Revisiting Operating Leverage

The Intangible Book-to-Market Case

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Abstract

A common explanation for the book-to-market effect is that book-to-market (B/M) ratios reflect operating leverage differences between firms. Recently, an intangible-adjusted book-to-market ratio (iB/M) has been shown to capture a stronger book-to-market effect. Motivated by evidence that labor is a key source of operating leverage, and that SG&A and R&D tend to be sticky among intangible-intensive firms, we test whether iB/M is more associated with operating leverage than B/M. In cross-sectional regressions, we find that adjusting for intangibles strengthens iB/M's association with operating leverage. Operating leverage is also positively associated with future returns. However, when controlling for operating leverage, both the adjusted (iB/M) and traditional (B/M) book-to-market measure retain their return predictability; as does the intangible (i/M) component of iB/M. We conclude that while iB/M appears more associated with operating leverage than B/M, operating leverage is unlikely to be the primary driver of the book-to-market effect under either specification.

Keywords:
Book-to-Market, Intangible Capital, Operating Leverage, Labor Leverage

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1. Introduction

The book-to-market (B/M) effect refers to the tendency of high B/M stocks to outperform low B/M stocks. Different explanations have been proposed, including mispricing (Lakonishok et al., 1994) and financial distress risk (Fama & French, 1992). Others have pointed toward the ability of B/M ratios to sort firms by operating leverage, which is viewed as a contributor to systematic risk exposure (Carlson et al., 2004; Cooper, 2006; Novy-Marx, 2011; L. Zhang, 2005). Operating leverage is broadly defined as the sensitivity of the firm's operating earnings to changes in sales, which tends to increase with fixed cost structures (Lev, 1974; Mandelker & Rhee, 1984; O'Brien & Vanderheiden, 1987). Recently, B/M has been seen as misspecified. The argument is that book values in B/M fail to recognize intangible investments, leading to a strong conservatism in B/M ratios for intangible-intensive stocks. When B/M is adjusted through the addition of intangible capital (i/M) in iB/M ratios, the book-to-market ratio has strengthened as a return predictor (Arnott et al., 2021; Eisfeldt et al., 2022; Gulen et al., 2025; Park, 2022). Yet, studies have done little to explore risk-based explanations for iB/M's performance.

This study revisits the operating leverage explanation for the book-to-market effect in the context of intangible adjustments to B/M in iB/M. First, we find evidence that iB/M reflects variation in operating leverage among firms. Moreover, the intangible capital component (i/M) in iB/M captures variation in operating leverage that is distinct from the variation captured by the unadjusted B/M ratio. Our data reveals that this distinction is most pronounced when the exclusion of intangible capital significantly affects a firm's relative ranking in the economy, as measured by iB/M compared to B/M. Our results further suggest that operating leverage is priced in the cross-section of returns. However, our results do not support the notion that operating leverage drives the return association of either the unadjusted B/M or the intangible-adjusted iB/M ratio. This suggests that other factors are behind the book-to-market effect.

Our study is motivated by recent findings that intangible capital is connected to operating leverage and that it, in general, induces fixed costs. Specifically, labor leverage has been argued as a dominant source of operating leverage, which is commonly found among intangible-intensive stocks (Belo et al., 2014; Danthine & Donaldson, 2002; Donangelo et al., 2019; Simintzi et al., 2015). Labor is considered significantly more fixed than other operating costs, with a 1%-point change in sales leading to only a 0.53% change in labor expenses, compared to 1.08% for other operating expenses (Donangelo et al., 2019). Moreover, labor is viewed as especially

sticky when firms hold specialized or non-routine labor (Eisfeldt & Papanikolaou, 2013; M. B. Zhang, 2019), and intangible capital often constitutes employee training, firm-specific routines, and culture that cannot be separated from the workforce (Peters & Taylor, 2017). Similarly, firing costs are often higher among knowledge-intensive firms (Brown & Petersen, 2011; Peters & Taylor, 2017). Other literature has focused directly on SG&A and R&D expenditures, regardless of their relation to labor, and found them to be especially sticky among intangible-intensive firms (Grabowski, 1968; Griliches & Hausman, 1986; Venieris et al., 2015).

Our study can also be framed in terms of the original arguments for why the book-to-market ratio, in particular, should be associated with operating leverage among firms. One view holds that book values in B/M proxy for physical capital, which increases fixed costs, and that high B/M firms tend to have low sales relative to these fixed costs; resulting in high operating leverage (Carlson et al., 2004; Cooper, 2006; L. Zhang, 2005). From this perspective, intangible capital may be connected to fixed cost structures missed in book values by B/M. As such, iB/M could have a balanced perspective of fixed costs tied to both intangible and physical capital. Another view is that B/M reflects operating leverage among firms to the extent that it is a good signal of profitability for the firm. However, B/M ratios may not only reflect profitability (through depressed market values) but also the capital intensity of the firm, whereas the former is more informative of operating leverage (Novy-Marx, 2011). From this perspective, iB/M may mute capital intensity differences among firms and more effectively proxy for operating leverage. Both views are consistent with an intangible-adjusted book-to-market ratio having an improved association with operating leverage.

Our results are consistent with the literature suggesting that intangible capital shares a positive association with operating leverage (Donangelo et al., 2019; Eisfeldt & Papanikolaou, 2013). The results are also consistent with findings that operating leverage is priced in the cross section, which previous literature has attributed to systematic risk exposure implications of operating leverage (Cooper, 2006; Lev, 1974; Mandelker & Rhee, 1984; O'Brien & Vanderheiden, 1987). Moreover, our results align with findings that the book-to-market ratio captures operating leverage differences across firms (Carlson et al., 2004; Cooper, 2006; García-Feijóo & Jorgensen, 2010; Novy-Marx, 2011; L. Zhang, 2005). However, the same studies also find that this association is the primary driver of the book-to-market ratio's association with future returns, which we do not. In this respect, our findings are instead more consistent with studies that challenge operating leverage as the primary explanation for the book-to-market effect (Cao, 2015; Kisser, 2014; Kogan et al., 2023; Ozdagli,

2012).

To the best of our knowledge, our study is the first to connect research on the operating leverage explanation for the book-to-market effect (Carlson et al., 2004; Cooper, 2006; Donangelo, 2021; Novy-Marx, 2011; L. Zhang, 2005), with studies arguing for the use of intangible-adjusted book-to-market ratios in asset pricing (Arnott et al., 2021; Eisfeldt et al., 2022; Gulen et al., 2025; Lev & Srivastava, 2019; Park, 2022). Thus, our study contributes to both academic and practical understanding of the risks captured by intangible-adjusted book-to-market ratios (iB/M), and the relevance this has for the stock return association of such ratios.

2. Literature review

This section provides an overview of existing literature on the book-to-market effect, its relation to operating leverage, recent intangible adjustments to book-to-market ratios, and unique features of intangibles. It concludes with the formal development of our hypotheses.

2.1. Efficient Market Hypothesis

The Efficient Market Hypothesis (EMH) holds that security prices fully reflect all available information, implying that differences in stock returns should primarily be driven by differences in risk exposure (Fama, 1970, 1991). Fama (1970) outlines three forms of market efficiency: weak (based on historical prices), semi-strong (based on all public information), and strong (including private information). While the weak and semi-strong forms are supported by substantial evidence, the strong form is best viewed as a benchmark model. These conclusions have been widely accepted in academic and practitioner circles (Jensen, 1978; Lintner, 1965; Sharpe, 1964).

In line with EMH, several asset pricing models have been developed to identify relevant risk factors. The Capital Asset Pricing Model (CAPM) is among the most influential (Lintner, 1965; Sharpe, 1964). It separates diversifiable (firm-specific) risk from non-diversifiable (systematic) risk, where only the latter commands a risk premium. Systematic risk is captured by a stock's comovement with the market portfolio (its beta). However, CAPM has been challenged by persistent return anomalies, leading to the development of models incorporating additional risk exposures - most notably in the Fama-French Three-Factor and Five-Factor Models (FF3 and FF5). FF3 adds size (SMB) and book-to-market (HML) factors, while FF5 further incorporates investment (CMA) and profitability (RMW). The HML factor includes a long (short) position in the top 30% (bottom 30%) of stocks ranked by B/M each year. (Fama & French, 1992, 2015).

2.2. Book-to-Market Effect

2.2.1. Initial Evidence

The book-to-market (B/M) effect refers to the tendency of high B/M firms to outperform low B/M firms, where B/M is the ratio of a firm's book value of equity to its market capitalization. It was popularized by Fama and French (1992), who found that high B/M firms ("value" firms) generated significantly higher returns than low B/M firms ("growth" firms) in the US between 1963 and 1990, without

significant CAPM beta differences. Generally, it has been found that B/M aligns with persistent profitability differences: low B/M firms are more profitable than high B/M firms for several years before and after portfolio formation. Over time, however, B/M ratios and earnings growth tend to converge - a process referred to as mean reversion. Even so, disagreement has persisted on whether book-to-market represents a risk premium or mispricing (Fama & French, 1992; Lakonishok et al., 1994; L. Zhang, 2005).

2.2.2. Mispricing Explanation

Lakonishok et al. (1994) argue that investors extrapolate past growth trends too far, resulting in overpricing of low B/M ("growth") stocks and underpricing of high B/M ("value") stocks. Book-to-market strategies then earn higher returns by exploiting these expectational errors as earnings revert to the mean, without necessarily bearing higher risk. According to the mispricing view, limits to arbitrage help sustain the B/M premium. Specifically, B/M strategies require long time horizons to pay off and exhibit highly volatile short-term returns. This unpredictability increases arbitrage risk, making professional investors reluctant to bet against potential mispricing in high B/M stocks (Shleifer & Vishny, 1997).

2.2.3. Financial Distress Explanation

Fama and French (1992) challenge the mispricing explanation, contending that a high B/M ratio simply indicates that the stock price of the firm is discounted, as the market rationally assesses the prospects to be poorer than firms with low B/M ratios. This discounting induces an involuntary leverage effect—as debt becomes a larger share of firm value, high B/M firms face dual distress from their weak earnings outlook and elevated leverage (Fama & French, 1992). Chen and Zhang (1998) similarly conclude that high returns for high B/M stocks are a compensation for risk since they are usually distressed, have high financial leverage, and face substantial earnings uncertainty. Vassalou and Xing (2004) finds that the book-to-market effect only exists in high-default risk segments. More recently, Ozdagli (2012) shows that the return spread between firms in the highest B/M decile to lowest B/M decile decreases from 16% to 4% when stock returns are unlevered with market financial leverage data. He relies on additional macroeconomic factors, such as the CAPM's failure to correctly price risk when there are multiple aggregate shocks, to explain why the book-to-market premium is missed by CAPM betas (Ozdagli, 2012).

Yet, the financial distress risk explanation has been contested. Dichev (1998) finds that bankruptcy risk is negatively related to returns, while Griffin and Lem-

mon (2002) show that the book-to-market factor in the Fama-French Three-Factor model fails to price returns among high-distress-risk stocks. Penman et al. (2007) decomposes the B/M ratio into an enterprise component (pertaining to operating risk) and a leverage component (pertaining to financial risk), and find that only the enterprise component is positively associated with returns. This supports the view that operating risk drives the B/M effect. George and Hwang (2010) argue that distress costs are priced, not distress risk. Because financial leverage and default risk are negatively related to distress costs under optimal capital structures, they conclude that the B/M effect cannot be attributed to financial leverage. Instead, similar to Penman et al. (2007), they support an operating distress risk explanation for the B/M–return relation (George & Hwang, 2010).

2.3. Operating Leverage and the Book-to-Market Effect

Operating leverage broadly refers to the amplification of cash flow risk, or earnings uncertainty, when operating costs do not fully adjust with changes in sales. In particular, firms with high fixed cost structures experience greater earnings sensitivity to demand shocks. Lev (1974) demonstrated that fixed operating costs, like debt obligations, expose firms to higher volatility in residual earnings because these costs must be paid regardless of current output levels. As such, both financial leverage (through interest payments) and operating leverage (through fixed costs) amplify equity risk. Indeed, there is a wide consensus in the literature that operating leverage among firms increases their systematic risk exposure, which warrants a risk premium. (Belo et al., 2014; Danthine & Donaldson, 2002; Donangelo, 2021; Lev, 1974; Mandelker & Rhee, 1984; O'Brien & Vanderheiden, 1987).

2.3.1. Book-to-Market: An Operating Leverage Explanation

Carlson et al. (2004) argue that book-to-market inevitably captures operating leverage risks. First, high B/M ("value") firms tend to have low revenues relative to their capital base, often reflecting weaker demand conditions. When product demand falls, their market value declines, while the capital stock from past investments remains. This capital stock, through long-term obligations, generates continued fixed costs - such as the costs of operating a plant, wage contracts, and supplier commitments. As a result, falling market values combined with stagnant capital stocks raise the B/M ratio, while fixed costs increase as a share of total costs as variable costs decrease with sales. This leads to higher operating leverage for high B/M firms; low sales relative to fixed costs, and therefore higher sensitivity to economic shocks. Cooper (2006) and L. Zhang (2005) similarly describe high B/M ("value")

stocks as low-productivity, inefficient producers that are stuck with excess capacity (low output relative to their capital) during demand contractions. However, while this increases their sensitivity to contractions, it also enables them to scale up in demand recoveries without incurring additional investment costs. As such, high B/M firms command a risk premium since they are more sensitive to aggregate shocks (Cooper, 2006). Generally, these explanations assume that fixed costs increase with the capital stock, or book values, captured in B/M ratios. They also assume that investments are largely irreversible; it is costly to liquidate capital that is already invested, which makes it difficult to reduce fixed costs in response to drops in sales. (Carlson et al., 2004; Cooper, 2006; L. Zhang, 2005).

Novy-Marx (2011) similarly offers an operating leverage explanation for the B/M effect. However, unlike other studies (Carlson et al., 2004; Cooper, 2006; L. Zhang, 2005), he does not emphasize that high book values (captured in B/M) increase fixed costs and operating leverage. Instead, Novy-Marx (2011) argues for a profitability-based channel; operating leverage tends to be related to the persistent low margins of high B/M ("value") firms. He illustrates this with a simple example: if the price of a good falls by 1%, a firm operating at 2% margins will see its margins cut in half, while a firm operating at 20% margins will see its margins cut by 5%. As such, Novy-Marx (2011) identifies two types of high B/M ("value") firms: those that are capital-intensive, with high book values due to large physical investments, and those that are inefficient producers, with low market values and thin margins. The first type describes brick-and-mortar business models, often captured by industries, and does not command a risk premium. However, the second type commands a risk premium, since profit margins provide a buffer against aggregate shocks; representing valuable insurance to investors. Supporting this view, Novy-Marx (2011) shows that high B/M ("value") firms in low B/M ("growth") industries outperform low B/M ("growth") firms in high B/M ("value") industries, and that the industry component of B/M is unrelated to returns. Moreover, B/M sorts within industries produce strong return spreads, where B/M is more indicative of margins instead of capital intensity. (Novy-Marx, 2011).

