The Role of Intangible Assets in Shaping Firm Value

Abstract

This study introduces a new metric to evaluate a firm's intangible asset intensity, focusing on its ability to generate revenue from non-physical assets. It finds a strong positive correlation between firm performance and both internally generated and externally acquired intangible assets. Firms with high intangible intensity outperform peers by 3% annually. The oversight of intangible assets is identified as a factor in value stocks' underperformance. Rigorous tests, including endogeneity checks, confirm these firms exhibit superior accounting quality, labor investment efficiency, and acquisition returns. A framework highlights how managerial attributes enhance firm value through decision-making.

Keywords: intangible assets; data envelopment analysis; labor investment efficiency; firm performance

JEL Classification: G11, G32, O30, O34

1 Introduction

Intangible value has become a fast-growing and critically important firm characteristic for investors in identifying firm fundamental value in the US and internationally (Haskel and Westlake, 2017; Bhandari and McGrattan, 2021). However, this essential corporate attribute is missing in traditional financial statements. Given that the US economy has transformed dramatically over the past century, simply using book value as a firm's intrinsic value, still a widely used method, first established in the 1920s, does not appear to be a reasonable approach today in a fast-transforming world economy relying less and less on physical assets. The high technology giants, such as Alphabet (Google), Amazon, Apple, and Meta (Facebook), have replaced traditional companies and dominated the market. Their firm values rely less on their physical assets but more on intangible assets, such as technology and human capital. From 1975 to the end of 2018, the total intangible asset value of all companies in the S&P500 index has increased from 0.12 trillion dollars to 21.05 trillion dollars, representing 84% of the entire enterprise value.[1] Based on Peters and Taylor (2017), only 19% of the firm's intangible assets are acquired externally, while the bulk of a firm's intangible assets is generated internally through expenses, such as research and development (R&D) and Selling, General, and Administrative (SG&A). On one hand, intangible assets play a critical role in driving a firm's long-term value by fostering innovation, improving operational efficiency, and creating competitive advantages. These assets, in turn, enhance a firm's ability to generate sustainable cash flows, adapt to market changes, and differentiate itself from competitors, ultimately contributing to higher profitability, market valuation, and shareholder returns over time. On the other hand, a firm's intangible assets do not appear on its balance sheet and cannot be reflected in its book value. Consequently, employing a firm's book value as a

[1] *Financial Impact of Intellectual Property & Cyber Assets*. Aon-Ponemon Global Report, 2020

surrogate for its fundamental worth constitutes an unreliable and deceptive practice. This underscores the principal rationale behind the heightened scrutiny and interest accorded to the assessment of corporate intangible assets within both academic circles and the finance industry.

Nevertheless, measuring the value of a company's intangible assets, such as intellectual property, copyrights, data, and human capital, can be very challenging. Numerous research papers have attempted to identify a firm's intangible capital (e.g., Eisfeldt, Kim, and Papanikolaou, 2020; Ewens, Peters, and Wang, 2021; Belo, Gala, Salomao, and Vitorino, 2022; Eisfeldt and Papanikolaou, 2013; Falato, Kadyrzhanova, and Sim, 2013; Corrado, Hulten, and Sichel, 2009). The perpetual inventory method, predicated upon the summation and amortization of intangible asset expenditures, notably those associated with research and development (R&D) and Selling, General, and Administrative (SG&A) expenses, stands as the most widely employed approach. However, it falls short of providing a precise and accurate evaluation of the firm's intangible assets. Primarily, it is crucial to recognize that the value of intangible capital is intricately intertwined with the firm's physical capital. To illustrate, an expenditure on advertising in isolation does not yield profits; however, it fosters customer recognition, subsequently augmenting revenues. Essentially, the value of intangible assets, encompassing human capital, customer loyalty, brand value, data, and intellectual property, lies in enhancing the profitability of physical assets and overall production inputs. Furthermore, the investment in knowledge capital, employees, and brand equity parallels a conventional investment project. In assessing the potential value of such an investment, conventional financial methodologies, such as Net Present Value (NPV), are employed. NPV entails calculating the present value of all future benefits deducted by the initial investment. This stands in stark contrast to the perpetual inventory method, which operates under the assumption that the investment in intangible assets resembles a zero NPV project, neglecting considerations of profitability and uncertainty.

Compared with the existing intangible asset measures, a performance-based measure of intangible assets offers equity investors a clearer view of how these assets, such as brand equity, human capital, and data, drive profitability and long-term value creation. This paper endeavors to establish a more efficacious and valid methodology for discerning a company's level of intangible assets. Unlike the perpetual inventory method, often used to measure tangible assets, has several limitations when applied to gauging corporate intangibles[2] our proposed performance-based approach evaluates how intangible assets enhance operational performance and integrate with physical capital to generate returns. This method accounts for profitability and uncertainty, aligning more closely with financial models like discounted cash flows. By reflecting the economic impact of intangibles, it provides investors with better insights into competitive advantages, growth potential, and the risk-reward profile of firms. Subsequently, employing our newly devised measure, we examine the correlation between a firm's intangibles and its value and performance. We define a firm's value of intangible assets as the overall firm's efficiency in generating benefits from the firm's total physical assets and total production costs. In other words, a company endowed with a substantial level of intangible assets possesses the capacity to employ its tangible resources with greater efficiency, thereby generating heightened revenues in comparison to its counterparts with lower levels of intangible capital. Inspired by Demerjian, Lev, and McVay (2012), we estimate the firm's intangible asset intensity score in two steps. First, we identify a company's

[2]The perpetual inventory method applied to measure intangible assets such as brand equity, patents, and customer relationships do not have physical forms, making it challenging to track and value them accurately. It also suffers from valuation subjectivity, lack of market transactions, deterioration and obsolescence, cost allocation concerns, failure to capture future potential, and lack of comprehensive overage (i.e., not all intangibles can be easily quantified or traced, such as employee expertise or organizational culture, which are critical for overall corporate value). These limitations highlight the challenges of perpetual inventory method to accurately measure intangible assets using the perpetual inventory method and suggest the need for complementary approaches for a more holistic assessment.

overall efficiency using data envelopment analysis (DEA) (Charnes, Cooper, and Rhodes, 1978). We then use Tobit regression to exclude firm-level characteristics (firm size, market share, international operation, and industry and year effects), which affect operating efficiency but do not represent a firm's intangible capital. The residual of the regression, noted as the *intangible asset intensity*, can be used to proxy a firm's overall level of intangible assets. We acknowledge the limitations of using Tobit regression residuals as a proxy for intangible asset intensity by capturing variation unexplained by observable firm-level factors. To mitigate the concern that our measure is influenced by other unobserved factors unrelated to intangible assets, we conduct several robustness checks. Firstly, we show that our measure is consistent with alternative intangible asset estimations (i.e., Eisfeldt et al., 2020). Secondly, we include market level factors to control for market level influences and noises. We also conduct a series of endogeneity tests, such as the Instrumental Variable (IV) method in a two stage least square (2SLS) analysis using the 3-digit ZIP codes of acquirer firms' headquarters and the Propensity Score Matching (PSM) analysis.

Although this approach cannot quantify the absolute value of intangible assets, intangible asset intensity effectively identifies firms with high intangible presence within industries. This scoring method generates significant investment alphas, helping shareholders assess corporate activities like acquisitions and labor investments. Our performance-based measure outperforms existing methods across multiple dimensions. Unlike market-based approaches, which rely on market value fluctuations, our measure directly captures intangible value, reducing noise and speculation. Compared to proxy-based methods (e.g., brand value, trademarks, patents), our measure aligns well with recognized intangible drivers while offering a more unified approach. It also surpasses income-based methods by reflecting real-time business performance without relying on uncertain forecasts. Additionally, by incorporating human capital insights through the MA-

Score, our measure links intangible value to labor market efficiency, demonstrating how talent drives value creation. Unlike the cost-based perpetual inventory method, which reflects historical costs, our measure captures the current economic value of intangibles, making it a more accurate and timely indicator. Overall, our approach overcomes key limitations of existing methods, providing a more practical, dynamic, and reliable framework for evaluating intangible assets.

Building on the seminal contributions of Bertrand and Schoar (2003) and Golubov et al. (2015), our study addresses the endogeneity concern surrounding our measure of intangible asset intensity in the context of acquisitions. Specifically, we do so by introducing acquirer fixed effects, which effectively encapsulate a substantial portion of the firm's intangible worth, including managerial contributions, into the regression, which is designed to explain the variation in acquisition outcomes. Our findings reveal a noteworthy augmentation in the F-statistics for the joint significance of these fixed effects, particularly within the subset of acquirers characterized by a high level of intangible assets. This result reveals a robust association between acquirer fixed effects and the intensity of intangible assets, underscoring that a pivotal portion of the explanatory capacity of these effects with regards to variations in acquisition abnormal returns emanates from M&A transactions conducted by acquirers endowed with a pronounced intangible asset intensity. These results are consistent when our analysis is restricted to occasional acquirers, defined as those with fewer than five M&A transactions within a three-year timeframe.

Additionally, we develop a theoretical framework, focusing on the top manager's managerial attributes as a critical corporate intangible asset to assess its impact on risky corporate decisions such as M&As and firm outcomes. This theoretic structure elucidates the channels through which the top manager's managerial attributes, acting as a pivotal corporate intangible asset, contribute to the enhancement of firm value through corporate decision-making.

Furthermore, our empirical evidence underscores that firms endowed with elevated (limited) intangible assets realize significantly superior (inferior) short- and long-term acquisition performance. This observation points out that the oversight of the role of intangible assets emerges as a determinant of the adverse abnormal returns documented in earlier M&As empirical studies. In our analysis, while we control for various firm-level characteristics, along with firm and year fixed effects, the likelihood of potential endogeneity may not be ruled out. Therefore, to address this concern of the effect of our intangible asset intensity measure on firm performance, we also carry out two additional endogeneity checks to mitigate endogeneity concerns: an IV method in a 2SLS analysis and the PSM analysis. The results from both methods mitigate endogeneity concerns and confirm the robustness of our new intangible asset intensity measure. Furthermore, the PSM analysis helps address the omitted variable bias by balancing observed covariates between high and low intangible asset intensity firms. The PSM method ensures that the M&A outcome differences are more likely to be attributed to the level of intangible assets rather than to confounding factors.

Additionally, our analysis extends to investigating the potential benefits to stockholders associated with firms of high intangible asset intensity. The findings reveal that companies characterized by high intangible asset intensity exhibit a noteworthy positive alpha, signifying a substantial annual return for stockholders. When we adjust the returns using the characteristics-adjusted benchmark (Daniel, Grinblatt, Titman, and Wermers, 1997; Wermers, 2004) instead of the risk-free rate, the alpha remains positive and significant. Additionally, our analysis demonstrates that the intangible asset intensity score is significantly associated with higher stock returns in the coming year, before or after controlling for firm characteristics, year fixed effects, and industry fixed effects. Furthermore, our study documents a noteworthy performance disparity between firms characterized by high and low levels of intangible assets.

Moreover, upon integrating the intangible asset intensity into the conventional value premium factor, traditionally grounded in the market-to-book ratio (M/B ratio), to elucidate the observed underperformance of value stocks, our results indicate that relying on book value as the intrinsic value of a firm for distinguishing between value and growth stocks may be misleading. The documented underperformance of value stocks in recent decades could potentially be attributed to the oversight of intangible assets in the estimation of a firm's value.

A crucial element of a firm’s intangible assets is associated with its managerial ability traits, and based on this notion, firms with high intangible assets should show high investment efficiency. Alternatively, since intangible assets cannot be easily valued by the market, the growth potential embedded in a firm’s intangibles is largely neglected. Thus, companies with high intangible asset intensity may display a tendency to overinvest, but this might be caused by the underestimation of growth capacities of such firms rather than investment inefficiency. Labor investment is of particular interest to us since it is an essential corporate investment across all industries and has a continuous impact on a firm’s future operating costs and earnings (Merz and Yashiv, 2005). Following Pinnuck and Lillis (2007) and Jung, Lee, and Weber (2014), we estimate labor investment efficiency as the absolute value of the difference between a firm’s actual change and the expected change in the number of employees. Additionally, since inefficient labor investment can be due to either overinvestment (actual hiring is greater than expected) or underinvestment (actual hiring is less than expected), we also explore the relation between a firm’s intangible asset intensity and its labor investment for these two subsamples.

Our results show that, overall, high intangible intensity firms exhibit significantly higher labor investment efficiency (negatively correlated with abnormal hiring), especially in the underinvestment subsample. Nevertheless, our investigation yields evidence suggesting that firms with high intangible intensity exhibit a tendency to engage in overinvestment in labor, with statistical significance at the 10% level, compared to their low intangible intensity counterparts. Previous research has documented many factors, such as moral hazard (Jensen and Meckling, 1976; Stulz, 1990), conditional conservatism (Ha and Feng, 2018), stock price informativeness (Ben-Nasr and Alshwer, 2016), financial reporting quality (Jung, Lee, and Weber, 2014), and CEO-director ties (Khedmati, Sualihu, and Yawson, 2020), that lead to corporate investment inefficiency and destroy shareholders' wealth. This paper contributes to the existing literature by demonstrating that the assessment of firms' intangible assets, derived from their growth potential, which is often underestimated due to the market's reliance on a flawed estimate of firms' book value, can elucidate patterns of corporate labor overinvestment.

Jung, Lee, and Weber (2014) provide empirical evidence revealing a significant correlation between a firm's accounting quality and the efficiency of its labor investments. This relationship is attributed to the notion that high-quality financial reporting has the capacity to alleviate information asymmetry between a company and its external investors, consequently fostering more effective and informed investment decisions. Similarly, corporate intangible assets, which represent a critical component of the firm's intrinsic value, can also cause a high information asymmetry between a firm and the market, but skilled managers have the incentive to reveal this information to increase the informativeness of stock prices in order to protect the value of their high human capital attributes in the competitive executive labor market (Doukas and Zhang 2020). Using the M-Score (Beneish, 1999) to capture company accounting quality, we find a significant and robust positive correlation between intangible asset intensity and firm accounting quality. Furthermore, this outcome is particularly intriguing as it suggests that companies characterized by a high level of intangibles and a tendency to over-invest in labor exhibit significantly superior accounting quality compared to their counterparts. In alignment with the argument posited earlier, which proposes that firms with high intangible asset intensity may overinvest in labor due to the market's underestimation of their growth potential, this finding substantiates the idea that companies with substantial intangibles strive to reduce information asymmetry between the firm and the market. This effort aims to ensure shareholders that they can derive benefits from firm's heightened stock price informativeness that turns out to be beneficial to firms' corporate decisions based on investors' signals sent to managers through their stock trading activities. (Dow and Gorton, 1997).

