Debt Amortisation Intensity and Firm Performance

Growth, Efficiency, and Stock Returns in U.S. Growth Firms

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Abstract

We study whether the intensity with which firms repay long-term debt affects investment, operating performance, and stock returns. Motivated by the increase in term loans with low or no amortisation, we analyse U.S. listed growth firms over 2015-2024 using a self-constructed accounting-based measure, Debt Amortisation Intensity (DAI), that captures the net cash outflow used to pay down long-term debt. In firm fixed-effects panel regressions, lower DAI is associated with higher CapEx intensity and faster sales and asset growth, whereas higher DAI is linked to modest improvements in operating profitability and efficiency. These patterns are consistent with agency cost views that required debt service disciplines managers and with the debt overhang theory that debt commitments can lead to underinvestment, and they suggest that DAI can operate as a lever: lower repayment intensity supports growth, while more intensive repayment improves efficiency. From a market perspective, lower subsequent DAI predicts higher returns, whereas trailing DAI has little explanatory power for both operating and return outcomes, suggesting that net repayment intensity mainly matters as a forward-looking financing choice.

Keywords:
Debt amortisation, Leveraged growth firms, Debt overhang and agency costs, Firm performance, Stock returns

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1. Introduction

Many firms rely on interest-bearing debt to finance growth, which creates a recurring claim on their cash flow through interest and principal payments. Every dollar used to repay debt is cash that cannot be reinvested in new projects, staff, or built capacity to support growth. Over the past few decades, however, the credit landscape has changed. Bank loans, traditionally characterised by shorter maturities and straight-line amortisation, have been replaced in large part by institutional term loans featuring longer maturities and substantially lower amortisation intensity, often in the form of backloaded or non-amortising structures (Settlements, 2008). As a result, managers now face a wider set of design choices that directly affect liquidity and financial flexibility. At one end, amortising bank loans with linear repayment schedules until maturity, and on the other end, bullet loans with no repayment before maturity. This has created a clear lever of "repayment speed", with higher repayment intensity decreasing leverage but increasing cash outflow each year, while low repayment intensity keeps leverage high but preserves internal funds for investment opportunities.

Foundational work on the operating effects of debt highlights two contrasting perspectives. In the Agency Cost of Free Cash Flow view (Jensen, 1986), managers may not always act in shareholders' best interest when they control large free cash flows. By committing a part of future cash flows to interest and principal payments, managers are forced to reduce slack and raise the cost of wasteful or low-return projects, forcing them to act more in line with the equity holders' interests (Jensen, 1986). At the same time, fixed payments can make it harder to finance attractive projects when they arise. In Myers' (1977) debt overhang logic, shareholders may skip positive-NPV investments because part of the gains would go to existing debt holders rather than equity holders.

However, these theories were developed in an environment where corporate debt was largely provided by banks on relatively standard amortising schedules. Today's market, mainly driven by institutional lenders, offers longer maturities and lower amortisation intensity (Settlements, 2008). As a result, the mechanisms of debt discipline and debt overhang may now operate not only through how much firms borrow and for how long, but also through how quickly they choose to repay. This suggests the need to revisit these established theories in the context of modern debt solutions.

Existing empirical work has mainly studied how much debt firms use and their maturity dates, rather than how and in what schedules they pay it back. Studies on debt maturity show that firms align maturities with asset lives, risk, and information problems, and that growth opportunities, monitoring (covenants), and market depth influence the choice between short- and long-term debt (Barclay & Smith, 1995; Stohs & Mauer, 1996; Johnson, 2003; Rauh & Sufi, 2010; Almeida et al., 2012). However, these studies focus on loan length rather than realised repayment behaviour. The limited existing evidence on repayment structure is nonetheless suggestive. Nini (2008) documents that the rise of private term loans, often structured as bullet loans, increased access to credit and funded greater CapEx and working capital investment. Nguyen (2022) shows that bullet term loans carry a higher spread than amortising loans, consistent with higher rollover risk. While maturity structure has received extensive empirical attention, amortisation intensity remains largely unexplored.

We study U.S. listed (non-financial, non-utility) firms with high growth opportunities and leverage, ensuring that both investment opportunities and debt choices are meaningful. In a post-2010 setting, managers have the power to choose how much cash to use to pay down existing debt versus to fund further expansion. To capture this choice, we construct an accounting-based measure of repayment intensity, Debt Amortisation Intensity (DAI), which reflects the realised net long-term debt repayment scaled by the opening balance of long-term debt. Firms with low DAI keep debt outstanding for longer and preserve more internal funds, and firms with high DAI reduce debt faster. Our central question is whether differences in net repayment intensity are systematically related to subsequent real and financial outcomes. Particularly, we examine how DAI is associated with subsequent investment intensity, asset and sales growth, and operating performance, and whether equity markets appear to price information in repayment behaviour. We address this using panel regressions that separate within-firm changes from between-firm differences in operating outcomes, and stock-return tests that relate DAI to subsequent equity performance.

2. Literature review

In basic corporate finance, a firm's value equals the present value of expected future cash flows discounted for risk (Modigliani & Miller, 1958; Damodaran, 2010). One way to increase these future cash flows is through value-creating investments, i.e., projects that generate returns above the firm's cost of capital. From this perspective, financing decisions influence both the cost of capital and the firm's capacity to invest. Debt commits the firm to fixed interest and principal payments, which reduces the financial flexibility available for new projects. For growth firms with many investment opportunities, this leads to a simple trade-off: cash used for new projects can drive future growth, while cash used to repay debt lowers leverage and risk today.

This link between investment, debt financing, value and operating performance is the foundation on which the literature review and thesis is built around.

2.1 Capital Structure Frictions: Agency costs, and Debt Overhang

Agency theory views the firm as a set of contracts between different parties. Managers control decisions about spending, hiring, and investment, while shareholders receive the residual cash flows after all obligations are paid. This separation creates agency costs when managerial decisions deviate from value maximisation (Jensen & Meckling, 1979). There are two main frictions. First, conflicts between shareholders and debtholders, where equity may favour risk-shifting once debt is in place; and second, conflicts between managers and shareholders, where managers with limited upside or downside may prefer perks, a "quiet life", or empire-building investments that raise size and status rather than shareholder value.

Jensen (1986) narrows this problem in the Agency Cost of Free Cash Flow (FCF) problem. When internal cash exceeds the funding needs of positive-NPV projects, managers are tempted to overinvest, grow excessive spending, or resist payouts. Debt can prevent this by committing the firm to scheduled interest and principal payments, increasing creditor monitoring, and raising the threat of loss of control if covenants are breached. These mechanisms motivate managers to reduce waste and improve efficiency. The disciplining effect is theoretically strongest in cash-rich, low-growth firms, where excess cash is most likely to be found.

For growth firms, the trade-off shifts. When positive-NPV investment opportunities are high, and cash conversion is weaker, high required payouts can starve valuable projects risking underinvestment. In such cases preserving principal through bullet structures preserves near-term liquidity and investment flexibility, allowing firms to fund e.g., capex and R&D. Amortising structures do the opposite, they run down principal faster, easing future rollover risk but tightening near-term cash flows.

Myers (1977) formalises this tension as the "debt overhang" problem. Firm value equals the value of assets in place plus the present value of future investment opportunities. With only equity, all positive-NPV projects are undertaken. With debt outstanding at the decision date, some positive-NPV projects are rejected because part of their payoffs would go to existing debt holders. Equity requires that new projects cover both their cost and the promised debt payment; otherwise, shareholders prefer not to invest. This underinvestment lowers today's equity value because markets anticipate that some profitable projects will be skipped and may operationally translate to slower growth.

As the distortion arises when risky debt remains outstanding at the time investment decisions are made, the timing of debt maturity matters. Rather than using leverage only to capture tax shields, Myers' analysis implies that firms face a trade-off between the benefits of debt and the value destroyed by underinvestment. In his framework, the maturity structure of risky debt is a key lever, if debt is set to mature or be retired before major investment opportunities arise, the underinvestment problem is reduced.

To summarise, agency cost theories explain why misaligned incentives may increase wasteful spending or underinvestment, Jensen's free cash flow view highlights recurring payouts as a mechanism to curb waste, and Myers' debt overhang view shows how debt can also block valuable projects when it survives into key investment windows.

2.2 Debt Structure and Design Choices

Within corporate debt contracts, two well-studied features are maturity structure and covenant intensity. Maturity determines when debt must be refinanced and how rollover risk evolve over time, while covenants function as monitoring and early-warning tools that shift controls to creditors when performance gets worse. These features together influence firms' flexibility, risk-taking incentives, and investment capacity.

Repayment structure interacts with these features by determining the timing of principal outflows within the maturity horizon, shaping near-term liquidity and the buildup of future refinancing pressure. In practice, amortisation profiles, maturities, and covenant packages are chosen together and jointly affect investment flexibility and risk.

Among these design elements, maturity structure is the closest research area to our setting because both maturity and amortisation intensity determine the timing of debt repayment and operate through similar channels such as liquidity management and rollover risk. Our study extends this literature by shifting the focus from when debt comes due to how intensively firms repay it within the maturity horizon. The following subsections review the evidence on these design choices.

2.2.1 Determinants and Effects of Maturity Structures

In general, maturity is shaped by fundamental firm characteristics and market conditions. Barclay and Smith (1995) find that US listed firms tend to align debt maturity with the life of their assets and with information frictions. Longer-lived assets, larger size, and lower information asymmetry are associated with longer maturities. Stohs and Mauer (1996) similarly show that firms with longer-lived assets and lower risk borrow at longer maturities, and that more highly levered firms tilt toward longer maturities, consistent with managing rollover and liquidity risk.

Differing from the general firm population, firms with substantial growth opportunities face other drivers of maturity choice. Consistent with Myers' (1977) underinvestment logic, Johnson (2003) finds that firms with more valuable growth opportunities tend to adopt shorter maturities, by using more frequent repricing and monitoring to mitigate debt overhang. Rauh and Sufi (2010) show that access to monitored bank debt with tighter covenants allows lower-quality borrowers to sustain longer maturities than they otherwise could, suggesting that creditor oversight can substitute for shorter tenors.

Maturity structure also has documented real effects on investment, growth, and profitability. Aivazian et al. (2005) find that a higher share of long-term debt is associated with lower investment, with the negative relation being strongest for firms with low growth opportunities. Schiantarelli and Sembenelli (1997) show that longer initial maturities are associated with slightly higher investment, higher sales growth, and improved medium-run profitability. Almeida et al. (2012) exploit the 2007-08 credit contraction and demonstrate that firms whose long-term debt happened to mature just after 2007 cut investment by roughly one-third relative to otherwise similar peers with later maturities.

2.2.2 Covenant Flexibility and Repayment Structure

Whereas maturity structure governs the timing of refinancing and liquidity risk, covenant design governs borrower behaviour by determining how lenders monitor performance and when control rights shift. Maintenance covenants act as early-warning mechanisms that trigger renegotiation or shift of control before distress, while covenant-light structures give managers greater freedom. Nini, Smith and Sufi (2009) show that covenant violations lead to tighter lender oversight and subsequent reductions in capex and asset growth, consistent with covenants mitigating free-cash-flow problems. Spyridopoulos (2019) finds that tighter covenant facilities are associated with higher profitability and firm value even in the absence of violations, suggesting an ex-ante disciplining role consistent with the free-cash-flow agency framework. Consistent with this evidence on the importance of monitoring and control rights, covenant-light loans are priced at higher spreads and exhibit higher default risk (Demerjian, Horne & Moon, 2020; Bräuning, Ivashina & Ozdagli, 2021), reflecting the additional risk lenders bear when contractual monitoring is reduced. In this thesis, we do not model covenant terms, but view them as part of the broader debt design environment that affects investment flexibility and risk.

In parallel with the monitoring role of covenants, the repayment structure determines the schedule of cash outflows that drives firms' liquidity positions and refinancing exposure over time. Empirical evidence on repayment structure is limited, partly due to the difficulty of observing amortisation schedules at scale. The available evidence however, points to meaningful effects. Nini (2008) shows that the rise of private term loans[1], often with bullet structure, increased accessibility of credit for riskier borrowers, with the issuers increasing their CapEx investments and working capital. Nguyen (2022) finds that US syndicated bullet term loans are priced at materially higher spreads than amortising loans and that borrowers on amortising schedules are more likely to refinance successfully, indicating that bullet repayment embeds higher rollover risk that lenders price accordingly.

The literature shows that debt structure and design choices have real economic effects. Research on maturity and covenants show that these features influence refinancing risk, control rights, and investment outcomes, and that growth firms in particular exhibit distinct maturity patterns relative to the general firm population. Existing work on repayment flexibility suggests that bullet repayment structures may relax near-term constraints and increase CapEx investments for some borrowers; yet, compared with the extensive evidence on maturity and covenants, the role of realised debt repayment remains relatively underexplored.

[1] Corporate loans with a fixed maturity that are drawn for a set term rather than on a revolving basis

2.3 Debt, Investment and Firm Outcomes

One main channel through which repayment structure should affect firm outcomes is investment. Repayment intensity affects internal liquidity and debt overhang; liquidity and financing conditions influence CapEx and expansion decisions; and the level and quality of investment feed into future growth and operating performance.

Prior work documents that higher investment, intuitively, is not automatically value-creating. Kothari, Lewellen and Warner (2020) show that periods of high profits are followed by rapid investments. However, these investments are subsequently followed by slower profit growth, suggesting that firms extrapolate past earnings into excessive expansion. Richardson (2006) finds that firms that over-invest free cash flow subsequently exhibit weaker operating performance, in line with free-cash-flow agency costs. Evidence for Swedish companies in Lööf and Heshmati (2008) show that investment and performance (sales, profits, cash flow, and employment) affect each other, but as many of these effects are only temporary and differ by firm, and suggest that investment does not, on average, lead to permanent improvements in operations. By contrast, Pandit, Wasley and Zach (2009) show that more productive R&D, as measured by patent outcomes, is associated with higher and more stable future operating performance. Real earnings management (REM) studies (e.g. Habib et al, 2022) report that opportunistic REM, on average, impairs long-run operating performance, suggesting that under-investment to manage earnings can also be value-reducing.

Leverage levels are also associated with differences in firm performance and behaviour. Lang, Ofek and Stulz (1996) show that leverage is negatively related to future growth, especially for firms with low Tobin's Q, which suggests that high debt levels constrain expansion when growth opportunities are weak. Dang (2011) finds that leverage has a negative effect on firm investment. Together with the maturity and repayment evidence in Section 2.2, this suggests that both under- and over-investment are costly. Tight debt and heavy scheduled debt repayments can force firms to skip good projects, while excessive internal cash and weak discipline can sustain value-destroying expansion.

For growth firms, a higher amortisation intensity tightens near-term liquidity and can increase the risk of inefficient under-investment, slowing subsequent growth but improving profitability. On the contrary, lower amortisation intensity preserves internal funds and should allow firms to undertake growth investments but also raises the risk of over-investment if governance and discipline are weak.