Operating leverage theories also elaborate on why CAPM may fail to account for the book-to-market effect. One component of this explanation is the distinction between assets in place (current productive capital) and growth options (future investment opportunities). Low B/M firms derive more of their value from growth options, while high B/M firms rely more on assets in place; a distinction that B/M ratios help capture. Traditionally, growth options are viewed as riskier: they are uncertain, sensitive to economic conditions, and levered on current operations, lead-

ing to higher betas. However, operating leverage flips this intuition by making high B/M firms more exposed to downturns. L. Zhang (2005) argues that the price of risk is counter-cyclical, rising in recessions when investors are most risk-averse. At the same time, high B/M firms exhibit counter-cyclical betas (due to operating leverage), while low B/M firms have pro-cyclical betas (low operating leverage but must invest in booms). This mismatch between beta dynamics and the price of risk generates a value premium that standard CAPM estimates, by smoothing risk over time, fail to capture (Carlson et al., 2004; Cooper, 2006; Novy-Marx, 2011; L. Zhang, 2005).

Other studies have independently shown that high B/M firms exhibit higher operating leverage, and that independent sorts on operating leverage and book-to-market produces groups of firms with similar characteristics (Donangelo, 2021; García-Feijóo & Jorgensen, 2010; George & Hwang, 2010). Under the argument that operating leverage negatively relates to financial leverage, as firms balance their total risk exposure, operating leverage proponents have also challenged the financial distress explanation for the book-to-market effect. (Carlson et al., 2004; Cooper, 2006; Donangelo, 2021; García-Feijóo & Jorgensen, 2010; George & Hwang, 2010; Novy-Marx, 2011).

2.3.2. Limits of Operating Leverage in Explaining the Book-to-Market Effect

Several studies have challenged or added nuance to the relationship between operating leverage, expected returns, and its connection to book-to-market. Guthrie (2011) argues that operating leverage is less risky when the firm can abandon unprofitable projects. In these cases, operating leverage can even have a negative relation to stock returns (Guthrie, 2011). Other studies have altogether challenged the relation between B/M and operating leverage, or even found that the B/M effect decreases with operating leverage (Cao, 2015; Kisser, 2014; Kogan et al., 2023). Lastly, a separate stream of studies argues that operating and financial leverage interact in the book-to-market effect. Choi (2013) finds that high B/M firms can have both high financial and operating leverage. By having a historically high asset base that can be posted as collateral, high B/M firms tend to have higher debt ratios than low B/M firms even before they experience demand shocks. As such, they can have involuntary high financial leverage on top of having high operating leverage. In contrast, Obreja (2013) shows that high B/M firms are typically low-productivity firms that have either high financial leverage or high operating leverage. Importantly, when operating leverage is already high, financial leverage is associated with lower returns (Obreja, 2013).

2.4. Declining Book-to-Market Effect and Intangibles

The book-to-market (B/M) ratio has shown a weakened association with stock returns in recent decades. Fama and French (2015) demonstrates that book-to-market returns have stagnated in a 1963-2013 US sample, and that the HML book-to-market factor becomes redundant when including a profitability (RMW) and investment (CMA) factor. Other studies report a steady decline in the HML (B/M) factor's performance since the 1980s, a brief rebound in the early 2000s, and sustained under-performance following the financial crisis (Arnott et al., 2021; Lev & Srivastava, 2019; Maloney & Moskowitz, 2020).

Several explanations have been proposed, such as falling bond yields which would impact the distress premium captured by B/M (Maloney & Moskowitz, 2020), data mining, crowding-out effects, or corrected mispricing after the popularization of anomalies (Arnott et al., 2021; McLean & Pontiff, 2016), as well as more constrained capital access for high B/M firms relative to low B/M firms post-financial crisis (Lev & Srivastava, 2019). One of the most popularized explanations for the decline of the book-to-market effect surrounds the rise of intangible capital.

2.4.1. Intangible Capital and Book Values

Intangible capital refers to a range of non-physical assets that contribute to a firm's productive capacity and future profitability. Researchers commonly distinguish between knowledge capital—such as innovation, patents, and proprietary technologies used by employees—and organization capital, which encompasses firm-specific routines, corporate culture, client relations, and human capital. Although intangible assets lack the physical form of other production assets (e.g., machinery and real estate), investments in software, proprietary technologies, human capital, and brand assets have become just as critical to production as traditional tangible assets. Importantly, a substantial portion of intangible capital resides within the workforce itself, being tacit and difficult to transfer, replicate, or redeploy across firms. (Gulen et al., 2025; Lev & Srivastava, 2019; Peters & Taylor, 2017).

The growing importance of intangible capital has been fueled by a broader shift in the economy from a manufacturing-based structure to one increasingly dominated by services and knowledge-intensive industries. Whereas US corporate investments were primarily tangible until the 1980s, the intangible investment rate had grown to roughly twice the tangible investment rate by the 2000s—a spread that continues to widen (Arnott et al., 2021; Lev & Srivastava, 2019). This trend reflects both economy-wide increases in intangible investments across sectors (Gulen et al., 2025; Lev & Srivastava, 2019), as well as industry-specific developments, with post-1970s

IPOs being increasingly concentrated in knowledge industries such as business services, pharmaceuticals, healthcare and computers (Srivastava, 2014).

Despite this growing recognition, tangible and intangible investments are treated differently under US GAAP. Specifically, tangible investments are capitalized to the balance sheet and depreciated in subsequent periods, whereas internally generated intangibles—such as R&D, brand development, and employee training—are generally immediately expensed. This accounting asymmetry has been argued to not only reduce the informativeness of earnings (Srivastava, 2014), but also systematically understate the book value of firms that heavily invest in intangibles. (Lev & Srivastava, 2019; Peters & Taylor, 2017).

Consequently, firms with large investments in intangible assets may be increasingly misclassified as "growth" stocks (low B/M), due to the conservative accounting treatment that biases their B/M ratios downward. In contrast, firms that allocate more investment toward tangible assets are more likely to be misclassified as "value" (high B/M) stocks, as they are less exposed to the conservatism from intangibles (Lev & Srivastava, 2019). Indeed, Gulen et al. (2025) find that B/M ratios have linearly decreased throughout the 2000s even as other valuation ratios have increased, while the intangible adjustments to B/M yield similar trends as other valuation ratios.

2.4.2. Intangible-Adjusted Book-to-Market

As a result of the critique that B/M is conservative, several papers have proposed that B/M can be adjusted by estimating and adding internally generated intangible capital to book equity, producing iB/M ratios. These iB/M ratios would then replace B/M in the HML factor in asset pricing (Arnott et al., 2021; Eisfeldt et al., 2022; Lev & Srivastava, 2019; Park, 2022). In these studies, intangible capital is estimated using a perpetual inventory method, where portions of firm-level SG&A and/or R&D expenditures are artificially capitalized to book equity and subsequently depreciated. The approach builds on Peters and Taylor (2017), who define intangible capital as the sum of organization and knowledge capital. Using this framework, Arnott et al. (2021) constructed an intangible-adjusted HML factor, assuming 30% capitalization for SG&A, 100% for R&D, and a 20% depreciation rate for both. Their factor outperformed the standard HML by 1.3% annually between 1963 and 2020, and by 2.2% between 2007 and 2020.

Other researchers have attempted to further refine the estimation of intangible capital. For instance, uniform capitalization and depreciation rates across firms may be unrealisic, since it assumes a constant contribution of SG&A and R&D to

intangible capital across firms and time, as well as similar rates of obsolescence of intangibles. Such assumptions are at odds with both heterogeneity in accounting treatments of intangible investments, as well as with differences in competitive dynamics and exposure to technological change. Assuming such differences are more stable within industries, researchers have estimated industry-specific capitalization and depreciation parameters using forward-looking profit models and market-based measures (like trading and liquidation prices) (Gulen et al., 2025; Li & Hall, 2016; Park, 2022). Others have simply relied on within-industry sorting to reduce estimation errors (Eisfeldt et al., 2022), or separated HML into two factors to account for differences in adjustment costs, reversibility, and cash flow skewness between intangible and physical assets (Gulen et al., 2025).

The resulting iHML factors have outperformed the traditional HML in an annual range of 1–4% from the 1970s to the late 2010s, with higher Sharpe ratios and better pricing performance in the Fama-French 3- and 5-factor models. However, all adjusted book-to-market factors have still shown flat returns since the financial crisis. Moreover, these studies do not explicitly explore whether the iB/M measure, used in their iHML factors, captures risk-based compensation or mispricing. (Arnott et al., 2021; Eisfeldt et al., 2022; Gulen et al., 2025; Lev & Srivastava, 2019; Park, 2022).

2.5. Labor Leverage, Operating Inflexibility, and Low Debt Capacity

2.5.1. Labor-Induced Operating Leverage

Recently, labor has been proposed as a dominant source of operating leverage, which can arise independently of the level of physical capital (or book values). Danthine and Donaldson (2002) argue that labor leverage is crucial to explaining the size of the equity risk premium. In their model, labor leverage arises as firms enter into long-term labor contracts that make wages rigid across the cycle. Since wage claims have priority on firm income over equity, this induces uninsurable risk, as profits become more pro-cyclical and investors cannot hedge against persistent shifts in labor income shares. Donangelo et al. (2019) lends support to labor as highly rigid, finding that a 1% drop in sales reduces labor costs by only 0.53%, compared to 1.08% for non-labor costs. Moreover, since wages account for 60–70% of GDP, compared to only $\sim$2% for interest payments, Danthine and Donaldson (2002) further argue that labor leverage creates substantially greater risk amplification than financial leverage in the economy. Indeed, later studies have shown that labor leverage is positively related to systematic risk and support the existence of a labor leverage risk premium (Belo et al., 2014; Donangelo, 2021; Donangelo et al., 2019; Eisfeldt

& Papanikolaou, 2013).

Researchers have suggested several mechanisms for generating labor leverage. Donangelo et al. (2019) argues that labor and physical capital are complementary, which limits firms from reducing labor independently of capital. Simintzi et al. (2015) finds that employment protection, often driven by labor market reforms, increases operating leverage. Eisfeldt and Papanikolaou (2013) suggest that firms with a greater reliance on key talent face higher labor leverage, as the risk of employee departures amplifies cash flow volatility and pressures firms to offer higher wages to retain productive capacity. Similarly, M. B. Zhang (2019) finds that higher labor specificity, or lower degrees of routine labor, is associated with higher labor leverage. Intangible-intensity has also been found to have a strong positive correlation with labor leverage among firms. (Donangelo et al., 2019; Eisfeldt & Papanikolaou, 2013).

Consistent with the general operating leverage hypothesis, labor leverage has also recently been described as having an equivalent effect on the book-to-market effect as other sources of operating leverage (Donangelo, 2021). Moreover, like production-based operating leverage models (Carlson et al., 2004; Cooper, 2006; L. Zhang, 2005), labor leverage mechanisms are not inherently tied to low profitability. Rather, rigid labor costs increase the sensitivity of profits to shocks, regardless of the firm's current profit level (Donangelo et al., 2019; Eisfeldt & Papanikolaou, 2013).

2.5.2. Inflexibility and Stickiness in R&D and SG&A

Other studies have taken a broader focus on operational inflexibility tied to intangibles, without making direct inferences to labor leverage models. For instance, intangible investments (in organization and knowledge capital) are often associated with high irreversibility and adjustment costs. Specifically, Peters and Taylor (2017) find that these investments are only half as responsive to growth opportunities as physical capital, and largely insensitive to current cash flows. They argue that adjusting intangibles often requires replacing highly skilled employees; a point which is reinforced by Brown and Petersen (2011). Grabowski (1968) and Griliches and Hausman (1986) emphasize that R&D projects are long-term and involve uncertain outcomes or large sunk costs, which makes them difficult to unwind without incurring significant losses. Venieris et al. (2015) find that R&D and SG&A are sticky, or tend to fall less in downturns than they rise in upturns, as a result of managerial reluctance to cut capacity that is costly to rebuild. Moreover, they find that stickiness in SG&A and R&D is higher among firms with high organization capital, showing a greater willingness to accept short-term overcapacity (Venieris et al., 2015). While

these studies do not explicitly frame their findings in terms of labor leverage, several of them point to similar dynamics: either that labor becomes more rigid through the accumulation of specialized knowledge, or that intangible-related project spending is inherently sticky.

2.5.3. Debt Limits of Intangibles and Labor

Intangible-intensive firms have also been found to face distinct financing constraints. Belo et al. (2014) demonstrates that firms with high labor adjustment costs face greater exposure to financing shocks and respond by reducing their use of external debt, while Berk et al. (2010) show that firms with large labor expenses face higher bankruptcy costs and rely less on debt. These findings align with Falato et al. (2022), who show that the rise of intangibles—particularly organization and knowledge capital—can explain approximately 75% of the increase in U.S. corporate cash ratios and accounts for the majority of the decline in debt ratios since the early 2000s. Specifically, intangible-intensive firms have lower debt capacity because intangibles are firm-specific, non-tradeable, and difficult to value, making them poorly suited as collateral. As a result, these firms pursue more conservative debt policies to smooth financing frictions. (Falato et al., 2022)

2.6. Hypotheses Development

In this section, we reiterate key research findings, integrate them into insights underpinning this study, and then formally state our hypotheses.

1. The recent decline of the book-to-market effect is often associated with a shift from tangible to intangible investments since the 1980s. Under US GAAP, internally generated intangibles are not capitalized to book values in the balance sheet, whereas tangible investments are. When B/M is replaced with an iB/M ratio where book values are adjusted for intangibles, the ratio has seen improved pricing power. Even so, iB/M has not been extensively explored in terms of its relation to risk or mispricing. (Arnott et al., 2021; Eisfeldt et al., 2022; Gulen et al., 2025; Lev & Srivastava, 2019; Park, 2022).

2. Risk-based explanations of the book-to-market effect have primarily focused on financial distress risks (Fama & French, 1992; Ozdagli, 2012; Vassalou & Xing, 2004) or operating leverage risks (Carlson et al., 2004; Cooper, 2006; García-Feijóo & Jorgensen, 2010; Novy-Marx, 2011). Since financial distress explanations for the book-to-market effect tend to focus on financial leverage, and intangible capital has been found to crowd out debt among firms (Falato

et al., 2022), we focus on the operating leverage explanation for iB/M. This is further supported by findings, in book-to-market studies, that operating risk has greater return implications when financial leverage is lower (George & Hwang, 2010; Obreja, 2013; Penman et al., 2007).