The existing literature extensively explores the role of intangible assets in shaping firm value; however, much of this research does not approach the issue from a finance perspective, particularly in terms of investment returns or traditional valuation metrics, such as M/B ratio. Instead, prior studies have largely concentrated on macroeconomic and strategic management viewpoints, often emphasizing intangible assets' role in global value chains (Jaax & Miroudot, 2021), corporate resilience during economic downturns (Uddin, Hasan, & Abadi, 2022), and institutional influences on firm success (Amankwah-Amoah, Boso, & Kutsoati, 2022; Aliyev & Kafouros, 2023). Additionally, most empirical evidence originates from international markets outside the United States, including European economies and emerging markets (Jancenelle, 2021), or with a particular focus on Germany (Roth, Sen, & Rammer, 2023), sub-Saharan Africa (Amankwah-Amoah, Boso, & Kutsoati, 2022), or the energy sector in Europe (Aliyev & Kafouros, 2023). While these studies confirm the importance of intangibles, they largely rely on broad categorizations, such as R&D spending (Crouzet, Eberly, Eisfeldt, & Papanikolaou, 2022; Hasan & Uddin, 2022), organizational capital (Hasan & Uddin, 2022), or intellectual capital (Mata et al., 2021), without adequately addressing measurement challenges in financial valuation.

A key limitation of these studies is that they do not fully capture the finance-based implications of intangible assets on firm valuation. For instance, while prior research examines the impact of intangible assets on corporate governance and investment decisions (Filatotchev, Lanzolla, & Syrigos, 2023), it does not directly assess their role in financial metrics like stock returns, cost of capital, or firm valuation from an investor's perspective. Moreover, many studies focus on policy implications, trade agreements, and legal frameworks related to intangible assets (Jaax & Miroudot, 2021; Amankwah-Amoah, Boso, & Kutsoati, 2022), rather than their role in corporate financial performance. In contrast, this paper introduces a performance-based intangible asset measurement approach, demonstrating that it provides a more reliable and finance-relevant assessment of firm value. Unlike traditional proxies, such as book-to-market ratios or reported R&D expenditures, this new approach directly incorporates the productivity, market impact, and financial performance of intangible assets. As evidenced in our empirical findings, this method proves superior in predicting investment returns and firm valuation, reinforcing the necessity of integrating a financial lens into intangible asset research.

This paper advances the growing literature on intangible assets in several ways. First, unlike prior studies that rely on cumulative and amortized intangible asset expenses (mainly R&D and SG&A), we introduce a more comprehensive measure. Our approach avoids the limitations of the perpetual inventory method and applies to a broader sample of firms than event-based measures (e.g., acquisitions, bankruptcies) (Ewens et al., 2021). Second, our empirical findings show that intangible assets contain critical information about a firm's growth potential, making their inclusion in intrinsic value assessments essential. Their omission in conservative accounting practices helps explain the underperformance of value stocks in recent decades. Third, this research highlights a firm's tendency to overinvest in labor due to market underestimation of intangible assets. Firms with high intangible levels prioritize quality financial reporting to enhance market transparency, allowing stockholders to benefit from price corrections. Lastly, we emphasize the role of intangible assets in evaluating corporate decision-making effectiveness, expanding their relevance in performance assessments.

The remainder of the paper proceeds as follows. Section 2 develops hypothesis and methodology. Section 3 describes the data selection. Section 4 presents and discusses the results. Section 5 concludes the paper.

2. Methodology

The value attributed to corporate intangible assets is fundamentally grounded in the firm's capacity to surpass its industry peers in revenue generation while employing similar physical assets and production inputs. Consequently, the assessment of intangible asset valuation remains intrinsically tied to the firm's efficiency in managing its tangible assets. We employ the DEA method to identify a firm's overall efficiency. DEA is a nonparametric method to estimate the input efficiency of all decision-making units (DMUs). DEA initially identifies the most efficient DMUs with varying input levels, forming a "best-practice frontier." Subsequently, DEA benchmarks all other units and calculates an efficiency score. Unlike many parametric methods, the DEA approach determines input efficiency exclusively from all possible input and output combinations within the available dataset. Specifically, to identify the operating efficiency of a company based on the DEA method within each industry, we use revenue as the only output measure and characterize a company with a high level of efficiency as one that can generate more sales with a given level of tangible assets and the cost directly related to the production. The selection of revenue as the preferred output measure is underpinned by two primary considerations. Firstly, companies with efficient production structures and stable supplier relationships can significantly reduce the cost of goods sold (COGS), a principal input in the DEA analysis. Consequently, gross profit or net income is not deemed suitable as the output measure, as it would inherently yield a negative relationship between input and output. Secondly, as evidenced in Ewens et al. (2021), measures tied to equity market value, such as stock price return, may not accurately reflect the true extent of a firm's intangible assets. Moreover, such measures are susceptible to the influence of market noise and various external factors.[3]

We classify all the inputs into two categories: total tangible assets and total production costs. We utilize property, plant, and equipment (PP&E), cash and cash equivalent, inventory, and net operating leases to capture the firm's level of tangible assets. We exclude construction work-in-progress from total PP&E since those assets are not in service currently. We include operating leases as part of the company's tangible assets since those assets are also used to generate profit for the company but are excluded from the company's balance sheet. Following Demerjian et al. (2012), we estimate the value of a firm's net operating leases as the discounted present value of the next five years of required operating lease payments. COGS is used to capture the total costs directly related to production. Specifically, we use the optimization equation (Equation (1)) to identify a firm's total efficiency level:[4, 5]

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[3] We also conduct estimations of our intangible asset intensity employing net income and raw stock returns. While all these results exhibit a consistent pattern, it is noteworthy that the utilization of revenue as the output measure yields the most robust correlations with all the proxies used to gauge intangible assets.
[4] We winsorized 1% highest and lowest observations for all variables to minimize the influence of outliers.
[5] The DEA model employs tangible assets, including PP&E, cash, inventory, and net operating leases, as primary input variables to assess firm efficiency in revenue generation. While accounts receivable and short-term investments are financial assets reported on the balance sheet, they primarily reflect credit policy, liquidity management, or investment strategy rather than operational resource deployment. Their exclusion ensures that the DEA measure captures the firm's true operational efficiency without distortion from financial management decisions.

$$\max \theta = \frac{Revenue}{\beta_1 Cash + \beta_2 Inventory + \beta_3 (PP\&E - PPENC) + \beta_4 Leases + \beta_5 COGS} \quad (1)$$

The DEA analysis, as shown in Equation (1), is used to determine the optimal weights of inputs (we set all βs to be non-negative and sum up to one) within each industry as categorized in Fama and French (1997). We exclude the financial industries because of the unique asset structure of financial firms, and the utilities industry due to restricted government regulation. As in Demerjian et al. (2012), our analysis does not adopt a yearly basis. This decision is rooted in the nature of the DEA method, where the initial step involves identifying the most efficient observation. Conducting the analysis on a yearly basis would result in the identification of a singular optimal case for each year within each industry, serving as the benchmark for estimating intangible asset intensity scores for other firms. Consequently, evaluating firm efficiency on an annual basis renders the time series analysis of intangible asset intensity unreliable.

Furthermore, it is imperative to acknowledge that, apart from a firm's intangible assets, there exist other factors—such as firm size, market share, and international diversification—that can exert an influence on a company's overall efficiency. Despite not being intrinsic components of intangible assets, these factors play a role in shaping the holistic efficiency profile of a company. To remove the influence of those factors, we use the Tobit model and regress the firm efficiency from the DEA analysis on those factors (Equation (2)):

$$Firm\ Efficiency_{i,t} = \alpha_{i,j} + \beta_1 log\ (TA)_{i,t-1} + \beta_2 Market\ Share_{i,t-1} + \beta_3 International_{i,t-1} + Year_t + Industry_i + \varepsilon_{i,t} \quad (2)$$

where $\log (TA)_{i,t-1}$ is the log value of the firm's total assets in the previous year; $Market\ Share_{i,t-1}$ is the percentage of the firm's total sales within the whole industry sales during the last year; and $International_{i,t-1}$ is a dummy variable, which equals one if a firm reports a nonzero value for foreign currency adjustment in the previous year. We also control for year-fixed effects to capture market conditions' influence and industry-fixed effects, and standard errors are clustered at the firm level. The residual from the Tobit regression is the intangible asset intensity that reveals a company's level of intangible assets. The rationale underpinning the residual-based intangible asset intensity measure aligns with our earlier point, emphasizing that the value of a firm's intangible assets is rooted in its profitability and efficiency in utilizing physical assets. Consequently, our measure initially calculates the firm's overall efficiency, but subsequently eliminates the influence of other firm-level characteristics that could contribute to variations in efficiency. The unattributed portion, encapsulated by the residuals, predominantly represents the value associated with intangible assets.

3. Data and Description Statistics

Our sample consists of all the US publicly traded companies in the Compustat database from 1980 to 2020. The sample period begins in 1980 since many of the variables were missing in Compustat before 1980. As noted before, we exclude the financial industries and the utilities industry from our sample. Observations with missing data or error data (e.g., non-positive sales, non-positive COGS) are deleted. We end up with 233,170 firm-year observations that span 42 industries. Data on stock information are collected from the Center for Research in Security Prices (CRSP) database.

Table 1 presents summary statistics for firm efficiency and intangible asset intensity scores for the whole sample and within each industry. The firm efficiency score from the DEA method is a score ranging from 0 to 1, while 1 indicates the optimal efficiency level. The average firm efficiency for all observations is 0.274, with a standard deviation of 0.206. The range of efficiency scores across the industries is from 0.073 (Business Services) to 0.790 (Boxes). The mean and standard deviation of intangible asset intensity score (the residual from the Tobit regression) is 0 and 0.206, respectively, ranging from -0.203 (Business Services) to 0.519 (Boxes). Since the intangible asset intensity score is derived as a Tobit regression residual, it is a relative measure, and the negative values indicate industries with lower-than-expected intangible asset intensity.

4. Results

In this section, we start with the comparison of our intangible asset intensity score with the widely used perpetual inventory method of the intangible asset value valuation, followed by additional validity tests using proxies of major intangible asset components, including corporate human capital, brand value, trademarks, intellectual property, network efficiency, and employee satisfaction. Next, we investigate the relationship between corporate intangible asset intensity score and stock performance and incorporate the intangible asset intensity score into the M/B ratio to explore the role of intangible assets in identifying value and growth stocks. Last, we analyze the correlations between corporate intangible asset intensity and labor investment efficiency as well as accounting quality.

4.1 Intangible Asset Intensity and Cumulative Intangible Asset Investment

Our initial examination focuses on testing the relationship between intangible asset intensity and a firm's investment in intangible assets. This test is of paramount importance as a considerable proportion of prior studies relies predominantly on cumulative and amortized intangible asset expenses for gauging a firm's intangible assets.

A firm can generate intangible assets through two primary approaches: internal investments and external acquisitions. Following Eisfeldt et al. (2020), we use the perpetual inventory method to estimate the cumulative internal intangible assets investment (*InternalInv*), as shown in Equation (3):

$$InternalInv_{i,t} = (1-\delta)InternalInv_{i,t-1} + \theta_1 R\&D_{i,t} + \theta_2 SG\&A_{i,t} \quad (3)$$

The initial *InternalInv* is set to (*SG&A+R&D*) / ($g + \delta$), using the firm's SG&A expenses and R&D expenses when the firm first appears in the Compustat. We set $g = 0.1$ and $\delta = 0.2$ as in Eisfeldt et al. (2020) and Eisfeldt and Papanikolaou (2014). Also, as suggested in Eisfeldt et al. (2020), we set $\theta_1 = 0.3$ for SG&A and $\theta_2 = 1$ for R&D expenditures. A firm can also generate intangible assets through acquisitions. The total amount of intangible assets through acquisitions (*ExternalAcq*) is available on a firm's balance sheet and contains two major parts: purchased goodwill and other acquired and capitalized intangibles. Purchased goodwill is the purchase price premium of the acquisition deal over the fair value of the target firm's total identifiable assets, which reflects the investment value of the target firm for the acquirer (synergy). Other acquired and capitalized intangibles include items such as a company's proprietary technology, copyrights, patents, and website domain names. By adding *InternalInv* and *ExternalAcq* together, we estimate the total intangible assets investment (*TotalIAInv*) of the firm. Since the intangible asset intensity is a ranking score rather than the actual value, we scaled intangible asset investments by total assets in our analysis. Table 2 presents a summary of our intangible intensity score and the level of other intangible asset measures and the correlations between the level of intangible assets measures and firm-level characteristics, which include return on equity (*ROE*), return on investment (*ROI*), the post year stock return (*Stock Return*), debt-to-equity ratio (*D/E ratio*), market-to-book ratio (*M/B ratio*), and the log value of firm's revenue (*Sales*).

(Table 2 here)

The correlation between our intangible asset intensity score and firm performance measures (i.e., ROE, ROI, and Stock Return), as shown in the first column of Panel B, are all positive and significant at a 10% significant level. This confirmation underscores the pivotal role played by intangible assets revealing a firm's intrinsic value and growth potential. Meanwhile, the other three measures of intangible assets display significantly negative correlations with firm ROE and ROI. For instance, the correlation between the overall intangible assets investment, scaled by firm size, and firm ROE (ROI) is -0.0716 (-0.0197). This result aligns with expectations, given that intangible asset investments are entirely expensed under the perpetual inventory method of estimation, leading to a reduction in the firm's earnings. Notably, two out of the three alternative measures exhibit significantly positive correlations with future stock returns, whereas the measure *ExternalAcq/TA* demonstrates an insignificant relationship.

There exists a debate in capital structure literature regarding the relationship between a firm's intangible assets and financial leverage. Previous research, such as Titman and Wessels (1988), Rajan and Zingales (1995), Hovakimian, Opler, and Titman (2001), and Barclay, Smith, and Morellec (2006), offers empirical evidence of a negative relationship between intangible assets and firm leverage. However, in a more recent study, Lim, Macias, and Moeller (2020), utilizing a recent accounting rule change and based on a diverse set of intangible assets instead of specific subsets like patents discover a strong positive relation between identifiable intangible assets and leverage. Our proposed intangible asset intensity measure supports their argument by showing a positive correlation between firm intangible capital and financial leverage (*D/E Ratio*). Two of the three alternative measures display negative correlations with firm leverage. At the same time, *ExternalAcq/TA*, which is the most identifiable one among the three, shows a positive correlation (0.0337) but is lower than our proposed measure (0.0452).

As anticipated, we identify a substantial and positive correlation between intangible asset intensity and a firm's revenue. This outcome aligns with expectations, considering that our measure is designed to encapsulate the firm's efficiency in generating revenues given a specific level of physical assets and production inputs.

Next, we examine the relation between a firm's intangible asset intensity score and InternalInv and *ExternalAcq*, jointly and separately, controlling for other firm characteristics and accounting for industry and year fixed effects. The multivariate regressions results are reported in Table 3.