2.4 Relationship between Investment, Leverage, and Returns

Modigliani-Miller (MM) propositions provide the starting point of this section. In a frictionless market, a firm's value should be independent of capital structure (Proposition I), and the cost of equity rises with leverage so that the weighted average cost of capital remains constant (Proposition II) (Modigliani & Miller, 1958). With corporate taxes, debt adds value via the interest tax shield (Modigliani & Miller, 1963), but absent frictions, the design of debt (e.g. covenants, duration, amortisation intensity) should not affect firm value.

Contrary to the MM propositions, early cross-sectional work by Bhandari (1988) documented a positive relationship between leverage and equity returns, suggesting that the premium associated with leverage is unlikely to be a mere risk premium. However, asset-pricing studies, most notably Fama and French (1992 & 1993), found that after accounting for value, profitability, and investment factors, those relations are largely absorbed. Further, Penman, Richardson, and Tuna (2007) decomposed market-to-book into operating and financing components, concluding that the "value premium" reflects operating fundamentals rather than leverage per se.

Investment and asset-growth research extend this view. Titman, Wei and Xie (2004) show that firms with high capital investment earn lower subsequent stock returns. Cooper, Gulen and Schill (2008) similarly find that firms with faster growth in total assets experience systematically lower future returns. Richardson (2006) links over-investment to poor abnormal returns.

Literature on rollover risk and debt design challenges the theory that leverage, or its design, has no effect on firm value. He and Xiong (2012) show that with short maturities and bunched refinancing needs, creditors face greater coordination and run risk, which raises the firm's endogenous default threshold and should be reflected in required returns. Gopalan, Song and Yerramilli (2014) provide empirical evidence that firms with larger near-term maturity walls exhibit weaker credit quality and wider spreads, consistent with markets pricing rollover exposure. Consistently, Nguyen (2022) found that "bullet" loans (loans without principal payments) carry, on average, an additional 46 bps in interest rate relative to amortised loans, which in the sample corresponds to 1.7 million USD in additional annual interest payments. Nguyen also shows that borrowers on amortising schedules are more likely to refinance successfully, consistent with lower rollover risk.

Together, the cross-sectional evidence offers little support for a persistent leverage-return relation. *However, most of this work emphasises how much rather than what debt firms use.* The open question is thus whether, and through what frictions, debt design is priced. Extending the MM propositions' logic, any systematic pricing of debt characteristics should arise from real-world frictions such as rollover risk and agency conflicts.

2.5 Hypotheses Development

In this section, we summarise main insights from the literature and translate them into testable hypotheses about how debt repayment intensity, measured through DAI (see 3.2.1), relates to operating and market performance for leveraged growth firms.

Debt frictions: discipline versus flexibility
Agency and free-cash-flow theories view debt as a way to limit wasteful investment by forcing regular payouts (Jensen & Meckling, 1979; Jensen, 1986). The debt overhang theory instead suggests that when debt is still outstanding in important investment periods, shareholders may skip positive-NPV projects because some of the gains go to existing debtholders, leading to underinvestment and lower firm value (Myers, 1977). Empirical work links these frictions to the design of debt. Maturity and repayment profile affect when cash leaves the firm, and in this way they shape the trade-off between discipline, investment flexibility, and rollover risk, especially for firms with growth opportunities (Barclay & Smith, 1995; Stohs & Mauer, 1996; Johnson, 2003; Aivazian et al., 2005; Schiantarelli & Sembenelli, 1997; Almeida et al., 2012; Nini, 2008; Nini, Smith & Sufi, 2009; Nguyen, 2022). In modern credit markets, this trade-off not only operates through how much firms borrow and when their debt matures, but also through the timing and intensity of amortisation.

Investment as the channel to operating firm performance
Several studies show that high or abnormal investment is often followed by slower profit growth and weaker operating performance, consistent with managers over extrapolating good times or overinvesting free cash flow (Richardson, 2006; Kothari, Lewellen & Warner, 2020; Lööf & Heshmati, 2008). Other studies show that more productive investment, for example, successful R&D, is linked to higher and more stable future earnings and cash flows, while cuts in investment to meet short-term earnings targets may harm long-run profitability (Pandit, Wasley & Zach, 2009; Habib et al., 2022). Leverage and debt structure help explain where firms end up in this spectrum, high leverage and tight debt structures limit investment and growth, especially when growth opportunities are weak, while firms with high growth opportunities often reduce leverage or adjust debt design to avoid severe underinvestment (Lang, Ofek & Stulz, 1996; Dang, 2011; Aivazian et al., 2005; Almeida et al., 2012). For leveraged growth firms, the way debt is repaid determines how much

internal cash is available for investment in each period and should therefore be linked to later growth, capex, and operating performance.

Debt design, and expected returns

Empirical work shows that leverage by itself contributes little to explaining stock-return differences once standard factors are considered (Fama & French, 1992, 1993; Penman, Richardson & Tuna, 2007). Meanwhile, investment and asset-growth studies demonstrate that high investment rates and rapid balance-sheet expansion predict lower subsequent returns, suggesting that investment policy is priced (Titman, Wei & Xie, 2004; Cooper, Gulen & Schill, 2008; Richardson, 2006). Research on debt design introduces a complementary view. Concentrated maturities and bullet structures elevate rollover risk, credit spreads, and default thresholds, whereas amortising structures improve refinancing outcomes (He & Xiong, 2012; Gopalan, Song & Yerramilli, 2014; Nguyen, 2022). Together, these findings imply that the structure of debt, especially the timing and intensity of repayment, may influence expected returns by shaping firms' risk profiles and investment behaviour.

Building on these findings, we focus on how debt design should matter for leveraged growth firms. In our setting, the key design margin is the intensity of debt repayment. We capture this through our self-developed measure *Debt Amortisation Intensity (DAI;* see section 3.2.1), an annual firm-level measure of how aggressively outstanding interest-bearing debt is paid down over a given horizon. We distinguish between **subsequent DAI** (relative to the base year), realised over future horizons (k = 1, 3, and 5 years), and **trailing DAI**, measured as a three-year average up to the base year.

Firm-level operational hypotheses

Lower subsequent DAI backloads principal payments, preserves cash in the near term, and reduces the underinvestment risk. In a debt overhang setting, this weakens the invest-or-skip distortion and relaxes internal financing constraints. At the same time, more back-loaded repayment keeps leverage higher for longer and increase refinancing risk. We expect years with lower subsequent DAI to be associated with stronger expansion and higher investment intensity.

***H_1*:** *For leveraged growth firms, lower subsequent DAI is associated with stronger expansion and investment over the 1-, 3-, and 5-year horizons, measured by higher growth in sales and total assets and a higher investment intensity*

If debt and increased repayment intensity curb wasteful spending and limit overinvestment, higher subsequent DAI should improve operating efficiency and margins. At the same time, greater repayment flexibility (lower DAI) allows firms to fund valuable projects. Thus, the net impact of subsequent DAI on operating performance is therefore ambiguous, but we expect repayment intensity to be systematically related to profitability and efficiency.

H_2: *For leveraged growth firms, subsequent DAI is associated with changes in operating performance over the 1-, 3-, and 5-year horizons, measured by changes in operating ROA, operating margin, and asset turnover.*

If firms' debt structures are persistent, past amortisation behaviour should carry information about how they will expand, invest, and perform going forward. A low trailing DAI means that the firm has historically chosen more back-loaded repayment, kept more cash inside the firm, and may have supported growth, but has also kept leverage higher for longer. As with subsequent DAI, this can either help or hurt future outcomes depending on the quality of the projects and how refinancing risk plays out. Ex ante, the net effect of trailing DAI on later expansion, investment, and operating performance is therefore ambiguous.

H_3: *For leveraged growth firms, trailing DAI is associated with changes in subsequent expansion, investment, and operating efficiency over the 1-, 3-, and 5-year horizons, using the same measures as in H1 and H2.*

Market-level hypotheses

Our literature suggests that repayment structure should be associated with differences in equity returns. Operationally, lower DAI supports investment and growth but raises risk, whereas higher DAI tends to improve efficiency and reduce volatility. From a market perspective, lower DAI increases rollover risk and keeps leverage elevated for longer, while higher DAI deleverages the firm and reduces financing risk. Although credit markets price these risk channels explicitly, equity investors may adjust more gradually, particularly since debt design is less salient than the quantum of debt. Consequently, firms that exhibit different DAI levels may display systematically different return patterns.

H_4: *For leveraged growth firms, DAI is related to subsequent stock returns over the 1-, 3-, and 5-year horizons, with lower DAI expected to be associated with higher future returns*

H_5: *A tradeable (ex-ante) portfolio strategy formed on differences in DAI produces economically meaningful return spreads*

3. Method

3.1 Data and Sample Selection

We collect firm-level financial statement data from Compustat and stock return data from CRSP. The sample includes all firms listed on major U.S. exchanges (NYSE, AMEX, NASDAQ) from December 31, 2014, to December 31, 2024. Following prior literature, we exclude financial firms (SIC 6000-6999), utilities (SIC 4900-4999), and public service, international affairs, or non-operating entities (SIC ≥ 9000) due to differences in book values and leverage (Peters & Taylor, 2017). We also remove firm-year observations lacking sufficient data to calculate book-to-market equity, stock returns, DAI, as well as those with negative book equity.

Additionally, because the Debt Amortisation Intensity (DAI) is only meaningful when firms use debt, we exclude low-leverage observations using both book and market leverage.

$$Book\ Leverage_t = \frac{Long - Term\ Debt_t + \ Current\ portion\ of\ Long - Term\ Debt_t}{Total\ assets_t}$$

$$Market\ Leverage_t = \frac{LTD_t + \ CPLTD_t}{LTD_t + \ CPLTD_t + Market\ Value\ of\ Equity_t}$$

Firms with BL < 15% OR ML < 15% are removed from the sample. Using both Book Leverage and Market Leverage avoids results hinging on accounting vs. market scaling. The following section describes how we identify growth firms in the sample.

Table 1: Sample Selection

Panel A: Sample selection (2015-2024)		
Description	**Firm-years**	*%*
All firm-year observations (excl. financial, utility)	44 231	*100%*
Growth firm-years (see 3.1.1)	14 690	*33%*
Significant leverage (>15%)	3 697	*8%*
Non-missing forward DAI, k = 1	3 160	*7%*
Non-missing forward DAI, k = 3	2 030	*5%*
Non-missing forward DAI, k = 5	1 390	*3%*

3.1.1 Tobin's Q as a Proxy for Growth Opportunities

To proxy for growth opportunities, we use Tobin's Q. It is the ratio between what the market values a firm and what it would cost to rebuild the firm (the replacement value of its assets). Intuitively, a Q > 1 means the market values the firm more highly than the cost of its physical assets alone, suggesting that investors expect the firm to have strong growth prospects and/or valuable intangible assets. A Q < 1 indicates the opposite, the firm's assets are worth more than what the market currently believes the firm can generate in future returns. Because of this forward-looking interpretation, Tobin's Q is widely used in empirical corporate finance (e.g., Lang & Stulz, 1993; Lang, Stulz & Walkling, 1991). In this study, a high-Q value proxies high growth opportunities.

For measurement, we use the Chung-Pruitt (1994) approximation, which builds Q from market equity, preferred stock, debt, and total assets. It is a simplified measure that's highly correlated with more detailed Q measures, making it suitable for large panels like ours. Chung-Pruitt's approximation is calculated using the following formula:

$$Q_{i.t} = \frac{MVE_{i,t} + PS_{i,t} + DEBT_{i,t}}{TA_{i,t}}$$

Where *MVE* is the market value of equity, *PS* is the liquidating value of the preferred stock, *DEBT* is the current liabilities net of current assets plus the book value of the long-term debt and *TA* is the book value of total assets.

Industry mapping and normalisation of Q

We standardise Tobin's Q in three steps, making the measure comparable across sectors and over time: (i) map firms to broad industries, (ii) yearly winsorisation, and (iii) industry-year benchmark.

i. Assign firm to industries

Each firm-year is mapped from its SIC code to one of the Fama-French 12 industries using the SIC conversion from the Kenneth French Data Library (Fama & French, 1997).

ii. Yealy winsorisation (1/99th percentiles)

Within each fiscal year, we winsorise the cross-section of raw Q at the 1st and 99th percentiles to reduce the influence of extreme observations.

iii. Define growth firms within industry-years

Because typical Q levels differ across industries, we first compute an industry-year adjusted Q by subtracting the industry-year median from each firm's winsorised Q. Within each industry-year, we then split the adjusted Q distribution into three terciles using the top tercile to denote "growth firms".

3.2 Key Variables

3.2.1 Debt Amortisation Intensity (DAI)

We developed *Debt Amortisation Intensity (DAI)* to quantify how much long-term debt a firm pays down with cash in year t, net of rollovers and refinancing, scaled by beginning long-term debt. *In our construction, a low DAI represents a lower debt repayment, and vice versa.* We acknowledge that this is not an either academically or professionally established measure, and thus, the results should be read with caution. We adopt this implementation because it isolates debt repayment with variables available at scale. The four-step construction follows.

Note: $\Delta X_t \equiv X_t - X_{t-1}$

1. **Net cash repayment of long-term debt**

$$LTDRepay_t = max\{0, LTD\ Reductions_t - LTD\ Issuance_t\}$$

Where *LTD Reductions* are cash repayments of long-term debt and *LTD Issuance* are cash proceeds from new long-term debt. The data is collected from firms' cash flow statements and aims not to misinterpret cash payments as scheduled principal payments when firms refinance their loans. If issuance ≥ reductions, we set LTDRepay to zero. Thus, we capture net repayment only (not net borrowing or rollovers).

2. **Short-term debt offset**

$$\Delta ST_t^{pure} = \Delta Current\ Debt_t - \Delta Current\ portion\ of\ LT\ Debt_t$$

Current Debt is the total current interest-bearing debt (including the *Current portion of LT Debt (CPLTD)*. This construction isolates new short-term borrowing rather than the mechanical bump when LT Debt moves into *Current portion of LT Debt*. We keep only the increases and cap the offset at the period's net LT repayment:

$$ST\ Offset_t = min\{max(0, \Delta ST_t^{pure}), LTDRepay_t\}$$

This only keeps increases in short-term funding; decreases are not credited as "extra" LT amortisation. The min cap limits the offset to the period's net LTD repayment, so that short-term borrowing can only offset actual LT paydown, never exceed it or make amortisation negative.

3. **Amortisation cash flow that reduces LT debt**

$$AmortCF_t = LTDRepay_t - ST\ Offset_t$$

This leaves us with the difference in cash that actually reduces long-term debt. If short-term borrowing fully funds the period's $LTDRepay$, then $AmortCF = 0$.

By construction $0 \leq ST\ Offset_t \leq LTDRepay_t$, so $AmortCF_t \geq 0$.

