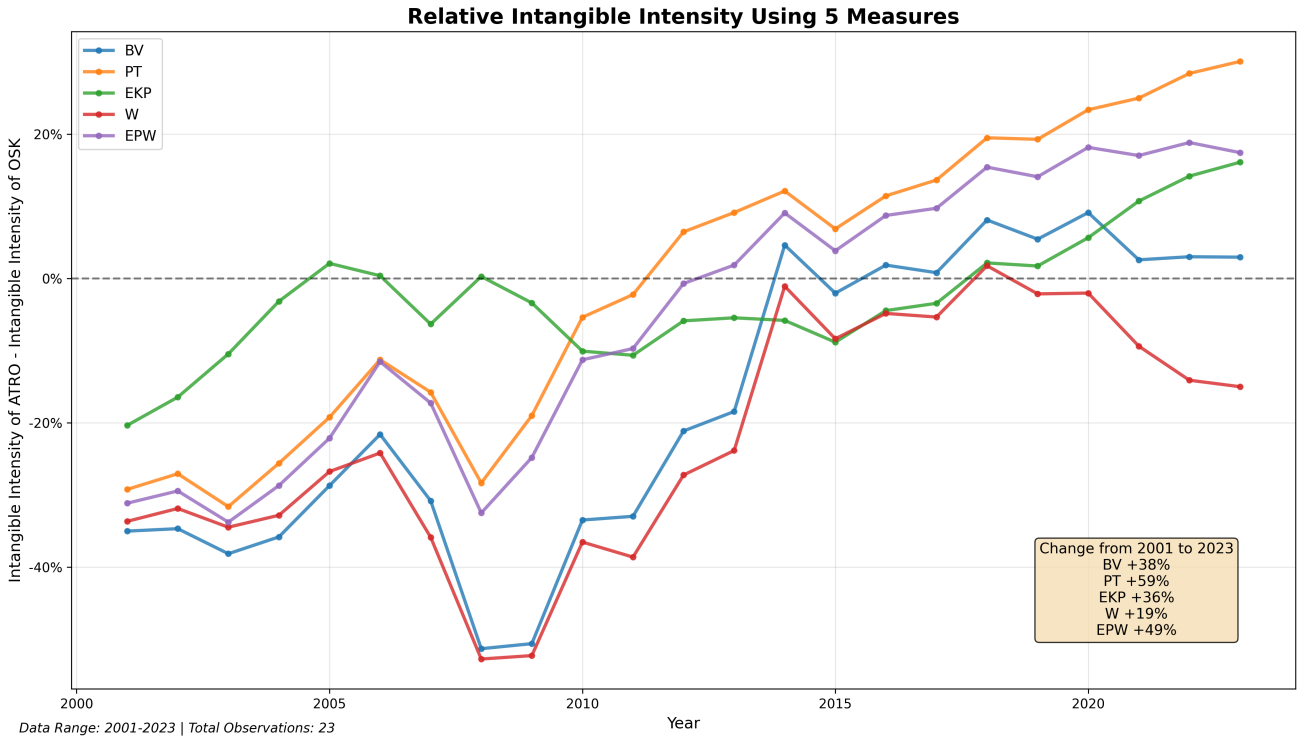
The approach used to measure intangible capital significantly affects a comparison of these companies over this time period. From the perspective of intangible assets on the balance sheet (BV) and patent capital (W), there appears to be little change (2%) in their relative amounts of intangible capital. However, measures that include knowledge and organizational capital (PT, EKP, and EPW) reveal that Best Buy accumulated substantially more intangible capital. Over this period, the relative increase in intangible intensity amounts to between 27% and 35% of total assets using these methods.

Appendix 4 Intangible Intensity: Astronics & Oshkosh



Note. The plot shows the difference in intangible intensity for Astronics (ATRO) and Oshkosh (OSK) from 2001 to 2023. Intangible intensity is the ratio of intangible assets to total assets. Intangible assets are measured using the following approaches: BV, PT, EKP, W, and EPW.

Appendix 5 Relative Intangible Intensity: Astronics & Oshkosh



Note. The plot shows the difference in intangible intensity for Astronics and Oshkosh from 2001 to 2023. Astronics and Oshkosh are industrial firms in the Capital Goods Industry, and both companies have significant sales to government clients. However, their business operations use different levels of intangible capital.

Astronics: Building Organizational Capital to Create Sticky Customer Relationships

- Highly engineered electronic systems and components,
- Skilled employees working closely with buyers to provide customized solutions,
- Builds capabilities internally or through smaller, strategic acquisitions.