(Table 3 here)

Table 3, in Columns (1) and (2), shows a strong positive correlation between a firm's intangible asset intensity and intangible asset investment, with a one-percentage-point increase in investment linked to a 0.41–0.44 percentage point rise in intensity score. Both internal (InternalInv/TA) and external (ExternalAcq/TA) investments contribute positively, but external acquisitions (0.117) have a much stronger impact than internal development (0.004). These results, consistent with Table 2, confirm that firms with higher intangible intensity allocate significantly more resources to intangible investments. This supports prior literature using the perpetual inventory method and highlights the new measure's stronger association with firm efficiency and growth potential. The findings emphasize the economic importance of intangible asset investments in shaping corporate performance and strategic decision-making.[6]

4.2 Intangible Asset Intensity and Proxies of Major Intangible Assets Components

In this section, we employ validity tests to illustrate the power of our intangible asset intensity measure by comparing it with proxies for major intangible asset components, including corporate human capital, brand value, trademarks, intellectual property, network efficiency, and employee satisfaction.

[6] To ensure the robustness of our measure across different industry contexts, we conducted a subsample analysis following the industry classification method proposed by Hall and Vopel (1996), categorizing industries into high-tech, medium-tech, and low-tech based on technological intensity and skill requirements. This analysis revealed distinct patterns in the role of internal and external intangible asset investments across industry segments. Specifically, internal investments, particularly in R&D, exert a stronger influence on intangible intensity in high-tech industries, whereas external intangible asset acquisitions play a more significant role in low-tech industries. The detailed results of this analysis are available upon request.

4.2.1 Intangible Asset Intensity and Corporate Human Capital

To test the validity of our intangible asset intensity measure, we start by exploring its relationship with the firm's human capital component. We use two measures to estimate human capital. The first measure is the managerial ability score (MA-Score) metric, which was introduced by Demerjian et al. (2012). This measure is also developed through DEA methodology and used to gauge the top executives' ability to transform firm resources (e.g., capital, labor, and innovative assets) into firm revenues relative to competitors in the same industry.[7] MA-Score data are collected from Demerjian's website from 1980 to 2018. Secondly, along with the argument of competitive labor markets (Lucas, 1978), we use the natural logarithmic value of the CEO's total compensation (Log (CEO Comp)) as a proxy for a firm's managerial talent since firms compensate top managers, as the key decision-makers within the management team, for their managerial talent in making value enhancing investment decisions (Gabaix and Landier, 2008; Chang, Dasgupta, and Hilary, 2010; Song and Wan, 2019).

We regress firm's intangible asset intensity score on these two human capital value measures, separately and together, while controlling for firm-level variables, industry, and year fixed effects. We exhibit the results in Table 4.

(Table 4 here)

The results in Table 4 show a significant and positive relationship between a firm's corporate intangible asset intensity and both measures of corporate human capital value. Specifically, the R^2 in regression (1) is much higher than that in regression (2) (11.1% vs. 4%,

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[7] The main difference between our intangible asset intensity measure and the MA-Score measure is that, in the process of estimating firm efficiency, Demerjian et al. (2012) considers part of the intangible assets (R&D expense and SG&A) as inputs, and they focus on how managers use all sources, both tangible and intangible, to generate revenues. In our analysis, we consider all intangible assets as the efficiency of a company in using just tangible assets and production costs to generate revenue. In untabulated results, we find that our intangible asset intensity score has a much stronger explanation power on a firm's operating performance and stock return.

respectively). This indicates that our intangible capital measure has a much stronger relationship with the MA-Score. As shown in Demerjian et al. (2012), the MA-Score measure is the most robust measure of a firm's managerial ability compared with other ability measures (i.e., historical return, historical ROA, CEO compensation, CEO tenure, and media mentions). Thus, the stronger relationship with the MA-Score validates our intangible asset intensity measure given that managerial ability is an essential component of a firm's intangible (human capital) assets. A one-unit increase in managerial ability is associated with a 0.191 increase in intangible asset intensity, indicating that more capable managers tend to invest more in intangibles, aligning with theories that skilled executives prioritize innovation and knowledge capital. This result holds when we control the intangible asset measure based on the perpetual inventory method as well, which indicates the superiority of our measure in serving as a proxy of a firm's intangible assets level. Overall, this test confirms the consistency of our intangible asset intensity score as the proxy of corporate intangible capital level.

4.2.2 Intangible Asset Intensity, Brand Value, and Trademarks

Next, we test the reliability of our intangible asset intensity measure by exploring its strength through its relationship with the firm's brand value and trademark features. Brand value is another essential intangible asset of a company's total capital (Mizik and Jacobson, 2008; Vomberg, Homburg, and Bornemann, 2015). We use two proxies to capture brand value. The first measure is the natural logarithmic value of corporate brand value collected from the BrandFinance website. This website lists 100 US companies with the highest brand values for each year. The data are available from 2014 to 2020. The second measure is firm's size scaled by advertising expenses in the past five years, as shown in Equation (4):

$$\frac{Cum.Avd.Exp.}{TA} = \frac{Adv.Exp._{t} + 0.8 * Adv.Exp._{t-1} + 0.6 * Adv.Exp._{t-2} + 0.4 * Adv.Exp._{t-3} + 0.2 * Adv.Exp._{t-4}}{TA} \quad (4)$$

We then regress the intangible asset intensity score on these two measures of firm brand value, separately and together, while controlling for firm-level variables, industry, and year fixed effects. Table 5 reports the results.

(Table 5 here)

Our hypothesis predicts a positive relation between intangible asset intensity score and firm brand value. Regression (1) in Table 5 shows that the intangible asset intensity score positively correlates with brand value at the 5% significance level. We also find a significant positive correlation between the intangible asset score and the cumulative advertising expense in the past five years. However, when both measures enter regression (3), the correlation of brand value turns out to be statistically insignificant though still positive. An explanation for this result is probably because past cumulative advertising expenses contribute significantly to the brand value and, thus, the effect of the brand value measure is subsumed by the advertising spending. Overall, the results in Table 5 show a positive relationship between brand value and intangible asset intensity, which supports the reliability of our intangible asset intensity measure as the proxy of firm's level of corporate intangible capital.

Additionally, to protect the high intangible value of their brands, companies have strong motivation to file for trademark protection (Ewens et al., 2021). Following the validation test of brand value, we analyze the relationship between the level of intangible assets and the firm's trademarks. To measure trademark value, we use two measures: the natural logarithmic value of the new trademark number and the natural logarithmic value of the cumulative trademark number for each company each year. The data are collected from 1980 to 2018, following Heath and Mace (2020).[8] Consistent with our hypothesis, the results in Table 6 reveal a significant positive

[8] The data are available in the Internet Appendix of Heath and Mace (2020).

relationship between a firm's trademarks and the intangible asset intensity score. This test implies that a firm's investment in trademarks, which eventually contributes to its brand value, builds up the company's intangible value and benefits the shareholders in the long run.

(Table 6 here)

4.2.3 Intangible Asset Intensity and Intellectual Property

For most companies, the critical intangible capital is the value of their intellectual property, which derives from the company's innovation and know-how. Previous studies have found that a firm's innovation activities raise the firm's intangible assets (i.e., knowledge base and human capital) (Dakhli and De Clercq, 2004; Hall, Jaffe, and Trajtenberg, 2005; Subramaniam and Youndt, 2005). To assess the intellectual property value of a company and how does relate to our intangible asset intensity measure, we use three intellectual property measures. The first measure comes from the information that is available on the Information Week website. This website identifies the companies with the most innovative information technology annually, and the data are available from 2005 to 2013. Each year, we set the dummy variable (*InformationWeek*) to one if the firm is on the list for that year and zero otherwise.[9] The second and third measures are based on the firm's patents. Previous literature has shown that the number of patents owned by the firm and the total citation of all the patents represent valuable ways to measure a firm's total intellectual property value. We use the natural logarithmic values of both intellectual property measures in the regressions. The patent data are available from the National Bureau of Economic Research and

[9] We also use the U.S. companies in the Forbes World's 100 Most Innovative Companies list as a supplement proxy of the Information Week companies list. Forbes has announced the 100 most innovative companies worldwide, and to be qualified, firms must have at least seven years of publicly available financial information and $10 billion market capitalization. Given the much smaller sample size comparing with the data from Information Week, we still find consistent results. Specifically, the coefficient between intangible asset intensity and the dummy variable created for the most innovative firms is positive and significant (t-value is 3.17). Additionally, we also conduct a propensity score matching analysis, and the result is consistent (the most innovative firms' average intangible asset intensity is significantly higher than the control group, with a t-value of 2.81). These results are available upon request.

range from 1980 to 2003. As shown in Table 7, the results of this analysis indicate that all three measures of firm intellectual property are significantly and positively correlated with the intangible asset intensity score. In sum, these results provide additional support for our intangible assets measure by showing a strong connection between a firm's innovation and the level of its intangible assets.

(Table 7 here)

4.2.4 Intangible Asset Intensity, Network Efficiency, and Employee Satisfaction

In the last validation test of our intangible asset intensity measure, we focus on the firm's network efficiency and employee satisfaction. Companies with highly efficient distribution networks, such as Walmart, can eliminate the costs of time, human resources, and capital required. We use the natural logarithmic value of Cash-to-cash Days, the sum of days sales in inventories and days sales in receivables, subtracting days sales in receivables, as a proxy of firm network efficiency. A larger (smaller) number of Cash-to-cash Days indicates lower (larger) network efficiency.

Edmans (2011) shows that employee satisfaction can benefit both the company and its shareholders since satisfaction works as an intrinsic motivator, which increases employee effort, and as a valuable recruitment tool to retain skilled employees. To measure employee satisfaction, we follow Ewens et al. (2021) and Das Swain, Saha, Reddy, Rajvanshy, Abowd, abd De Choudhury (2020) and use the information from Glassdoor.com to identify the top companies with the highest employee satisfaction. Glassdoor.com reports the "Best Places to Work" every year, based on previous and current employees' ratings posted on this website. Glassdoor.com collects the overall company rating and workplace factor ratings from a company's employees in all categories (i.e., full-time, part-time, contract, and freelance).[10] To be considered, a company must have an overall company rating of at least 3.5 out 5 and workplace factor ratings of at least 2.5 during the year. It also considers the quality of the reviews left by the employees and the trends over time. We set the dummy variable (*Glassdoor Dummy*) to one if the firm's name is on the list for that year and zero otherwise. The data are available from 2009. The results in Table 8 show a significant and negative coefficient for the natural logarithmic value of Cash-to-cash days, suggesting a positive relationship between a firm's network efficiency and its intangible asset intensity. Additionally, we find that employee satisfaction is a significant determinant of corporate intangible asset intensity, which contributes to a firm's operating efficiency and growth capacity.

(Table 8 here)

4.3 Intangible Asset Intensity in Mergers and Acquisitions: Performance and Endogeneity

Understanding the role of intangible assets in mergers and acquisitions is crucial, as these assets significantly influence both deal valuation and post-merger integration success. Unlike tangible assets, intangible capital—such as brand value, intellectual property, financial flexibility, investment efficiency, and managerial expertise—directly affects the synergies realized from an acquisition. Firms with high intangible asset intensity often exhibit stronger competitive advantages, which can enhance acquisition performance by improving operational efficiencies, increasing market share, and facilitating innovation. However, traditional valuation methods often overlook intangible assets, leading to potential mispricing and underestimation of long-term value creation. This section examines how intangible asset intensity impacts acquisition outcomes and addresses potential endogeneity concerns to ensure robust inference.

[10] Workplace factor ratings contain career opportunities, compensation and benefits, culture and values, diversity and inclusion, senior management, work-life balance, recommend to a friend, and six-month business outlook.

4.3.1 Acquirer Fixed Effects and Acquisition Performance

In this section, our primary objective is to scrutinize the endogenous consideration pertaining to the efficacy of our performance-based metric for intangible asset intensity in gauging the intangible dimension of a firm. Inspirated from the seminal study of Bertrand and Schoar (2003) as well as the more recent work of Golubov et al. (2015), we address this issue by focusing on corporate acquisition activities. Specifically, we embark upon an empirical examination by means of a statistical test, centering on alterations in the fixed effects F-statistic within acquirer groups characterized by disparate levels of intangible asset intensity. This investigation is conducted through the augmentation of acquirer-specific fixed effects to the regression model, which is meticulously tailored to elucidate the variation in outcomes observed in the context of corporate M&As.

To test this conjecture, we use completed acquisitions recorded by the Thomson One of Security Data Corporation (SDC), which consist of M&As announced by public-traded U.S. firms with market value higher than $1 million. Additionally, we only keep acquisitions with transaction value more than $1 million, and neither the acquirer nor the target belongs to the financial, government and agencies, or energy and power industrial sectors. Also, we exclude deals if the acquirer announced another acquisition within three days or the acquirer does not have the control power after the deal completed (i.e., the acquirer owns less than 50% of the target's equity after the deal's completion date). Other firm-level variables are collected from CRSP and Compustat databases. The sample is stratified into distinct cohorts based on the pre-acquisition intangible asset intensity of the acquirer companies, specifically distinguishing the uppermost quartile (top 50% or 20%) from the lowermost quartile (bottom 50% or 20%). Subsequently, within each group, we perform a regression analysis, wherein we gauge the short-term performance of acquisitions.

This performance metric is quantified through the computation of the acquirer's cumulative abnormal return (CAR) over a five-day interval (from t-2 to t+2), as well as the buy-and-hold abnormal return (BHAR). Additionally, we assess the eleven-day CAR (from t-5 to t+5) centered around the announcement of the acquisition. In our regression model, we incorporate an array of pertinent deal-level and firm-level variables, encompassing dummy variables for various deal characteristics. These include the classification of transactions as pure stock-finance deals (Stock Dummy), acquisitions involving public target companies (Public Dummy), those involving non-US target companies (International Dummy), and transactions in which both the acquiring and target firms operate within the same industry (Focused Dummy). Furthermore, our model accounts for deal size and an assortment of acquirer-specific firm-level attributes, such as firm size, age, financial leverage, and Tobin's Q. To provide a comprehensive assessment, we conduct the regression analysis both with and without the inclusion of acquirer fixed effects, thereby elucidating alterations in the explanatory power of fixed effects as indicated by changes in the associated F-statistics. We also replicate the analysis by focusing only on occasional acquirers, defined as acquirers with fewer than five M&A deals within a three-year window, to enable a nuanced exploration of the unique strategic, operational, and performance implications associated with infrequent engagement in acquisition activities. By doing so, researchers can shed light on the distinctive dynamics that shape the M&A endeavors of firms with less extensive acquisition histories.

Moreover, we replicate the regression by restricting the investigation to occasional acquirers, delineated as entities that have executed fewer than five M&A transactions within a three-year temporal span. This refinement in the sample selection facilitates a meticulous examination of the distinct strategic, operational, and performance ramifications entailed in infrequent involvement in acquisition pursuits. Detailed findings are presented in Table 9.