4. **Scale by the opening balance of long-term debt**

$$DAI_t = min\left\{1, \frac{AmortCF_t}{Total\ LT\ Debt_{t-1}}\right\} \text{ (defined only if } Total\ LT\ Debt_{t-1} > 0\text{)}$$

Scaling by LTD_{t-1} results in an intensive share. In theory, $DAI_t \leq 1$ because issuance is netted and $ST_t^{Pure} \leq LTDRepay_t$. We cap at 1 only as a safeguard against denominator mismatches or classification noise[2].

Numeric example

Inputs		**Firm A**	**Firm B**
Opening long-term Debt(Total LT $Debt_{t-1}$):		100	100
Long-term debt reduction (LTD $Reductions_t$):		30	30
Long-term debt issuance (LTD $Issuance_t$):		10	50
Change of Current debt, excl. CPLTD (ΔS_t^{pure})		5	3
Step	Definition	**Firm A**	**Firm B**
1	max{0, LTD $Reductions_t$ - LTD $Issuance_t$}	max(0, 30-10) = 20	max(0, 30 - 50) = 0
2	min{max(0, ΔST_t^{pure}), $LTDRepay_t$}	min(max(0, 5), 20) = 20	min(max(0, 3), 0) = 0
3	$LTDRepay_t$ - ST $Offset_t$	20 - 5 = 15	0 - 0 = 0
4	min{1, $AmortCF_t$ / Total LT $Debt_{(t-1)}$}	min(0, 15/100) = 15%	min(0, 0/100) = 0%

3.2.2 Operating Performance and Investment Activity

To test whether trailing (ex-ante) and subsequent (ex-post) measures of *Debt Amortisation Intensity* (DAI) predict or are contemporaneously associated with real operating outcomes, we are using standard accounting measures of investment and operating performance over +1, +3, and +5 years. All variables are constructed at the fiscal-year level and aligned on the base year t in which we observe DAI, so that outcomes reflect subsequent developments. Our choice of metrics follows the corporate finance and accounting literatures that evaluate firm performance using growth, profitability, and efficiency measures (Fama & French, 1995; Lang, Ofek, and Stulz, 1996; Fairfield and Yohn, 2001; Fairfield, Whisenant, and Yohn, 2003; Cai & Zhang, 2011).

[2] Such cases can arise if, for example, convertibles are included in cash flows but excluded from LTD, or around M&A, or FX effects

Firstly, we capture investment activity using capital expenditure intensity, defined as capital expenditure scaled by the opening balance of total assets. For the three- and five-year horizons, we take the simple average of CapEx intensity over years *t+1* to *t+3* and *t+1* to *t+5*, respectively. These averages proxy for how persistently firms invest following the debt-design observation.

$$CapEx\ Intensity_t = \frac{CapEx_t}{Total\ Assets_{t-1}}$$

Secondly, we track scale and operating expansion using cumulative growth in Sales, Total Assets, and Operating Income (EBITDA). For each horizon $k \epsilon \{1,3,5\}$, we measure growth as the log change between year *t* and *t+k*:

$$\Delta ln(Sales_k) = ln(Sales_{t+k}) - ln(Sales_t),$$

with analogous definitions for Total Assets and Operating Income.

Finally, we measure profitability and efficiency through changes in Operating Return on Assets, Operating Margin, and Asset Turnover. For each firm-year, we define:

$$Op.ROA_t = \frac{EBITDA_t}{Total\ assets_t},$$

$$Op.Margin_t = \frac{EBITDA_t}{Sales_t},$$

$$Asset\ Turnover_t = \frac{Sales_t}{Total\ assets_t}$$

and compute horizon-*k* changes as level differences, e.g.:

$$\Delta Op.ROA_k = Op.ROA_{t+k} - Op.ROA_k,$$

with analogous definitions of Operating Margin and Asset Turnover. These deltas capture whether firms with different DAI-profiles improve profitability and efficiency relative to their base-year position. All outcome variables are winsorised by the fiscal year at the 1st and 99th percentiles.

3.3 Research Design

3.3.1 Hypothesis 1-3: Fixed Effects and Correlated Random Effects

We test *Hypothesis 1-3* by estimating panel regressions of subsequent growth, investment, and operating efficiency on *Debt Amortisation Intensity (DAI).* The unit of observation is the firm-year, and the dependent variables are growth in sales, assets, and operating income, investment intensity (CapEx/Assets), and changes in operating efficiency (ΔOp.ROA, ΔOp.Margin, ΔAsset Turnover) over horizons of +1, +3, and +5 years. All specifications condition on firms being classified as "growth firms" in the base year and on meeting our leverage cut-off and data availability screens (see *Sections 3.1-3.2*).

To capture both within-firm and cross-sectional links between DAI and operating performance, we use firm fixed effects (FE) and correlated random effects (CRE) models, following panel regression designs in Aivazian, Ge, and Qiu (2005) and Denis and Sibilkov (2010), and the Mundlak-type CRE implementation in La Cava (2016). The FE specification is our main test and captures how changes in DAI within a firm over time are associated with changes in outcomes, controlling for time-invariant firm characteristics and fiscal year fixed effects. The CRE specification follows a Mundlak approach, where we add firm-level averages of DAI and the controls to a random-effects model so that we can separate the within-firm effect from the between-firm effect, i.e. operating differences between firms that on average have high versus low DAI (Mundlak, 1978; Wooldridge, 2010). Although the CRE specification is rarely used in similar corporate-finance and accounting settings, we implement it to add a dimension that captures differences between firms that persistently operate with high versus low DAI.

Our main subsequent specification can be written as:

$$Y_{i,t+k} = \beta_k^{sbsq} DAI_{i,t,k}^{sbsq} + \gamma_k X_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t+k}$$

where $Y_{i,t+k}$ is the outcome for firm i over horizon k, $DAI_{i,t,k}^{sbsq}$ is the horizon-specific subsequent DAI measure (defined below), $X_{i,k}$ is the vector of controls, μ_i are firm effects, λ_i are year effects, and $\varepsilon_{i,t+k}$ is the error term. The control vector $X_{i,k}$ includes book leverage, operating profitability, cash holdings, and firm size (log total assets).

In the CRE model, we keep a random firm effect and add firm-level averages of DAI and the controls:

$$Y_{i,t+k} = \beta_k^{sbsq} DAI_{i,t,k}^{sbsq} + \Theta_k^{sbsq}\, \overline{\mathrm{DAI}_{\iota,k}^{sbsq}} + \gamma_k X_{i,t} + \delta_i \overline{X}_\iota + \eta_i + \lambda_t + \varepsilon_{i,t+k}$$

where $\overline{\mathrm{DAI}_{\iota,k}^{sbsq}}$ and $\overline{X}_\iota$ are the firm-level averages of subsequent DAI and the controls, and η_i is a random firm effect. In this setup, β_k^{sbsq} captures the within-firm effect of DAI (directly comparable to the FE estimate), while Θ_k^{sbsq} captures the between-firm association between a firm's average DAI and its average operating performance.

Main specification: Subsequent DAI

Our main tests use an ex-post measure of subsequent DAI. For each base year t and horizon *(1, 3, 5)*, we compute subsequent DAI as the simple average of annual DAI over years $t+1$ to $t+k$. This measure shows a firm's realised net repayment of the long-term debt after the base year of growth indication. In the regressions, horizon-k subsequent DAI is the key explanatory variable and is aligned with outcomes constructed over the same horizon, so we ask whether firms that choose a more or less amortisation-intensive profile in years $t+1$ to $t+k$ differ in their subsequent growth, investment, and operating performance.

Predictive specification: Trailing DAI

As a complementary design, we also estimate predictive specifications based on trailing DAI (ex-ante). Here, we replace subsequent DAI with a three-year trailing average of DAI up to and including year t, and relate this historical repayment behaviour to outcomes over the same horizons. These regressions use the same outcome variables and FE/CRE setups as the main tests but address a different question: whether past amortisation patterns help predict later growth, investment, and operating performance.

All regressions are estimated on the panel of growth and levered firms defined in Section 3.1. We estimate separate models for each outcome and horizon using OLS with firm and year fixed effects (FE) as our main specification, and CRE as a complementary benchmark. Standard errors are clustered at the firm level to account for serial correlation within firms. All outcome variables and controls are winsorised by fiscal year at the 1st and 99th percentiles, and DAI is capped at 1 after winsorisation to limit the influence of outliers and classification noise. In the results tables, we report coefficients, clustered t-statistics, and standard significance levels. To help interpretation, we also scale the DAI coefficient by a 0.10 change in DAI.

3.3.2 Hypothesis 4-5: Cross-Sectional and Portfolio-Based Market tests

To test whether DAI is reflected in expected stock returns, we implement two complementary asset-pricing approaches, (i) Fama-MacBeth (1973) cross-sectional regressions and (ii) portfolio-sorting tests with Fama-French five-factor (FF5) risk adjustment. The two approaches are often combined (Fama & French, 1992 & 2015; Park, 2022) as each address different inferential challenges. Whilst both tests whether DAI is associated with returns, they examine different dimensions of this relationship. Fama-MacBeth regressions use all firms and the full distribution of DAI values to estimate a continuous marginal effect. Portfolio tests, by contrast, apply a simpler and more intuitive approach by examining whether the economic return spread between high- and low-DAI firms is large, persistent, and robust. Consistent evidence across both methods strengthens the inference that DAI carries information about expected returns; divergence informs whether effects are non-linear, economically small, or absorbed by established factors. Consistent with the accounting tests, the market-return regressions use the same panel of growth and levered firms defined in Section 3.1.

Fama-MacBeth cross-sectional regressions

Following long-horizon return studies, we compute firm-level buy-and-hold abnormal returns (BHAR) over 12-, 36-, and 60-month windows using log-compounded returns after adjusting stock returns for stock splits, cash distributions, and delisting returns.

$$BHAR_{i,t}^{k} = \prod_{h=0}^{k-1} \left(1 + r_{i,t+j}\right) - 1$$

Long-horizon dependent variables are constructed as in Barber and Lyon (1997), who emphasise the importance of compounding and overlapping windows when studying multi-year performance. We align horizons with subsequent DAI measures (DAI_k) to examine whether repayment intensity predicts short-, medium- and long-run returns.

Given that Fama and French (1992) showed that Bhandari's leverage-return relation weakens substantially once standard controls are applied, we draw inspiration from both their choice of control variables and their specification. Firm size is measured as market equity, calculated as the stock price times shares outstanding, $ME_{i,t} = Price_{i,t} \times Shares_{i,t}$ and we use the log of market equity in the regressions. Book-to-market is defined as common equity scaled by market equity, $B/M_{i,t} = CEQ_{i,t} / ME_{i,t}$. Market leverage follows their market-value formulation, computed as long-term debt divided by the sum of long-term debt and market equity, $LEV_{i,t} = DLTT_{i,t} / (DLTT_{i+t} + ME_{i,t})$.

However, while Fama and French (1992) estimate Fama-MacBeth regressions using raw firm characteristics, our setting differs in two important ways that motivate standardising all variables within each cross-section. First, we analyse long-horizon BHARs (12, 36, and 60 months), which exhibit substantially different cross-sectional volatilities and fat-tailed distributions compared with the monthly excess returns used in Fama and French (1992). Second, DAI is measured on a bounded 0-1 scale, whereas the size and book-to-market measures exhibit results on different scales. Scaling thus helps comparability of coefficients across characteristics and horizons while mitigating the influence of extreme observations.

$$z_{i,t} = \frac{x_{i,t} - \bar{x}_t}{\sigma_t(x)}$$

where

- $x_{i,t}$ is the raw characteristic for firm i in cross-section t
- $\bar{x}_t$ is the cross-sectional mean
- $\sigma_t(x)$ is the cross-sectional standard deviation

For each month, we then estimate the following standardised cross-sectional regression:

$$z(BHAR_{i,t+k}) \equiv \alpha_t + \beta_t z(DAI_{i,t}) + \gamma_1 z(BM_{i,t}) + \gamma_2 z(Size_{i,t}) + \gamma_3 z(Lev_{i,t}) + \varepsilon_{i,t}$$

We then average the monthly coefficients over time, using Newey-West (1987) standard errors with lags of 11, 35, and 59 months for the 12-, 36-, and 60-month horizons, respectively, to correct for serial correlation induced by overlapping long-horizon returns (as recommended in Fama, 1998).

The Fama-MacBeth procedure is thus a two-step regression that first estimates monthly cross-sectional slopes and then averages them over time, which allows us to obtain coefficient estimates that are robust to time-series dependence and common shocks.

Portfolio sorting test

Following Fama and French (1993) and standard anomaly studies (e.g., Jegadeesh & Titman, 1993; Cooper, Gulen & Schill, 2008), we sort firms each month into three equally sized portfolios based on their trailing three-year DAI: P1 (Low DAI), P2 (Mid DAI), and P3 (High DAI).

Monthly equal-weighted (EW) and value-weighted (VW) returns are then computed. Value-weighting uses market capitalisation to approximate investable strategies and avoid over-weighting microcaps.

High-minus-Low (HL) spreads are calculated for each month:

$$HL_t^{EW} = R_{P3,t}^{EW} - R_{P1,t}^{EW}, \qquad HL_t^{VW} = R_{P3,t}^{VW} - R_{P1,t}^{VW}$$

These spreads provide a non-parametric test of whether rigid repayment structures are systematically associated with higher or lower realized returns.

We then regress HL returns on the FF5 factors (Fama and French, 2015), imported from the Kenneth French data library and:

$$R_t^{HL} = \alpha + \beta_{MKT} MKT_t + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \beta_{RMW} RMW_t + \beta_{CMA} CMA_t + \varepsilon_t$$

And then add Newey-West standard errors with three lags to account for short-horizon autocorrelation.

The FF5 regression evaluates whether the DAI-sorted long-short portfolio earns abnormal returns beyond standard risk exposures. The CMA loading is of particular interest given its direct relation to investment intensity and thus provides a test consistent with the investment-channel mechanisms.

3.4 Robustness Tests

To ensure that the relation between DAI and both operating and market outcomes is not driven by specific modelling choices, we are re-estimate the regressions under alternative sample constructions, variable definitions, and estimation approaches.

Specifically, we (i) test different leverage cut-offs used to define the high-leverage sample (5% and 10%), (ii) replace the FF12-adjusted growth indicator with an industry unadjusted growth indicator (using only Tobin's Q), and (iii) run the main specification regression on all non-growth firms. We also (iv) restrict $k = 3$ and $k = 5$ to non-overlapping horizons and (v) redefine profitability so that ROA and margins are based on EBIT instead of EBITDA. Finally, we (vi) strengthen the outlier treatment by winsorising all main variables at the 5th and 95th percentiles and (vii) re-estimate the models using pooled OLS without firm fixed effects.

The same robustness checks are applied to the market-based analyses (Fama-MacBeth regressions and portfolio-sorting tests), with a few exceptions. Because the Fama-MacBeth estimator is constructed without fixed effects, we instead complement it with (viii) traditional panel regressions that include firm fixed effects as an additional robustness exercise. Fixed effects are likewise not applicable in the portfolio setting, as portfolio formation aggregates firm-level observations into portfolio-level returns, removing the within-firm variation required for fixed-effects estimation. In contrast to the other tests, the portfolio test is naturally non-overlapping, since portfolios are rebalanced monthly and returns are computed at the portfolio level; instead, we assess robustness by (ix) forming quintile portfolios rather than terciles. Lastly, non-overlapping horizons are not feasible for the Fama-MacBeth regressions, as doing so would eliminate most monthly cross-sections and prevent valid second-stage inference.