3. Operating leverage increases with fixed costs, and is generally supported as a contributor to systematic risk exposure among firms (Danthine & Donaldson, 2002; Donangelo, 2021; Lev, 1974; Mandelker & Rhee, 1984). One field of studies states that book values in B/M proxy for physical capital, which increases fixed costs. Since capital is costly to liquidate, firms face difficulties reducing their fixed costs in response to demand shocks. High B/M firms have depressed sales but stagnant capital stocks, which yield high operating leverage as fixed costs remain. (Carlson et al., 2004; Cooper, 2006; L. Zhang, 2005).

4. Recently, labor has been viewed as a dominant source of operating leverage among firms. Labor leverage can be induced without the presence of physical capital, and is overrepresented among firms with high intangible-intensity (Donangelo et al., 2019). Labor leverage has also been found to be higher in firms that rely more on skilled or specialized labor, making labor costly to adjust in response to sales (Eisfeldt & Papanikolaou, 2013; M. B. Zhang, 2019). Meanwhile, intangible capital is often embedded in employees and linked to firm-specific knowledge (Gulen et al., 2025; Lev & Srivastava, 2019; Peters & Taylor, 2017). In addition, SG&A and R&D expenses are reported to be sticky in the short run, particularly among firms with high levels of organization capital (Brown & Petersen, 2011; Venieris et al., 2015).

5. From the perspective of Carlson et al. (2004), Cooper (2006), and L. Zhang (2005), intangible capital could subsequently be viewed as equivalent to physical capital in the generation of the book-to-market effect. Both physical and intangible capital are associated with fixed costs. Both capital stocks are difficult to adjust or are inflexible, either through low liquidation values, firing costs of employees, or short-term commitment to projects. As such, i/M should be comparable to B/M in inducing operating leverage. Since intangible adjustments to book-to-market create substantially different book-to-market ratios across firms (Gulen et al., 2025; Lev & Srivastava, 2019), and because labor, R&D, and SG&A costs tend to be especially sticky in intangible-intensive firms, it is also plausible that traditional B/M overlooks key components of intangible-related operating leverage (Brown & Petersen, 2011; Donangelo et

al., 2019; Eisfeldt & Papanikolaou, 2013; Venieris et al., 2015). This would make the i/M component in iB/M especially valuable for capturing operating leverage differences across firms, which may help explain the mixed evidence for operating leverage as a driver of the book-to-market effect when using unadjusted B/M (Cao, 2015; Kisser, 2014; Kogan et al., 2023).

6. Novy-Marx (2011) also views operating leverage as a driver of the B/M effect. He states that B/M is informative of returns when it reflects persistent profitability differences, where low margins indicate higher operating leverage. However, B/M ratios can also reflect cross-industry capital intensity differences, which Novy-Marx (2011) views as less indicative of operating leverage and returns. The rise of intangible investments has not only been viewed as an economy-wide effect, but also been connected to industry-specific developments with higher IPO activity in knowledge-intensive industries (Gulen et al., 2025; Lev & Srivastava, 2019; Srivastava, 2014). Consequently, iB/M may be well-suited to neutralize cross-industry differences in capital intensity, and better reflect operating leverage differences among firms.

Combined, we view this literature as consistent with the idea that iB/M is more strongly associated with operating leverage than B/M is. Specifically, the intangible component of iB/M (i/M) likely captures cross-firm differences in operating leverage that B/M alone overlooks. Accordingly, we expect both iB/M and i/M to exhibit a strong positive association with operating leverage, with i/M continuing to do so even when controlling for B/M. Furthermore, the shift from B/M to iB/M significantly changes the book-to-market rankings of some firms, but not all. If iB/M is more associated with operating leverage than B/M, we expect the results to persist even among the firms most affected by the shift. We state this as a single hypothesis:

H_1: *Both iB/M and i/M are positively associated with operating leverage, and i/M remains positively associated with operating leverage even after controlling for B/M. These relationships hold even among firms whose book-to-market rankings change significantly when moving from B/M to iB/M.*

Our second hypothesis focuses directly on the book-to-market effect. If operating leverage drives the book-to-market effect, the return association of the book-to-market measure should disappear in controls for operating leverage. We test this hypothesis for B/M on the one side (H2a), and iB/M and i/M on the other (H2b). We state the following hypotheses in alternative forms:

H_{2a}: *The traditional B/M does not remain a positive predictor of stock returns after controlling for operating leverage*

H_{2b}: *At least one of iB/M or i/M does not remain a positive predictor of stock returns after controlling for operating leverage*

We include all book-to-market specifications as we are interested not only in iB/M, but also how it might differ to B/M. Moreover, since iB/M is the sum of B/M and i/M, we accept H2b if either iB/M or i/M becomes insignificant in controls for operating leverage.

3. Method

3.1. Data

We gather firm financial statement data from Compustat and stock return data from CRSP. The sample starts with all firms listed on the main exchanges in the US (NYSE, AMEX, NASDAQ), covering the period July 1st, 1977 to December 31st, 2023. We start in 1977 to give firms 2 years to comply with FASB's 1975 R&D reporting requirement (Peters & Taylor, 2017). Due to regulatory differences in book values and leverage, we exclude financial firms (SIC 6000–6999), utility firms (SIC 4900–4949), and firms in public service, international affairs, or non-operating establishments (SIC 9000 and up) (Park, 2022; Peters & Taylor, 2017). We further exclude firm-year observations with insufficient data to compute book-to-market equity, stock returns, operating leverage (DOL), or that have negative book equity. Stock returns are adjusted for stock splits, cash distributions, and delisting returns. If the delisting return is missing, and the delisting is performance-related, we set the delisting return to -30% (Shumway, 1997). We winsorize all key test variables and stock returns at the 0.5% and 99.5% levels (García-Feijóo & Jorgensen, 2010). Our final sample consists of 120,656 firm-year observations and 1,441,864 firm-month observations.

3.2. Key Variables

3.2.1. Book-to-Market Equity (B/M)

We define book-to-market equity in line with Davis et al. (2000), which is the definition referenced on the official Kenneth R. French database.[1] The market value of equity is then defined as the number of shares outstanding times the stock price (using stock data at the end of December year $t-1$), and book-to-market equity (B/M) is computed as the ratio of book value of equity for the fiscal year ending in calendar year $t-1$ to the market value of equity.

[1]Book equity is the book value of stockholders' equity, plus balance sheet deferred taxes and investment tax credit (if available), minus the book value of preferred stock. Depending on availability, we use the redemption, liquidation, or par value (in that order) to estimate the book value of preferred stock. If stockholder's equity is unavailable in Compustat, we measure stockholders' equity as the book value of common equity plus the par value of preferred stock, or the book value of assets minus total liabilities (in that order). https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data$_l$*ibrary.html*

3.2.2. Intangible-Adjusted Book-to-Market Equity (iB/M)

We define intangible capital as the sum of organization capital (S) and knowledge capital (G). For greater generalizability, we use the most common depreciation and capitalization parameters, assuming capitalization rates of 30% for SG&A and 100% for R&D, and a flat 20% depreciation rate for SG&A (Arnott et al., 2021; Park, 2022; Peters & Taylor, 2017). For R&D depreciation rates (δ_G), we use industry-specific estimates from the Bureau of Economic Analysis (BEA) (Li & Hall, 2016; Park, 2022; Peters & Taylor, 2017). We summarize these estimates in Appendix A.1.

Organization capital (S) and knowledge capital (G) are then computed using the perpetual inventory method:

$$S_{i,t} = (1 - 0.2) \cdot S_{i,t-1} + 0.3 \cdot \text{SG\&A}_{i,t}$$

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

We follow the method of Peters and Taylor (2017) for separating R&D and SG&A components from Compustat's xsga variable, as well as for computing firms' initial intangible capital stocks (Arnott et al., 2021; Gulen et al., 2025; Park, 2022). We set missing R&D and SG&A values to zero, with some exceptions pre-1977 and for firm-year observations that exhibit signs of temporary delisting periods (Appendix A.1). Furthermore, we estimate pre-IPO growth rates and age-specific growth in R&D and SG&A in our sample to back-fill intangible investments between a firm's first appearance in Compustat and its founding year. We then compute the initial knowledge capital and organization capital stock using the perpetual inventory method. Further details on the separation of R&D and SG&A components, as well as the computation of the initial intangible capital stock, are provided in Appendix A.1 (Arnott et al., 2021; Gulen et al., 2025; Park, 2022; Peters & Taylor, 2017). Lastly, intangible capital (OBS) is computed as the sum of organization and knowledge capital:

$$\text{OBS}_{i,t} = S_{i,t} + G_{i,t}$$

and the intangible-adjusted book-to-market ratio (iB/M), following Park (2022) is defined as:

$$iB/M_{i,t} = \frac{B_{i,t} + \text{OBS}_{i,t}}{M_{i,t}}.$$

3.2.3. Intangible Capital-to-Market Equity (i/M)

We compute i/M, or the intangible capital component of iB/M, in precisely the same manner as iB/M except for the exclusion of book equity in the numerator.

Specifically, i/M is defined as:

$$i/M_{i,t} = \frac{\text{OBS}_{i,t}}{M_{i,t}}.$$

3.2.4. Operating Leverage (DOL)

Operating leverage is commonly defined in terms of earnings sensitivity to sales. As such, we follow a wide array of literature and use a time-series regression approach to estimate the Degree of Operating Leverage (DOL) as an elasticity measure of EBIT to sales (Cao, 2015; García-Feijóo & Jorgensen, 2010; Mandelker & Rhee, 1984; O'Brien & Vanderheiden, 1987).

However, we first de-trend firm-level EBIT and sales data. O'Brien and Vanderheiden (1987) argue that direct time-series regressions of EBIT on sales, as proposed by Mandelker and Rhee (1984), are biased toward reflecting long-term growth trends instead of operating leverage. Specifically, if both EBIT and sales grow at similar rates, then DOL would become close to 1, even if real earnings sensitivity (operating leverage) is high. As such, we run the following regressions over five-year overlapping intervals (1977-1982, 1978-1983, etc.) to separate short-term deviations in EBIT and sales from their long-term trends:

$$\ln(\text{EBIT}_t) = \ln(\text{EBIT}_0) + g_{\text{ebit}} \cdot t + \varepsilon_{t,\text{ebit}}$$

$$\ln(\text{Sales}_t) = \ln(\text{Sales}_0) + g_{\text{sales}} \cdot t + \varepsilon_{t,\text{sales}}$$

where g_{sales} and g_{ebit} represent the most recent five-year log growth trends in sales and EBIT. The residuals, $\varepsilon_{t,\text{sales}}$ and $\varepsilon_{t,\text{ebit}}$, represent the current year's short-term deviations in sales and EBIT relative to these trends.

To accommodate negative values in logs, we use log transformations (García-Feijóo & Jorgensen, 2010):

$$\text{logEBIT} = \begin{cases} \ln(1 + \text{EBIT}) & \text{if EBIT} \geq 0 \\ -\ln(1 - \text{EBIT}) & \text{if EBIT} < 0 \end{cases}$$

Finally, we estimate DOL by regressing the deviation of EBIT from its trend on the deviation of sales from its trend:

$$\varepsilon_{t,\text{ebit}} = \text{DOL} \cdot \varepsilon_{t,\text{sales}} + \eta_t$$

This leaves DOL as our measure of operating leverage. It captures the sensitivity of short-term deviations in operating profits to short-term deviations in sales; mit-

igating biases from stationarity assumptions in earnings and sales. Economically, one can interpret the DOL value as the percentage change in earnings for a given change in sales – unrelated to its long-term trend. For example, a DOL of 2 would imply that a 1% change in sales is expected to lead to a 2% corresponding change in earnings, when both are stripped of long-term trends. We motivate following the two-step regression approach by O'Brien and Vanderheiden (1987) since their growth adjustments to DOL have been shown to yield more accurate estimates by several independent studies (Appendix A.2). We use five-year rolling regressions, rather than any other interval, to balance short-term noise reduction while still maintaining the flexibility to capture firm-level changes in cost structures over time (García-Feijóo & Jorgensen, 2010). [2]

3.3. Research Design

3.3.1. Hypothesis 1: OLS Regressions

First, to establish the association operating leverage (DOL) has with each book-to-market specification, we run annual cross-sectional regressions with DOL as the dependent variable and then compute the time-series average of coefficients across years in line with García-Feijóo and Jorgensen (2010). We report Newey-West standard errors to correct for potential autocorrelation and heteroskedasticity in yearly estimates. All variables represent natural logarithms to reduce the positive skewness of DOL and book-to-market measures, and are standardized to have a mean of zero and standard deviation of one:

[2] We do not adjust DOL for intangible expensing in EBIT, for several reasons. First, operating leverage generates risk from fixed operating payments that lever residual earnings, or free cash flows, similar to interest (Lev, 1974). R&D and SG&A, even when value-generating, are often persistent, smooth, and costly to adjust (Grabowski, 1968; Griliches & Hausman, 1986; Peters & Taylor, 2017). Second, DOL should increase in fixed costs, and most empirical measures treat SG&A as the most robust fixed cost estimate (Kisser, 2014; Kogan et al., 2023; Novy-Marx, 2011). In line with this, studies on organizational capital do not remove SG&A from earnings when estimating operating leverage (Eisfeldt & Papanikolaou, 2013). Third, intangible capitalization is noisy (Eisfeldt et al., 2022): capitalizing major expenses risks understating a firm's economic sensitivity, which is precisely what DOL aims to capture, particularly if R&D and SG&A are particularly sticky for intangible-intensive firms (Venieris et al., 2015).

$$\ln(\text{DOL}_{i,t}) = \alpha + \beta_1 \ln(\text{B/M}_{i,t}) + \gamma \ln(\text{Size}_{i,t}) + \varepsilon_{i,t} \quad (1)$$

$$\ln(\text{DOL}_{i,t}) = \alpha + \beta_1 \ln(\text{iB/M}_{i,t}) + \gamma \ln(\text{Size}_{i,t}) + \varepsilon_{i,t} \quad (2)$$

$$\ln(\text{DOL}_{i,t}) = \alpha + \beta_1 \ln(\text{i/M}_{i,t}) + \gamma \ln(\text{Size}_{i,t}) + \varepsilon_{i,t} \quad (3)$$

$$\ln(\text{DOL}_{i,t}) = \alpha + \beta_1 \ln(\text{B/M}_{i,t}) + \beta_2 \ln(\text{i/M}_{i,t}) + \gamma \ln(\text{Size}_{i,t}) + \varepsilon_{i,t} \quad (4)$$

where B/M is the traditional book-to-market ratio, iB/M is the intangible-adjusted version, and i/M is a pure intangible capital ratio that includes only off-balance sheet intangible capital in the numerator. We control for firm size (market capitalization), following García-Feijóo and Jorgensen (2010). The decision to regress DOL on i/M serves two purposes: first, to test whether the intangible capital component of iB/M is independently associated with DOL, as in specification (3); and second, to examine whether i/M or B/M subsumes the other in its association with DOL or if they complement each other, as in specification (4).