(Table 9 here)

The findings, presented in Table 9, show that the incorporation of acquirer-specific fixed effects yields a discernible increase in the F-statistics pertaining to fixed effects across both subsamples, with particularly pronounced enhancements observed within cohorts characterized by high intangible asset intensity. This outcome substantiates a robust correlation between acquirer fixed effects and the intensity of intangible assets held by the acquiring entities. It underscores that a substantive portion of the explanatory efficacy of acquirer fixed effects, with regard to the variations in abnormal returns stemming from acquisitions, is attributable to M&A transactions executed by acquirers boasting a pronounced prevalence of intangible assets. In particular, the acquirer fixed effects primarily capture the attributes of the top manager within a firm, constituting a pivotal intangible asset of the firm (Dong and Doukas, 2021). Subsequently, in the following section we describe and substantiate the assertion that adept managerial ability correlates with heightened corporate value and performance. This is exemplified through the facilitation of value-enhancing M&A decisions, distinguishing skilled managers from their counterparts who, conversely, exert a detrimental influence on firm value. Notably, our analysis attains heightened statistical robustness when replicated exclusively among occasional acquirers. For example, when employing the 5-day CAR as the dependent variable, the inclusion of acquirer fixed effects yields an augmentation in the F-statistics. Specifically, for acquirers characterized by a high level of intangible assets (top 50%), this augmentation is notable, escalating from 0.63 to 2.02. In contrast, the effect is comparatively modest for acquirers with a lower level of intangible asset intensity, transitioning from 1.39 to 1.53. This observed trend persists consistently across all metrics of acquisition performance and classifications based on intangible asset levels.

It has been shown in previous empirical research that at least half of the acquisitions fail to create value for the shareholders eventually. Prior studies have examined numerous factors to explain acquisition performance, but few of them investigate the role of acquirer company's intangibles in explaining the acquisition returns. For instance, recent research has highlighted the critical role of managerial attributes in M&As. Studies show that high-ability managers are more adept at utilizing stock price informativeness and firm-specific fundamentals to drive successful M&A outcomes (Chen & Doukas, 2023). Investment efficiency significantly influences cross-border M&As, with high-efficiency acquirers realizing superior shareholder returns (Dong & Doukas, 2022). Managerial ability also affects post-merger performance, particularly in stock-financed acquisitions, indicating that skilled managers navigate complex M&A transactions more effectively (Dong & Doukas, 2021). Moreover, corporate social responsibility plays a role in shaping corporate culture during M&As, as firms with high CSR engagement and cultural alignment experience better merger synergies (Doukas & Zhang, 2021). Providing a broader perspective, Cumming et al. (2023) examine historical and emerging trends in M&A research, emphasizing the importance of governance mechanisms, shareholder wealth effects, and the role of financial expertise in driving successful transactions. These findings underscore the importance of managerial decision-making, corporate culture, investment efficiency, and corporate governance in determining M&A success. Besides high managerial attributes, we conjecture those other components of intangible assets, such as corporate brand value and intellectual property, can also enhance firm's negotiation power, smooth the transition process, and increase investors' confidence in acquisition decisions.

To demonstrate the practical value of our intangible asset intensity measure, we use it to explain the performance variation of M&As and offer an intangible based explanation for the previously observed results on the M&A literature. Specifically, we conjecture that high (low) intangible asset intensity is expected to elicit investors' positive (negative) and significant reactions around the M&A announcement date and lead to an increased (decreased) long-term performance. To examine the merits of this hypothesis, we account for intangible asset intensity into our regression analysis to determine whether and how investors react around the M&A announcement date. We replicate this analysis by focusing on the firm's long-term performance, measured by the one-year CAR after the acquisition announcement, as dependent variables. All the regressions contain industry and year fixed effects, and the results are presented in Table 10.[11]

(Table 10 here)

Unsurprisingly, we find positive and significant coefficients between acquisition performance and firm intangible asset intensity, indicating that acquirer firms with higher levels of intangible assets realize higher abnormal acquisition returns in the short- and long-term. The results in Table 10, consistent with our previous reported results, point out that companies possessing high intangible assets conduct more efficient and profitable corporate decisions. Specifically, a one-unit increase in intangible asset intensity leads to a 0.021 percentage point increase in short-term CAR (-2,2) and a 0.198 percentage point increase in one-year CAR, highlighting the long-term value of intangible-driven acquisitions. This finding demonstrates the efficacy of our intangible asset intensity score in explaining the performance variation of corporate

[11] We also replace industry fixed effects with firm fixed effects, and the results are basically the same. These results are available upon request.

M&As decisions and its potential applications in assessing whether other corporate decisions serve shareholder interests when carried out by firms with high intangible intensity score.[12, 13]

Besides, the effectiveness of intangible asset-intensive firms in acquisitions may depend on the legal and institutional environment, particularly in protecting intellectual property (IP). Since IP protection varies significantly across countries**,** foreign acquisitions may introduce additional risks that obscure the true relationship between intangible asset intensity and acquisition performance. Given the potential complexity of cross-border deals, including differences in IP enforcement, regulatory frameworks, and integration challenges**,** we re-estimate our analysis by excluding foreign M&As and focusing only on domestic deals. The unreported results reveal an even stronger relationship between intangible asset intensity and M&A performance. These results suggest that, by controlling intellectual property protection, regulatory consistency, and integration complexity in domestic markets, intangible asset-intensive firms generate greater acquisition synergies when operating within their home country.

4.3.2 Robustness Tests for Endogeneity: IV and PSM

We further address the endogeneity concerns in our results within the M&A context. We follow Pirinsky and Wang (2006), Hossain and Mitra (2023), and Chatjuthamard and Jiraporn (2023) by using the average firm intangible asset intensity within a specific ZIP code as an instrumental variable. Headquarters locations are determined exogenously, and ZIP codes are generally unrelated to firm-level corporate policies (Jiraporn et al., 2014), reducing the risk of

[12] We replace our short-term and long-term performance measures with Buy-and-Hold Abnormal Returns (BHAR), and the results are highly consistent.

[13] To further explore the role of efficiency in acquisitions, we incorporate two additional efficiency measures following Dong and Doukas (2022): investment inefficiency and financial flexibility. The correlation between intangible asset intensity and these measures is -9.14% and 10.53%, respectively, both significant at the 1% level based on Pearson p-values. These findings support our argument that a firm's intangible asset level captures broader operational efficiency. Moreover, adding these measures into the regression analysis does not alter our main findings in Table 10, confirming the robustness and priority of intangible asset intensity in explaining acquisition performance. The full regression results are available upon request.

reverse causality between intangible asset intensity and M&A performance. Furthermore, M&A decisions are typically influenced by strategic considerations rather than geographic factors, making it unlikely that headquarters ZIP codes directly affect acquisition outcome.[14] The instrument also aligns with the view that local environments influence firms' innovation capacity and intangible development (Audretsch & Feldman, 1996), which indirectly may affect M&A performance. Although firms within the same geographical area may be exposed to unobservable regional shocks, this risk is mitigated by the fact that headquarters are usually established long before any relevant state-level policies are implemented. Nevertheless, the results from the 2SLS model using such an IV, as reported in Panel A of Table 11, would complement other efforts to address endogeneity concerns. Additionally, in order to account for broader regional policies, economic conditions, and institutional factors that influence firm location choices, we also include state fixed effects in the first stage of 2SLS, which controls for variation in tax policies, infrastructure, and regulatory environments that may systematically affect both the instrument and the outcome, enhancing the robustness of the IV strategy.

(Table 11 here)

The results effectively address the endogeneity concern by demonstrating the validity and relevance of the ZIP-based intangible asset intensity instrument. In the first stage (Column 1), the instrument is strongly and significantly associated with the endogenous variable (intangible asset intensity), with a coefficient of 0.097 ($p < 0.01$). In the second stage (Column 2), the fitted value of intangible asset intensity is positively associated with CAR (-2, 2), with a coefficient of 0.122,

[14] The IV and 5-day CAR are not highly correlated, as the correlation between them is only 4%, indicating a weak direct relationship.

significant at the 10% level. These results suggest that, after accounting for endogeneity through the instrument, higher intangible asset intensity leads to better M&A performance.[15]

Additionally, we address endogeneity concerns through Propensity Score Matching (PSM) analysis, employing logistic regression and nearest-neighbor matching with a single neighbor. PSM mitigates the risk of omitted variable bias by pairing firms with similar observable characteristics, thereby ensuring that any observed differences in M&A performance are more likely attributable to variations in intangible asset intensity rather than confounding factors. The results, as shown in Panel B of Table 11 indicate that the treated group (firms with high intangible asset intensity) exhibits an average 5-day CAR that is 0.62 percentage points higher than that of the control group (t-value is 2.43). This positive and statistically significant Average Treatment Effect on the Treated underscores the substantial and beneficial impact of a firm's intangible asset level on acquisition outcomes.

Following Heaton (2019), we develop a theoretical framework linking top managers' managerial attributes to corporate decision-making as a key intangible asset. Managers with higher attributes exhibit greater caution and transparency, prioritizing the protection of their human capital and firm value. In contrast, managers with lower attributes tend to engage in riskier decisions due to reduced sensitivity to firm risks. This distinction is crucial in times of economic uncertainty, where high-attribute managers mitigate adverse effects by incorporating market signals, enhancing firm stability, and reinforcing investor confidence. The detailed proof of this framework is provided in Appendix 1.

4.4 Intangible Asset Intensity and Stock Performance

[15] To provide robustness checks and ensure our results are not driven by location changes, we exclude firms that relocated during the study period, and the result is highly consistent with the result in Table 11.

In this section, we examine whether the firm's intangible asset intensity score is positively associated with its stock return performance. By comparing the raw return of high and low intangible asset intensity firms, we examine whether a firm's intangible asset intensity is linked to its stock return performance. As shown in Appendix 2, firms with high intangible asset intensity exhibit an average annual return of 12.33%, compared to 9.315% for those with low intensity. The return difference of 3.015% per year (t-value = 2.61) suggests a modest performance advantage for firms with greater intangible asset intensity.[16]

More importantly, to ensure that the outperformance of high intangible asset intensity firms is not driven by the market wide risk factors, we employ both the Carhart four-factor model (Carhart, 1997) and Fama and French five-factor model (Fama and French, 2017) to estimate the monthly risk-adjusted excess returns (i.e., stock alphas). The dependent variables of these two models are monthly portfolio raw return in excess of the risk-free rate or in excess of the characteristic-adjusted benchmark, as introduced by Daniel, Grinblatt, Titman, and Wermers (1997) and Wermers (2004) (noted as the DGTW benchmark). The DGTW benchmark groups each stock into a portfolio of stocks with similar size, book to market ratio, and momentum, and we include this benchmark to further eliminate the influence of size, value, and momentum. We also create hypothetical portfolios by holding high intangible asset intensity stocks and short selling low intangible asset intensity ones. The results of these two models are presented in Table 12.

(Table 12 here)

Table 12 shows that firms with high intangible asset intensity generate significantly higher risk-adjusted excess returns than their low-intangible peers. Using portfolio returns over the risk-

[16] We also sort all companies in quintiles and deciles, and the results are highly consistent.

free rate, high-intangible firms achieve a 0.215% monthly four-factor alpha (2.574% annually) and 0.146% monthly five-factor alpha (1.746% annually). In contrast, low-intangible firms yield negative alphas (-0.917% four-factor and -0.740% five-factor per year). The hypothetical portfolio produces significant excess returns in both models (3.491% four-factor and 2.486% five-factor annually). Similar patterns emerge using the DGTW benchmark, with high-intangible firms outperforming significantly at 0.343% monthly four-factor alpha (4.11% annually) and 0.212% monthly five-factor alpha (2.545% annually), while low-intangible firms underperform (-4.501% and -5.378% annually). The hypothetical portfolio maintains strong positive alphas (8.67% four-factor and 7.981% five-factor annually). These results highlight that high intangible firms' growth potential and profitability stem from their intangibles, which remain unrecognized in book value yet efficiently priced by the market.

We also conduct a robustness test to determine whether the overperformance documented in the previous analysis is due to other firm-level characteristics, such as ROE and ROI, which are available to the public. To do that, we regress the firm's stock return on the previous year's intangible asset intensity while controlling for other firm-level characteristics. The regression results, reported in Appendix 3, indicate that firms with high intangible asset intensity consistently generate higher stock returns than their low intangible asset intensity peers holding constant the influence of the firm-level characteristics.

4.5 Traditional Value Factor and Intangible Asset Intensity Adjusted Value Factor

The M/B ratio has been used to determine whether a stock is overvalued or undervalued. As shown in Fama and French (1992; 1993), companies with low M/B ratios, known as value stocks, should outperform those with high M/B ratios, known as growth stocks. The difference between those two groups of stocks is referred to as the value premium (i.e., the HML factor in the Fama-French three-factor model). However, the value factor has underperformed for at least a decade.[17] Eisfeldt et al. (2020) posit that the primary driver behind the subpar performance of the value factor lies in the oversight of intangible assets in a firm's book value. In alignment with their proposition, our study investigates whether our intangible asset intensity can elucidate the underperformance observed in the value factor.

To carry out this test, we first group firms into four groups according to their previous year's M/B ratio and intangible asset intensity score. Given that a firm's book value does not account for its intangible assets (i.e., firm's book value omits intangible assets), we define those with low M/B ratios and high levels of intangible assets as intangible adjusted value stocks, while stocks with high M/B ratios and low intangible assets levels are defined as intangible adjusted growth stocks. Then, we estimate the difference between the average stock returns of the intangible asset adjusted value stocks) and the intangible asset adjusted growth stocks and create our intangible assets adjusted value premium.

The yearly average intangible assets adjusted value premium factor is reported in Appendix 4. We also report the average returns for stock groups simply based on the M/B ratio, representing the return spread between companies with low and high M/B ratios and the value premium factor (HML), as described in Fama and French (1992, 1993),[18] for comparison.vThe findings indicate that the mean return differential between stocks categorized into low and high market-to-book (M/B) ratio groups is 4.23% (with a t-value of 2.62 and an excess return of 0.31%), comparable to the HML factor premium observed over the corresponding period (3.41%). In contrast, the mean

[17] For instance, from 2010 to 2021, the value factor shows negative values for eight out of twelve years.
[18] The HML data are collected from https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

return differential between groups of value stocks, adjusted for intangible assets, is notably more pronounced (6.69%, with a t-value of 3.09 and an excess return of 2.77%).[19]

To highlight the oversight of intangible assets in a firm's book value, we proceed to calculate the cumulative returns of the hypothetical portfolios formed by taking long positions in value stocks and short positions in growth stocks throughout the sample period (from 1980 to 2021). The results, depicted in Figure 1, reveal a pattern akin to the HML value factor, wherein the cumulative return of the low-high M/B ratio portfolio experiences a decline, particularly after 2006. In contrast, the intangible asset-adjusted low-high M/B ratio portfolio demonstrates a persistently ascending trajectory. This observation lends credence to the assertion made by Eisfeldt et al. (2020) that the omission of intangible assets in the estimation of a firm's book value constitutes one of the reasons behind the underperformance of the value factor.