4. Results

This section presents the descriptive statistics for our sample, reports the main tests of our hypotheses, and concludes with the robustness checks.

4.1 Operating Outcomes

4.1.1 Sample Characteristics and Descriptive Statistics

Table 2 reports baseline descriptive statistics and correlations for DAI and other key variables in our k = 5 sample. The table is based on 1,347 leveraged growth firm-year observations that satisfy our selection and horizon filters (see Section 3.1). All variables are measured in the initial year t of the 5-year window.

The distribution of DAI is tightly centred around zero. The mean is about 0.04 and the interquartile range runs from 0.00 to 0.06, with a 95th percentile of roughly 0.16. This means that a typical leveraged growth firm uses pays down a few percent on their long-term debt each year (net; see section 3.2.1 for DAI construction), while a small group of firms either amortise much more aggressively or are net issuers.

Panel B shows that firms that amortise more intensively tend to be slightly less levered and smaller, reflected in the slightly negative correlations with Book Leverage and Size. Correlations with operating profitability, cash holdings, investment intensity, margins, and asset turnover are all very small, suggesting that most of the cross-sectional variation in DAI reflects differences in financing choices rather than obvious differences in firms' operating profiles.

Table 2: Baseline Descriptive Statistics and Correlations

Panel A: Baseline Descriptive Statistics								
Variable	mean	sd	p5	p25	p50	p75	p95	count
DAI	0.04	0.06	0.00	0.00	0.02	0.06	0.16	1347
Book Leverage	0.65	0.43	0.26	0.36	0.48	0.78	1.73	1347
Size (ln Assets)	7.71	2.10	3.77	6.63	7.82	9.22	10.67	1347
Op.ROA	0.07	0.36	-0.46	0.09	0.13	0.18	0.30	1347
Cash/Assets	0.11	0.15	0.00	0.02	0.05	0.14	0.46	1347
CapEx/Assets	0.06	0.06	0.00	0.02	0.04	0.08	0.17	1347
Op.Margin	0.02	0.98	-1.09	0.12	0.20	0.33	0.47	1347
Asset turnover	0.80	0.63	0.15	0.38	0.64	1.02	2.09	1347
Panel B: Pearson Correlation Matrix								
	DAI	Book Leverage	Size	Op.ROA	Cash/Assets	CapEx/Assets	Op.Margin	Asset turnover
DAI	1.00							
Book Leverage	-0.12	1.00						
Size (ln Assets)	-0.25	-0.23	1.00					
Op.ROA	-0.05	-0.22	0.42	1.00				
Cash/Assets	-0.02	0.37	-0.28	-0.24	1.00			
CapEx/Assets	-0.03	-0.08	0.06	-0.02	-0.19	1.00		
Op.Margin	-0.09	-0.25	0.41	0.74	-0.24	0.00	1.00	
Asset turnover	0.10	0.03	-0.20	0.12	0.00	-0.11	0.09	1.00

Note: This table reports means, standard deviations, selected percentiles (Panel A) and Pearson correlations (Panel B) for baseline variables in the $k = 5$ sample. DAI is Debt Amortisation Intensity (see section 3.2.1), Size is the natural logarithm of Total Assets (ln Assets). All variables are winsorised by fiscal year at the 1st and 99th percentiles.

4.1.2 Fixed-Effects Results on Subsequent DAI

Table 3 reports fixed-effects regressions of operating outcomes on subsequent DAI over one-, three- and five-year horizons. Throughout, we interpret coefficients for a 10% (0.1) change in DAI. Delta-variables are denoted “Changes in X”.

In the medium- to long-run, lower Debt Amortisation Intensity (DAI) is associated with stronger expansion in sales, total assets and investment (Panel B-C). The coefficients on DAI for Sales growth and Total Asset growth are negative on all horizons, with Sales growth significantly lower at k = 3 and k = 5 and Total Asset growth significantly lower at k = 1 and k = 5. Most notable, a 10% lower DAI is associated with around 20 percentage points higher cumulative sales and asset growth over five years. This suggests that sustained differences in amortisation policy matter most, as firms retaining more internal funds over longer horizons see the largest cumulative growth effects. CapEx Intensity also increases when DAI is lower, a 10% reduction in DAI corresponds to roughly 0.5-1 pp higher CapEx/Assets, significant at all horizons but with a relatively low Adj. R^2. Op.Income growth is estimated with noise and is insignificant throughout, also reflected in the comparatively low Adj. R^2.

For profitability and efficiency, the patterns are more favourable for higher DAI. The coefficients on Changes in Op.ROA are positive and statistically significant at the one- and three-year horizons, implying that a 0.10 higher DAI is associated with roughly 1-2 percentage points higher Op.ROA over these windows, while the k = 5 estimate is relatively smaller and imprecise. Changes in Op.Margin show a positive and significant association at k = 3, corresponding to an improvement in operating margin of about 2 percentage points for a 10% higher DAI. Changes in Asset Turnover tend to improve when DAI is higher, with a positive and significant coefficient at k = 1, but imprecise at longer horizons. Although imprecisely estimated, the efficiency regressions exhibit the highest Adj. R^2, indicating that the specification explains a relatively large share.

Together, the FE results show a pattern of a trade-off. Firms with lower DAI expand faster and invest more intensively, measured in Assets, CapEx Intensity and Sales. At the same time, higher DAI is associated with improvements in Op.ROA, Op.Margins and Asset Turnover, suggesting some efficiency gains when firms amortise more aggressively. The Changes in Asset Turnover and Op.ROA, are expected and consistent with a smaller asset base, while the positive Changes in Op.Margin at k = 3 points to some (although small) improvements in operating efficiency. Overall, we interpret the efficiency improvement as a reflection of a tightened balance sheet rather than a shift toward more efficient operations.

Table 3: Fixed-Effects Regressions of Operating Outcomes on Subsequent DAI (2015-2024)

Panel A: Fixed Effect Estimates, One-Year Horizon (k = 1)							
Expl. V	**Sales (g)**	**Total Assets (g)**	**Op.Income (g)**	**CapEx Intensity**	**Op.ROA (Δ)**	**Op.Margin (Δ)**	**A.Turn (Δ)**
DAI	-0.12	-0.39***	0.12	-0.05***	0.09***	0.03	0.29**
t-stat	(-1.5)	(-2.79)	(0.75)	(-5.00)	(3.00)	(1.00)	(2.42)
N	2339	2339	2339	2339	2339	2339	2339
Adj. R^2	0.29	0.15	0.23	0.10	0.33	0.46	0.22
Panel B: Fixed Effect Estimates, Three-Year Horizon (k = 3)							
DAI	-0.55*	-0.59	0.62	-0.09***	0.18**	0.20**	0.20
t-stat	(-1.67)	(-1.31)	(1.15)	(-3.0)	(2.57)	(2.22)	(0.56)
N	1614	1614	1614	1614	1614	1614	1614
Adj. R^2	0.25	0.23	0.26	0.15	0.46	0.46	0.27
Panel C: Fixed Effect Estimates, Five-Year Horizon (k = 5)							
DAI	-1.96***	-1.96***	-2.09	-0.10***	0.18	-0.02	0.47
t-stat	(-2.65)	(-2.76)	(-1.60)	(-3.33)	(1.64)	(-0.10)	(0.69)
N	1151	1151	1151	1151	1151	1151	1151
Adj. R^2	0.29	0.33	0.27	0.15	0.41	0.41	0.23

*Note: This table reports coefficients on Debt Amortisation Intensity (DAI) from firm fixed-effects regressions of operating outcomes on subsequent DAI over horizons $k = 1,3$, and 5 years. All specifications include firm and year fixed effects and the control variables described in Section 3.3.1. Standard errors are clustered at the firm level. All variables are winsorised at the 1st and 99th percentiles by fiscal year. *, **, *** denote significance at the 10%, 5% and 1% levels.*

4.1.3 Correlated Random Effect Results: Within versus Between Firms

Table 4 presents the Correlated Random Effects (CRE) regressions using the subsequent DAI measure. In contrast to the FE models, this model let us split the association between DAI and the outcome measures into a within-firm component (β^W) and a between-firm component (β^B), allowing us to compare how changes in a firm's amortisation intensity over time relate to performance versus how firms with persistently high or low DAI differ from each other.

Within-firm coefficients closely mirror the FE results, and the estimates support the FE evidence that changes in DAI are primarily reflected in a growth-efficiency trade-off. A lower DAI is linked to stronger expansion, and higher DAI with modest gains in Op.ROA and efficiency. Adjusted R^2 is similar to the FE specifications, which indicates that this decomposition is achieved without any meaningful loss of explanatory power.

Between-firm coefficients are generally small and statistically insignificant across outcomes and horizons. Firms with persistently higher versus lower average DAI do not differ systematically in asset growth, CapEx Intensity, profitability, or efficiency. The only exception is sales growth at $k = 5$, where β^B is positive and significant, indicating higher long-run sales growth for high-DAI firms, in contrast to the negative within-firm pattern.

Table 4: Correlated Random Effects (CRE) Estimates of Operating Outcomes on Subsequent DAI (2015-2024)

Panel A: CRE - Subsequent DAI, k = 1							
Expl. V	**Sales (g)**	**Total Assets (g)**	**Op.Income (g)**	**CapEx Intensity**	**Op.ROA (Δ)**	**Op.Margin (Δ)**	**A.Turn (Δ)**
DAI (within β^W)	-0.11	-0.38***	0.12	-0.05***	0.09***	0.03	0.29**
t-stat (β^W)	(-1.38)	(-2.71)	(0.75)	(-5)	(3)	(1)	(2.42)
DAI (between β^B)	-0.01	0.04	0.03	-0.06	-0.02	-0.03	-0.06
t-stat (β^B)	(-0.08)	(0.21)	(0.07)	(-1.5)	(-0.4)	(-0.75)	(-0.33)
N	2239	2239	2239	2239	2239	2239	2239
Adj. R^2	0.29	0.14	0.22	0.09	0.33	0.13	0.21
Panel B: CRE - Subsequent DAI, k = 3							
DAI (within β^W)	-0.55*	-0.56	0.60	-0.09***	0.18**	0.18**	0.18
t-stat (β^W)	(-1.67)	(-1.24)	(1.11)	(-3)	(2.57)	(2)	(0.5)
DAI (between β^B)	0.38	-0.54	-0.82	-0.01	-0.05	-0.12	0.34
t-stat (β^B)	(0.86)	(-1.17)	(-1.12)	(-0.25)	(-0.56)	(-1.09)	(0.89)
N	1 614	1 614	1 614	1 614	1 614	1 614	1 614
Adj. R^2	0.25	0.22	0.25	0.14	0.45	0.16	0.27
Panel C: CRE - Subsequent DAI, k = 5							
DAI (within β^W)	-1.97***	-1.96***	-2.12	-0.10***	0.18	-0.04	0.45
t-stat (β^W)	(-2.66)	(-2.72)	(-1.62)	(-3.33)	(1.64)	(-0.19)	(0.66)
DAI (between β^B)	1.80**	0.89	2.13	0.05	-0.10	0.08	0.00
t-stat (β^B)	(2.12)	(1.16)	(1.5)	(1)	(-0.77)	(0.36)	(0)
N	1 151	1 151	1 151	1 151	1 151	1 151	1 151
Adj. R^2	0.28	0.32	0.26	0.14	0.40	0.17	0.22

*Note: This table reports within-firm (β^W) and between-firm (β^B) coefficients on subsequent DAI from correlated random effects (Mundlak) regressions of outcomes over horizons k = 1, 3, and 5 years. All specifications include firm and year effects and the same control variables as in the FE model, with standard errors clustered at the firm level. *, **, *** denote significance at the 10%, 5% and 1% level.*

4.1.4 Trailing DAI: Predictive Estimates

Table 4 and 5 present predictive tests based on trailing DAI. In these specifications, we relate operating performance to the firm's Three-Year Trailing Average Debt Amortisation Intensity ("Trailing DAI") up to year t, using the same sample and control set as in the subsequent tests. Table 5 reports the fixed-effects coefficients on trailing DAI for all outcomes and horizons, while Table 4 reports the Correlated Random Effects (CRE) estimates on trailing DAI, for the same horizons and outcomes.

For the growth and investment outcomes in the FE regression, trailing DAI has little predictive power. Coefficients on Sales growth, Total Assets growth, Op.Income growth, and CapEx Intensity are small, change sign across horizons, and are statistically insignificant throughout.

For the efficiency outcomes, the picture is similar. Changes in Op.ROA and asset turnover are small and insignificant at all horizons, and the margin coefficients at $k = 3$ and $k = 5$ are close to zero. Adjusted R^2 is highest for Op.ROA and Op.Margin, but trailing DAI contributes little systematic predictive variation. At $k = 1$, however, the coefficient on the Change in Op.Margin is negative and statistically significant (−0.11 at the 5% level), implying that a 0.10 lower trailing DAI predicts roughly a 1 pp increase in Op.Margin over the following year. Although this is an economically meaningful effect, it is limited to the short run, and the effect does not persist over the longer horizons.

Table 6 reports the CRE regressions with trailing DAI. The within-firm coefficients (β^W) are close to the FE estimates, and adjusted R^2 is similar to the FE models. Trailing DAI does not predict sales growth, asset growth, operating income growth, CapEx Intensity, Op.ROA, or asset turnover at any horizon. The only notable effect is the negative short-run effect on Op.Margin at k = 1 already noted in the FE results.

The between-firm coefficients show a stronger pattern at longer horizons. At $k = 3$, firms with lower average trailing DAI have significantly higher Op.Income growth, higher CapEx Intensity, and stronger operating profitability (both Op.ROA and Op.Margin). At $k = 5$, lower trailing DAI remains associated with even higher Op.Income growth and higher ROA and margins, with the Op.Income coefficient of -2.21** indicating a 30 pp higher Op.Income growth for a 10% lower DAI. The Op.ROA also show the higher adjusted R^2, indicating that differences in trailing DAI and the control set together explain a meaningful share of the variation in the longer horizons. Although, we interpret these between-firm effects as capturing differences between firms that systematically amortise more versus less aggressively, they likely reflect more mature and cash-generative firms.