We also re-estimate the original specifications (1–4) in two sub-samples: an "Agreement" and a "Disagreement" sample. These consist of all firm-year observations where the economy-wide decile rankings based on iB/M and B/M differ by less than 3 ("Agreement") or by 3 or more ("Disagreement"). For H1, the "Disagreement" sample is consequential. While the sample cut-off is arbitrary, the purpose is to highlight scenarios where iB/M and B/M differ significantly, while ensuring a sufficient number of observations in each subsample. The cut-off is further motivated by cut-offs used in the HML book-to-market factors (Fama & French, 1993, 2015; Park, 2022).

3.3.2. Hypothesis 2: Fama-Macbeth Regressions and Double-Sorted Tables

In the testing of our second hypothesis, we employ both Fama and MacBeth (1973) regressions and dependent double-sorted tables.

The use of Fama and MacBeth (1973) regressions to test the operating leverage hypothesis for the book-to-market effect follows Cao (2015). First, we estimate separate regressions of future returns on each key variable (DOL, B/M, iB/M, and i/M), including relevant controls. This is done to assess the individual associations with future returns for key variables (models 5-8). Then, to test whether the association between each book-to-market measure (B/M, iB/M, and i/M) and future returns can be explained by DOL, we include DOL as a control variable in separate Fama-MacBeth regressions. This is done separately for each book-to-market

measure (models 9-11). If the book-to-market measure (B/M, iB/M, or i/M) remains statistically significant in its regression with DOL, it would suggest that it contains information about future returns beyond what is captured by DOL. Conversely, if the measure becomes insignificant after including DOL, this would suggest that DOL subsumes the return-relevant information previously attributed to that book-to-market measure. This would be viewed as supportive of the alternative hypothesis specified for that book-to-market measure. In line with H2b, we test i/M alongside DOL in a separate regression, since i/M may be subsumed by DOL even if iB/M is not, particularly if the B/M component of iB/M remains significant when controlling for DOL in H2a.

All independent variables use information available at month t. For variables requiring accounting information, the month t value is calculated using the latest available annual report.[3] Control variables ($\mathbf{X}'_{i,t}\boldsymbol{\gamma}_t$) include *momentum* defined as the cumulative returns from month t-11 to month t-1, *reversal* defined as the return in month t and *size* defined as market capitalization of month t. Our control variables are those most commonly used in Fama and MacBeth (1973) regressions and are consistent with prior empirical studies (Cao, 2015; Novy-Marx, 2011; Park, 2022).

$$R^e_{i,t+1} = \alpha + \beta_1 \ln(\text{DOL}_{i,t}) + \mathbf{X}'_{i,t}\boldsymbol{\gamma}_t + \varepsilon_{i,t+1} \tag{5}$$

$$R^e_{i,t+1} = \alpha + \beta_1 \ln(\text{B/M}_{i,t}) + \mathbf{X}'_{i,t}\boldsymbol{\gamma}_t + \varepsilon_{i,t+1} \tag{6}$$

$$R^e_{i,t+1} = \alpha + \beta_1 \ln(\text{iB/M}_{i,t}) + \mathbf{X}'_{i,t}\boldsymbol{\gamma}_t + \varepsilon_{i,t+1} \tag{7}$$

$$R^e_{i,t+1} = \alpha + \beta_1 \ln(\text{i/M}_{i,t}) + \mathbf{X}'_{i,t}\boldsymbol{\gamma}_t + \varepsilon_{i,t+1} \tag{8}$$

$$R^e_{i,t+1} = \alpha + \beta_1 \ln(\text{DOL}_{i,t}) + \beta_2 \ln(\text{B/M}_{i,t}) + \mathbf{X}'_{i,t}\boldsymbol{\gamma}_t + \varepsilon_{i,t+1} \tag{9}$$

$$R^e_{i,t+1} = \alpha + \beta_1 \ln(\text{DOL}_{i,t}) + \beta_2 \ln(\text{iB/M}_{i,t}) + \mathbf{X}'_{i,t}\boldsymbol{\gamma}_t + \varepsilon_{i,t+1} \tag{10}$$

$$R^e_{i,t+1} = \alpha + \beta_1 \ln(\text{DOL}_{i,t}) + \beta_2 \ln(\text{i/M}_{i,t}) + \mathbf{X}'_{i,t}\boldsymbol{\gamma}_t + \varepsilon_{i,t+1} \tag{11}$$

The double-sorted tables are constructed using a 5×3 dependent double-sorting strategy. Specifically, to assess whether the book-to-market measure maintains a positive return association, we sequentially sort firms into portfolios; first based on DOL levels (quintiles), and then based on book-to-market levels (terciles). Se-

[3]For example, the first return regression is conducted in July 1977, using explanatory variables observed in June 1977. In this case, B/M is constructed using book values from the latest annual report divided by the market capitalization at year-end 1976. The same holds for other book-to-market variables.

quential double sorting tests whether book-to-market retains its return association among firms with similar DOL levels. We avoid independent double-sorting to reduce the risk of unbalanced portfolios, to the extent that DOL and book-to-market are correlated measures (García-Feijóo & Jorgensen, 2010). Moreover, dependent double sorts is the most direct way to control for DOL. We sort firms into DOL quintiles, instead of terciles, to more meaningfully restrict variation in DOL across firms ranked on book-to-market. The choice of sequence follows other studies that examine whether the book-to-market effect holds after controlling for other variables, including DOL (Kisser, 2014; Kogan et al., 2023; Vassalou & Xing, 2004).

We sort firms into portfolios at the end of June each year, using accounting information from the latest annual report. The portfolios are held from $July_t$ to $June_{t+1}$. Reported returns represent the average monthly excess returns over each holding period, averaged over time. t-statistics are time-series averages divided by time-series standard errors. We compute the H–L returns (the difference between the highest and lowest book-to-market tercile returns) across each DOL quintile and the full sample. To the extent that book-to-market only has a return association since it captures variation in DOL among firms, H–L returns should become insignificant within DOL quintiles or materially weaken relative to the full sample. For H2a, we test this using DOL x B/M sorts. For H2b, we test this using DOL x i/M and DOL x iB/M sorts. We report double-sorted tables based on both value-weighted (VW) and equal-weighted (EW) returns.

Combined, the Fama-Macbeth regressions and the double-sorted tables provide complementary evidence. Specifically, Fama-Macbeth regressions gives insight into the marginal effects of DOL, iB/M and B/M, while the double-sorted tables are less reliant on linear relationships.

3.4. Robustness Tests

Since operating leverage is inherently difficult to measure (Appendix A.2), we include alternative measures of DOL in our robustness tests. First, we examine whether our results are driven by noise, as regressions typically require a long series of data to produce reliable estimates, but we only use 5 years of annual data in our main method. Following Cao (2015), we re-estimate DOL using quarterly data, restricting the sample to firms with 20 consecutive quarters of sales and EBIT data. Second, Damodaran (2011) argues that free cash flows are more appropriate than earnings for evaluating intangible-intensive firms, as they are more neutral to accounting distortions. As such, we re-estimate DOL using a simplified unlevered free cash flow proxy in place of EBIT. We note that using free cash flows in the measurement of

operating leverage (DOL) was recently supported by Aharon et al. (2019).

As our first hypothesis (H1) is sensitive to the cut-off points for our "Disagreement" and "Agreement" samples, we also perform our annual cross-sectional regressions when the economy-wide decile rankings based on iB/M and B/M differ by less than 2 ("Agreement") or by 2 or more ("Disagreement").

4. Results

This section presents the descriptive statistics for our sample, the results for the hypotheses, and concludes with robustness tests.

4.1. Sample Data and Descriptive Statistics

Table 1: Descriptive Statistics and Correlation Matrix for Key Variables

Panel A. Descriptive Statistics for the Test Variables

Variable	Mean	SD	P5	P25	P50	P75	P95
B/M	0.82	0.78	0.11	0.33	0.61	1.03	2.20
iB/M	1.55	1.76	0.24	0.59	1.02	1.81	4.60
i/M	0.72	1.19	0.00	0.14	0.34	0.78	2.68
DOL	4.40	7.02	0.29	1.01	2.08	4.52	16.75
Size	5.24	2.38	1.57	3.47	5.12	6.90	9.30

Panel B. Pearson Correlation Coefficients for the Test Variables

	B/M	iB/M	i/M	DOL	Size
B/M	1.00				
iB/M	0.84	1.00			
i/M	0.46	0.81	1.00		
DOL	0.12	0.16	0.16	1.00	
Size	-0.39	-0.52	-0.48	0.02	1.00

Note: This table reports descriptive statistics and correlations for the key variables used in the analysis. B/M is the traditional book-to-market ratio, and iB/M is the intangible-adjusted book-to-market ratio. i/M is intangible assets relative to market value, and size represents market capitalization. DOL represent the degree of operating leverage.In Panel A, the variable 'size' is presented as the natural logarithm, while in Panel B, all variables are transformed into natural logarithms. P5, P25, P50, P75, and P95 represent the 5th, 25th, 50th (median), 75th, and 95th percentiles, respectively.

Table 1 shows descriptive statistics and the correlation between test variables. The traditional book-to-market (B/M) and the intangible-adjusted book-to-market (iB/M) have a high full sample correlation coefficient of 84%. The intangible-to-market (i/M) measure has a 46% correlation with the B/M metric. The degree of operating leverage (DOL) has a full-sample correlation coefficient of 16% for both iB/M and i/M, compared to 12% for B/M.

Table 2 presents descriptive statistics by quintiles of B/M (panel A), iB/M (panel B), i/M (Panel C), and DOL (panel D). Across all panels, there is a positive monotonic trend between the three book-to-market measures (iB/M, B/M, i/M) and DOL. Panel D further demonstrates that intangible capital increases with the de-

gree of operating leverage (DOL), consistent with the notion that higher intangible capital is associated with higher operating leverage. Sorts by DOL quintiles exhibit a monotonic relationship with Size (market equity), INV (investment) and OP (operating profitability) but with smaller differences between the first and fifth quintiles compared to sorts based on the three book-to-market variables (Panel A to C). Furthermore, L/K (employees-to-PPE) is increasing in iB/M and i/M quintiles, slightly increasing in DOL quintiles, but is decreasing across B/M quintiles. Notably, in contrast to iB/M and B/M, DOL quintiles appear to have a negative relationship with Lev (book leverage), in line with literature suggesting a trade-off between financial and operating leverage levels among firms (Mandelker & Rhee, 1984).

Table 3 reports portfolio characteristics for 5x5 portfolios independently double-sorted based on i/M and B/M. Panel A shows the average equal-weighted excess returns (% per month) and average monthly number of firms per portfolio. Panel B shows the average DOL and iB/M (in parentheses) per portfolio. In Panel A, the portfolios with the highest average number of firms are those where i/M and B/M are aligned (the top left to bottom right diagonal). Furthermore, EW-returns are the lowest when both B/M and i/M are in the bottom quintile, and highest when both are in the highest quintile. Nonetheless, B/M appears to have a stronger impact on returns, as equal-weighted returns tend to increase more visibly across B/M quintiles than they do across i/M quintiles. Panel B further reveals that the transition from a low-to-high i/M quintile within the highest B/M quintile (top-to-bottom transition) results in a larger increase in iB/M than moving from a low-to-high B/M quintile within the highest i/M quintile (left-to-right transition). This pattern suggests that variation in i/M may contribute more to cross-sectional differences in iB/M than does variation in B/M. Although less pronounced, DOL appears to exhibit a similar pattern, with increases in i/M within B/M quintiles visually corresponding to larger increases in DOL than those observed across B/M within i/M quintiles.

Table 2: Descriptive Statistics by Book-to-Market and DOL Quintiles

Panel A: B/M Quintiles

Quintile	B/M	iB/M	i/M	DOL	Int	L/K	Size	Lev	INV	OP
1	0.19	0.35	0.15	1.52	3.52	3.75	5.66	-0.04	0.18	0.26
2	0.42	0.67	0.24	1.79	3.97	3.68	5.69	0.06	0.12	0.26
3	0.65	1.00	0.35	2.05	3.94	3.61	5.39	0.13	0.08	0.22
4	0.97	1.44	0.47	2.29	3.62	3.52	4.90	0.16	0.05	0.18
5	1.64	2.73	0.91	2.88	3.29	3.51	3.83	0.19	0.01	0.11

Panel B: iB/M Quintiles

Quintile	B/M	iB/M	i/M	DOL	Int	L/K	Size	Lev	INV	OP
1	0.22	0.34	0.09	1.47	3.26	3.59	5.99	-0.02	0.23	0.27
2	0.47	0.69	0.20	1.72	3.71	3.48	5.80	0.10	0.12	0.25
3	0.71	1.05	0.34	1.94	3.79	3.48	5.49	0.14	0.08	0.21
4	0.98	1.60	0.61	2.43	3.80	3.63	4.72	0.14	0.04	0.17
5	1.56	3.13	1.59	3.11	3.69	3.90	3.41	0.15	-0.01	0.09

Panel C: i/M Quintiles

Quintile	B/M	iB/M	i/M	DOL	Int	L/K	Size	Lev	INV	OP
1	0.48	0.52	0.03	1.48	2.23	2.33	6.11	0.18	0.15	0.21
2	0.43	0.59	0.16	1.70	3.76	3.47	5.69	0.07	0.14	0.24
3	0.58	0.91	0.32	1.98	4.13	3.63	5.37	0.09	0.09	0.22
4	0.78	1.42	0.62	2.41	4.13	3.80	4.71	0.09	0.05	0.18
5	1.20	2.96	1.61	3.04	3.99	4.04	3.48	0.13	-0.02	0.09

Panel D: DOL Quintiles

Quintile	B/M	iB/M	i/M	DOL	Int	L/K	Size	Lev	INV	OP
1	0.57	0.93	0.29	0.46	3.63	3.55	5.34	0.15	0.08	0.22
2	0.61	0.96	0.29	1.17	3.91	3.58	5.60	0.16	0.08	0.24
3	0.66	1.06	0.34	2.04	3.92	3.59	5.36	0.12	0.07	0.23
4	0.74	1.26	0.45	3.75	3.90	3.68	4.97	0.10	0.06	0.19
5	0.87	1.56	0.60	10.20	4.27	3.65	4.98	0.11	0.03	0.14

Note: Panels A, B, C and D report time-series averages of median characteristics of portfolios sorted on B/M, iB/M, i/M, and DOL, respectively. B/M is book-to-market ratio, iB/M is intangible-adjusted book-to-market ratio, i/M is intangible-to-market ratio, DOL is degree of operating leverage, Int is the natural logarithm of intangible capital (numerator) in iB/M and i/M, L/K is employees over PPE (in millions) (Donangelo et al., 2019), Size is the natural logarithm of market capitalization, Lev is leverage (net debt over assets net of cash), INV is investment, and OP is operating profitability as defined in Fama and French (2015).