(Figure1 here)

4.6 Intangible Asset Intensity, Labor Investment Efficiency and Accounting Quality

Firms' investments often deviate from optimal levels due to factors such as moral hazard (Jensen & Meckling, 1976; Stulz, 1990), stock price informativeness (Ben-Nasr & Alshwer, 2016), and financial reporting quality (Jung, Lee, & Weber, 2014). Prior studies suggest that such deviations lead to underinvestment or overinvestment, reducing firm profitability. Since intangible assets are difficult to measure, firms with high intangible asset intensity may exhibit overinvestment due to the market's underestimation of their growth potential.

We examine how intangible asset intensity affects labor investment efficiency, given that human capital is a key driver of firm value. Following Pinnuck and Lillis (2007) and Jung, Lee,

[19] Novy-Marx (2013) documented a similar enhancement of the M/B ratio strategy by involving gross profitability. However, the correlation between our intangible asset intensity score and gross profitability is only 15% and insignificant.

and Weber (2014), we estimate labor investment inefficiency as the absolute deviation from expected hiring levels based on firm fundamentals. Our findings, presented in Appendix 5, reveal a significant negative correlation between intangible asset intensity and labor investment inefficiency, supporting the hypothesis that firms with high intangible capital exhibit greater investment efficiency. However, these firms also tend to overinvest in labor, aligning with our expectation that the market undervalues their growth potential.

Additionally, we explore the relationship between intangible asset intensity and accounting quality, as high-quality financial reporting can mitigate information asymmetry (Doukas & Zhang, 2020). Using Beneish's M-Score (Beneish, 1999), we find that firms with high intangible asset intensity demonstrate better accounting quality, despite tendencies toward labor overinvestment. This suggests that such firms seek to reduce information asymmetry and enhance stock price informativeness. These results, detailed in Appendix 6, confirm that intangible asset intensity plays a crucial role in investment efficiency and financial reporting quality, benefiting both firms and shareholders.

4.7 Mechanism Tests

To further explore the mechanisms through which intangible asset intensity influences firm performance, we conduct a series of PSM analyses. Specifically, we examine whether the impact of intangible assets operates through human capital, competition and pricing power, operational risk, or efficiency. In the matching process, we control for key firm-level characteristics and ensure that firms are matched within the same industry and year to mitigate industry- and time-specific biases.

Our findings indicate that firms with high intangible asset intensity experience significantly higher employee growth rates and sales per employee, suggesting that intangible investments facilitate workforce expansion and enhance labor productivity. These results are consistent with the notion that firms with greater reliance on intangibles—such as technology, R&D, and brand reputation—require a more skilled workforce and benefit from improved human capital utilization. We also observe that high intangible intensity level firms exhibit higher gross profit margins and greater asset turnover, indicating that intangible assets contribute to competitive differentiation and pricing power. This suggests that these firms are able to charge premium prices, optimize resource utilization, and generate superior profitability. Interestingly, we find that high intangible assets firms have slightly lower market share compared to their matched counterparts. This result suggests that while intangible asset-intensive firms excel in productivity, efficiency, and pricing power, they may operate in more specialized or niche markets rather than achieving broad-market dominance.

In terms of risk and efficiency, we find no significant difference in operational risk, measured by the five-year standard deviation of EBIT, between high and low intangible assets firms. This suggests that intangible investments do not necessarily expose firms to greater earnings volatility. However, intangible-intensive firms demonstrate significantly higher firm efficiency, as measured using the firm efficiency methodology of Demerjian, Lev, and McVay (2012), indicating that they are more effective in utilizing their resources. Overall, these results suggest that intangible assets enhance firm performance primarily through human capital development, competitive positioning, and operational efficiency, rather than through increased risk-taking. The detailed results of these mechanism tests are available upon request.

5. Conclusion

In today's knowledge economy, corporate success hinges on the development and utilization of intangible assets such as knowledge, technological know-how, and intellectual property. While tangible assets remain valuable, intangible assets are increasingly crucial in corporate valuations. However, their absence from financial statements makes book-value-based valuations misleading. Accurately quantifying intangible assets is essential for assessing a firm's intrinsic value.

This study introduces a new corporate intangible asset intensity score, derived using the DEA methodology, which evaluates a firm's efficiency in generating revenue from physical assets and total production inputs. Empirical findings show that this measure is significantly correlated with both internally generated and externally acquired intangible assets. To address endogeneity concerns, we employ 2SLS analysis using an instrumental variable based on the 3-digit ZIP codes of acquiring firms' headquarters, alongside PSM analysis. Results from both approaches confirm the robustness of our measure. Additionally, extensive validation tests show a strong positive relationship between our measure and major intangible asset proxies.

We find that intangible asset intensity is significantly associated with stock returns. Relying on book value to classify value and growth stocks can be misleading, as the omission of intangible assets helps explain the underperformance of value stocks in recent decades. This finding suggests that traditional accounting metrics should be adjusted to reflect corporate intangible assets more accurately. Furthermore, firms with high intangible asset intensity scores exhibit higher labor investment efficiency and accounting quality. High-intangible firms mitigate labor underinvestment, yet they also tend to overinvest due to market underestimation of their growth potential. Lastly, unlike prior studies that overlook intangibles, our results show that acquisition returns vary depending on a firm's intangible asset intensity. This underscores the relevance of our measure in evaluating corporate decisions beyond valuation.

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Table 1. Summary Statistics on Firm Efficiency and Intangible Asset Intensity

This table reports summary statistics on firm efficiency and intangible asset intensity for the whole sample of US public traded companies and each industry, based on Fama and French (1997). The sample consists of 233,170 firm-year observations from 1980 to 2020. Firm Efficiency is measured using the data envelopment analysis (DEA) method as shown in Equation (1), and Intangible Asset Intensity is residual from the Tobit model as shown in Equation (2).

		Firm Efficiency		Intangible Asset Intensity	
Industry	Obs.	Mean	Std. Dev.	Mean	Std. Dev.
All	233,170	0.274	0.206	0.000	0.206
Agriculture	985	0.418	0.226	0.138	0.227
Food Products	4,714	0.445	0.146	0.173	0.146
Candy & Soda	722	0.618	0.195	0.343	0.195
Beer & Liquor	1,115	0.560	0.189	0.287	0.189
Tobacco Products	300	0.656	0.180	0.381	0.184
Recreation	2,136	0.460	0.175	0.181	0.174
Entertainment	4,653	0.165	0.167	-0.112	0.165
Printing & Publishing	1,989	0.307	0.161	0.032	0.160
Consumer Goods	4,569	0.344	0.123	0.069	0.125
Apparel	3,235	0.584	0.118	0.309	0.118
Healthcare	4,470	0.356	0.164	0.077	0.164
Medical Equipment	8,123	0.267	0.157	-0.012	0.158
Pharmaceutical Products	14,719	0.118	0.133	-0.159	0.135
Chemicals	5,173	0.403	0.152	0.135	0.151
Rubber & Plastic Products	2,643	0.481	0.176	0.204	0.176
Textiles	1,489	0.674	0.106	0.397	0.107
Construction Materials	6,310	0.438	0.158	0.164	0.157
Construction	3,120	0.492	0.230	0.217	0.230
Steel Works Etc.	3,922	0.621	0.136	0.351	0.133
Fabricated Products	1,094	0.715	0.138	0.434	0.135
Machinery	8,629	0.397	0.124	0.124	0.122
Electrical Equipment	4,089	0.280	0.135	0.003	0.133
Automobiles & Trucks	4,226	0.382	0.142	0.113	0.139
Aircraft	1,442	0.738	0.125	0.466	0.124
Shipbuilding & Railroad Equipment	497	0.773	0.151	0.494	0.150
Defense	392	0.689	0.176	0.406	0.177
Precious Metals	3,168	0.218	0.173	-0.054	0.173
Non-Metallic Mining	2,813	0.260	0.164	-0.010	0.166
Coal	624	0.646	0.183	0.370	0.180
Petroleum & Natural Gas	16,919	0.144	0.094	-0.129	0.094
Communication	10,392	0.296	0.158	0.029	0.157
Personal Services	3,001	0.242	0.168	-0.034	0.167
Business Services	30,572	0.073	0.073	-0.203	0.073
Computers	9,654	0.156	0.092	-0.121	0.091
Electronic Equipment	14,599	0.255	0.127	-0.020	0.125
Measuring & Control Equipment	5,210	0.327	0.149	0.049	0.147
Paper Products	3,625	0.558	0.149	0.288	0.147
Shipping Containers	796	0.790	0.111	0.519	0.109
Transportation	7,941	0.272	0.133	0.005	0.129
Wholesale	10,544	0.257	0.175	-0.018	0.174
Retail	13,282	0.200	0.082	-0.072	0.080
Restaurants, Hotels, Motels	5,274	0.314	0.133	0.037	0.131

Table 2. Intangible Assets Level Measures Summary and Univariate Correlations

This table presents the summary statistics of the intangible assets level measures and the univariate correlations between these measures and firm-level characteristics. *Intangible Asset Intensity* is estimated using DEA methodology, as shown in Equation (1) and Equation (2). The *InternalInv* is calculated using the perpetual inventory method (Eisfeldt, Kim, and Papanikolaou, 2020), as shown in Equation (3). *ExternalAcq* is the total amount of intangible assets acquired externally, available on a firm's balance sheet. The *TotalIAInv* is the sum of *InternalInv* and *ExternalAcq*. All the intangible asset investment measures are scaled by the firm size. *Panel A* presents the summary statistics of all the intangible assets level measures. *Panel B* shows the univariate correlations between each measure and the firm-level characteristics, which include return on equity (*ROE*); return on investment (*ROI*); the stock return one year ahead (*Stock Return*); debt-to-equity ratio (*D/E ratio*); and the log value of firm's revenue (*Sales*). All firm-level variables are winsorized at the top and bottom 1%. * denotes significance at the 10% level.

Panel A	Obs.	Mean	Std. Dev.	25%	Median	75%
Intangible Asset Intensity	233170	0.000	0.206	-0.157	-0.045	0.111
TotalIAInv/TA	233170	0.657	1.484	0.172	0.420	0.748
InternalInv/TA	233170	0.557	1.482	0.102	0.286	0.595
ExternalAcq/TA	233170	0.100	0.169	0.000	0.010	0.131

Panel B	Intangible Asset Intensity	TotalIAInv/TA	InternalInv/TA	ExternalAcq/TA
ROE	0.1041*	-0.0716*	-0.0670*	-0.0410*
ROI	0.1178*	-0.0197*	-0.0189*	-0.0070*
Stock Return	0.0088*	0.0050*	0.0055*	-0.0020
D/E Ratio	0.0452*	-0.0566*	-0.0606*	0.0337*
Sales	0.2470*	-0.2151*	-0.2371*	0.1906*

Table 3. Intangible Asset Intensity and Cumulative Intangible Asset Investment

This table reports the results of regressing the time-series of intangible asset intensity score on a firm's cumulative intangible asset investment. The *InternalInv* is estimated using the perpetual inventory method (Eisfeldt, Kim, and Papanikolaou, 2020), as shown in Equation (3). *ExternalAcq* is the total amount of intangible assets acquired externally, available on a firm's balance sheet. It contains two major parts: purchased goodwill and other acquired and capitalized intangibles. The *TotalIAInv* is the sum of *InternalInv* and *ExternalAcq*. All the intangible asset investment measures are scaled by the firm size. The control variables contain *International Dummy*, which equals one if the firm reports a nonzero value for foreign currency adjustment (FCA); market-to-book ratio (*M/B ratio*); return on equity (*ROE*); return on investment (*ROI*); debt-to-equity ratio (*D/E ratio*); the log value of firm's total assets (*Log (TA)*). All control variables are winsorized at the top and bottom 1%. We also control for industry and year fixed effects, and the standard errors are clustered at the firm level. ***, **, * denotes significance at the 1%, 5% or 10% level.

	Intangible Asset Intensity Score							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TotalIAInv/TA	0.00411***	0.00442***						
	(0.000191)	*(0.000204)*						
InternalInv/TA			0.00293***	0.00308***			0.00399***	0.00374***
			(0.000190)	*(0.000204)*			*(0.000190)*	*(0.000203)*
ExternalAcq/TA					0.103***	0.115***	0.106***	0.117***
					(0.00180)	*(0.00187)*	*(0.00180)*	*(0.00187)*
International Dummy		0.00175**		0.00181**		0.00383***		0.00351***
		(0.000714)		*(0.000714)*		*(0.000709)*		*(0.000708)*
M/B Ratio		-9.88e-07*		-1.00e-06*		-9.63e-07		-9.34e-07
		(5.96e-07)		*(5.96e-07)*		*(5.91e-07)*		*(5.91e-07)*
ROE		0.0147***		0.0146***		0.0154***		0.0156***
		(0.000314)		*(0.000314)*		*(0.000311)*		*(0.000311)*
ROI		0.0143***		0.0144***		0.0147***		0.0145***
		(0.000330)		*(0.000330)*		*(0.000327)*		*(0.000327)*
D/E Ratio		0.000852***		0.000849***		0.000627***		0.000652***
		(0.000115)		*(0.000115)*		*(0.000114)*		*(0.000114)*
Log (TA)		-0.000215		-0.000409***		-0.00229***		-0.00163***
		(0.000134)		*(0.000134)*		*(0.000130)*		*(0.000135)*
Constant	-0.00179	-0.00794***	-0.00121	-0.00656***	-0.00240	-0.00137	-0.00413**	-0.00538**
	(0.00196)	*(0.00221)*	*(0.00196)*	*(0.00222)*	*(0.00194)*	*(0.00219)*	*(0.00194)*	*(0.00220)*
Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Observations	233,170	210,134	233,170	210,134	233,170	210,134	233,170	210,134
R-squared	0.002	0.024	0.001	0.023	0.014	0.039	0.016	0.041

Table 4. Intangible Asset Intensity and Corporate Human Capital

This table reports the results of regressing the time-series of intangible asset intensity score on proxies of a firm's human capital. We use two measures of corporate human capital. The first is *MA Score*, which is obtained following Demerjian, Lev, and McVay (2012) and ranges from 1980 to 2018. The second is the log value of the CEO's total compensation (Log (CEO Comp)) in the previous year, collected from the ExecuComp database and from 1980 to 2020. The control variables contain *International Dummy*, which equals one if the firm reports a nonzero value for foreign currency adjustment (FCA); market-to-book ratio (*M/B ratio*); return on equity (*ROE*); return on investment (*ROI*); debt-to-equity ratio (*D/E ratio*); the log value of firm's total assets (*Log (TA)*); and *TotalIAInv/TA*, which is the intangible assets estimation based on the perpetual inventory method. All control variables are winsorized at the top and bottom 1%. We also control for industry and year fixed effects, and the standard errors are clustered at the firm level. ***, **, * denotes significance at the 1%, 5% or 10% level.