Table 5: Fixed-Effects Estimates of Operating Outcomes on Trailing DAI (2015-2024)

Panel A: Fixed Effects Regression Estimates using Trailing DAI 2015-2024 (k = 1)							
Expl. V	**Sales (g)**	**Total Assets (g)**	**Op.Income (g)**	**CapEx Intensity**	**Op.ROA (Δ)**	**Op.Margin (Δ)**	**A.Turn (Δ)**
DAI	0.14	0.01	-0.10	0.00	-0.08	-0.11**	0.17
t-stat	(0.82)	(0.05)	(-0.32)	(0)	(-1.6)	(-2.2)	(1.06)
N	1969	1969	1969	1969	1969	1969	1969
Adj. R^2	0.28	0.11	0.22	0.09	0.31	0.12	0.21
Panel B: Fixed Effects Regression Estimates using Trailing DAI 2015-2024 (k = 3)							
DAI	0.31	-0.20	0.45	0.05	0.13	0.05	0.42
t-stat	(0.76)	(-0.59)	(0.63)	(1)	(1.63)	(0.63)	(1.2)
N	1367	1367	1367	1367	1367	1367	1367
Adj. R^2	0.22	0.18	0.24	0.10	0.43	0.17	0.26
Panel C: Fixed Effects Regression Estimates using Trailing DAI 2015-2024 (k = 5)							
DAI	0.09	-0.40	0.59	-0.01	0.08	0.05	0.18
t-stat	(0.23)	(-0.98)	(0.83)	(-0.25)	(1.14)	(0.5)	(0.75)
N	997	997	997	997	997	997	997
Adj. R^2	0.20	0.22	0.22	0.08	0.37	0.18	0.22

*Note: This table reports coefficients on Debt Amortisation Intensity (DAI) from firm fixed-effects regressions of operating outcomes on Trailing DAI over horizons k = 1, 3, and 5 years. All specifications include firm and year fixed effects and the control variables described in Section 3.3.1. Standard errors are clustered at the firm level. All variables are winsorised at the 1st and 99th percentiles by fiscal year. *, **, *** denote significance at the 10%, 5% and 1% levels*

Table 6: Correlated Random Effects (CRE) Estimates of Operating Outcomes on Trailing DAI (2015-2024)

Panel A: CRE - Subsequent DAI, k = 1							
Expl. V	**Sales (g)**	**Total Assets (g)**	**Op.Income (g)**	**CapEx Intensity**	**Op.ROA (Δ)**	**Op.Margin (Δ)**	**A.Turn (Δ)**
DAI (within β^W)	0.16	0.04	-0.06	0.00	-0.07	-0.10*	0.17
t-stat (β^W)	(0.94)	(0.20)	(-0.19)	(0.00)	(-1.40)	(-2.00)	(1.06)
DAI (between β^B)	-0.03	0.05	-0.31	-0.05	0.04	0.04	-0.08
t-stat (β^B)	(-0.11)	(0.17)	(-0.76)	(-0.83)	(0.57)	(0.57)	(-0.40)
N	1969	1969	1969	1969	1969	1969	1969
Adj. R^2	0.27	0.10	0.21	0.09	0.30	0.12	0.21
Panel B: CRE - Subsequent DAI, k = 3							
DAI (within β^W)	0.30	-0.21	0.46	0.05	0.13	0.06	0.40
t-stat (β^W)	(0.73)	(-0.62)	(0.64)	(1)	(1.63)	(0.75)	(1.14)
DAI (between β^B)	-0.58	-0.41	-1.66**	-0.18***	-0.22**	-0.19**	-0.24
t-stat (β^B)	(-1.32)	(-0.87)	(-1.98)	(-3.6)	(-2.44)	(-1.90)	(-0.59)
N	1367	1367	1367	1367	1367	1367	1367
Adj. R^2	0.22	0.17	0.23	0.10	0.42	0.17	0.25
Panel C: CRE - Subsequent DAI, k = 5							
DAI (within β^W)	0.10	-0.38	0.62	-0.01	0.08	0.05	0.17
t-stat (β^W)	(0.26)	(-0.93)	(0.87)	(-0.25)	(1.14)	(0.56)	(0.71)
DAI (between β^B)	-0.59	-0.35	-2.21**	-0.09	-0.23*	-0.23*	0.00
t-stat (β^B)	(-1.11)	(-0.6)	(-2.17)	(-1.50)	(-1.92)	(-1.77)	(0.00)
N	997	997	997	997	997	997	997
Adj. R^2	0.20	0.21	0.21	0.08	0.37	0.17	0.22

*Note: This table reports within-firm (β^W) and between-firm (β^B) coefficients on trailing average DAI from Correlated Random Effects (Mundlak) regressions of outcomes over horizons k = 1, 3, and 5 years. All specifications include firm and year effects and the same control variables as in the FE model, with standard errors clustered at the firm level. *, **, *** denote significance at the 10%, 5% and 1% level.*

4.1.5 Robustness Summary of Operating Outcomes

As a robustness check, we re-estimate the operating outcome regressions under alternative sample definitions, variable definitions, and estimation choices, as specified in Section 3.4. The core pattern remains, a lower DAI is consistently associated with higher sales and asset growth and higher CapEx intensity, while higher DAI is linked to better operating profitability and efficiency. The most notable differences are that Sales growth effects diminish as we loosen the leverage cut (*Robustness Test I*), and that the profitability gains weaken when we move from EBITDA- to EBIT-based measures (*Robustness Test V).* Full regression outputs can be found in Appendix A.2.

In *Robustness Test I*, we change the leverage cutoff from >15% to >10% and >5% For Total Asset growth, CapEx Intensity, and Op.ROA, the FE coefficients on DAI remain similar to the main results in both sign and significance across all horizons. However, the Sales growth effect weakens as we relax the leverage cut-off, and the k = 3 and k = 5 coefficients decreases when moving from >15% (−0.55*, −1.96***) to >10% (−0.43*, −0.94**) and become small and insignificant at >5% (−0.15, −0.16), even though standard errors are of comparable size. This suggests that the negative association between higher DAI and Sales growth is, as expected, strongest in the more highly levered part of the sample, while Total Asset growth, investment, and Op.ROA patterns are robust to the inclusion of firms with lower leverage.

In *Robustness Test II*, we redefine growth firms using only Tobin's Q (industry unadjusted). The long-run growth pattern remains in the FE regressions, higher DAI is still clearly linked to lower five-year sales and asset growth, and the k = 5 asset-growth effect is even larger (−2.60*** vs −1.96*** in the main test). At the same time, several medium-horizon effects weaken asset growth at k = 3 becomes small and insignificant, CapEx Intensity is clearly lower only at k = 1, and the positive profitability and efficiency effects are reduced. Standard errors are larger in this smaller and more heterogeneous sample, so this likely reflects lower precision rather than a change in signs. In the CRE results, some long-run between-firm coefficients become significant (higher asset growth and lower Op.ROA at k = 5), but most between-firm estimates remain imprecise.

For the non-growth sample (*Robustness Test III*), the coefficients become but somewhat smaller in size. Higher DAI is now significantly associated with lower sales growth, asset growth and CapEx Intensity, and with higher Op.ROA, margins and asset turnover at all horizons, while operating income growth remains close to zero. Compared to the growth sample, the Sales growth coefficients are less negative (for example −0.78*** vs −1.96*** at k = 5) but are estimated much more precisely. This pattern suggest that amortisation policy has a stronger impact on long-run sales expansion for growth firms, while non-growth firms mainly see more modest but systematic improvements in profitability and efficiency when amortising more aggressively, consistent with the debt overhang theory.

Restricting the horizons to be non-overlapping (*Robustness Test IV*) leaves the 1-year FE coefficients almost unchanged but makes the 3-year trade-off sharper. At k = 3, the Sales and Total Asset growth coefficients roughly double in magnitude (from −0.55* and −0.59 to −1.15* and −1.76**), CapEx Intensity becomes more negative (−0.17** vs −0.09***), and the Op.ROA and Op.Margin gains become much larger (0.57*** and 0.57* vs 0.18** and 0.20**), although standard errors increase because the number of non-overlapping 3-year windows is much smaller (N = 463 vs 1,614). The results for k = 5 results are not reported as it leaves too few observations.

When we based profitability outcomes on EBIT rather than EBITDA (Robustness Test V), the effects on operating income growth remain negligible and insignificant across all horizons, as in the main tests. For ROA, the short-run effect survives but weakens, as EBIT-ROA is still positive and significant at k = 1 (0.07** vs 0.09***), but the k = 3 effect loses significance, and the k = 5 coefficient is similar in size yet imprecisely estimated. For margins, the earlier k = 3 improvement (0.20**) disappears, with all EBIT-margin coefficients being insignificant and close to zero, and the CRE profitability estimates remain insignificant throughout.

With 5/95 winsorisation (*Robustness Test VI*), the results look very similar to the main tests but weakened at the longest horizon, as expected when trimming extremes. The large five-year growth effects become smaller in absolute value (Sales from −1.96*** to −1.14**, Total Assets from −1.96*** to −1.40**), while CapEx, Op.ROA and margins keep the direction and significance pattern and are, if anything, slightly stronger for Op.ROA at k = 3-5. CRE profitability estimates remain insignificant.

Without firm fixed effects (Pooled OLS; *Robustness Test VII*), the signs of many coefficients line up with the FE results, and a higher DAI is still associated with lower asset growth and CapEx Intensity and higher Op.ROA and Asset Turnover. The main differences are that the negative sales-growth effects become much smaller and lose significance at all horizons. Further asset growth is now significantly lower at k = 3 (−0.91*** vs insignificant −0.59), and asset turnover is significantly higher at k = 3 and k = 5. A plausible explanation is that pooled OLS loads on time-invariant differences across firms, such as business model, leverage, and repayment structure, so firms that both grow assets more slowly and run with higher DAI pull the asset-growth and efficiency coefficients further from zero, while the same cross-sectional mix weakens the link to Sales growth when heterogeneity is not stripped out.

4.2 Return-Based Evidence

This section reports the results from the two return-based tests: (i) Fama-MacBeth (FM) cross-sectional regressions using subsequent DAI, and (ii) portfolio-sorting tests using trailing DAI and FF5 risk adjustment. While both approaches tests whether *DAI associated with equity returns*, they capture different dimensions of the pricing relation.

4.2.1 Fama-MacBeth Regressions

Table 7 reports the Fama-MacBeth estimates for the 12-, 36-, and 60-month BHAR specifications. Across all horizons, the coefficient on DAI is negative and statistically significant, with the effect strongest at the 36-month horizon. Because all variables are standardized within each cross-section, the coefficients should be interpreted as *the change in* BHAR *(in standard deviations) associated with a one-standard-deviation increase in DAI.* For example, the 12-month DAI coefficient of −0.02 implies that a one-standard-deviation increase in subsequent DAI is associated with a 0.02 standard-deviation lower 12-month BHAR. The effect increases in magnitude at the 36-month horizon (−0.08) and then moderates at the 60-month horizon (−0.06), consistent with the pricing relevance of DAI fading as its information becomes less current.

The control variables behave in line with expectations from the cross-sectional asset-pricing literature. Size loads positively, consistent with the well-documented size premium (Fama & French, 1992; Fama & French, 2015). Market leverage loads negatively at longer horizons, consistent with evidence that higher leverage is associated with higher risk and lower future equity performance after controlling for book-to-market (Fama & French, 1992). Book-to-market displays weak pricing power in this growth-firm sample, which is common when value characteristics are applied to low-book-to-market subsamples. .

Average cross-sectional R^2 values (6-7%) fall within the typical range reported in prior Fama-MacBeth studies (Fama & French (1992) report cross sectional R^2 values between 4-8%), reflecting the inherently high noise-to-signal ratio in cross-sectional return regressions rather than any deficiency in model specification.

Together, the FM regressions provide consistent evidence that subsequent DAI is negatively priced in the cross-section, particularly at the three-year horizon, *supporting the notion that lower amortisation intensity is associated with higher future returns for growth firms.*

Table 7: Cross-Sectional Relation Between DAI and Future Abnormal Returns

Panel A: Fama-MacBeth Estimates at 12-, 36-, and 60-Month Horizons			
Indep. Vars.	**12m**	**36m**	**60m**
Const	**-0.98*****	**-0.66*****	**-0.63*****
t-stat	(-3.79)	(-3.54)	(-4.31)
DAI	**-0.02****	**-0.08****	**-0.06*****
t-stat	(-2.56)	(-2.53)	(-3.04)
BM	**0.02**	**-0.03***	**0.01**
t-stat	(0.87)	(-1.92)	-0.57
Size	**0.16*****	**0.15*****	**0.14*****
t-stat	(3.31)	(3.47)	(3.98)
Leverage	**-0.03**	**-0.04***	**-0.09*****
t-stat	(-1.00)	(-1.89)	(-5.08)
R^2	0.07	0.06	0.06

*Note: This table reports Fama-MacBeth cross-sectional regressions of standardised buy-and-hold abnormal returns (BHAR) on subsequent Debt Amortisation Intensity (DAI) over 12-, 36-, and 60-month horizons. Reported coefficients are the time-series averages of the underlying monthly cross-sectional regressions: 109 for the 12-month BHAR, 85 for the 36-month BHAR, and 61 for the 60-month BHAR. All variables are winsorised at the 1st and 99th percentiles within each month and z-scored cross-sectionally. Standard errors are Newey-West adjusted using horizon-appropriate lags to correct for return overlap. Coefficients reflect the change in BHAR (in standard deviations) associated with a one-standard-deviation increase in each predictor. *, **, *** denote significance at the 10%, 5%, and 1% levels.*

4.2.2 Portfolio Tests

Table 8 summarises the characteristics of the DAI-sorted portfolios. The sorting procedure produces clear separation in amortisation intensity across terciles, as the Low-DAI portfolio consists predominantly of firms with 0% amortisation intensity, while the High-DAI portfolio (P3) includes firms whose repayment patterns are closer to a five-year linear amortisation schedule. Both equal- and value-weighted average returns show only modest differences across portfolios and no clear monotonic pattern, as reflected in the High-Low excess returns of only 0.1% and 0.0%. Equal-weighted returns are consistently lower than value-weighted returns, indicating that smaller firms underperform larger firms in this sample, fully consistent with the positive size loading observed in the Fama-MacBeth regressions in Section 4.2.1.

Table 8: Average Returns and DAI Levels for DAI-Sorted Portfolios

Panel A: Summary Statistics for DAI-Sorted Portfolios			
DAI Tercile	**Mean EW Return**	**Mean VW Return**	**Avg. DAI**
Low	0.8%	1.6%	0.1%
Mid	1.0%	1.4%	3.5%
High	0.9%	1.6%	17.7%
H-L	0.1%	0.0%	-

Note: This table reports equal-weighted (EW) and value-weighted (VW) average monthly returns and average Debt Amortisation Intensity (DAI) for portfolios formed each month by sorting firms into terciles based on three-year trailing DAI. Reported returns and trailing DAI represent means over the full sample of 121 monthly observations. All variables are winsorised at the 1st and 99th percentiles within each month. Portfolio 1 (Low) consists of the firms with the lowest DAI in month t, while Portfolio 3 (High) consists of firms with the highest DAI in month t. VW returns are computed using market capitalization (Price × Shares Outstanding).