Table 3: Independent Double Sorts on i/M and B/M Quintiles

Panel A: Equal-weighted Returns and Number of Firms

	Low B/M	Q2	Q3	Q4	High B/M
Low i/M	0.29 (N=172)	0.56 (N=105)	0.70 (N=91)	0.78 (N=94)	1.04 (N=55)
Q2	0.52 (N=165)	0.74 (N=143)	0.76 (N=99)	0.76 (N=68)	0.95 (N=44)
Q3	0.71 (N=94)	1.02 (N=140)	1.01 (N=132)	0.98 (N=96)	0.97 (N=59)
Q4	0.69 (N=51)	0.83 (N=90)	1.14 (N=129)	1.13 (N=141)	1.08 (N=111)
High i/M	0.49 (N=36)	0.82 (N=43)	1.06 (N=72)	1.16 (N=124)	1.26 (N=262)

Panel B: Average DOL and iB/M

	Low B/M	Q2	Q3	Q4	High B/M
Low i/M	2.66 (0.25)	3.03 (0.50)	3.55 (0.73)	3.40 (1.02)	4.32 (1.79)
Q2	3.15 (0.40)	2.90 (0.64)	3.40 (0.87)	4.25 (1.18)	4.99 (1.90)
Q3	3.62 (0.59)	3.79 (0.82)	3.75 (1.06)	4.02 (1.37)	5.23 (2.16)
Q4	4.23 (0.90)	4.60 (1.13)	4.80 (1.38)	4.91 (1.71)	5.33 (2.55)
High i/M	4.50 (2.28)	5.01 (2.32)	5.88 (2.60)	6.25 (2.96)	6.51 (4.88)

Note: Panel A reports equal-weighted (EW) returns in percent per month and average monthly number of firms per portfolio. Panel B shows average degree of operating leverage and iB/M (iB/M in parentheses). Portfolios are formed by independently sorting firms into quintiles of i/M (rows) and B/M (columns) each June, using accounting information from the most recent fiscal year-end. Portfolios are held from July of year t to June of year t+1.

4.2. Book-to-Market and the Operating Leverage Association

Table 4 reports annual pooled cross-sectional regressions for the degree of operating leverage (DOL) and different book-to-market measures (iB/M, B/M, and i/M) for the full sample, and separately for the "Agreement" and "Disagreement" samples; sorted based on the difference in iB/M and B/M economy-wide decile rankings for firms.

Across all samples there appears to be a statistically significant, positive association between the degree of operating leverage (DOL) and the book-to-market measures; except for B/M that is insignificant in the "Disagreement" sample (Panel

Table 4: Annual Regression Results at Firm Level Across Subsamples

Panel A: Full Sample (Avg Firms/Year = 2623)

	Intercept	B/M	iB/M	i/M	Size
Model 1	0.0645	0.1904***	–	–	0.0026
	(1.20)	(13.86)	–	–	(0.10)
Model 2	0.0505	–	0.2473***	–	0.0565**
	(1.04)	–	(15.05)	–	(2.09)
Model 3	0.0559	–	–	0.2024***	0.0375
	(1.23)	–	–	(12.00)	(1.28)
Model 4	0.0528	0.1314***	–	0.1579***	0.0585**
	(1.07)	(13.39)	–	(10.20)	(2.19)
Panel B: Agreement Sample (Avg Firms/Year = 2369)					
Model 1	0.0685	0.2023***	–	–	0.0077
	(1.17)	(10.89)	–	–	(0.25)
Model 2	0.0718	–	0.2510***	–	0.0474
	(1.32)	–	(15.53)	–	(1.53)
Model 3	0.0844	–	–	0.2274***	0.0280
	(1.64)	–	–	(15.61)	(0.89)
Model 4	0.0706	0.1217***	–	0.1660***	0.0477
	(1.29)	(7.85)	–	(11.43)	(1.55)
Panel C: Disagreement Sample (Avg Firms/Year = 253)					
Model 1	0.0140	-0.0457	–	–	0.0407**
	(0.46)	(-1.27)	–	–	(2.38)
Model 2	-0.0466	–	0.2203***	–	0.1020***
	(-1.65)	–	(9.36)	–	(5.37)
Model 3	-0.1112***	–	–	0.1888***	0.1423***
	(-5.67)	–	–	(10.44)	(7.61)
Model 4	-0.0874***	0.0106	–	0.1836***	0.1436***
	(-3.37)	(0.38)	–	(9.62)	(7.52)

Note: This table reports annual cross-sectional regressions of ln(DOL) on value measures (ln(B/M), ln(iB/M), ln(i/M)) controlling for ln(size). The "Agreement" sample consists of firm-year observations where economy-wide decile rankings based on iB/M and B/M differ by less than 3. Conversely, the "Disagreement" sample consists of firm-year observations where rankings differ by more than 3. Variables are standardized. t-statistics are Newey–West adjusted with 3 lags. Significance: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

C). In the full sample (Panel A), all book-to-market measures are significant at the 1% level, both independently (models 1-3) and when B/M and i/M are regressed jointly (model 4). Beyond statistical significance, the magnitudes of the coefficients (full sample) indicate that there appears to be a material economic relationship with a 1% increase in iB/M (model 2) being associated with a 0.25% increase in DOL, where both variables are standardized. Comparatively, a 1% increase in B/M (model 1) is associated with a 0.19% increase in DOL, where both variables are standardized.[4] When B/M and i/M are included jointly (model 4), both coefficients are statistically significant, suggesting that the intangible component (i/M) of iB/M contains additional information about firms' operating leverage beyond what is reflected in the traditional B/M.

Panel B presents results for the "Agreement" sample, which largely mirror those of the full sample. All book-to-market measures maintain significance at the 1% level, with coefficients broadly consistent with those in Panel A. This suggests that when traditional (B/M) and intangible (iB/M) book-to-market measures align in firm-level rankings, both are positively associated with operating leverage. Notably, i/M is highly significant even in joint regressions with B/M.

Finally, a different pattern is seen in Panel C for the "Disagreement" sample. Compared to the full sample and "Agreement" sample, the association between the book-to-market measures and DOL differs. Specifically, the traditional B/M measure is not statistically significant. In contrast, the iB/M coefficient is still significant at the 1% level but with a smaller coefficient and t-stat than in the full and "Agreement" samples. When B/M and i/M are included jointly, only the i/M coefficient is statistically significant. This suggests that for firms where the economy-wide rankings on iB/M and B/M disagree materially, iB/M is significantly positively associated with DOL while B/M is not (on average). Importantly, these findings have significant economic implications. Specifically, iB/M appears to outperform B/M in its association with operating leverage precisely when the choice of using one measure over the other should matter most in terms of predicting stock returns. Moreover, the "Disagreement" sample represents a considerable chunk of the stock market, representing approximately 10% of all firms per year in our sample (253 out of 2,623 firms).

These results support the notion that iB/M ratios among firms tend to capture variation in operating leverage (DOL) that the traditional B/M ratio misses. Moreover, the fact that i/M is jointly significant in all samples with B/M, and iB/M

[4] A 1% increase in the standardized iB/M (B/M) variable is associated with a 0.20% (0.15%) increase in DOL, in regressions where ln(DOL) is left unstandardized

maintains a significantly positive association with DOL throughout all samples, suggests that the addition of i/M in iB/M is meaningful for capturing variation in DOL among firms when compared to B/M. This is particularly evident in the "Disagreement" sample where B/M is the only specification that is not significantly associated with DOL. This suggests that iB/M tends to be more associated with DOL than B/M alone. As such, the results support H1.

4.3. Operating Leverage and Book-to-Market Returns

We now investigate whether the association each book-to-market measure (B/M, iB/M and i/M) has with operating leverage (DOL) can help explain their respective relationship with future returns.

In Table 5 we estimate Fama-Macbeth regressions of monthly excess returns on DOL and book-to-market measures (B/M, iB/M and i/M). The models control for size, momentum, and short-term reversal. All book-to-market measures and DOL in the regressions are expressed in natural logarithms, and all independent variables are standardized. When included independently, DOL is positively associated with future returns at the 1% significance level (model 5). Economically, a one percent increase in the standardized DOL variable predicts a 0.08 percentage point increase in monthly excess returns – approximately a 1% increase in yearly returns. When included independently, all book-to-market ratios load positively at the 5% significance level, which is lower than DOL, but with B/M and iB/M coefficients approximately twice as large as that of DOL (models 6-8). iB/M consistently tends to exhibit the strongest association with future returns among book-to-market ratios, having both the highest coefficients and t-statistics across specifications. When DOL and book-to-market measures are included jointly (models 9-11), the statistical significance of DOL declines. It remains significant at the 5% level for B/M (model 9), marginally significant at the 10% level for i/M (model 11) but, becomes insignificant when included with iB/M (model 10).

Overall, the results in Table 5 suggest that DOL and each book-to-market measure are positively associated with future returns individually. DOL's association diminishes after controlling for B/M and i/M and is insignificant when controlling for iB/M, suggesting that a substantial part of DOL's association with future returns is captured by variation in book-to-market measures. Importantly, book-to-market measures maintain significant coefficients when controlling for DOL. This suggests that they capture return-relevant information that is not explained by operating leverage alone. As such, our Fama-Macbeth regressions are not supportive of H2a and H2b.

Table 5: Fama-Macbeth Regressions

Expl. V	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Intercept	0.727***	0.727***	0.731***	0.736***	0.716***	0.719***	0.726***
	(2.94)	(2.90)	(2.94)	(2.98)	(2.87)	(2.90)	(2.95)
DOL	0.080***	–	–	–	0.050**	0.035	0.047*
	(3.07)	–	–	–	(2.10)	(1.48)	(1.96)
B/M	–	0.159**	–	–	0.151**	–	–
	–	(2.46)	–	–	(2.34)	–	–
iB/M	–	–	0.168**	–	–	0.161**	–
	–	–	(2.53)	–	–	(2.45)	–
i/M	–	–	–	0.123**	–	–	0.116**
	–	–	–	(2.29)	–	–	(2.16)
Size	−0.132	−0.074	−0.054	−0.068	−0.073	−0.052	−0.072
	(−1.58)	(−0.87)	(−0.68)	(−1.02)	(−0.85)	(−0.65)	(−0.98)
Momentum	0.292***	0.272***	0.248***	0.254***	0.273***	0.248***	0.254***
	(3.17)	(3.03)	(2.74)	(2.76)	(3.05)	(2.75)	(2.77)
Reversal	−0.090*	−0.094*	−0.092*	−0.092*	−0.095*	−0.093*	−0.093*
	(−1.82)	(−1.94)	(−1.89)	(−1.88)	(−1.96)	(−1.91)	(−1.90)
Adj. R^2	2.92%	3.29%	3.20%	3.04%	3.47%	3.37%	3.22%

Note: This table presents Fama–MacBeth (1973) average regression coefficients and t-statistics (in parentheses). Independent variables are standardized to have mean zero and unit variance. DOL, B/M, iB/M, and i/M are log-transformed before standardization. Dependent variable is monthly excess return (percent). The sample consists of monthly U.S. common stock returns from July 1977 to December 2023. t-statistics are based on Newey–West (1987) standard errors with four lags. Reported adjusted R^2 values are time-series averages of cross-sectional regression R^2. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 6 reports average equal-weighted (EW) and value-weighted (VW) monthly returns to portfolios of stocks sorted dependently; first on operating leverage (DOL), and then on different book-to-market measures. Specifically, Panel A reports the double-sorted portfolio based on DOL and B/M, while Panels B and C present analogous results for DOL and iB/M, and DOL and i/M, respectively. Reported returns represent the average monthly returns over each holding period, averaged over time in our sample. High minus low (H–L) returns are shown for the full cross-section, and within each DOL quintile. The H–L spread is constructed by taking a long position in the High B/M (iB/M, i/M) tercile and a short position in the Low B/M (iB/M, i/M) tercile.

Firt, we consider B/M tercile spreads. In the "Overall" row for Panel A, average monthly value-weighted and equal-weighted H–L returns are 0.09% (t-stat = 0.67) and 0.65% (t-stat = 5.15) respectively. Value-weighted H–L returns are significant at the 10% level in the High DOL quintile, and insignificant across the remaining

DOL quintiles (in line with the "Overall" row). In contrast, while equal-weighted returns appear smaller within DOL quintiles compared to the "Overall" sample (except in the lowest quintile), all return spreads remain statistically significant at the 1% level.

Second, we consider the iB/M tercile spreads. In the "Overall" row for Panel B, average monthly value-weighted and equal-weighted H–L returns are 0.34% (t-stat = 2.35) and 0.53% (t-stat = 4.37), respectively. Value-weighted H–L returns are only significant in DOL quintiles one (t-stat = 2.15) and five (t-stat = 1.89), where they appear relatively aligned with the "Overall" sample. In contrast, equal-weighted H–L returns are significant across all DOL quintiles at the 1% level, and appear relatively aligned with the "Overall" sample (only marginally lower in quintile 2-3, and marginally higher in quintile 1).

Third, we consider i/M tercile spreads. Panel C exhibits similar patterns to Panel B. Unconditioned on DOL, average monthly H–L returns are 0.35% (t-stat 2.70) and 0.54% (t-stat 4.73) for value-weighted and equal-weighted returns respectively. Value-weighted H–L returns are statistically significant and appears to exceed those of the full sample in all but DOL quintile two and four. Moreover, equal-weighted H–L returns are significant across all DOL quintiles, with quintile five, showing marginally higher average returns than for the overall sample.

Overall, the evidence is inconsistent with H2a and H2b. Stated differently, operating leverage does not appear to be the primary driver of the return information contained in either of B/M, iB/M and i/M. Equal-weighted H–L returns are statistically significant, even after controlling for operating leverage through dependent double-sorts. On a value-weighted basis, the results are more mixed, but nonetheless suggest that H–L returns are positive and statistically different from zero in 2 out of 5 DOL quintiles for iB/M, and in 3 out of 5 for i/M. While no significant H–L returns are observed within DOL quintiles for B/M, this likely reflects the absence of significance in the overall sample for value-weighted returns. An additional observation is that if operating leverage induces systematic risk, which warrants a risk premium, then high operating leverage firms should outperform low operating leverage firms on average. We find evidence consistent with this notion on an equal-weighted basis (but not on a value-weighted basis) where returns appear to increase monotonically with DOL quintiles. Consequently, this pattern supports the findings of Table 5 that DOL is associated with future returns at some level.