	Intangible Asset Intensity			
	(1)	(2)	(3)	(4)
MA Score	0.328***		0.207***	0.19154***
	(0.00237)		*(0.00378)*	*(0.00374)*
Log (CEO Comp)		0.00518***	0.00359***	0.00256***
		(0.000529)	*(0.000529)*	*(0.00052)*
TotalIAInv/TA				0.04958***
				(0.00138)
M/B Ratio	0.000218***	0.00195***	0.00107***	0.00108***
	(0.000054)	*(0.000114)*	*(0.000121)*	*(0.00012)*
ROE	0.00908***	0.00779***	0.00508***	0.00655***
	(0.000321)	*(0.000843)*	*(0.000896)*	*(0.00088)*
ROI	0.0116***	0.0309***	0.0237***	0.02697***
	(0.000355)	*(0.00135)*	*(0.00145)*	*(0.00142)*
D/E Ratio	0.00111***	-0.00257***	-0.000705**	-0.00075***
	(0.000124)	*(0.000268)*	*(0.000279)*	*(0.00027)*
Log (TA)	-0.00427***	-0.00247***	-0.00571***	-0.00182***
	(0.000129)	*(0.000395)*	*(0.000401)*	*(0.00041)*
International Dummy	0.000793	0.00664***	0.00649***	0.00425***
	(0.000704)	*(0.00115)*	*(0.00116)*	*(0.00114)*
Constant	0.0129***	-0.00155	0.0235***	-0.01786***
	(0.00209)	*(0.00698)*	*(0.00682)*	*(0.00679)*
Fixed Effects	YES	YES	YES	YES
Observations	193,032	38,301	35,168	35,168
R-squared	0.111	0.040	0.114	0.146

Table 5. Intangible Asset Intensity and Brand Value

This table reports the results of regressing the time-series of intangible asset intensity score on proxies of a firm's brand value. To measure brand value, we use two measures: the first measure is the log value of corporate brand value data estimated and reported by BrandFinance.com. This website gives the 100 US companies with the highest brand values for each year. The data are available from 2014 to 2020. The second measure is firm size scaled cumulative advertising expenses in the past five years, as shown in Equation (4). The control variables contain *International Dummy*, which equals one if the firm reports a nonzero value for foreign currency adjustment (FCA); market-to-book ratio (*M/B ratio*); return on equity (*ROE*); return on investment (*ROI*); debt-to-equity ratio (*D/E ratio*); the log value of firm's total assets (*Log (TA)*); and *TotalIAInv/TA*, which is the intangible assets estimation based on the perpetual inventory method. All control variables are winsorized at the top and bottom 1%. We also control for industry and year fixed effects, and the standard errors are clustered at the firm level. ***, **, * denotes significance at the 1%, 5% or 10% level.

	Intangible Asset Intensity			
	(1)	(2)	(3)	(4)
Brand Value	0.0118**		0.00468	-0.00035
	(0.00565)		*(0.00531)*	*(0.00455)*
Cum. Avd. Exp./TA		0.110***	0.138***	0.14153***
		(0.00250)	*(0.0287)*	*(0.02880)*
TotalIAInv/TA				-0.02251
				(0.02303)
M/B Ratio	-0.00108*	0.000822***	-0.000744	-0.00078
	(0.000605)	*(0.000811)*	*(0.000602)*	*(0.00058)*
ROE	-0.169**	0.0122***	-0.0681	-0.06249
	(0.0752)	*(0.000527)*	*(0.0763)*	*(0.07528)*
ROI	0.0216	0.0130***	-0.0161	-0.02608
	(0.0288)	*(0.000550)*	*(0.0301)*	*(0.02979)*
D/E Ratio	0.000968	0.000119	0.00163	0.00166
	(0.00165)	*(0.000195)*	*(0.00163)*	*(0.00159)*
Log (TA)	-0.0241***	-0.000856***	-0.0187***	-0.02134***
	(0.00367)	*(0.000212)*	*(0.00344)*	*(0.00461)*
International Dummy	0.0249***	0.00465***	0.0208***	0.02243***
	(0.00716)	*(0.00118)*	*(0.00790)*	*(0.00764)*
Constant	0.179***	-0.0209***	0.157***	0.23569***
	(0.0528)	*(0.00312)*	*(0.0493)*	*(0.05474)*
Fixed Effects	YES	YES	YES	YES
Observations	319	71,721	231	231
R-squared	0.211	0.048	0.372	0.377

Table 6. Intangible Asset Intensity and Trademarks

This table reports the results of regressing the time-series of intangible asset intensity score on proxies of the firm's trademark value. To measure trademark value, we use two measures: the log value of the new trademark number and the log value of the cumulative trademark number for the company each year. The data are collected following Heath and Mace (2020), from 1980 to 2018. The control variables contain *International Dummy*, which equals one if the firm reports a nonzero value for foreign currency adjustment (FCA); market-to-book ratio (*M/B ratio*); return on equity (*ROE*); return on investment (*ROI*); debt-to-equity ratio (*D/E ratio*); the log value of firm's total assets (*Log (TA)*); and *TotalIAInv/TA*, which is the intangible assets estimation based on the perpetual inventory method. All control variables are winsorized at the top and bottom 1%. We also control for industry and year fixed effects, and the standard errors are clustered at the firm level. ***, **, * denotes significance at the 1%, 5% or 10% level.

	Intangible Asset Intensity			
	(1)	(2)	(3)	(4)
Log (New Trademarks)	0.00849***		0.00416***	0.00400***
	(0.000533)		*(0.000660)*	*(0.00066)*
Log (Total Trademarks)		0.00778***	0.00583***	0.00476***
		(0.000423)	*(0.000524)*	*(0.00053)*
TotalIAInv/TA				0.00937***
				(0.00051)
M/B Ratio	0.00154***	0.00156***	0.00153***	0.00155***
	(0.000102)	*(0.000101)*	*(0.000101)*	*(0.00010)*
ROE	0.0114***	0.0113***	0.0113***	0.01183***
	(0.000668)	*(0.000668)*	*(0.000668)*	*(0.00067)*
ROI	0.0215***	0.0210***	0.0212***	0.02121***
	(0.000755)	*(0.000755)*	*(0.000755)*	*(0.00075)*
D/E Ratio	-0.00125***	-0.00123***	-0.00120***	-0.00120***
	(0.000239)	*(0.000239)*	*(0.000239)*	*(0.00024)*
Log (TA)	-0.00322***	-0.00441***	-0.00462***	-0.00292***
	(0.000272)	*(0.000298)*	*(0.000299)*	*(0.00031)*
International Dummy	0.0127***	0.0120***	0.0121***	0.01124***
	(0.00117)	*(0.00117)*	*(0.00117)*	*(0.00117)*
Constant	0.0219***	0.0299***	0.0290***	0.01695***
	(0.00414)	*(0.00419)*	*(0.00419)*	*(0.00423)*
Fixed Effects	YES	YES	YES	YES
Observations	52,228	52,228	52,228	52,228
R-squared	0.038	0.040	0.040	0.047

Table 7. Intangible Asset Intensity and Intellectual Property

This table reports the results of regressing the time-series of intangible asset intensity score on proxies of a firm's intellectual property value. To measure intellectual property value, we use three measures. The first measure is from InformationWeek.com. This website identifies the most innovative companies in information technology for each year, and the data are available from 2005 to 2013. We set the dummy variable (*InformationWeek*) to one if the firm is on the list and zero otherwise. The second and third measures are based on the patents belonging to the firm. We use the log values of the number of patents owned by the firm and the total citation of all the patents in the regressions. The patent data are available from the National Bureau of Economic Research and range from 1980 to 2003. The control variables contain *International Dummy*, which equals one if the firm reports a nonzero value for foreign currency adjustment (FCA); market-to-book ratio (*M/B ratio*); return on equity (*ROE*); return on investment (*ROI*); debt-to-equity ratio (*D/E ratio*); the log value of firm's total assets (*Log (TA)*); and *TotalIAInv/TA*, which is the intangible assets estimation based on the perpetual inventory method. All control variables are winsorized at the top and bottom 1%. We also control for industry and year fixed effects, and the standard errors are clustered at the firm level. ***, **, * denotes significance at the 1%, 5% or 10% level.

	Intangible Asset Intensity					
	(1)	(2)	(3)	(4)	(5)	(6)
InformationWeek	0.00552*	0.00457*				
	(0.00300)	*(0.00260)*				
Log (Patent)			0.00626***		0.00531***	0.00407***
			(0.000757)		*(0.000890)*	*(0.00089)*
Log (Patent Citations)				0.00218***	0.00128***	0.00114**
				(0.000458)	*(0.000492)*	*(0.00049)*
TotalIAInv/TA		0.00245***				0.01079***
		(0.00027)				*(0.00075)*
M/B Ratio	0.00114***	0.00117***	0.000887***	0.00116***	0.00118***	0.00113***
	(0.000113)	*(0.00011)*	*(0.000093)*	*(0.000115)*	*(0.000116)*	*(0.00012)*
ROE	0.0127***	0.01302***	0.0147***	0.0139***	0.0140***	0.01455***
	(0.000665)	*(0.00067)*	*(0.000670)*	*(0.000809)*	*(0.000813)*	*(0.00081)*
ROI	0.0149***	0.01466***	0.0239***	0.0245***	0.0245***	0.02465***
	(0.000681)	*(0.00068)*	*(0.000664)*	*(0.000825)*	*(0.000830)*	*(0.00083)*
D/E Ratio	-0.000858***	-0.00088***	0.000867***	0.000582**	0.000432	0.00060**
	(0.000286)	*(0.00029)*	*(0.000245)*	*(0.000295)*	*(0.000298)*	*(0.00030)*
Log (TA)	-0.00190***	-0.00124***	-0.00164***	-0.000720**	-0.00171***	-0.00017
	(0.000256)	*(0.00027)*	*(0.000279)*	*(0.000296)*	*(0.000337)*	*(0.00035)*
International Dummy	0.000337	0.00016	0.0140***	0.0157***	0.0148***	0.01334***
	(0.00129)	*(0.00129)*	*(0.00122)*	*(0.00138)*	*(0.00140)*	*(0.00140)*
Constant	-0.0103***	-0.01574***	0.0263***	0.0257***	0.0306***	0.02094***
	(0.00210)	*(0.00218)*	*(0.00282)*	*(0.00341)*	*(0.00350)*	*(0.00355)*
Fixed Effects	YES	YES	YES	YES	YES	YES
Observations	45,175	45,175	58,946	40,456	39,806	39,806
R-squared	0.022	0.024	0.042	0.043	0.044	0.049

Table 8. Intangible Asset Intensity, Network Efficiency, and Employee Satisfaction

This table reports the results of regressing the time-series of intangible asset intensity score on proxies of a firm's network efficiency and employee satisfaction. Network efficiency is measured by the log value of cash-to-cash days (*Log (Cash-to-Cash Days)*), which is the sum of days sales in inventories and days sales in receivables, subtracting days sales in receivables. To measure employee satisfaction, we follow Luo, Zhou, and Shon (2016) and use the information from Glassdoor.com to identify the top companies with the highest employee satisfaction. The data are available from 2009 to 2020. We set the dummy variable (*Glassdoor Dummy*) to one if the firm is on the list and zero otherwise. The control variables contain *International Dummy*, which equals one if the firm reports a nonzero value for foreign currency adjustment (FCA); market-to-book ratio (*M/B ratio*); return on equity (*ROE*); return on investment (*ROI*); debt-to-equity ratio (*D/E ratio*); the log value of firm's total assets (*Log (TA)*); and *TotalIAInv/TA*, which is the intangible assets estimation based on the perpetual inventory method. All control variables are winsorized at the top and bottom 1%. We also control for industry and year fixed effects, and the standard errors are clustered at the firm level. ***, **, * denotes significance at the 1%, 5% or 10% level.

	Intangible Asset Intensity			
	(1)	(2)	(3)	(4)
Log (Cash-to-Cash Days)	-0.144921***	-0.01415***		
	(0.000290)	*(0.00029)*		
Glassdoor Dummy			0.0133*	0.01147*
			(0.00758)	*(0.00657)*
TotalIAInv/TA		0.00789***		0.00357***
		(0.00041)		*(0.00030)*
M/B Ratio	0.000789***	0.00051***	0.00102***	0.00106***
	(0.000512)	*(0.00006)*	*(0.000942)*	*(0.00009)*
ROE	0.0139***	0.01412***	0.0149***	0.01526***
	(0.000317)	*(0.00037)*	*(0.000619)*	*(0.00062)*
ROI	0.0155***	0.01955***	0.0136***	0.01328***
	(0.000338)	*(0.00044)*	*(0.000625)*	*(0.00062)*
D/E Ratio	0.00003	0.00101***	-0.000800***	-0.00084***
	(0.000127)	*(0.00014)*	*(0.000242)*	*(0.00024)*
Log (TA)	-0.000979***	-0.00084***	-0.00148***	-0.00067***
	(0.000129)	*(0.00015)*	*(0.000229)*	*(0.00024)*
International Dummy	0.00215***	0.00335***	0.000560	0.00048
	(0.000716)	*(0.00076)*	*(0.00116)*	*(0.00116)*
Constant	-0.00352	0.07006***	-0.00963***	-0.01733***
	(0.00222)	*(0.00258)*	*(0.00220)*	*(0.00229)*
Fixed Effects	YES	YES	YES	YES
Observations	206,566	160,437	54,451	54,451
R-squared	0.023	0.044	0.022	0.025

Table 9. Acquirer fixed effects

This table reports the significant level of acquirer fixed effects (FE) by regressing acquirer abnormal returns ((t-2, t+2) announcement period CAR, (t-2, t+2) announcement period BHAR, and (t-5, t+5) announcement period CAR) on M&A deal and firm characteristic control variables, for the full sample (Panel A) and occasional acquirers (Panel B). We define occasional acquirers as those having completed less than 5 M&As within a 3-year window. We divide all deals into high-level intangible asset acquirers (top 50% or top 20%) and low-level intangible asset acquirers (bottom 50% or bottom 20%) subsamples. *Year FE* indicates that only year FE is included, and *Year FE and Acquirer FE* indicates that both year FE and acquirer FE are included. F-statistics for the significance of the fixed effects are reported.