The FF5 time-series regressions in Table 9 confirm that the High-minus-Low (H-L) portfolio does not earn abnormal returns. The equal-weighted H-L portfolio produces an alpha of 0.001 (t = 1.35), while the value-weighted version yields an alpha of 0.000 (t = 0.29), indicating no statistically significant excess performance after controlling for the market, size, value, profitability, and investment factors. The SMB factor loads significantly in the equal-weighted regression but not in the value-weighted specification, reflecting that equal-weighting gives greater weight to small firms while value-weighting is dominated by larger firms. This pattern mirrors the lower equal-weighted returns across portfolios and the positive size loading observed in the Fama-MacBeth regressions in Section 4.2.1. R^2 values of 23-36% fall within the typical range for long-short portfolios in FF5 settings. The factor-adjusted results reinforce the descriptive evidence, historical (trailing) amortisation intensity does not generate abnormal returns, suggesting that past repayment behaviour is largely incorporated into prices (if any) at the portfolio-formation date.

Table 9: Risk-Adjusted Returns on High-Minus-Low DAI Portfolios (Fama-French Five-Factor Model)

Panel A: Equal-Weighted High-Minus-Low DAI Portfolio							
	Int	**R_M-R_F**	**SMB**	**HML**	**RMW**	**CMA**	**R^2**
Coef	0.00	0.02	0.16***	0.06**	0.05	0.03	0.23
t-stat	(1.35)	(0.72)	(4.15)	(1.65)	(0.9)	(0.42)	
Panel B: Value-Weighted High-Minus-Low DAI Portfolio							
Coef	0.00	0.01	0.09	-0.08	0.12	-0.04	0.36
t-stat	(0.29)	(0.11)	(1.19)	(-1.19)	(1.09)	(-0.36)	

*Note: This table reports Fama-French five-factor (FF5) regressions for the High-minus-Low (H-L) DAI portfolio return spread, using both equal-weighted (EW) and value-weighted (VW) returns on 121 monthly observations. All variables used in portfolio construction and returns are winsorised at the 1st and 99th percentiles within each month. Factors (MKT, SMB, HML, RMW, CMA) follow Fama & French (2015). Alphas measure abnormal returns relative to the FF5 model. Newey-West standard errors with 3 lags are applied. *, **, *** denote significance at the 10%, 5%, and 1% levels.*

Overall, the return results present a mixed pricing pattern. Subsequent DAI loads negatively and significantly in the Fama-MacBeth regressions, especially at the 36-month horizon, indicating that firms with lower amortisation intensity earn higher subsequent abnormal returns. By contrast, the portfolio sorts based on trailing DAI produce economically small and statistically insignificant High-Low spreads, and FF5 alphas close to zero.

4.2.3 Robustness Summary of Market Tests

For robustness check, we re-estimate the Fama-MacBeth regressions and the DAI portfolios under the alternative specifications described in Section 3.4. Across all tests, the main conclusions remain unchanged. The Fama-MacBeth regressions continue to show a statistically significant negative relation between DAI and future returns, while the portfolio-sorting results consistently yield no evidence of abnormal returns.

In *Robustness Test I*, we change the leverage cut-offs to include firms above the 10% and 5% leverage thresholds instead of the baseline 15%. As these lower thresholds expand the sample, the cross-sections become larger and more heterogeneous. In the Fama-MacBeth regressions, the DAI coefficients remain negative across all horizons but become somewhat smaller in magnitude and less precisely estimated. In the portfolio regressions, the high-minus-low (H-L) spreads remain insignificant and the factor loadings closely match the baseline. This indicates that the return patterns are not driven by the specific leverage restriction applied in the main tests.

In *Robustness Test II*, we redefine growth firms using an unadjusted Tobin's Q measure. The Fama-MacBeth coefficients on DAI remain negative and close in magnitude to the baseline, though statistical precision declines somewhat. The portfolio results again remain unchanged, as the H-L returns continue to show no abnormal performance, and factor exposures are identical to the baseline. Suggesting that our results are not sensitive to the definition of growth firms.

For *Robustness Test III*, we remove the growth filter entirely and estimate the market tests on the full sample after filtering on firms with leverage above 15%. The Fama-MacBeth slopes remain negative similar to the baseline but become much more precisely estimated. The portfolio tests still show zero abnormal returns, although some factor loadings become more precisely estimated. Overall, expanding the universe increases precision but does not alter the economic conclusions.

In *Robustness Test VI*, we apply stronger winsorisation at the $5^{th}/95^{th}$ percentiles. The Fama-MacBeth estimates remain stable, with slightly reduced noise at longer horizons, while the portfolio alphas remain insignificant and factor loadings move only marginally, indicating that outliers are not responsible for the observed patterns.

In *Robustness Test IX*, we refine the portfolio formation by sorting firms into quintiles instead of terciles. Increasing the granularity of the portfolio sorts does not reveal any return differential associated with DAI. Both equal- and value-weighted H-L spreads remain close to zero with the same general factor exposure structure, confirming that the absence of pricing effects is not sensitive to portfolio formation.

Finally, because the Fama-MacBeth estimator is cross-sectional and cannot include fixed effects, *Robustness Test VIII* complements the FM regressions with firm fixed-effects panel models. Once firm-level time-invariant characteristics are absorbed, the DAI coefficients become small and statistically insignificant, consistent with the fact that the FM estimator operates on cross-sectional variation. Fixed effects are not meaningful for portfolio tests, as portfolio formation aggregates firm-level data into portfolio-level returns.

In conclusion, the full set of robustness tests confirms that the market-based evidence is highly robust. The Fama-MacBeth results consistently show a modest negative relation between DAI and future returns, while the portfolio tests uniformly show no abnormal return spread. Our findings are thus likely not driven by sample restrictions, growth definitions, outlier treatment, or portfolio construction choices, and therefore reinforce the robustness of these results.

5. Discussion

5.1 Main Findings

5.1.1 Operating Outcomes: Growth versus Profitability

Our FE estimates on subsequent DAI show a clear growth-efficiency trade-off. Years in which a firm amortises less intensively (low DAI) are associated with stronger medium- to long-run growth in sales and total assets, supported by slightly higher CapEx intensity, whereas years with higher DAI suggest modest improvements in Op.ROA, Op.Margin, and Asset Turnover, although mostly at shorter horizons. These results align with *H1* and are consistent with the idea that lighter near-term repayment helps ease debt overhang and enable valuable investments (Myers, 1977, Nini, 2008). For *H2*, the results are consistent with tighter payouts limiting wasteful spending and slack and improving efficiency (Jensen & Meckling, 1979; Jensen, 1986). Part of the efficiency effect is purely mechanical, as faster repayment shrinks the balance sheet and thus raises Op.ROA and Asset Turnover; in contrast, the signal on Op.Margin at the three-year horizon points to an underlying improvement in operations rather than pure denominator effects.

In practice, amortisation intensity is partly a choice and partly a constraint. Within a given rating and leverage range, firms may negotiate heavier or lighter repayment profiles or amortisation holidays when they put new term loans in place or refinance existing ones, but lenders will price theses choices through spreads or monitoring (Nini, 2008; Nguyen, 2022). Our estimates show what happens when that margin is actually used. For the same firm, years with lower subsequent DAI are the years that turn into stronger growth in Sales and Total Assets, and increased CapEx Intensity over the following 3-5 years, while years with higher DAI yield only relatively small, mainly short-run gains in Op.ROA, Op.Margins, and Asset Turnover. The horizon pattern is important. The growth benefits of lower DAI accumulate over time, whereas the efficiency benefits of higher DAI appear mainly in shorter horizons and do not continue to increase at the longer horizon. This is consistent with evidence and theory that firms may benefit from lighter debt repayment in critical "investment windows", and can be tightened once the firm is more mature to limit excess spending or low-return projects (Myers, 1977; Johnson, 2003; Almeida et al., 2012). However, choosing back-loaded debt repayments is not a free option. By pushing repayments into the future, the firm also exposes itself to whatever credit and business conditions prevail when that wall arrives, so using the flexibility to lower DAI during growth phases is a risky but meaningful bet that it can handle that future refinancing risk and that the projects will deliver results.

A key feature of our setting is that DAI captures how quickly existing long-term debt is repaid, not how levered the firm is. The cash-flow impact of a given change in DAI therefore scales with the stock of debt: for a lightly levered firm, a 10 pp shift in DAI moves relatively little cash, whereas for a highly levered growth firm, the same shift can free up a large share of annual operating cash flow. This makes the growth-efficiency trade-off we document much sharper exactly where leverage is high, in line with evidence that debt constraints bite hardest for highly levered firms and that long-term debt can depress investment when growth opportunities are weak (Lang, Ofek & Stulz, 1996; Aivazian et al., 2005; Dang, 2011). At the same time, lower DAI today mechanically leaves more principal outstanding and builds a larger maturity wall later, whereas higher DAI does the opposite. Whether a "low DAI now, big wall later" profile is appropriate depends on the credit environment. In favourable markets, rolling a future wall may be straightforward; in stressed markets, it can be difficult or expensive (Gopalan, Song & Yerramilli, 2014; Nguyen, 2022). Our results quantify the operating payoff from lowering DAI, but an actual amortisation policy must balance those gains against the firm's leverage level, its tolerance for future refinancing risk , and a realistic view of what credit conditions might look like when the maturity wall comes.

On the efficiency side, years with higher subsequent DAI are followed by slightly better Op.ROA, Op.Margin, and Asset Turnover, mainly at the one- to three-year horizons. Some of this reflects mechanical effects from smaller asset base, as when the asset base is run down faster, Op.ROA and Asset Turnover naturally improve. The Op.Margin effect at k = 3 is more interesting, because it points to a genuine improvement in operations rather than a pure mechanical effect. This fits the free cash flow view that higher required payouts can force managers to cut weaker projects, reduce slack, and decline marginal investments (Jensen, 1986; Richardson, 2006; Kothari, Lewellen & Warner, 2020). At the same time, the efficiency gains are modest compared with the growth differences, particularly over five years. Higher amortisation intensity therefore appears most useful tool to slim and discupline firms in more mature phases, but may be expensive if applied in the middle of periods when growth opportunities high.

Together, the FE estimates on subsequent DAI show that for leveraged growth firms, amortisation intensity is an operating lever with clear consequences. Lower DAI is systematically associated with stronger medium- to long-run growth in Sales, Total Assets, and increased CapEx Intensity, while higher DAI predicts modest improvements in Op.ROA, Op.Margin, and Asset Turnover. These findings complement prior work on leverage and maturity structure by showing that repayment intensity itself is a distinct and economically meaningful design margin. In a setting where repayment schedules are flexible rather than fixed, the timing of amortisation may directly shape how strongly debt overhang forces constrain investment and how far free-cash-flow concerns are addressed through tighter payouts. Overall, our results indicate that repayment intensity has an economic effect on firms' real and operating outcomes, regardless of leverage level or the duration of it.

It should be noted that a large share of firms in our sample exhibit very low or even negative DAI values, reflecting either minimal principal repayment or net issuance of long-term debt. This pattern is consistent with the broader transition toward institutional term loans with lower amortisation requirements.

5.1.2 DAI as a Within-Firm Lever Rather Than a Cross-sectional Type

The CRE estimates let us separate two questions: what happens when a given firm changes its amortisation intensity over time (as in the FE regression), and how firms that typically run with high versus low DAI differ from each other in the cross-section? The within-firm results closely track the results in the FE, while cross-sectional differences (between-firm) in average DAI contain almost non-systematic prediction of operating performance, so H1-H2 are effectively driven by within-firm variation rather than by firm type.

The within-firm coefficients (β^{W}) in Table 4 are almost identical to the FE estimates. When DAI is lower, growth is higher, and when DAI is higher, growth slows and efficiency improves slightly, consistent with the debt overhang and agency cost of Free Cash Flow theories (Myers, 1977; Jensen, 1986). This also confirms that using a Correlated Random-Effects (Mundlak) specification instead of Fixed Effects leaves the core pattern unchanged. The interpretation and discussion are therefore the same as in Section 5.1.1, and we refer to that section.

In the between-firm regression, most coefficient are small and insignificant across horizons and outcomes, with one exception (Sales growth at $k = 5$; 1.80**). A plausible explanation is that average DAI is driven by other factors such as business model, maturity, and risk profile, in line with evidence that maturity structures reflect asset lives, risk, and growth opportunities (Barclay & Smith, 1995; Johnson, 2003). Mature, cash-generative firms can run with higher DAI and still grow, while more constrained growth firms may push for lower DAI to gain flexibility. Thus, once we control for leverage, profitability, cash holdings, and size, there is little to no systematic relation left between average DAI and outcomes in the cross-section. This suggest that subsequent average DAI between firms is not informative on its own - what matters for operating outcomes in H1-H2 is how each firm moves its amortisation intensity up or down over time, rather than whether it is a "high-DAI" or "low-DAI" firm in the cross-section.

5.1.3 Limited Predictive Power of Trailing DAI

Trailing DAI reflects how intensively a firm has repaid debt over the three years before the base year, and H3 asks whether this history is linked to later expansion, investment, and operating performance. In the within-firm FE and CRE specifications, trailing DAI is generally unrelated to subsequent growth, CapEx intensity, and operating outcomes once we condition on firm and year effects, with only a small, short-run effect Op.Margin. The between-firm CRE results do show that firms that typically operate with lower trailing DAI have somewhat higher subsequent Op.Income growth, CapEx Intensity, and Op.Margin. Thus, we find little support for H3 in the within-firm tests.

The FE and within-firm CRE results for trailing DAI are generally small and insignificant, with the only exception of a signal on operating margin at k = 1. This indicates that modest differences in past amortisation intensity are overshadowed by other factors that drive firm performance. Compared with the subsequent DAI tests, this suggest that under- and over-investment risks are mainly affected by the "simultaneous" amortisation structure for the years ahead, rather than by if the recent periods years were slightly more or less amortising, consistent with the idea that distortions increase when debt survives into key decision windows (Myers, 1977; Almeida et al., 2012). This indicates that DAI matters primarily as a forward-looking operating choice rather than as a legacy of past repayment behaviour.

In the between-firm CRE results, firms that have typically run with lower trailing DAI show a pattern of stronger Op.Income growth over the next 3-5 years, along with a slightly higher CapEx Intensity and stronger Op.Margins. This contrasts with the within-firm evidence and suggests that the cross-sectional signal is picking up differences between types of firms rather than the effect of moving DAI up or down. Persistent low-DAI firms are likely to be those with both good growth opportunities and flexible repayment terms, thereby avoiding the underinvestment risk predicted for firms with higher amortisation or debt (Myers, 1977; Lang, Ofek & Stulz, 1996; Aivazian et al., 2005). Once we control for fundamentals, the remaining variation in trailing DAI therefore likely reflects this mix of business models and financing conditions, rather than a clean "constrained versus unconstrained" scale.

Overall, these patterns suggest that trailing DAI carries some cross-sectional information about firm type but adds little incremental within-firm predictive power for subsequent outcomes, implying that DAI matters mainly as a forward-looking choice variable, rather than as stable historical characteristic.