Table 6: Portfolio Returns: Dependent Sorts on DOL and Book-to-Market Measures

Panel A: B/M Returns

	VW-returns						EW-returns					
	Overall	Low	Mid	High	H–L	*t*-stat	Overall	Low	Mid	High	H–L	*t*-stat
Overall		0.68	0.69	0.77	0.09	0.67		0.38	0.83	1.04	0.65***	5.15
Low DOL	0.67	0.67	0.65	0.79	0.12	0.84	0.68	0.30	0.75	0.98	0.68***	4.88
Q2	0.73	0.80	0.60	0.62	-0.18	-1.10	0.80	0.59	0.83	0.99	0.40***	3.38
Q3	0.79	0.79	0.87	0.65	-0.14	-0.81	0.89	0.64	0.95	1.07	0.43***	3.46
Q4	0.67	0.65	0.62	0.92	0.28	1.64	0.94	0.74	0.98	1.11	0.37***	2.84
High DOL	0.73	0.67	0.69	1.07	0.41*	1.92	0.98	0.79	1.05	1.11	0.32**	2.13

Panel B: iB/M Returns

	VW-returns						EW-returns					
	Overall	Low	Mid	High	H–L	*t*-stat	Overall	Low	Mid	High	H–L	*t*-stat
Overall		0.68	0.71	1.03	0.34**	2.35		0.58	0.89	1.11	0.53***	4.37
Low DOL	0.67	0.58	0.79	0.91	0.32**	2.15	0.68	0.33	0.75	0.95	0.61***	4.29
Q2	0.73	0.76	0.62	0.81	0.04	0.24	0.80	0.55	0.85	1.01	0.46***	3.64
Q3	0.79	0.77	0.84	0.93	0.16	0.87	0.89	0.61	0.95	1.10	0.49***	3.88
Q4	0.67	0.64	0.72	0.94	0.30	1.55	0.94	0.70	0.95	1.17	0.47***	3.89
High DOL	0.73	0.61	0.88	1.00	0.39*	1.89	0.98	0.69	1.08	1.17	0.48***	3.31

Panel C: i/M Returns

	VW-returns						EW-returns					
	Overall	Low	Mid	High	H–L	*t*-stat	Overall	Low	Mid	High	H–L	*t*-stat
Overall		0.60	0.79	0.95	0.35**	2.70		0.57	0.90	1.11	0.54***	4.73
Low DOL	0.67	0.54	0.72	0.99	0.45***	2.91	0.68	0.42	0.73	0.88	0.46***	2.99
Q2	0.73	0.65	0.81	0.78	0.13	0.82	0.80	0.55	0.88	0.98	0.42***	3.39
Q3	0.79	0.66	0.88	1.04	0.38**	2.16	0.89	0.60	0.92	1.14	0.54***	4.40
Q4	0.67	0.59	0.83	0.83	0.24	1.28	0.94	0.67	0.96	1.20	0.53***	4.05
High DOL	0.73	0.56	0.87	1.02	0.46**	2.38	0.98	0.67	1.01	1.26	0.58***	4.32

Note: Each panel presents value-weighted (VW) and equal-weighted (EW) average excess returns and high-minus-low (H–L) spreads sorted dependently first by degree of operating leverage (DOL, rows) and then by book-to-market measures (columns). Returns are expressed in percent per month. Portfolios are constructed using the Fama–French methodology: Firms are sorted at the end of June based on the most recent annual accounting data, held from July to June of the following year. Reported returns are time-series averages of monthly returns for each portfolio, t-statistics are time-series averages divided by time-series standard errors. Significance: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

4.4. Robustness Tests

We re-estimate our annual cross-sectional regressions and Fama-Macbeth regressions using alternative measures of DOL. These include DOL^{Q} – using 20 quarters of data – and DOL^{FCF} using FCF[5] instead of EBIT. Table 8 shows the results analogous to Table 4 for DOL^{Q}. T-statistics are greater for iB/M than B/M across all samples. Moreover, i/M is statistically significant both when included independently (model 3) and jointly with B/M (model 4) across all sub-samples, suggesting that i/M captures unique variation in DOL. Table 9 reports comparable results for DOL^{FCF}. The results align with Table 8. Overall, these results are consistent with those reported in Table 4, although we acknowledge that B/M is statistically significant when included independently in the "Disagreement" sample for the DOL^{Q} specification. Finally, Table 10 shows the Fama-Macbeth results for DOL^{Q} (Panel A) and DOL^{FCF} (Panel B) comparable to our main results in Table 5. Consistent with our main results, Panel A shows that DOL^{Q} and all book-to-market measures are positively associated with future returns (models 5-8). However, in contrast to our main results, when DOL^{Q} is regressed jointly with B/M (model 9), iB/M (model 10) and i/M (model 11), DOL^{Q} maintains statistical significance at a 1% level, while significance levels for all book-to-market measures decline from 5% to 10%. Nonetheless, we are still unable to support hypotheses 2a and 2b. In Panel B, results are similar to those reported in Table 5 across all model specifications. Notably, DOL^{FCF} is significant at a 10% level when included jointly with B/M (model 9) and i/M (model 11), but is insignificant when included jointly with iB/M (model 10).

As our first hypothesis is sensitive to the cut-off point for our "Disagreement" and "Agreement" samples, Table 11 reports results analogous to Table 4. The evidence is consistent with those reported in our main results. Specifically, iB/M and i/M is significant across all subsamples, and i/M maintains significance when controlling for B/M. In Panel C ("Disagreement" sample), the coefficient for B/M in Model 1 is marginally significant at the 10% level (t-stat 1.87). In contrast, both iB/M (t-stat 15.05) and i/M (t-stat 12.00) are highly significant at the 1% level in Models 2 and 3. When B/M and i/M are included together in Model 4, B/M regains statistical significance (t-stat 6.98). This suggests that i/M and B/M are complementary, as the inclusion of i/M enhances the explanatory power of B/M in explaining DOL.

[5] DOL^{FCF} is calculated using the same method as for DOL but with FCF instead of EBIT. We define unlevered free cash flows as FCF = (1-t)EBIT + D&A - CAPEX - Δ(NWC). For simplicity, we assume a 30% marginal tax rate following Peters and Taylor (2017), who found it was the average marginal tax rate for firms in their 1975-2011 US sample. Moreover, we assume that firms hold no excess cash.

5. Discussion

In this section, we discuss our main findings: (1) iB/M is positively associated with operating leverage, and the inclusion of i/M strengthens iB/M's association with operating leverage compared to B/M; and (2) operating leverage cannot explain the association book-to-market measures have with future returns. We also discuss our data and methodology, including choices made and limitations.

5.1. Main Findings

5.1.1. Strong Association with iB/M compared to B/M for Operating Leverage

In H1, we find support that iB/M is positively associated with DOL. Moreover, the inclusion of i/M strengthens iB/M's association with operating leverage compared to B/M, as both i/M and B/M capture distinct variation in operating leverage. Similarly, in the main results of H2, we find that DOL remains statistically significant when combined with B/M and i/M separately in Fama and MacBeth (1973) regressions but not when combined with iB/M. This suggests that iB/M captures return-relevant information in DOL that both B/M and i/M misses individually. While the primary aim of this study is not to identify the mechanisms underlying the association with DOL for iB/M and B/M, we offer some interpretations below.

One possibility is that operating leverage (DOL) is related to margin differences across firms which iB/M is better able to capture. Novy-Marx (2011) suggests that high B/M values arise either from low profitability, or due to high book values - the second being mostly related to industry differences. Consequently, if iB/M neutralizes cross-industry differences in book values, it would better differentiate between margin levels across firms and, by extension, operating leverage. If this explanation holds, we would expect profitability to vary more across iB/M levels than across i/M and B/M levels separately, given that only iB/M subsumes DOL in Fama and MacBeth (1973) regressions. We would also expect profitability to decline more steeply with DOL levels than with book-to-market levels. The evidence offers some, but limited support for this view. In our descriptive statistics, we do observe that operating profit varies slightly more across iB/M quintiles than across i/M and B/M (Table 2, Panels A and B). Yet, the difference is marginal. Moreover, operating profit varies less significantly across DOL quintiles than across any of the book-to-market-based quintile sorts (Table 2, Panel C). Indeed, operating leverage can be low (high) despite low (high) average margins if the cost base is primarily variable (fixed).

As such, we consider a second interpretation: operating leverage (DOL) increases

with both intangible and tangible capital, as both types of capital contribute to fixed costs. This view is consistent with studies suggesting that operating leverage is primarily driven by cost rigidities associated with various forms of capital, including physical, organization, and labor-based capital (Carlson et al., 2004; Cooper, 2006; Donangelo et al., 2019; Eisfeldt & Papanikolaou, 2013; Venieris et al., 2015; L. Zhang, 2005). iB/M may be best suited to capture this by combining the capital stocks reflected in both i/M and B/M. In contrast, traditional B/M may fall short due to its exclusion of intangible capital from book values. In line with this view, cost rigidities that drive DOL would only be partially captured by i/M and B/M separately, but would be jointly reflected when combined in iB/M. This interpretation is supported by our H1 finding that i/M and B/M are jointly significantly associated with DOL in OLS regressions, and that iB/M appears to have the largest coefficients and t-statistics. Similarly, it is consistent with iB/M subsuming DOL in Fama and MacBeth (1973) regressions, whereas i/M and B/M do not when tested individually. Furthermore, if iB/M is strongly associated with operating leverage due to its ability to combine tangible and intangible capital, one would expect to see the association between B/M and operating leverage to weaken in scenarios where intangible capital is likely to be especially important.[6] The evidence supports this, with i/M being significant in the "Disagreement" sample of Table 4 while B/M is not. Note that this does not imply that i/M should not have an association with DOL in the "Agreement" sample, as labor complements physical capital (Donangelo et al., 2019).[7] In this sense, our results are consistent with both a capital-induced operating leverage perspective, but also studies that suggest labor as a dominant source of operating leverage (Carlson et al., 2004; Cooper, 2006; Donangelo et al., 2019; Eisfeldt & Papanikolaou, 2013; García-Feijóo & Jorgensen, 2010; Venieris et al., 2015; L. Zhang, 2005).

A third possibility relates to the trade-off between financial and operating leverage. Firms with high operating leverage tend to avoid high financial leverage to manage total risk (Mandelker & Rhee, 1984). This is consistent with Table 2 where book leverage (Lev) decreases monotonically with DOL quintiles. Traditional B/M rankings may capture firms with either high operating or high financial leverage (Obreja, 2013), in part because firms with large, safe book values often rely more

[6]In unreported statistics, we note that the median B/M is 0.45 and median i/M is 0.92 in the "Disagreement" sample, compared to the median B/M of 0.61 and median i/M of 0.34 in the full sample. This suggests that firms in the "Disagreement" sample differ very meaningfully in intangible-intensity but less so for tangible-intensity compared to the full sample of firms.

[7]For example, an integrated manufacturing-based company cannot simply own factories; it must also employ labor to operate them, and it operates knowledge-based functions to market its products.

on debt (Choi, 2013). In contrast, firms ranked highly on iB/M are more likely to be intangible-intensive (through high i/M), which is associated with lower debt capacity (Falato et al., 2022) and higher operating risk through labor leverage and the stickiness of SG&A and R&D expenses (Donangelo et al., 2019; Eisfeldt & Papanikolaou, 2013; Venieris et al., 2015). As such, when iB/M diverges from B/M, it may isolate firms with high operating risk that have historically maintained conservative financial policies. In contrast, high B/M values may reflect a mix of firms with either high financial or high operating leverage, making B/M less indicative of operating leverage levels alone. Indeed, debt levels rise less steeply across i/M and iB/M quintiles than across B/M quintiles (Table 2, Panels A, B, and C). Moreover, this explanation could be consistent with DOL not being subsumed by B/M but being subsumed by iB/M in Fama and MacBeth (1973) regressions.

Finally, it is possible that iB/M and i/M differ in their exposure to biases in the measurement of operating leverage than B/M. We discuss this possibility more in section 5.2.

5.1.2. Operating Leverage Does Not Explain Book-to-Market Returns

In Fama-Macbeth regressions (Table 5, model 1), we find evidence that operating leverage is associated with future returns, consistent with prior studies that suggest operating leverage warrants a risk premium through systematic risk exposure (Cooper, 2006; Lev, 1974; Mandelker & Rhee, 1984; O'Brien & Vanderheiden, 1987). However, while operating leverage (DOL) is significantly associated with future returns, both iB/M and B/M retain their return relation even after controlling for DOL. We interpret these findings as follows: the association between DOL and future returns weakens when including different book-to-market specifications (B/M, iB/M, and i/M), suggesting that these measures capture overlapping information about future returns. This finding is consistent with the positive association between these measures, discussed in section 5.1.1. Nevertheless, iB/M, its intangible component (i/M), and the tangible component (B/M) continue to show a significant association with future returns. This suggests that operating leverage cannot account for the book-to-market effect under either specification.

These results are supported by both Fama-Macbeth regressions and double-sorted tables. Moreover, these findings are robust to alternative DOL specifications (Appendix A.3), mitigating concerns regarding test assumptions and measurement specifications. Therefore, the findings in H2 are consistent with studies that challenge the operating leverage explanation for the book-to-market effect (Cao, 2015; Kisser, 2014; Kogan et al., 2023; Ozdagli, 2012), and contrast with those that sup-

port it (Carlson et al., 2004; Cooper, 2006; Novy-Marx, 2011; L. Zhang, 2005).

Several untested explanations could account for our results. SG&A and R&D stickiness, firing costs, and labor specificity may attenuate operating leverage but vary across firms (Eisfeldt & Papanikolaou, 2013; Venieris et al., 2015; M. B. Zhang, 2019); but intangible capital is computed equivalently across firms (Eisfeldt et al., 2022; Park, 2022). Similarly, (Guthrie, 2011) finds that options to abandon reverse the operating leverage return-relation, and literature may overstate the stickiness in far-reaching intangible projects (Brown & Petersen, 2011; Grabowski, 1968; Griliches & Hausman, 1986). It is also possible that operating leverage interacts with financial leverage, so that operating leverage can better explain book-to-market returns among low-debt firms (Choi, 2013; George & Hwang, 2010; Obreja, 2013; Penman et al., 2007). The return relation for i/M and iB/M may subsequently be driven by operating leverage in select segments, but not on an economy-wide level. This could be consistent with book-to-market measures capturing return-relevant information contained in DOL, while controls for DOL do not materially weaken the return association of book-to-market measures themselves in Table 5. Nonetheless, these possibilities would not impact the main findings of this study, which focuses on operating leverage as the primary explanation for the full book-to-market effect.

Consequently, while our study suggests that all three book-to-market measures (B/M, iB/M, and i/M) are positively related to operating leverage, and that operating leverage itself predicts future returns, we find no support that the association with operating leverage by itself can account for the book-to-market effect under any specification.

5.2. Data and Method

The greatest vulnerability in our study lies in the measurement of operating leverage which, despite its strong theoretical underpinnings, is inherently difficult to estimate with precision. This concern persists despite our use of the DOL measure developed by Mandelker and Rhee (1984) and extended by O'Brien and Vanderheiden (1987), which is widely considered one of the most robust options available (Cao, 2015; Dugan & Shriver, 1992; García-Feijóo & Jorgensen, 2010; Stelk et al., 2015). Appendix A.2 outlines key limitations commonly discussed in the literature on the measurement of operating leverage (DOL), many of which could potentially bias our results. Among other factors, the generalizability of our study is limited by: DOL's sensitivity to the chosen regression window, data requirements to produce reliable estimates, changing and unobservable cost structures, varying data availability across firms, and DOL instability when sales growth is low or margins

approach the break-even point.