Panel A: Full Sample												
	Top 50%			Bottom 50%			Top 20%			Bottom 20%		
CAR(-2, 2)		F-statistic	Prob>F		F-statistic	Prob>F		F-statistic	Prob>F		F-statistic	Prob>F
Year FE	F(31, 4943)	*1.42*	0.061	F(31, 5078)	*1.35*	0.095	F(31, 1983)	*1.39*	0.073	F(31, 2058)	*1.20*	0.207
Year FE and Acquirer FE	F(1995, 2948)	*1.69*	0.000	F(2160, 2808)	*1.45*	0.000	F(1019, 966)	*1.75*	0.000	F(1247, 811)	*1.39*	0.000
F-statistic difference		*0.27*			*0.10*			*0.36*			*0.19*	
BHAR(-2, 2)												
Year FE	F(31, 4943)	*1.41*	0.065	F(31, 5078)	*1.41*	0.067	F(31, 1983)	*1.16*	0.251	F(31, 2058)	*1.46*	0.049
Year FE and Acquirer FE	F(1995, 2948)	*1.59*	0.000	F(2270, 2808)	*1.57*	0.000	F(1019, 966)	*1.40*	0.000	F(1247, 811)	*1.63*	0.000
F-statistic difference		*0.18*			*0.16*			*0.24*			*0.17*	
CAR(-5, 5)								/				
Year FE	F(31, 4953)	*1.17*	0.233	F(31, 5084)	*1.32*	0.112	F(31, 1992)	*1.30*	0.123	F(31, 2060)	*1.28*	0.138
Year FE and Acquirer FE	F(1997, 2956)	*1.80*	0.000	F(2273, 2811)	*1.46*	0.000	F(1020, 974)	*1.78*	0.000	F(1248, 812)	*1.29*	0.000
F-statistic difference		*0.63*			*0.14*			*0.48*			*0.01*	
Panel B: Occasional Acquirers												
CAR(-2, 2)												
Year FE	F(24, 794)	*0.63*	0.916	F(23, 575)	*1.39*	0.105	F(22, 282)	*0.63*	0.898	F(17, 123)	*1.46*	0.122
Year FE and Acquirer FE	F(144, 651)	*2.02*	0.000	F(134, 442)	*1.53*	0.001	F(67, 216)	*1.53*	0.012	F(48, 78)	*1.76*	0.013
F-statistic difference		*1.39*			*0.14*			*0.90*			*0.30*	
BHAR(-2, 2)												
Year FE	F(24, 794)	*0.67*	0.885	F(23, 575)	*1.33*	0.137	F(22, 282)	*0.62*	0.908	F(17, 123)	*1.57*	0.082
Year FE and Acquirer FE	F(144, 651)	*2.04*	0.000	F(134, 442)	*1.59*	0.000	F(67, 216)	*1.50*	0.015	F(48, 78)	*1.93*	0.005
F-statistic difference		*1.37*			*0.26*			*0.88*			*0.36*	
CAR(-5, 5)												
Year FE	F(24, 795)	*1.00*	0.462	F(23, 575)	*0.74*	0.804	F(22, 283)	*0.78*	0.711	F(17, 123)	*1.60*	0.045
Year FE and Acquirer FE	F(144, 652)	*1.99*	0.000	F(134, 442)	*1.13*	0.178	F(67, 217)	*1.19*	0.245	F(48, 78)	*1.54*	0.011
F-statistic difference		*0.99*			*0.39*			*0.41*			*-0.06*	

Table 10. Acquirer Intangible Asset Intensity and Acquisition Performance

This table presents the regression results of intangible asset intensity on acquisition short-term performance. ((t-2, t+2) announcement period CAR) or long-term performance (one-year CAR after the announcement day). *Stock Dummy* refers to 100% stock-financed deals; *Public Dummy* refers to deals with public target firm; *Foreign Dummy* refers to international target, *Focused Dummy* refers to deals in which acquirer and target firms are in the same industry, *Log (Acq. Value)* refers to the log value of acquirer's market capitalization 20 days prior to the deal's announcement, *Log (Trans. Value)* refers to the log value of deal size, *Log(Age)* refers to the acquirer age, which is computed as the difference between the M&A announcement year and the firm's IPO year (if IPO date is missing, we use the year when the acquirer entered the CRSP database), *D/E Ratio* is the ratio of acquirer's debt to equity ratio in the most recent quarter obtained from Compustat, *Tobin's Q* is the acquiring firm's Tobin's Q in previous year. The asterisks *, **. and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)
	CAR (-2, 2)	One-year CAR
Intangible Asset Intensity	0.0207**	0.198***
	(0.00889)	*(0.0594)*
Stock Dummy	-0.00475*	-0.0234
	(0.00278)	*(0.0169)*
Public Dummy	-0.0215***	0.0176
	(0.00262)	*(0.0155)*
Foreign Dummy	-0.00171	-0.0162
	(0.00261)	*(0.0152)*
Focus Dummy	0.000141	0.00538
	(0.00222)	*(0.0129)*
Log (Acq. Value)	-0.0161***	-0.0489***
	(0.00152)	*(0.00900)*
Log (Trans. Value)	0.00772***	-0.0122
	(0.00162)	*(0.00959)*
Log (Age)	0.00861***	0.0674***
	(0.00263)	*(0.0156)*
D/E ratio	0.00105*	-0.00246
	(0.000629)	*(0.00390)*
Tobin's Q	0.000527	-0.0129***
	(0.000428)	*(0.00258)*
Constant	0.0145	0.0685
	(0.0199)	*(0.132)*
Year FE	YES	YES
Industry FE	YES	YES
# of obs.	10,126	9,120
Adj. R-squared	0.028	0.041

Table 11: Robustness Tests for Endogeneity: IV and PSM

The table reports in *Panel A* the result for endogeneity test using instrumental variable (IV) regression of acquisition short-term performance (5-day announcement period CAR) on firm's intangible asset intensity and in *Panel B*, the results of the Propensity Score Matching (PSM) analysis. The IV, *ZIP-based Intangible Asset Intensity,* is the acquirer headquarters' three-digit Zip-code-based intangible asset intensity scores. In column (2), *Fitted Value* is the predicted intangible intensity scores from the first stage. *Stock Dummy* refers to 100% stock-financed deals; *Public Dummy* refers to deals with public target firm; *Foreign Dummy* refers to international target, *Focused Dummy* refers to deals in which acquirer and target firms are in the same industry, *Log (Acq. Value)* refers to the log value of acquirer's market capitalization 20 days prior to the deal's announcement, *Log (Trans. Value)* refers to the log value of deal size, *Log(Age)* refers to the acquirer age, which is computed as the difference between the M&A announcement year and the firm's IPO year (if IPO date is missing, we use the year when the acquirer entered the CRSP database), *D/E Ratio* is the ratio of acquirer's debt to equity ratio in the most recent quarter obtained from Compustat, *Tobin's Q* is the acquiring firm's Tobin's Q in previous year. Panel B reports the result of the Propensity Score Matching (PSM) using nearest-neighbor matching with one neighbor. The propensity scores were estimated through logistic regression. Average Treatment Effect on the Treated (ATT) measures are reported, along with the t-values. The asterisks *, **. and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: IV Analysis

	(1)	(2)
	Intangible Asset Intensity	CAR (-2, 2)
ZIP-based Intangible Asset Intensity	0.097***	
	(0.023)	
Fitted Value		0.122*
		(0.066)
Stock Dummy	-0.014***	-0.002
	(0.003)	*(0.003)*
Public Dummy	-0.001	-0.018***
	(0.003)	*(0.003)*
Foreign Dummy	-0.003	-0.001
	(0.003)	*(0.003)*
Focus Dummy	-0.004	-0.002
	(0.003)	*(0.002)*
Log (Acq. Value)	0.005***	-0.017***
	(0.002)	*(0.002)*
Log (Trans. Value)	0.001	0.007***
	(0.002)	*(0.002)*
Log (Age)	-0.013***	0.009***
	(0.003)	*(0.003)*
D/E ratio	0.000	0.000
	(0.000)	*(0.000)*
Tobin's Q	0.002***	0.002***
	(0.000)	*(0.000)*
Constant	-0.154**	0.023
	(0.075)	*(0.020)*
Year FE	YES	YES
Industry FE	YES	YES
State FE	YES	NO
# of obs.	8,549	8,549
Adj. R-squared	0.271	0.364

Panel B: PSM analysis

Variable	**Sample**	**Treated**	**Controls**	**Difference**	**t-value**
CAR(-2,2)	Unmatched	0.0198	0.0095	1.0341***	5.54
	ATT	0.0198	0.0136	0.6252**	2.43

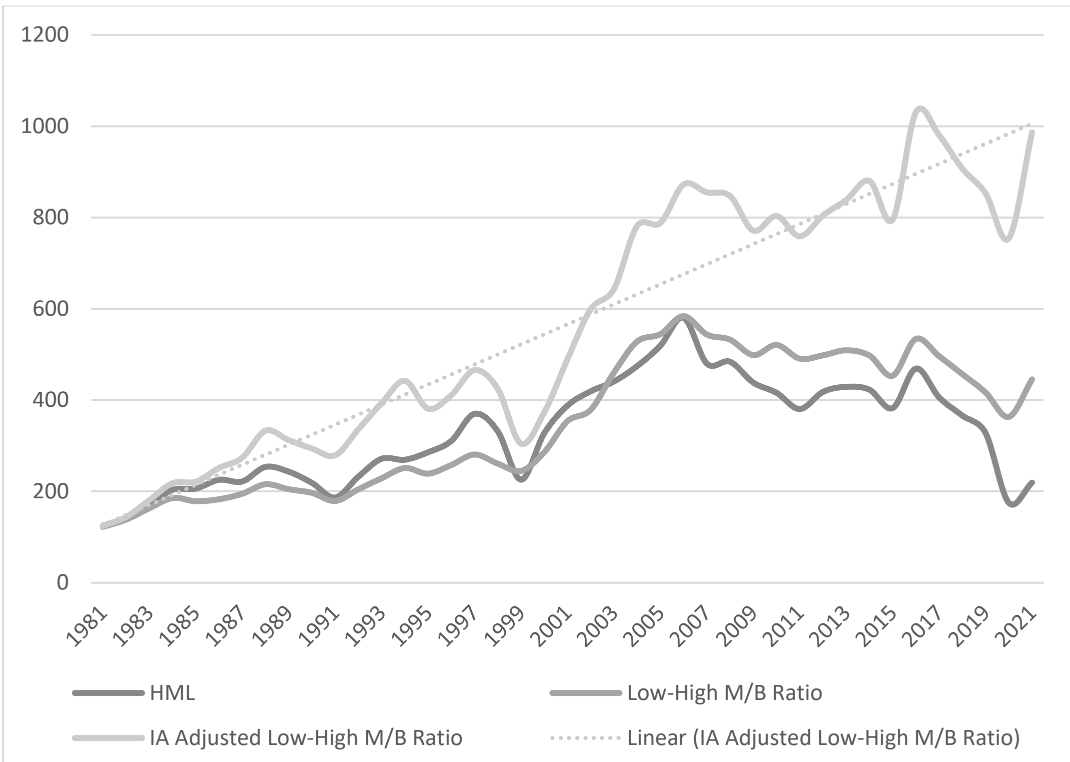
Table 12. Intangible Asset Intensity and Stock Alpha

In this table, we present the monthly risk-adjusted portfolio return (i.e., alpha) using Carhart four-factor model (Carhart, 1997) and Fama and French five-factor model (Fama and French, 2017). The dependent variable is the portfolio returns of high or low intangible asset intensity firms less either the risk-free rate or the characteristics-matched portfolio returns following Daniel, Grinblatt, Titman, and Wermers (1997) and Wermers (2004), which are available on Dr. Russ Wermers' website. We identify high and low intangible asset intensity firms using the median intangible asset intensity number within each industry in the previous year. We also create hypothetical portfolios by holding high intangible asset intensity companies and short selling low intangible asset intensity companies (High-Low). The sample period for regressions (1) to (6) is January 1981 to December 2021, and for regressions (7) to (12) is January 1981 to December 2012. ***, **, * denotes significance at the 1%, 5% or 10% level.

	Return over the risk-free rate:1981-2021						Return over the DGTW benchmark:1981-2012					
	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Alpha	0.2145***	-0.0764*	0.2909***	0.1455**	-0.0617	0.2072***	0.3426***	-0.3751*	0.7225**	0.2121***	-0.4482*	0.6651**
	(0.0706)	*(0.0404)*	*(0.0462)*	*(0.0702)*	*(0.0946)*	*(0.0392)*	*(0.0612)*	*(0.2204)*	*(0.2837)*	*(0.0747)*	*(0.2569)*	*(0.2882)*
MKT	1.0045***	1.0113***	-0.0067	1.0309***	1.0288***	0.0021	-0.0042	0.6402***	-0.6479***	0.0288	0.6728***	-0.6472***
	(0.0165)	*(0.0204)*	*(0.0108)*	*(0.0192)*	*(0.0226)*	*(0.0094)*	*(0.0139)*	*(0.0661)*	*(0.0644)*	*(0.0176)*	*(0.0704)*	*(0.0680)*
SMB	0.8017***	0.9470***	-0.1452***	0.7808***	0.8209***	-0.0401***	-0.0427**	0.3726***	-0.4147***	-0.0371	0.2948***	-0.3336***
	(0.0238)	*(0.0295)*	*(0.0156)*	*(0.0291)*	*(0.0343)*	*(0.0142)*	*(0.0201)*	*(0.0953)*	*(0.0934)*	*(0.0261)*	*(0.1040)*	*(0.1008)*
HML	0.0523**	0.0335	0.0188	0.0372	0.0504	-0.0132	-0.1410***	-0.0677	-0.0685	-0.0406	-0.1988	0.1648
	(0.0243)	*(0.0301)*	*(0.0159)*	*(0.0339)*	*(0.0400)*	*(0.0166)*	*(0.0218)*	*(0.1034)*	*(0.1011)*	*(0.0332)*	*(0.1318)*	*(0.1281)*
MOM	-0.2010***	-0.2436***	0.0426***				-0.1648***	-0.1074*	-0.0619			
	(0.0165)	*(0.0204)*	*(0.0108)*				*(0.0133)*	*(0.0630)*	*(0.0615)*			
RMW				-0.1128***	-0.4017***	0.2890***				0.0247	-0.2318*	0.2491**
				(0.0366)	*(0.0432)*	*(0.0179)*				*(0.0328)*	*(0.1301)*	*(0.1265)*
CMA				-0.0287	0.0019	-0.0307				-0.1007**	0.3563*	-0.4553**
				(0.0537)	*(0.0633)*	*(0.0262)*				*(0.0497)*	*(0.1981)*	*(0.1915)*
Observations	492	492	492	492	492	492	378	378	378	378	378	378
Adj. R-squared	0.934	0.913	0.192	0.919	0.902	0.445	0.330	0.293	0.289	0.056	0.302	0.308

Figure 1. Cumulative Returns of the Long-value/Short-growth Hypothetical Portfolios

This figure reports the cumulative returns for three long-value/short-growth hypothetical portfolios assuming an $100 initial investment in January 1981. The value/growth stocks are classified using HML factor following Fama and French (1993), the median number of previous year's M/B ratio, and the combination of previous year's M/B ratio with intangible asset intensity.