5.1.4 Amortisation Intensity as a Return Driver

The relationship between leverage and equity returns has long been debated. Bhandari (1988) first documented a positive leverage-return relation, but Fama and French (1992) showed that this effect becomes economically negligible once size and book-to-market are included, suggesting that leverage itself carries little independent pricing power. Consistent with the Modigliani-Miller propositions, this implies that any systematic return premia linked to debt must arise from real-world frictions rather than from the quantum of leverage. In this study, we find confirming support for H4, as DAI is negatively associated with subsequent stock returns across all horizons. However, H5 shows that the portfolio strategy based on trailing DAI generates negligible and statistically insignificant spreads. These findings are especially noteworthy because they suggest that returns depend not on the *level* of leverage but on the *structure* of debt repayment. Unlike broad leverage ratios, DAI captures a specific cash-flow friction, pointing to a mechanism through which debt design, rather than debt level, becomes priced in the cross-section.

A central empirical observation is the divergence between H4, based on subsequent DAI, and H5, based on trailing DAI. This highlights that timing is critical for understanding how amortisation intensity relates to market performance. The Fama-MacBeth regressions capture returns *during* periods when firms are actively operating with low or high amortisation intensity, whereas the portfolio test captures return *after* firms have already gone through such periods. The fact that only subsequent DAI predicts returns suggests that value creation emerges while firms benefit from lower net amortisation intensity, rather than when past amortisation patterns become observable. This interpretation aligns with the operating outcomes documented in Section 4.1. By the time higher investment, faster sales growth, and asset expansion materialise, much of the related return effect appears to have already been priced.

The association between DAI and returns is consistent with the classic debt overhang mechanism articulated by Myers (1977). When positive-NPV opportunities are many and cash conversion is weak, high required payouts constrain investment and increase underinvestment risk. Deferring principal payments through bullet structures preserves near-term liquidity and investment flexibility, enabling firms to fund capex and R&D. The results in Section 4.1 strongly support this mechanism: low-DAI firms invest significantly more and exhibit materially higher CapEx intensity and faster sales and asset growth. DAI therefore appears to be translated directly into productive expansion.

From a valuation perspective, these outcomes align with basic corporate-finance logic. If firm value equals the present value of expected future free cash flows, then the higher investment, faster sales growth, and larger asset base observed among low-DAI firms suggest stronger future cash-flow potential. Taken together, the evidence indicates that the benefits of low amortisation intensity outweigh the risk-increasing effects of increased rollover risk documented by He and Xiong (2012) and Gopalan, Song and Yerramilli (2014), offering a clear rationale for why low-DAI firms subsequently earn higher equity returns.

These investment patterns also help explain the divergence between the two return tests. The investment-return literature (Titman, Wei & Xie, 2004; Cooper, Gulen & Schill, 2008) predicts that increased investment and asset growth should be followed by lower returns. Because low-DAI firms invest more aggressively, any return drag induced by such patterns should be most visible when forming portfolios on *trailing* DAI, offering an explanation for the negligible spreads observed in H5. The *subsequent* DAI specification, by contrast, captures the period in which the investment benefits of repayment flexibility are still materialising, before any potential anomaly-related reversal materialises, resulting in the strong negative DAI-return relation found in H4. That the coefficient weakens at the five-year horizon is consistent with the interpretation that some of these reversal effects begin to set in over longer horizons.

An alternative interpretation is that subsequent DAI may function as a managerial signal about future investment opportunities. Managers anticipating valuable projects may intentionally choose lower amortisation schedules to preserve liquidity, whereas firms with weaker prospects may prioritise paying down debt, particularly relevant for the high-market-to-book sample used in this study. Under this view, DAI reflects both financial flexibility and managerial expectations about future growth. This would help explain why only subsequent DAI predicts returns, as any signal embedded in repayment choices would be priced by the market before trailing-DAI portfolios are formed.

5.2 Key Variables and Method

Our main concern is the construction and use of our self-developed *DAI*. The measure has several limitations that affect how the results should be interpreted. Firstly, DAI is capped at zero, so firms that are net issuers create a mass of "zero DAI" observations that are tilted towards high-growth debt-financed firms. Secondly, DAI does not distinguish contractual amortisation, voluntary repayments, and bank-force cash sweeps, and the same repayment rate can mean different things for mature "cash-cow" firms and constrained growth firms. Lastly, one-off transactions, leverage levels, and the absence of covenant and creditor information add noise and limit causal interpretation. We discuss these issues, and why we still view DAI as a useful repayment-intensity proxy, in more detail in Appendix A.1.

We study listed, non-financial, non-utility firms from 2014 onwards, and include them in each horizon (1, 3, or 5 years) whenever we can compute both DAI and the corresponding outcome. The results, therefore, speak to established growth firms with access to debt markets, and not to private SMEs or early-stage ventures, that may see an even larger effect of non-amortising debt design. We use industry-adjusted Tobin's Q as our growth screen because it is a widely used proxy for growth opportunities in papers studying leverage relationship to growth (e.g. Lang, Ofek & Stulz, 1996), however this measure may miss some firms whose growth is not fully reflected in Q, such as R&D intensive or intangible-heavy firms where conservative accounting and noisy market valuations make Q a noisy signal future growth opportunities. Our used leverage cut-off (excluding firms with market and book leverage $<15\%$) further narrows the sample to firms where debt significantly constrain or support investment. To our knowledge there is no standard leverage cut-off in the literature, so this threshold is a judgment choice rather than a convention. Thus, we test the robustness using lower leverage cut-offs to help check that this specific choice does not drive our main patterns. However, the results should still be read as being a (significantly) leveraged growth firm rather than the whole universe of high-growth firms.

Our main specification relies on firm fixed effects, which control for all time-invariant firm characteristics (e.g. business model, average profitability, governance style, sector position) and focus on how changes in a firm's DAI over time relate to changes in its own growth and performance. This reduces bias from unobserved but stable differences across firms. However, the FE estimates are still exposed to time-varying omitted variables and reverse causality e.g. shifts in demand, strategy, or covenant pressure may affect both amortisation policy and outcomes, and good or bad performance can itself affect changes in DAI. To test for differences in low- vs high-DAI firms, we use a correlated random effects (Mundlak) specification, which augments the random effects model with firm-level means of the regressors. In our setting, this is useful because we are interested both in DAI as a choice margin inside firms (shifts in repayment intensity relative to their own history) and in whether firms that on average operate with higher or lower DAI has systematically different outcomes in terms of growth and performance. The within-firm CRE estimates closely mirror the FE results, which supports the interpretation that the main patterns are not a result of one estimator. The between-firm component is mostly small but helps show where persistent differences in DAI line up with long-run outcomes, especially for trailing DAI and operating performance. However, CRE does not solve endogeneity problems as the time-varying omitted factors and feedback from performance to DAI remain. Thus, we treat the CRE results as improving the interpretation of how DAI matters (within versus between) rather than providing causal identification.

For the market-based tests, two design considerations are particularly important. First, the use of 12-, 36-, and 60-month BHARs creates overlapping return windows, which induces autocorrelation in the monthly Fama-MacBeth coefficient series. We address this using Newey-West standard errors with horizon-specific lags, the standard approach in long-horizon returns tests, but this adjustment mitigates rather than fully eliminates dependence in the error structure. Second, the return tests rely on monthly stock-data while the accounting variables underlying DAI and the sample screens are observed annually. This frequency mismatch introduces timing imprecision, as markets may incorporate information about firms' repayment behaviour before it appears in annual statements. Together, these issues mean that the return results should be interpreted as correlational evidence on pricing rather than precise causal estimates.

Lastly, even with firm and year fixed effects, the link between DAI and later outcomes may be affected by endogeneity. Firms can adjust repayment intensity based on expected future performance, and unobserved factors such as financing constraints may influence both DAI and outcomes. The sample of leveraged growth firms also introduces some selection effects. Therefore, the results should be interpreted as associations rather than causal effects and establishing causality would require an exogenous shock or a dedicated identification strategy, which is beyond the scope of this thesis.

6. Conclusion

Debt can both help and hurt growing firms. According to the debt overhang and agency cost of free cash flow theories, leverage and scheduled payouts improve discipline by reducing excess spending and making low-return projects less attractive, but it can also crowd out value-creating investments when growth opportunities are high. To examine this trade-off in the setting where it should matter most, we study leveraged growth firms and ask two related questions. First, do leveraged growth firms that repay their debt less intensively, as measured by our self-constructed DAI, invest more and grow faster? Second, do markets recognise and price any potential benefits from lower net repayment intensity, or do these effects mainly play out inside the firm?

Our main results show that when leveraged growth firms repay debt more slowly, they do not simply pile that extra cash. On average, they expand their balance sheets faster, increase their CapEx Intensity, and, over longer horizons, grow sales faster. At the same time, increased net repayment intensity is linked to slight improvements in margins and efficiency, suggesting an increased discipline, consistent with the agency cost of free cash flow theory. The CRE-within results confirm this and suggest that DAI is mainly a within-firm choice margin. A change in DAI shifts the firm along a growth-efficiency trade-off, rather than separating "good" and "bad" firms, suggesting that DAI itself is a distinct operating margin, over and above the amount of debt a firm carries and its duration.

Over longer horizons, the between-firm results of past net amortisation intensity (Trailing DAI) suggest that repayment style becomes part of the firm's long-run profile. However, one should be careful not to interpret this as "flexibility always wins". By contrast, our within-firm tests show little systematic association between trailing DAI and subsequent outcomes once fundamentals and firm effects are controlled for. Firms cannot grow on debt forever and at some point, they must either refinance or pay lenders back, and our DAI measure cannot separate "smart flexibility" from simply being a stronger firm that can roll over debt on good terms. Thus, the fact that low-DAI firms in our sample grow their profits faster and improve their margins may partly reflect that they are better businesses to begin with, not only that lower DAI enable better outcomes. Still, within a sample of leveraged growth firms, the pattern is consistent with Myers (1977) underinvestment frictions, that when a large share of cash flow is committed to amortisation, firms seem to leave some long-run growth and profitable projects on the table.

From a market perspective, we find that amortisation intensity is statistically associated with stock returns, although the results are not entirely straightforward.

Lower amortisation intensity predicts higher future returns, suggesting that repayment flexibility is priced when it supports ongoing value creation, whereas past repayment behaviour appears largely incorporated into prices. This asymmetry is consistent with markets responding to the investment and growth enabled by low amortisation intensity, rather than to historical repayment patterns, and may also reflect the influence of well-documented return reversals following periods of high investment and asset expansion. The results suggest that net amortisation intensity matters for expected returns when it reflects forward-looking financial flexibility or managerial expectations about future opportunities, but not as a persistent cross-sectional return factor.

Overall, the findings suggest that net amortisation intensity (DAI) can be a meaningful operating lever for leveraged growth firms. Lower DAI is associated with higher investment and faster expansion, while higher DAI is associated with modest efficiency improvements. The results are thus consistent with both the agency cost and the debt overhang mechanisms. The results should, however, be interpreted with caution. DAI is an observed managerial choice that may itself reflect underlying operating conditions or market expectations, so firms with stronger opportunities may simply be more inclined to maintain low repayment intensity. Even so, the evidence indicates that low DAI supports long-run growth and value creation, while higher intensity improves discipline. Taken together, the evidence shows that net repayment intensity, the pace at which firms pay down existing debt, is a component of modern debt design, with measurable consequences for investment, growth, efficiency, and, to some extent, expected returns.

7. Future Research

This study highlights a directional relationship between amortisation intensity, firm performance and market valuation, leaving several questions for further research open. A first direction concerns the growing role of private credit in corporate financing. Future research could examine whether the economic mechanisms documented in this thesis help explain the rise of private credit, and whether firms that borrow from private credit providers exhibit different investment behaviour, operating performance, or return dynamics than firms that borrow from banks. Such work could shed light on the sudden demand for private credit and whether the structural differences between these markets generate distinct operating or financial effects.

A second interesting direction is to contextualise amortisation intensity within the broader set of contractual lending terms. Existing empirical studies typically analyse one contractual feature at a time, such as maturity, covenants, collateralisation, lender type, or amortisation, when studying firm behaviour or performance. To our knowledge, no study has evaluated combinations of these features jointly, even though real-world debt contracts bundle multiple terms that collectively determine repayment schedules and financial flexibility. Future research could therefore study how amortisation intensity operates alongside covenant tightness, collateral requirements, maturity structure, and lender identity, forming a more informative view of a firm's overall contractual environment. Such work would clarify whether amortisation intensity is an independent mechanism or part of a broader configuration of lending terms that shapes investment capacity, risk-taking, and firm value.

A third area concerns the mechanism linking DAI, investments, and firm value. This thesis finds that low amortisation intensity is associated with higher capital investment, faster growth, and greater asset expansion rewarded by increased returns. Future research could examine the timing of low DAI and its associated benefits more closely. One approach would be to test whether the observed association reflects a causal relation, where lower DAI directly enables greater investments, whether managers anticipating future growth deliberately choose flexible amortisation schedules, or whether lower amortisation is simply a result of managers increasing investment and therefore deferring principal payments.

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A. Appendices

A.1. Limitations of DAI

Our main concern with *Debt Amortisation Intensity (DAI)* measure is how it is defined for net issuers. By construction, DAI is capped at zero, so any firm that issues more debt than it repays over the horizon is recorded as DAI = 0. This creates a mass of observations at zero that mixes firms that truly make no net repayments with firms that repay large amounts and then refinance or upsize their borrowing. In practice, this zero groups will be tilted towards fast-growing, debt-financed firms, which means that "zero DAI" should be read as "no net amortisation" rather than a clean signal of a particular debt design.

A second concern is that DAI does not separate different reasons for repayment. Contractual amortisation, voluntary prepayments from excess cash, and forced deleveraging after covenant pressure all show up as higher DAI. Likewise, the same repayment rate can mean different things for different types of firms. For a mature "cash-cow, a high DAI can reflect an intentional choice to de-lever, while for a younger growth firm it can also reflect constraint or bank-forced cash sweeps. This heterogeneity, together with possible reverse causality (strong or weak performance affecting how much firms amortise), means that our estimates should not be interpreted as clean causal effects of one specific mechanism.

There are also measurement issues that add noise. Large one-off repayments, such as equity issues that are used to pay down debt, can temporarily push DAI up even if the underlying long-run repayment policy has not changed. DAI is only defined for firms with interest-bearing debt (although at >15% leverage) and is scaled by opening debt, so small nominal repayments for low-debt firms can translate into high percentage DAI. The three-year trailing average DAI can be influenced by temporary policies that do not fully reflect the current design. In addition, DAI don't consider covenant structure and creditor type; it cannot distinguish bank monitoring from bond-market pressure and should be seen as a complement, not a substitute, to facility-level data.

However, the construction has features that fit our research question. It is built directly from realised cash flows and captures what firms actually pay to creditors over a given horizon. Netting repayments against new issues means that pure rollovers do not appear as very high amortisation, which is important as many growth firms refinance rather than run loans to contractual maturity. The separate measures for k = 1, 3, and 5 years match our investment and performance horizons and allow us to study both short- and medium-term effects. Conditional on leverage controls and the growth-firm sample restriction, our intention was to design a variable close to a repayment-policy variable than a “more or less debt”-variable.