Oshkosh: Portfolio of Leading Industrial Brands

- Leading market share in each of its businesses,
- Extensive dealer network driving sales,
- History of large-scale, transformative acquisitions.

From 2014–2023, the companies had similar intangible intensity when measured using the book values. The measures including OBS intangible capital all indicate larger differences between the two firms, and these are consistent with the differences in the business models.

Appendix 6 Incremental Intangible Capital

Measuring Price Informativeness (PI)

Following Bai et al. (2016), we define price informativeness (PI) as the coefficient on the log of the market-to-assets ratio:

$$LMA_{j,i,t} = \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right),$$

where $M_{i,t}$ is the market capitalization and $A_{j,i,t}$ represents total assets for firm i at time t, calculated using one of five approaches: $j \in \{\text{BV}, \text{PT}, \text{EKP}, \text{W}, \text{EPW}\}$.

Derivation of Incremental Intangible Capital

In Equation (7), we extend Bai et al. (2016) by incorporating a measure of off-balance sheet (OBS) intangible capital. This incremental capital is defined as the difference between the log market-to-assets ratio using the book value of assets (LMA_{BV}) and the ratio using an alternative asset measure (LMA_j). Applying the logarithmic identity $\ln(x) - \ln(y) = \ln(x/y)$, this difference simplifies to:

$$\ln\left(\frac{M_{i,t}}{A_{BV,i,t}}\right) - \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right) = \ln\left(\frac{M_{i,t}/A_{BV,i,t}}{M_{i,t}/A_{j,i,t}}\right) = \ln\left(\frac{M_{i,t}}{A_{BV,i,t}} \cdot \frac{A_{j,i,t}}{M_{i,t}}\right) = \ln\left(\frac{A_{j,i,t}}{A_{BV,i,t}}\right).$$

This term, $LMA_{BV} - LMA_j$, effectively isolates the intangible capital that is incremental to the assets recognized on the balance sheet. Consequently, the measure equals zero for firms without OBS intangibles and increases proportionally with the value of unrecognized intangible capital.

Model Misspecification and Value Relevance

We incorporate this measure of incremental intangible assets in multiple models, and the results are consistent with the critical role of OBS intangible capital in the modern economic landscape. Our findings suggest that the traditional accounting measure of total assets fails to fully capture the value-relevant information for firm assets. Consequently, excluding these unrecognized assets likely results in misspecified models of price informativeness.

Appendix 7 A q-theory Framework

In this section, we present the economic rationale for our price informativeness measure, which adapts the framework of Bai et al. (2016) to test the paper's main predictions. In q-theory, a firm with investment k in new capital and productivity shock z has an ex post fundamental value of

$$v(z,k) = (1+z)(\bar{k}+k) - k - \frac{\gamma}{2\bar{k}}k^2,$$

where $\bar{k}$ is the firm's current assets and γ is a parameter that governs adjustment costs. Assuming that the discount rate is normalized to zero, the q-theory investment equation becomes

$$\gamma\frac{k^*}{\bar{k}} = E[z|\mathcal{I}_m],$$

where $\mathcal{I}_m$ is the information set of the firm's manager and k^* is the value-maximizing level of capital, that is $k^* = \text{argmax}_k E[v(z,k)|\mathcal{I}_m]$. Therefore, the ex post maximized value of the firm is

$$\frac{v(z,k^*)}{\bar{k}} = 1 + z + \frac{z}{\gamma}E[z|\mathcal{I}_m] - \frac{1}{2\gamma}E[z|\mathcal{I}_m]^2.$$

The expected firm value conditional on the manager's information set is given by

$$E\left[\frac{v(z,k^*)}{\bar{k}}|\mathcal{I}_m\right] = 1 + E[z|\mathcal{I}_m] + \frac{1}{2\gamma}E[z|\mathcal{I}_m]^2.$$

Assume that z has a mean of zero. Then, the aggregate efficiency is defined as the ex ante firm value

$$E[v(z,k^*)] = \bar{k} + \frac{\bar{k}}{2\gamma}\,Var(E[z|\mathcal{I}_m]).$$

As reflected in the above equation, the aggregate welfare depends on the value of current assets $\bar{k}$ and on the variance of the forecastable productivity under the manager's information set.