Operating leverage estimates are also sensitive to the specific earnings or cash flow measure used in DOL, which varies (Aharon et al., 2019; Eisfeldt & Papanikolaou, 2013; Mandelker & Rhee, 1984), as well as accounting practices. Intangible expensing could also affect DOL (Srivastava, 2014). However, it is not obvious that this should always be viewed as a bias in DOL, nor that any biases would cause overstated DOL among intangible-intensive firms in particular.[8] Even so, any bias on DOL from intangible expensing would be greater with larger expenses, which coincides with intangible-intensity. We attempt to mitigate potential concerns through several approaches: When choosing time windows and data requirements, we follow landmark studies (Cao, 2015; García-Feijóo & Jorgensen, 2010). We also attempt to control for several biases in DOL measurement in our robustness tests (Appendix A.3). This includes testing measures less distorted by accounting practices, and increasing the data requirement for DOL to increase the reliability of regression estimates (20 quarterly observations instead of 5 yearly observations in rolling-window regressions). While we note that our results are robust to alternative specifications of operating leverage (DOL), these measures are also exposed to similar biases as our main measurement. For instance, estimating DOL with free cash flows, while recently suggested (Aharon et al., 2019), is not the most widely used alternative, and using quarterly data further restricts the sample size. All in all, while we take several steps to improve the reliability of our results, we note that operating leverage is an inherently difficult measure to estimate accurately, and that future studies could produce different results. This is especially true considering that true operating leverage is forward-looking and unobservable, whereas operating leverage estimates rely on historical accounting data (Stelk et al., 2015).

For all tests, we adhere to established methodologies that have previously been utilized in the operating leverage context. Specifically, we follow García-Feijóo and Jorgensen (2010) when testing associations with operating leverage. Similarly, Fama-Macbeth regressions and double-sorted portfolios are established methods that follow landmark studies when testing the operating leverage explanation for the book-to-market effect (Cao, 2015; Fama & French, 2015; Kisser, 2014; Kogan et al.,

[8]First, SG&A, R&D, and labor costs have been found to be particularly sticky among intangible-intensive firms (Brown & Petersen, 2011; Donangelo et al., 2019; Eisfeldt & Papanikolaou, 2013; Venieris et al., 2015). In these cases, costs are more non-discretionary and justifiably increase DOL. Instead, DOL should be viewed as more biased by intangible expensing when it is discretionary and lumpy. Such large year-over-year changes in R&D and SG&A, unconnected to sales, could even be more likely for tangible-intensive firms. Moreover, if SG&A and R&D expenditures are viewed as discretionary investments by the firm, and targeted as a % of sales, they would be variable in nature and not increase DOL.

2023; Novy-Marx, 2011; Park, 2022; Vassalou & Xing, 2004).

We highlight that no regressions reported in this paper have VIF factors above 5, even as i/M and B/M are jointly included in regressions. For the linear regressions used in both H1 and the Fama-Macbeth regressions in H2, we take the natural logarithm of our key independent variables to reduce positive skewness and linearize the relationship between the variables. Moreover, we follow data cleaning processes of benchmark studies that study operating leverage in the context of the book-to-market effect (Cao, 2015; García-Feijóo & Jorgensen, 2010).

6. Conclusion

Explanations for the book-to-market effect, or the return spread between high B/M ("value") and low B/M stocks ("growth"), are far from few. One view is that B/M captures operating leverage differences between firms, generally defined as the level of operating earnings sensitivity to sales, which increases with fixed costs. Recently, B/M has been criticized for excluding internally generated intangibles, leading to conservative B/M ratios for intangible-intensive stocks. When B/M is adjusted for intangibles, resulting in substantially different iB/M ratios among firms, book-to-market has strengthened as a return predictor. However, beyond proposing iB/M as an improved version of B/M, research has done little to explore risk-based explanations for iB/M's return association.

In this study, we take a step toward addressing this gap by revisiting one explanation commonly associated with the traditional book-to-market effect: the operating leverage explanation. Specifically, we test if the explanation is better applied to iB/M, through the addition of intangible capital (i/M), than to B/M. We are motivated by findings that intangible-intensive firms often face labor-induced operating leverage, that they have stickier SG&A and R&D expenses, and by the critique that B/M often fails to capture operating leverage by fixating too much on differences in book values (Donangelo et al., 2019; Eisfeldt & Papanikolaou, 2013; Novy-Marx, 2011; Venieris et al., 2015; M. B. Zhang, 2019). Indeed, we find that iB/M is more strongly associated with operating leverage than B/M, where the addition of i/M captures unique variation in operating leverage. The impact is most evident when omitting intangibles substantially affects a firm's book-to-market ranking relative to other firms. This aligns with studies finding that intangible capital is associated with operating leverage (Donangelo et al., 2019; Eisfeldt & Papanikolaou, 2013). With regard to stock returns, operating leverage and book-to-market measures appear to capture some overlapping information, which is especially true for iB/M. However, neither iB/M, B/M, nor i/M materially weakens as return predictors when controlling for operating leverage. As such, we find insufficient support for operating leverage being the primary driver of neither specification of the book-to-market effect, even if intangible-adjusted book-to-market (iB/M) appears to share more return-related variation with operating leverage than B/M.

To the best of our knowledge, our study is the first to connect literature that proposes adjusting book-to-market for intangibles in asset pricing (Arnott et al., 2021; Eisfeldt et al., 2022; Gulen et al., 2025; Lev & Srivastava, 2019; Park, 2022), and literature that examines operating leverage as an explanation for the book-

to-market effect (Cao, 2015; Carlson et al., 2004; Cooper, 2006; Donangelo, 2021; García-Feijóo & Jorgensen, 2010; Novy-Marx, 2011; L. Zhang, 2005). Generally, our study should be viewed in support of studies that challenge operating leverage as the primary explanation for the book-to-market effect (Cao, 2015; Kisser, 2014; Kogan et al., 2023; Ozdagli, 2012).

7. Future Research

Since our study has inherent limitations, we propose several interesting areas of future research.

First, since studies have found that the return information embedded in the high-minus-low (HML) book-to-market (B/M) factor can be explained by an investment (RMW) and profitability (CMA) factor, it would be interesting to test the extent to which operating leverage relates to these factors (Fama & French, 2015). If these factors (or their ability to explain HML returns) are not impacted in controls for operating leverage, then it would strengthen the case that the book-to-market effect is not primarily driven by operating leverage.

Second, our study is limited by our chosen measures of operating leverage and intangible capital. Since methods to compute intangible capital are continuously developed (Arnott et al., 2021; Eisfeldt et al., 2022; Gulen et al., 2025; Park, 2022; Peters & Taylor, 2017), it is possible that more accurate intangible capital estimates would yield a different association between iB/M and operating leverage. Similarly, it would be valuable to test whether our results hold if less noisy measures of operating leverage are developed, or in a horse race with other feasible specifications of operating leverage. If they do, this would further support the conclusion that operating leverage is unlikely to be the primary driver of the book-to-market effect.

Third, we considered the financial distress explanation as less relevant for iB/M ratios, given the lower documented debt ratios for intangible-intensive firms. Nonetheless, it is feasible that higher distress costs—stemming from ongoing operating expenses and non-collateralizable intangible assets—could result in a larger risk premium for a given level of financial leverage in these stocks (Belo et al., 2014; Falato et al., 2022). Similarly, operating leverage could interact with financial leverage in the book-to-market effect as specified by iB/M (Choi, 2013; Obreja, 2013).

Lastly, we invite future studies to explore whether iB/M has a stronger association with operating leverage than B/M in international markets. For instance, regions with stronger employment protection, or greater wage rigidities, could yield greater labor-induced operating leverage Danthine and Donaldson (2002), Donangelo et al. (2019), and Simintzi et al. (2015). In such regions, the link between iB/M and operating leverage could be clearer.

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A. Appendices

A.1. Measuring Intangible Capital

A.1.1. Industry-Specific R&D Depreciation Rates

Table 7: R&D Depreciation Rates

Industry	**SIC Codes**	**dXRD**
Computers and peripheral equipment	3570–3579, 3680–3689, 3695	40%
Software	7372	22%
Pharmaceuticals	2830, 2831, 2833–2836	10%
Semiconductor	3661–3666, 3669–3679	25%
Aerospace product and parts	3720, 3721, 3724, 3728, 3760	22%
Communication equipment	3576, 3661, 3663, 3669, 3679	27%
Computer system design	7370, 7371, 7373	36%
Motor vehicles, bodies, trailers, and parts	3585, 3711, 3713, 3716	31%
Navigational, measuring, electromedical, and control instruments	3812, 3822, 3823, 3825, 3826, 3829, 3842, 3844, 3845	29%
Scientific research and development	8731	16%

Source: Li and Hall (2016) and Park (2022). For industries not listed, we assume a 15% depreciation rate in line with Park (2022).

A.1.2. Defining SG&A for Organization Capital

The Compustat xsga variable tends to include both SG&A and R&D for firms. As such, we disaggregate SG&A from R&D in line with Park (2022) and Peters and Taylor (2017). First, we define SG&A as xsga minus xrd minus rdip. We subtract rdip (in-process R&D) since Compustat codes the variable as negative. When xrd exceeds xsga, we set SG&A to xsga; and when xsga is missing we simply set it to zero. Generally, we set xsga, xrd, and rdip to zero when missing (with exceptions for xsga and xrd detailed in the next section). (Peters & Taylor, 2017).

A.1.3. Initial Intangible Capital and Back-filling SG&A and R&D

We follow the detailed method of Peters and Taylor (2017) for back-filling SG&A and R&D investments between a firm's first appearance in Compustat and its founding year, and imputing selected missing post-IPO observations. We initiate the Compustat sample for computing intangible capital in 1950, in line with Peters and Taylor (2017). We gather data for the founding year from Jay Ritter's website (https://site.warrington.ufl.edu/ritter/files/founding-dates.pdf). The method of Peters and Taylor (2017) has been accepted by a wide array of studies (Eisfeldt et al., 2022; Gulen et al., 2025; Lev & Srivastava, 2019; Park, 2022).

The method requires estimating two categories of growth rates for SG&A and R&D, namely pre-IPO growth rates and age-specific growth rates. For pre-IPO growth rates, we isolate firms that report SG&A and R&D in the two years prior to their IPO. We then compute the average log change in SG&A and R&D (separately) within this sample. For age-specific growth rates, we use the full Compustat database to compute the average log change in SG&A and R&D (separately) for each yearly category of age since IPO. We apply these aggregate growth rate estimates across firms as detailed below. (Peters & Taylor, 2017).

There are three main problems considered in the method. First, the FASB only required firms to report R&D from 1975 in the US. As such, assuming no R&D for all missing firm-year observations prior to 1975 is arguably too conservative. Second, firms can have erratic Compustat records if they are temporarily taken private, as there would be no SG&A or R&D records reported to the public during these years. Third, founding year and IPO year is not available for all firms. (Peters & Taylor, 2017).

To deal with the first issue, we give firms two years to comply to the FASB's R&D reporting requirements. If the firm has missing records in 1977, we assume the firm is not a typical R&D spender and set all missing pre-1977 R&D observations in Compustat to zero. If the firm reports R&D in 1977, we assume that the firm is an R&D spender. In this case, we linearly interpolate missing R&D observations between the firm's nearest non-missing observations. When we reach the earliest non-missing observation, we use age-specific growth rates to back-fill R&D until the firm's IPO year, and from there use pre-IPO growth rates to estimate R&D until the founding year. (Peters & Taylor, 2017).

For the second issue, we make exceptions for missing SG&A and R&D observations when the firm-year observation also has missing total asset data. For these years, we assume the firm was private and subsequently interpolate between the firm's nearest non-missing observations. (Peters & Taylor, 2017).

When firms have missing IPO dates, we back-fill SG&A and R&D spending between the firm's first appearance in Compustat to its founding year using age-specific growth rates. When firms have missing founding years, we estimate the founding year as the minimum of (a) the firm's first appearance in compustat and (b) the firm's IPO year minus 7, which is the median age between firm's founding and IPO year in Jay Ritter's data set between 1980 and 2023. (Peters & Taylor, 2017).

All adjustments for missing R&D and SG&A observations are only used to computing intangible capital. We do not include adjustments to estimate SG&A or R&D in any other variable or result reported. (Peters & Taylor, 2017).

A.2. Measurement of Operating Leverage

A.2.1. Limitations of Operating Leverage Measures

Limitations of point-to-point-based operating leverage measures, which simply measure operating leverage as the % change in operating profits to the % change in sales between two points in time. The list is non-comprehensive:

1. **Offsetting cost structures:** When firms increase fixed costs while simultaneously reducing unit variable costs at a specific rate, their estimated degree of operating leverage can remain unchanged, or even decrease, despite the rise in fixed costs. This is counter-intuitive, as higher fixed costs should be associated with greater operating leverage. (Lord, 1998).

2. **Constant-cost assumptions yield DOL below one:** Elasticity-based DOL measures that assume constant unit variable costs, unit prices, and fixed costs can produce biased estimates, often yielding values below one. This commonly refers to text-book estimates of DOL. (Dugan & Shriver, 1992; Lord, 1998).

3. **Time window discretion:** When DOL is measured between two points in time, it is highly sensitive to the choice of time window; whereas the firm can change its cost structure over time (Lord, 1998).

4. **Arc elasticity bias:** When DOL is measured between two points in time, a small change in sales (the denominator) can cause DOL estimates to become highly volatile or artificially inflated, even if changes in earnings are small (Lord, 1998).

5. **Instability at near-zero margins:** If the firm operates at near-zero profit margins, small changes in EBIT induce large percentage changes in EBIT,

destabilizing the DOL estimate. As the initial profit margin approaches zero, a given change in EBIT will yield DOL values closer to infinity. (Lord, 1998).

6. **Directional asymmetry:** When DOL is estimated between two dates, it can yield different values depending on the direction of measurement (i.e., from point A to point B versus from point B to point A) (Lord, 1998).

7. **Accounting policies and discretionary cost timing:** In general, firms can defer costs in the short-run as part of earnings management. Moreover, earnings are sensitive to differing accounting treatment across firms, where some costs are capitalized and others are immediately expensed Srivastava (2014). Both accounting and earnings management can obscure the firm's true operating leverage.

8. **DOL is forward-looking:** Since the theoretical degree of operating leverage needs forward-looking values, which are unobservable, the true operating leverage is not possible to compute. Instead, researchers tend to rely on historical accounting data (Stelk et al., 2015).

Limitations to elasticity-based operating leverage measures based on regression models (non-comprehensive):

1. **Instability at near-zero margins:** If the firm operates at near-zero profit margins, small changes in EBIT induce large percentage changes in EBIT, destabilizing the DOL estimate. As the initial profit margin approaches zero, a given change in EBIT will yield DOL values closer to infinity. (Lord, 1998).