Appendix 1. A Key Corporate Intangible Asset: Top Manager's Managerial Attributes

We develop a theoretical framework linking top managers' attributes to firm decision-making as a key intangible asset. Managers with higher attributes exhibit greater caution and transparency, prioritizing the protection of their human capital and firm value. In contrast, lower-attribute managers take riskier decisions due to reduced sensitivity to firm risks. This effect is amplified in economic uncertainty, where high-attribute managers mitigate adverse outcomes to preserve their reputation and firm stability. Their decisions reflect the heightened impact of risk on their personal wealth and standing in the competitive executive labor market.

Let **U (•)** symbolize a manager's utility function, and **V** denote the manager's current value state (i.e., human value). The potential corporate outcomes in favorable (**f**) and unfavorable (**u**) conditions, with a proportional impact on manager wealth, are denoted as $\mathbf{V_f}$ and $\mathbf{V_u}$ ($\mathbf{V_f > V > V_u}$). **p** represents the optimistic manager's probability of favorable outcomes. Since the utility function for a risk-averse manager is concave, the manager's utility level is:

$$U\,(p\,V_f + (1 - p)\,V_u) > p\,U\,(V_f) + (1 - p)\,U\,(V_u)$$

Assuming **E** is the certainty equivalent of the manager's decisions that satisfies:

$$U\,(E) = p\,U\,(V_f) + (1 - p)\,U\,(V_u)$$

We can identify the risk-neutral probabilities in a two-stage set up. Since the manager has indifferent preference between the certainty equivalent **E**s in both favorable ($\mathbf{V_f}$) and unfavorable ($\mathbf{V_u}$) events, implies that there is a probability **e** such that

$$E = e\,E + (1 - e)\,E$$

$$E = e\,V_f + (1 - e)\,V_u$$

with the solution as

$$e = (E - V_u) / (V_f - V_u)$$

Since **e** is a probability number, which ranges from 0 to 1, $\mathbf{V_f}$ must be greater than **E**, while both **E** and $\mathbf{V_f}$ should be greater than $\mathbf{V_u}$. Since **E** is the certainty equivalent of the expected utility of the corporate decision, we have that

$$U(E) < U(p V_f + (1 - p) V_u)$$

$$p > (E - V_u) / (V_f - V_u) = e$$

This observation indicates that the probability under a risk-neutral framework (**e**) is lower than the corresponding subjective probability (**p**). For a very optimistic, risk-averse manager with a standard concave utility function, **e** is greater than the true probability of the favorable outcomes ($\mathbf{p_t}$). In essence, high managerial qualities prompt a manager to adopt a more pessimistic stance than his inherent subjective optimism would suggest. Consequently, these managerial attributes serve as a potent influence, compelling a manager to behave as a well-calibrated but less risk-averse individual. This suggests that when optimism rises or risk aversion diminishes, managers with such attributes may exhibit behaviors akin to those of risk-seeking or risk-neutral managers. This pattern persists whenever

$$p_t < (E - V_u) / (V_f - V_u) < p$$

where $(\mathbf{V_f - V_u})$ represents the impact of corporate decisions on a manager's human worth. More precisely, the effects should be more pronounced for managers possessing high levels of human capital, characterized by substantial intangible assets.

This prediction of this theoretical framework posits that managers with lower attributes take greater risks as their personal wealth is less tied to firm value, while higher-attribute managers prioritize risk mitigation due to their heightened financial sensitivity to firm outcomes. Unfavorable decisions impose costs on both firms and managers, particularly through job loss and reputational damage. In economic uncertainty, high-attribute managers safeguard firm value by aligning decisions with investor signals, ensuring transparency, and protecting their reputation in the executive labor market. Their strategic caution fosters stability and trust, reinforcing their role as valuable intangible assets in corporate decision-making.

Appendix 2. Average Stock Returns Sorted Based on Intangible Asset Intensity

This table presents the average annual stock returns, sorted on intangible asset intensity, from 1981 to 2021. Companies are grouped at the beginning of each year into high and low intangible asset intensity groups based on their lagged intangible asset intensity scores. The High-Low column presents the annual stock returns of the hypothetical portfolio by holding a high intangible asset intensity portfolio and short selling a low intangible asset intensity portfolio.

Year	High IA Intensity	Low IA Intensity	High-Low
1981	3.212	-2.815	6.027
1982	27.497	22.524	4.973
1983	37.921	26.611	11.309
1984	-9.209	-18.122	8.913
1985	23.363	17.954	5.409
1986	10.534	-1.322	11.856
1987	-6.283	-8.751	2.468
1988	23.285	11.874	11.411
1989	13.352	14.453	-1.101
1990	-19.932	-17.754	-2.178
1991	40.852	37.130	3.723
1992	17.484	10.910	6.574
1993	22.570	17.091	5.478
1994	-1.708	-4.497	2.789
1995	20.525	29.550	-9.025
1996	14.719	14.302	0.417
1997	17.733	11.791	5.942
1998	-6.832	-4.289	-2.543
1999	7.698	32.343	-24.645
2000	-7.420	-17.360	9.941
2001	14.144	3.861	10.283
2002	-8.582	-25.715	17.132
2003	53.979	68.173	-14.194
2004	22.799	14.486	8.313
2005	5.042	7.235	-2.193
2006	18.923	14.764	4.159
2007	4.788	-0.087	4.874
2008	-44.728	-45.826	1.098
2009	53.034	57.588	-4.554
2010	26.955	27.254	-0.299
2011	-10.280	-10.366	0.086
2012	15.926	11.372	4.554
2013	42.200	40.325	1.875
2014	4.618	-2.580	7.198
2015	-9.079	-8.955	-0.123
2016	20.626	8.949	11.677
2017	18.070	15.775	2.295
2018	-13.154	-13.569	0.415
2019	20.218	17.427	2.790
2020	21.558	20.626	0.932
2021	19.125	9.573	9.552
Average	12.330	9.315	3.015
t-value	*4.01*	*2.75*	*2.61*

Appendix 3. Intangible Asset Intensity and Stock Performance

This table reports regression results of intangible asset intensity score, estimated in the prior year, on the firm's stock return while controlling other firm-level control variables. The control variables contain *International Dummy*, which equals one if the firm reports a nonzero value for foreign currency adjustment (FCA); market-to-book ratio (*M/B ratio*); return on equity (*ROE*); return on investment (*ROI*); debt-to-equity ratio (*D/E ratio*); the log value of firm's total assets (*Log (TA)*). All control variables are winsorized at the top and bottom 1%. We also control for industry and year fixed effects, and the standard errors are clustered at the firm level. ***, **, * denotes significance at the 1%, 5% or 10% level.

	Stock Return	
	(1)	(2)
Intangible Asset Intensity	0.0826***	0.0679***
	(0.0116)	*(0.0123)*
M/B Ratio		6.84e-06
		(0.0000)
ROE		0.00642**
		(0.0028)
ROI		0.0313***
		(0.00260)
D/E Ratio		-0.000750
		(0.0007)
Log (TA)		0.0143***
		(0.00076)
International Dummy		0.00881**
		(0.00368)
Constant	-0.00202	-0.0575***
	(0.0102)	*(0.0109)*
Fixed Effects	YES	YES
Observations	148,070	141,943
R-squared	0.116	0.122

Appendix 4. Traditional Value Factor and Intangible Asset Intensity Adjusted Value Factor

This table presents the average annual stock returns of the hypothetical portfolio by holding value stocks and short-selling growth stocks from 1981 to 2021. *Low M/B-High M/B* column represents the hypothetical portfolio based on the traditional market-to-book ratio. At the beginning of each year, all stocks in the sample are sorted into high and low M/B ratio portfolios based on the median number of the prior year's M/B ratios. *Low M/B&High IA-High M/B-Low IA* column represents the hypothetical portfolio based on the intangible asset intensity adjusted market-to-book ratio. Specifically, at the beginning of each year, we sort all companies into four groups based on their prior year's M/B ratios and intangible asset intensity scores. We define value stocks as the ones with low M/B ratios and high intangible asset intensity scores and growth stocks as the ones with high M/B ratios and low intangible asset intensity scores. *HML* is the value premium factor representing the return spread between companies with low and high M/B ratios. The data are described in Fama and French (1992, 1993) and are available from Dr. Kenneth French's website.

	Low M/B-High M/B	Low M/B &High IA-High M/B & Low IA	HML
1981	22.40	24.55	25.12
1982	12.91	15.50	13.36
1983	17.99	25.81	20.49
1984	13.81	20.47	19.07
1985	-3.78	1.50	1.37
1986	2.43	13.57	9.33
1987	6.55	8.91	-1.62
1988	10.67	21.61	14.37
1989	-5.02	-6.15	-4.12
1990	-3.90	-5.90	-10.04
1991	-8.98	-5.04	-14.72
1992	14.23	20.42	24.49
1993	11.79	16.95	16.86
1994	9.79	12.52	-0.77
1995	-4.88	-13.82	6.05
1996	7.93	7.74	8.70
1997	8.88	13.37	19.11
1998	-7.07	-8.78	-10.32
1999	-6.16	-28.29	-31.96
2000	16.67	22.49	45.02
2001	23.84	31.20	18.50
2002	7.02	22.39	8.09
2003	21.55	7.35	5.11
2004	14.79	21.54	7.67
2005	3.05	0.81	9.43
2006	7.24	10.70	11.75
2007	-6.88	-1.97	-17.28
2008	-2.06	-0.95	0.83
2009	-6.37	-8.94	-9.42
2010	4.48	4.18	-5.10
2011	-5.77	-5.57	-8.54
2012	1.49	6.04	9.85
2013	2.21	4.22	2.65
2014	-2.26	5.00	-1.46
2015	-8.87	-9.62	-9.53
2016	17.78	29.53	22.64
2017	-7.11	-4.89	-13.48
2018	-7.91	-7.48	-9.80
2019	-8.80	-5.95	-10.48
2020	-12.78	-11.53	-46.60
2021	22.57	30.77	25.33
Average	4.23	6.69	3.41
t-value	*2.62*	*3.09*	*1.33*

Appendix 5. Intangible Asset Intensity and Labor Investment Efficiency

This table reports regression results of intangible asset intensity score on the firm's labor investment efficiency while controlling other firm-level control variables. We estimate labor investment efficiency as the absolute value of the difference between a firm's actual change and the expected change in the number of employees following Pinnuck and Lillis (2007) and Jung, Lee, and Weber (2014). We also present the regression results for the over hiring (actual hiring is greater than expected) and under hiring (actual hiring is less than expected) subsamples. The control variables contain *International Dummy*, which equals one if the firm reports a nonzero value for foreign currency adjustment (FCA); market-to-book ratio (*M/B ratio*); return on equity (*ROE*); return on investment (*ROI*); debt-to-equity ratio (*D/E ratio*); the log value of firm's total assets (*Log (TA)*). All control variables are winsorized at the top and bottom 1%. We also control for industry and year fixed effects, and the standard errors are clustered at the firm level. ***, **, * denotes significance at the 1%, 5% or 10% level.

	Abnormal Hiring		
	All	Over Hiring	Under Hiring
	(1)	(2)	(3)
Intangible Asset Intensity	-0.0570***	0.0147*	-0.126***
	(0.00440)	*(0.00841)*	*(0.00446)*
M/B Ratio	0.000602***	0.00103***	-4.03e-05
	(0.000101)	*(0.00019)*	*(0.000104)*
ROE	-0.0153***	0.00343**	-0.0233***
	(0.000576)	*(0.00139)*	*(0.000515)*
ROI	-0.00899***	-0.00932***	-0.00961***
	(0.000659)	*(0.00142)*	*(0.000618)*
D/E Ratio	0.000948***	0.00270***	7.95e-05
	(0.000228)	*(0.000457)*	*(0.000224)*
Log (TA)	-0.0173***	-0.0174***	-0.0158***
	(0.000242)	*(0.000504)*	*(0.000234)*
International Dummy	-0.00662***	-0.0120***	-0.00342***
	(0.00126)	*(0.00257)*	*(0.00122)*
Constant	0.228***	0.245***	0.215***
	(0.00382)	*(0.00948)*	*(0.00338)*
Fixed Effects	YES	YES	YES
Observations	161,275	64,529	96,746
R-squared	0.055	0.032	0.106

Appendix 6. Intangible Asset Intensity, Accounting Quality, and Labor Investment Efficiency

This table presents the regression results of intangible asset intensity score and the firm's labor investment efficiency on the firm's accounting quality (M-Score), while controlling other firm-level control variables. M-Score is estimated following Beneish (1999). Labor investment efficiency is estimated as the absolute value of the difference between a firm's actual change and the expected change in the number of employees following Pinnuck and Lillis (2007) and Jung, Lee, and Weber (2014). We also include the product of intangible asset intensity and labor investment efficiency in the regression. The control variables contain *International Dummy*, which equals one if the firm reports a nonzero value for foreign currency adjustment (FCA); market-to-book ratio (*M/B ratio*); return on equity (*ROE*); return on investment (*ROI*); debt-to-equity ratio (*D/E ratio*); the log value of firm's total assets (*Log (TA)*). All control variables are winsorized at the top and bottom 1%. We also control for industry and year fixed effects, and the standard errors are clustered at the firm level. ***, **, * denotes significance at the 1%, 5% or 10% level.

	M-Score			
	(1)	(2)	(3)	(4)
Abnormal Hiring	0.847***		0.843***	0.843***
	(0.023)		*(0.023)*	*(0.023)*
Intangible Asset Intensity		-0.425***	-0.400***	-0.293***
		(0.040)	*(0.039)*	*(0.044)*
Abnormal Hiring* Intangible Asset Intensity				-0.570***
				(0.106)
M/B Ratio	0.004***	0.005***	0.005***	0.005***
	(0.001)	*(0.001)*	*(0.001)*	*(0.001)*
ROE	-0.158***	-0.164***	-0.153***	-0.152***
	(0.005)	*(0.005)*	*(0.005)*	*(0.005)*
ROI	0.024***	0.023***	0.029***	0.030***
	(0.006)	*(0.006)*	*(0.006)*	*(0.006)*
D/E Ratio	-0.008***	-0.008***	-0.009***	-0.008***
	(0.002)	*(0.002)*	*(0.002)*	*(0.002)*
Log (TA)	-0.058***	-0.072***	-0.059***	-0.059***
	(0.002)	*(0.002)*	*(0.002)*	*(0.002)*
International Dummy	0.000	-0.003	0.001	0.001
	(0.011)	*(0.011)*	*(0.011)*	*(0.011)*
Constant	-1.980***	-1.782***	-1.969***	-1.971***
	(0.032)	*(0.031)*	*(0.032)*	*(0.032)*
Fixed Effects	YES	YES	YES	YES
Observations	125,181	125,181	125,181	125,181
R-squared	0.268	0.312	0.411	0.417