Regarding the information environment, a firm's manager has information about z produced from the firm itself (inside information), which is denoted by

$$\eta = z + \varepsilon_\eta, \quad \varepsilon_\eta \sim N(0, \sigma_\eta^2).$$

Similarly, informed traders also have information about z, denoted by

$$s = z + \varepsilon_s, \quad \varepsilon_s \sim N(0, \sigma_s^2).$$

Bai et al. (2016) also assumes that traders observe an additional signal from the manager, denoted by

$$\eta' = \eta + \varepsilon'_\eta, \quad \varepsilon'_\eta \sim N(0, \sigma_{\eta'}^2).$$

Firm managers use their information set to determine k, so their optimal decision is

$$k^* = \frac{\bar{k}}{\gamma} E[v(z, k^*)|\eta, \eta', p].$$

The stock market aggregates these signals into the stock price p. In equilibrium, the stock price depends on the firm's fundamental value conditional on the informed trader's information set, $\mathcal{I}_T = \{\eta', s\}$, that is

$$p = \alpha E[v(z, k^*)|\eta', s] + \beta u,$$

where u is noise trading demand, and α and β are endogenous coefficients in the rational expectation equilibrium. Bai et al. (2016) defines forecasting price efficiency (FPE) as the variance of the predictable component of firm value $v/\bar{k}$ given q, where $q = p/\bar{k}$ is the firm's market-to-book ratio. That is

$$\mathcal{V}_{FPE} = Var(E[z|q]).$$

Similar to Bai et al. (2016), our analysis focuses on FPE, which measures the total amount of information about future payoffs contained in market prices.

Appendix 8 Price Informativeness of R&D and Patents

This table reports regression estimates of two forward-looking outcomes using book values of assets ($A_{BV,i,t}$) as scaling variables. Panel A presents regressions of one-year-ahead R&D expenditures scaled by assets, specified as $\frac{R\&D_{i,t+1}}{A_{BV,i,t}}$ and Panel B displays regressions for the one-year-ahead change in patents, scaled similarly as $\frac{\Delta PAT_{i,t+1}}{A_{BV,i,t}}$. Both panels employ the following regression specification:

$$Y = \alpha + \beta_1 \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right) + \beta_2 \ln\left(\frac{A_{j,i,t}}{A_{BV,i,t}}\right) + \beta_H \mathcal{I}_H \times \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right) + \beta_L \mathcal{I}_L \times \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right) + \gamma Z_{i,t} + \epsilon_{i,t+1},$$

where Y corresponds to the outcome variable of interest in each respective panel. All regressions include industry and year fixed effects, as well as the firm-level control variables. Robust standard errors are used in all specifications. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Forecasts of $R\&D/A_{BV}$				
Dep. Var	$R\&D/A_{BV}$			
LMA_j Metric	LMA_{PT}	LMA_{EKP}	LMA_W	LMA_{EPW}
	(1)	(2)	(3)	(4)
LMA_{BV}	0.380***	0.351***	0.382***	0.409***
	(0.053)	(0.052)	(0.053)	(0.053)
$LMA_{BV} - LMA_j$	1.265***	0.391***	0.528***	1.006***
	(0.255)	(0.115)	(0.128)	(0.335)
$\mathcal{I}_H \times \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right)$	-0.110***	-0.106***	-0.103***	-0.107***
	(0.031)	(0.031)	(0.032)	(0.031)
$\mathcal{I}_L \times \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right)$	0.174***	0.178***	0.173***	0.179***
	(0.058)	(0.056)	(0.058)	(0.057)
F: $\beta_H = \beta_L$	16.38	17.19	14.93	17.06
	0.0001	0.0000	0.0001	0.0000
F: $\beta_H = \beta_L = 0$	18.57	18.66	16.23	18.54
	0.0001	0.0001	0.0003	0.0001
Panel B: Forecasts of $\Delta PAT/A_{BV}$				
Dep. Var.	$\Delta PAT/A_{BV}$			
LMA_j Metric	LMA_{PT}	LMA_{EKP}	LMA_W	LMA_{EPW}
	(1)	(2)	(3)	(4)
LMA_j	0.380***	0.343***	0.401***	0.422***
	(0.037)	(0.038)	(0.033)	(0.038)
$LMA_{BV} - LMA_j$	1.772***	0.704***	1.799***	2.236***
	(0.133)	(0.079)	(0.099)	(0.166)
$\mathcal{I}_H \times \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right)$	-0.097***	-0.090***	-0.092***	-0.091***
	(0.022)	(0.022)	(0.018)	(0.022)
$\mathcal{I}_L \times \ln\left(\frac{M_{i,t}}{A_{j,i,t}}\right)$	0.026	0.033	0.017	0.033
	(0.033)	(0.032)	(0.033)	(0.032)
F: $\beta_H = \beta_L$	9.99	10.12	8.82	10.49
	0.0016	0.0014	0.0008	0.0012
F: $\beta_H = \beta_L = 0$	20.85	17.74	27.79	18.80
	0.0000	0.0001	0.0000	0.0001