2. **DOL as a growth measure:** The method of Mandelker and Rhee (1984) tends to produce downward biased estimates for growing firms. Specifically, it tends to capture the relationship between operating earnings growth and sales growth, instead of earnings sensitivity to sales. If the firm has earnings growth similar to sales growth, operating leverage estimates tend to cluster around one. (O'Brien & Vanderheiden, 1987; Stelk et al., 2015).

3. **Accounting policies and discretionary cost timing:** In general, firms can defer costs in the short-run as part of earnings management. Moreover, earnings are sensitive to differing accounting treatment across firms, where some costs are capitalized and others are immediately expensed Srivastava (2014). Both accounting and earnings management obscure the firm's true operating leverage.

4. **Changing cost structures vs. model accuracy:** García-Feijóo and Jorgensen (2010) uses a 5-year rolling window to compute DOL. Lower windows produce more recent estimates for the cost structure; whereas longer windows yield more regression accuracy (García-Feijóo & Jorgensen, 2010).

5. **Sample size reduction:** Estimating DOL with greater accuracy means increasing data requirements, reducing the sample size (Cao, 2015; García-Feijóo & Jorgensen, 2010).

6. **DOL is forward-looking:** Since the theoretical degree of operating leverage needs forward-looking values, which are unobservable, it is not possible to compute. Instead, researchers tend to rely on historical accounting data (Stelk et al., 2015).

A.2.2. Preference for O'Brien and Vanderheiden's (1988) Measure

When researchers evaluate estimates of the degree of operating leverage (DOL), they refer to the classical model (Stelk et al., 2015). It defines DOL as the percentage deviation in operating earnings from its expected value relative to the percentage deviation in sales from its expected value:

$$DOL = \frac{\left(\frac{X_t}{\mathbb{E}(X)_t} - 1\right)}{\left(\frac{S_t}{\mathbb{E}(S)_t} - 1\right)} \tag{1}$$

where:
DOL = the degree of operating leverage;
X_t = realized operating earnings in period t;
S_t = realized sales volume in period t; and
$\mathbb{E}(\cdot)$ = the expected value of $(\cdot)$.

In the classical model, differences in DOL are solely due to differences in variable costs to fixed costs (Stelk et al., 2015). As such, if you set X_t as sales times one minus the contribution margin (% variable costs of sales) less the firm's fixed costs (F), you can simplify the expression as:

$$DOL = 1 + \frac{F}{\mathbb{E}(X_t)}$$

This means that DOL will be exactly one if there are no fixed costs and greater than one otherwise in the classical model. DOL values below one indicate either negative earnings or negative fixed costs. Since no fixed costs is unrealistic, DOL estimation techniques that yield many firm-level DOL estimates clustering around one are viewed as problematic. (Dugan & Shriver, 1992; Lord, 1998; O'Brien & Vanderheiden, 1987; Stelk et al., 2015).

Since the theoretical degree of operating leverage needs forward-looking values, which are unobservable, it is not possible to compute. Instead, researchers tend to rely on historical accounting data (Stelk et al., 2015). Mandelker and Rhee (1984), one of the most popular DOL estimation methods, simply define DOL as:

$$\ln EBIT_{jt} = a_j + c_j \ln Sales_{jt} + \mu_{jt} \tag{2}$$

where,
$EBIT_{jt}$ = operating earnings for firm j at time t;
$Sales_{jt}$ = net sales for firm j at time t;
μ_{jt} = a disturbance term; and
c_j = the DOL estimate for firm j.

O'Brien and Vanderheiden (1987) critiques this method (the "M&R" technique) since it takes actual values in sales and operating earnings, instead of expected values. As such, for growing firms, they argue that the Mandelker and Rhee (1984) method simply captures the relative growth trends in earnings and sales, and not the sensitivity around expected values of earnings and sales. When applied to data, they find that the M&R method computes values around one for firms that should have values around three. As such, O'Brien and Vanderheiden (1987) propose that sales and earnings data should be de-trended before estimating DOL (the "O&V" technique).

Dugan and Shriver (1992) compares the original DOL estimation procedure of Mandelker and Rhee (1984) and the extension of O'Brien and Vanderheiden (1987), and find that the latter is more consistent with the classical definition of operating leverage in a 1976-1985 US sample. Specifically, the M&R technique provides many more DOL estimates below one than the O&V technique. This opposes the intuition of operating leverage, where sales increases should most often yield higher earnings

increases as fixed costs decrease as a proportion of total costs. Since the O&V and M&R techniques provide substantially different values, and the O&V technique is more realistic, Dugan and Shriver (1992) concludes that the O&V technique is worth the extra computational effort.

Stelk et al. (2015) similarly compared the M&R and O&V technique in a US sample of 16,289 firms between 1998 and 2012; and argue that they provide the first real evidence that the M&R technique mostly proxies for growth in earnings relative to growth in sales, and not operating leverage. Specifically, Stelk et al. (2015) use the O&V method to compute growth trends in earnings and sales. They then test whether firms where estimated earnings and sales trends from O&V are equivalent produce DOL values around one when using the M&R technique. They find that this is the case, and subsequently support the method by O&V to detrend earnings and sales before computing DOL Stelk et al. (2015).

A.3. Robustness tests

Table 8: DOL^Q Regressions Across Subsamples

Panel A: Full Sample (Avg Firms/Year = 2255)

	Intercept	B/M	iB/M	i/M	Size
Model 1	-0.0655***	0.2160***	–	–	0.2748***
	(-3.03)	(11.86)	–	–	(10.48)
Model 2	-0.0795***	–	0.2513***	–	0.3209***
	(-3.26)	–	(15.58)	–	(11.42)
Model 3	-0.0617***	–	–	0.1668***	0.2809***
	(-3.32)	–	–	(10.91)	(9.17)
Model 4	-0.0779***	0.1856***	–	0.1027***	0.3130***
	(-3.20)	(9.19)	–	(6.27)	(11.00)
Panel B: Agreement Sample (Avg Firms/Year = 2025)					
Model 1	-0.0726***	0.2328***	–	–	0.2781***
	(-3.12)	(11.86)	–	–	(9.28)
Model 2	-0.0829***	–	0.2641***	–	0.3109***
	(-3.26)	–	(15.53)	–	(10.21)
Model 3	-0.0643***	–	–	0.1887***	0.2736***
	(-3.33)	–	–	(13.60)	(8.62)
Model 4	-0.0816***	0.1863***	–	0.1016***	0.3063***
	(-3.21)	(8.79)	–	(8.01)	(10.05)
Panel C: Disagreement Sample (Avg Firms/Year = 229)					
Model 1	-0.0333***	0.0572***	–	–	0.3108***
	(-2.73)	(2.77)	–	–	(13.39)
Model 2	-0.0316***	–	0.1031***	–	0.3550***
	(-3.23)	–	(3.53)	–	(13.38)
Model 3	-0.0305***	–	–	0.0969***	0.3614***
	(-2.99)	–	–	(3.02)	(13.84)
Model 4	-0.0318***	0.0614***	–	0.1027***	0.3551***
	(-3.20)	(3.67)	–	(3.29)	(13.90)

Note: This table reports annual cross-sectional regressions of $\ln(DOL^{FCF})$ on value measures (ln(B/M), ln(iB/M), ln(i/M)) controlling for ln(size). The "Agreement" ("Disagreement") sample consists of firm-year observations where economy-wide decile rankings based on iB/M and B/M differ by less than 3 (more than 3) t-statistics are Newey–West adjusted with 3 lags. Significance: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 9: DOL^{FCF} Regressions Across Subsamples

Panel A: Full Sample (Avg Firms/Year = 2607)

	Intercept	B/M	iB/M	i/M	Size
Model 1	1.0617***	0.2804***	–	–	0.0008
	(12.17)	(13.96)	–	–	(0.07)
Model 2	0.9249***	–	0.2742***	–	0.0139*
	(10.63)	–	(14.72)	–	(1.18)
Model 3	1.0586***	–	–	0.2634***	0.0097
	(13.32)	–	–	(14.64)	(0.81)
Model 4	0.9517***	0.1904***	–	0.2066***	0.0144*
	(11.60)	(8.60)	–	(12.95)	(2.11)
Panel B: Agreement Sample (Avg Firms/Year = 2355)					
Model 1	1.0429***	0.2985***	–	–	0.0021
	(10.32)	(8.85)	–	–	(0.16)
Model 2	0.9472***	–	0.2707***	–	0.0112
	(10.16)	–	(14.34)	–	(0.90)
Model 3	1.0743***	–	–	0.2852***	0.0068
	(13.01)	–	–	(17.78)	(0.55)
Model 4	0.9768***	0.1811***	–	0.2067***	0.0114
	(10.58)	(5.77)	–	(12.13)	(0.92)
Panel C: Disagreement Sample (Avg Firms/Year = 252)					
Model 1	1.1454***	0.0734	–	–	0.0136*
	(21.65)	(0.95)	–	–	(1.28)
Model 2	0.7932***	–	0.2919***	–	0.0350***
	(13.55)	–	(8.42)	–	(3.70)
Model 3	0.8499***	–	–	0.2567***	0.0420***
	(16.52)	–	–	(8.60)	(4.50)
Model 4	0.7976***	0.1517*	–	0.2663***	0.0400***
	(17.38)	(1.94)	–	(8.72)	(4.25)

Note: This table reports annual cross-sectional regressions of $\ln(DOL^{FCF})$ on value measures (ln(B/M), ln(iB/M), ln(i/M)) controlling for ln(size). The "Agreement" ("Disagreement") sample consists of firm-year observations where economy-wide decile rankings based on iB/M and B/M differ by less than 3 (more than 3) t-statistics are Newey–West adjusted with 3 lags. Significance: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 10: Fama–MacBeth Regressions: Robustness Tests with Different DOL Measures

Expl. V	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Panel A: DOL^{Q}							
DOL^{Q}	0.142***	–	–	–	0.116***	0.099***	0.114***
	(4.32)	–	–	–	(4.11)	(3.60)	(3.79)
B/M	–	0.135**	–	–	0.110*	–	–
	–	(2.16)	–	–	(1.80)	–	–
iB/M	–	–	0.170**	–	–	0.122*	–
	–	–	(2.36)	–	–	(1.93)	–
i/M	–	–	–	0.110**	–	–	0.122*
	–	–	–	(2.21)	–	–	(1.93)
Panel B: DOL^{FCF}							
DOL^{FCF}	0.061***	–	–	–	0.035*	0.025	0.037*
	(2.66)	–	–	–	(1.77)	(1.29)	(1.72)
B/M	–	0.184***	–	–	0.168***	–	–
	–	(2.85)	–	–	(2.79)	–	–
iB/M	–	–	0.207***	–	–	0.204***	–
	–	–	(3.11)	–	–	(3.09)	–
i/M	–	–	–	0.160***	–	–	0.156***
	–	–	–	(2.94)	–	–	(2.90)

Note: This table reports Fama–MacBeth (1973) average regression coefficients and Newey–West adjusted t-statistics (four lags). All independent variables are standardized to have mean zero and unit variance. Each specification includes controls for size, momentum, and reversal. DOL^{Q}, DOL^{FCF}, B/M, iB/M, i/M and size are log-transformed before standardization. The sample consists of U.S. common stocks from July 1977 to December 2023. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 11: Annual Regression Results at Firm Level Across Subsamples: Robustness test

	Intercept	B/M	iB/M	i/M	Size
Panel A: Full Sample (Avg Firms/Year = 2623)					
Model 1	0.0645	0.1904***	–	–	0.0026
	(1.20)	(13.86)	–	–	(0.10)
Model 2	0.0505	–	0.2473***	–	0.0565**
	(1.04)	–	(15.05)	–	(2.09)
Model 3	0.0559	–	–	0.2024***	0.0375
	(1.23)	–	–	(12.00)	(1.28)
Model 4	0.0528	0.1314***	–	0.1579***	0.0585**
	(1.07)	(13.39)	–	(10.20)	(2.19)
Panel B: Agreement Sample (Avg Firms/Year = 1893)					
Model 1	0.0735	0.2200***	–	–	0.0274
	(1.27)	(10.59)	–	–	(0.80)
Model 2	0.0761	–	0.2477***	–	0.0533
	(1.42)	–	(13.98)	–	(1.59)
Model 3	0.0829	–	–	0.2291***	0.0252
	(1.57)	–	–	(14.20)	(0.74)
Model 4	0.0714	0.1399***	–	0.1407***	0.0510
	(1.31)	(7.61)	–	(9.75)	(1.52)
Panel C: Disagreement Sample (Avg Firms/Year = 730)					
Model 1	0.0299	0.0425*	–	–	-0.0186
	(0.72)	(1.87)	–	–	(-1.25)
Model 2	-0.0021	–	0.2369***	–	0.0578***
	(-0.05)	–	(11.56)	–	(3.72)
Model 3	-0.0036	–	–	0.1645***	0.0747***
	(-0.12)	–	–	(9.15)	(4.00)
Model 4	0.0134	0.1161***	–	0.1806***	0.0742***
	(0.32)	(6.98)	–	(10.65)	(4.05)

Note: This table reports annual cross-sectional regressions of ln(DOL) on value measures (ln(B/M), ln(iB/M), ln(i/M)) controlling for ln(size). The "Agreement" sample consists of firm-year observations where economy-wide decile rankings based on iB/M and B/M differ by less than 2. Conversely, the "Disagreement" sample consists of firm-year observations where rankings differ by more than 2. Variables are standardized. t-statistics are Newey–West adjusted with 3 lags. Significance: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

A.4. Usage of AI

AI has contributed to this thesis in three primary ways: (1) Chat GPT was used to aid in writing parts of the python and LaTeX code used to generate our results and final pdf-file. We want to highlight that in all such cases, we provided clear instructions regarding the intended purpose and functionality of the code. We acknowledge the risk that AI can produce inaccurate output; therefore we always ensured we understood and agreed with code generated by AI. In addition, we believe AI usage likely reduced errors in the code as we often prompted Chat GPT to highlight potential issues with the code written by us. (2) In certain instances, AI has been used for language and grammatical purposes. In these cases, AI has only been used to give suggestions on how to improve clarity in phrasing without changing any of the original content or arguments made. (3) When searching for information related to specific literature areas, Chat GPT with search was sometimes used to find articles. However, we noted that it often gave inaccurate descriptions of content in recommended studies. Consequently, all sources referenced in this study have been fact checked and read independently. Since we do not use any proprietary data in our thesis, we see no material risk in data security. Moreover, no data used in our thesis has been gathered from AI output.

Reflecting on our thesis process; our perception is that AI tools have solely contributed to improving efficiency in the writing and coding process. Importantly, none of the findings or analyses in this thesis were produced by AI. All research insights and interpretations are the result of our own critical thinking and discussions.