Overall, DAI is an imperfect but informative measure of repayment intensity at the firm-year level. It cannot isolate one contractual feature or mechanism, and the mass at zero complicates the interpretation of the group. However, it does capture variation in how aggressively leveraged growth firms actually pay down outstanding debt over time. Our results should therefore be read as evidence on the consequences of observed repayment intensity for growth firms, rather than a causal effects of any single element of debt contract design.

A.2. Usage of AI

Artificial intelligence tools, primarily ChatGPT, were used in this thesis in three limited and clearly defined ways. First, ChatGPT was used to support the writing process by suggesting improvements in phrasing, grammar, and clarity. It was also used to create and refine parts of the Stata code applied in the thesis. In all such cases, the intended purpose of the code was clearly described, and all AI-generated suggestions were carefully reviewed and validated by us.

Second, AI tools were used to provide support during the initial stages of the writing process. This included organising preliminary notes, proposing possible outlines, and highlighting potential gaps in logic. These tools contributed only to efficiency and organisation; all analytical decisions, interpretations, and conclusions were made independently by us.

Third, ChatGPT and the literature-mapping tool Research Rabbit were used to identify relevant academic areas and potential sources. All referenced literature was sourced through academic databases and read independently. No theoretical discussions or literature summaries in the thesis rely on AI output.

No proprietary or sensitive data were used, and no empirical data in this thesis was generated through AI tools. Overall, AI has contributed to improving efficiency in writing, coding, and structuring. All findings, analyses, and conclusions are the result of our own critical thinking and work.

A.3. Robustness Tests

A.3.1 Alternative Sample Definitions

Table 10: FE Estimates using Subsequent DAI at 5% leverage cutoff (2015-2024)

Panel A: FE Regression Estimates using Subsequent DAI 2015-2024 at 5% leverage cut-off, k = 1							
Expl. V	**Sales (g)**	**Total Assets (g)**	**Op.Income (g)**	**CapEx Intensity**	**Op.ROA (Δ)**	**Op.Margin (Δ)**	**A.Turn (Δ)**
DAI	-0.04	-0.31***	0.17**	-0.04***	0.08***	0.03	0.26***
t-stat	(-1.00)	(-6.2)	(1.89)	(-4.00)	(8.00)	(1.50)	(4.33)
N	4166	4166	4166	4166	4166	4166	4166
Adj. R^2	0.29	0.16	0.23	0.10	0.34	0.14	0.23
Panel B: FE Regression Estimates using Subsequent DAI 2015-2024 at 5% leverage cut-off, k = 3							
DAI	-0.15	-0.45**	0.47*	-0.11***	0.14***	0.09**	0.27
t-stat	(-0.94)	(-2.5)	(1.74)	(-3.67)	(4.67)	(2.25)	(1.50)
N	2888	2888	2888	2888	2888	2888	2888
Adj. R^2	0.26	0.26	0.22	0.17	0.46	0.19	0.29
Panel C: FE Regression Estimates using Subsequent DAI 2015-2024 at 5% leverage cut-off, k = 5							
DAI	-0.16	-0.94***	0.16	-0.11***	0.23***	0.10	0.52**
t-stat	(-0.52)	(-3.03)	(0.33)	(-3.67)	(3.29)	(1.25)	(2.0)
N	2025	2025	2025	2025	2025	2025	2025
Adj. R^2	0.26	0.32	0.24	0.19	0.42	0.20	0.28

Note: Firm fixed-effects regressions of operating outcomes on subsequent DAI over horizons k = 1, 3, and 5 years, for firm-years with leverage ≥ 5% in year t. All regressions include firm and year fixed effects and the baseline controls (Section 3.3.1). Standard *errors are clustered by firm; all variables are winsorised at the 1st and 99th percentiles by fiscal year. *, **, *** denote significance at the 10%, 5%, and 1% levels.*

Table 11: FE Estimates using Subsequent DAI at 10% leverage cutoff (2015-2024)

Panel A: FE Regression Estimates using Subsequent DAI 2015-2024 at 10% leverage cut-off, k = 1							
Expl. V	**Sales (g)**	**Total Assets (g)**	**Op.Income (g)**	**CapEx Intensity**	**Op.ROA (Δ)**	**Op.Margin (Δ)**	**A.Turn (Δ)**
DAI	-0.12**	-0.45***	-0.01	-0.05***	0.08***	-0.01	0.31***
t-stat	(-2.0)	(-5.00)	(-0.08)	(-5.00)	(4.00)	(-0.50)	(4.43)
N	3212	3212	3212	3212	3212	3212	3212
Adj. R^2	0.29	0.16	0.24	0.09	0.35	0.16	0.22
Panel B: FE Regression Estimates using Subsequent DAI 2015-2024 at 10% leverage cut-off, k = 3							
DAI	-0.43*	-0.63**	0.10	-0.09***	0.13***	0.09	0.16
t-stat	(-1.87)	(-2.17)	(0.27)	(-4.50)	(2.60)	(1.29)	(0.73)
N	2243	2243	2243	2243	2243	2243	2243
Adj. R^2	0.26	0.23	0.27	0.13	0.47	0.19	0.28
Panel C: FE Regression Estimates using Subsequent DAI 2015-2024 at 10% leverage cut-off, k = 5							
DAI	-0.94**	-1.44***	-0.68	-0.10***	0.27**	0.10	0.61
t-stat	(-2.19)	(-3.27)	(-0.84)	(-3.33)	(2.08)	(0.63)	(1.42)
N	1603	1603	1603	1603	1603	1603	1603
Adj. R^2	0.28	0.28	0.28	0.15	0.42	0.22	0.24

*Note: Firm fixed-effects regressions of operating outcomes on subsequent DAI over horizons k = 1, 3, and 5 years, for firm-years with leverage ≥ 10% in year t. All regressions include firm and year fixed effects and the baseline controls (Section 3.3.1). Standard errors are clustered by firm; all variables are winsorised at the 1st and 99th percentiles by fiscal year. *, **, *** denote significance at the 10%, 5%, and 1% levels.*

Table 12: CRE Estimates using Subsequent DAI at 5% leverage cutoff (2015-2024)

Panel A: CRE Regression Estimates using Subsequent DAI with 5% leverage cut-off, k = 1							
Expl. V	**Sales (g)**	**Total Assets (g)**	**Op.Income (g)**	**CapEx Intensity**	**Op.ROA (Δ)**	**Op.Margin (Δ)**	**A.Turn (Δ)**
DAI (between β^B)	0.12	0.09	0.02	0.01	-0.03	0.00	-0.03
t-stat (β^B)	(1.5)	(1.29)	(0.13)	(0.50)	(-1.50)	(0.00)	(-0.43)
N	4166	4166	4166	4166	4166	4166	4166
Adj. R^2	0.28	0.16	0.23	0.10	0.33	0.14	0.23
Panel B: CRE Regression Estimates using Subsequent DAI with 5% leverage cut-off, k = 3							
DAI (between β^B)	-0.10	-0.41*	-0.76*	0.03	-0.06	-0.09*	0.12
t-stat (β^B)	(-0.42)	(-1.78)	(-1.95)	(0.75)	(-1.50)	(-1.80)	(0.60)
N	2888	2888	2888	2888	2888	2888	2888
Adj. R^2	0.26	0.26	0.22	0.17	0.45	0.19	0.29
Panel C: CRE Regression Estimates using Subsequent DAI with 5% leverage cut-off, k = 5							
DAI (between β^B)	-0.16	0.07	-0.36	0.07	-0.16**	-0.06	-0.20
t-stat (β^B)	(-0.39)	(0.16)	(-0.60)	(1.40)	(-2.00)	(-0.60)	(-0.71)
N	2025	2025	2025	2025	2025	2025	2025
Adj. R^2	0.26	0.32	0.24	0.18	0.42	0.19	0.27

*Note: Correlated random-effects (Mundlak) regressions of operating outcomes on subsequent DAI over horizons k = 1, 3, and 5 years, for firm-years with leverage ≥ 5% in year t. Reported coefficients are between-firm (β^B) estimates with t-statistics in parentheses. All models include firm and year effects and the baseline controls (Section 3.3.1). Standard errors are clustered by firm; variables are winsorised at the 1st and 99th percentiles by fiscal year. *, **, *** denote significance at the 10%, 5%, and 1% levels.*

Table 13: CRE Estimates using Subsequent DAI with 10% leverage cutoff (2015-2024)

Panel A: CRE Regression Estimates using Subsequent DAI with 10% leverage cut-off, k = 1							
Expl. V	**Sales (g)**	**Total Assets (g)**	**Op.Income (g)**	**CapEx Intensity**	**Op.ROA (Δ)**	**Op.Margin (Δ)**	**A.Turn (Δ)**
DAI (between β^B)	-0.04	-0.31***	0.17**	-0.04***	0.08***	0.03	0.26***
t-stat (β^B)	(-1.0)	(-6.20)	(1.89)	(-4.00)	(8.00)	(1.50)	(4.33)
N	4166	4166	4166	4166	4166	4166	4166
Adj. R^2	0.29	0.15	0.24	0.09	0.35	0.15	0.21
Panel B: CRE Regression Estimates using Subsequent DAI with 10% leverage cut-off, k = 3							
DAI (between β^B)	-0.15	-0.45**	0.47*	-0.11***	0.14***	0.09**	0.27
t-stat (β^B)	(-0.94)	(-2.50)	(1.74)	(-3.67)	(4.67)	(2.25)	(1.50)
N	2888	2888	2888	2888	2888	2888	2888
Adj. R^2	0.26	0.23	0.26	0.13	0.47	0.19	0.27
Panel C: CRE Regression Estimates using Subsequent DAI with 10% leverage cut-off, k = 5							
DAI (between β^B)	-0.16	-0.94***	0.16	-0.11***	0.23***	0.10	0.52**
t-stat (β^B)	(-0.52)	(-3.03)	(0.33)	(-3.67)	(3.29)	(1.25)	(2.00)
N	2025	2025	2025	2025	2025	2025	2025
Adj. R^2	0.27	0.28	0.28	0.14	0.42	0.22	0.23

*Note: Correlated random-effects (Mundlak) regressions of operating outcomes on subsequent DAI over horizons k = 1, 3, and 5 years, for firm-years with leverage ≥ 10% in year t. Reported coefficients are between-firm (β^B) estimates with t-statistics in parentheses. All models include firm and year effects and the baseline controls (Section 3.3.1). Standard errors are clustered by firm; variables are winsorised at the 1st and 99th percentiles by fiscal year. *, **, *** denote significance at the 10%, 5%, and 1% levels.*

Table 14: Risk-Adjusted Returns on High-Minus-Low DAI Portfolios (Fama-French Five-Factor Model) with Leverage Cut-offs

Panel A: Equal-Weighted High-Minus-Low DAI Portfolio using 10% Leverage Cut-off							
	Int	**R_M-R_F**	**SMB**	**HML**	**RMW**	**CMA**	**R^2**
Coef	0.00	-0.02	0.16***	0.06*	0.05	-0.03	0.20
t-stat	(1.35)	(-0.72)	(4.15)	(1.65)	(0.90)	(-0.42)	
Panel B: Value-Weighted High-Minus-Low DAI Portfolio using 10% Leverage Cut-off							
Coef	0.00	0.00	0.09	-0.08	-0.11	-0.04	0.25
t-stat	(0.29)	(0.11)	(1.19)	(-1.19)	(-1.09)	(-0.36)	

*Note: This table reports Fama-French five-factor (FF5) regressions for the High-minus-Low (H-L) DAI portfolio return spread, using both equal-weighted (EW) and value-weighted (VW) returns on 121 monthly observations. All variables used in portfolio construction and returns are winsorised at the 1st and 99th percentiles within each month. Factors (MKT, SMB, HML, RMW, CMA) follow Fama & French (2015). Alphas measure abnormal returns relative to the FF5 model. Newey-West standard errors with 3 lags are applied. *, **, *** denote significance at the 10%, 5%, and 1% levels.*

Table 15: Risk-Adjusted Returns on High-Minus-Low DAI Portfolios (Fama-French Five-Factor Model) with Leverage Cut-offs

Panel A: Equal-Weighted High-Minus-Low DAI Portfolio using 5% Leverage Cut-off							
	Int	**R_M-R_F**	**SMB**	**HML**	**RMW**	**CMA**	**R^2**
Coef	0.00	-0.02	0.16***	0.06*	0.05	-0.03	0.17
t-stat	(1.35)	(-0.72)	(4.15)	(1.65)	(0.05)	(-0.42)	
Panel B: Value-Weighted High-Minus-Low DAI Portfolio using 5% Leverage Cut-off							
Coef	0.00	0.00	0.09	-0.08	-0.11	-0.04	0.21
t-stat	(0.29)	(0.11)	(1.19)	(-1.19)	(-1.09)	(-0.36)	

*Note: This table reports Fama-French five-factor (FF5) regressions for the High-minus-Low (H-L) DAI portfolio return spread, using both equal-weighted (EW) and value-weighted (VW) returns on 121 monthly observations. All variables used in portfolio construction and returns are winsorised at the 1st and 99th percentiles within each month. Factors (MKT, SMB, HML, RMW, CMA) follow Fama & French (2015). Alphas measure abnormal returns relative to the FF5 model. Newey-West standard errors with 3 lags are applied. *, **, *** denote significance at the 10%, 5%, and 1% levels.*

Table 16: Cross-Sectional Relation Between DAI and Future Abnormal Returns with Different Leverage Cuts

Panel A: Fama-MacBeth Estimates at 12-, 36-, and 60-Month Horizons with 10% leverage cut-off

Indep. Vars.	**12m**	**36m**	**60m**
Const	**-0.76*** **	**-0.53*** **	**-0.48*** **
t-stat	(-2.94)	(-3.02)	(-4.7)
DAI	**-0.02** **	**-0.04**	**-0.02**
t-stat	(-2.08)	(-1.34)	(-1.23)
BM	**0.03***	**-0.02**	**0.02**
t-stat	(1.95)	(-0.98)	(0.97)
Size	**0.14*** **	**0.13*** **	**0.12*** **
t-stat	(3.6)	(4.94)	(6.95)
Leverage	**-0.06*** **	**-0.06*** **	**-0.11*** **
t-stat	(-2.76)	(-4.11)	(-7.22)
$\mathbf{R^2}$	0.06	0.05	0.05

Panel B: Fama-MacBeth Estimates at 12-, 36-, and 60-Month Horizons with 5% leverage cut-off

Indep. Vars.	**12m**	**36m**	**60m**
Const	**-0.45***	**-0.38** **	**-0.45*** **
t-stat	(-1.75)	(-2.22)	(-6.83)
DAI	**-0.01**	**-0.03**	**0.03*** **
t-stat	(-1.24)	(-1.4)	(4.68)
BM	**0.04** **	**-0.04*** **	**-0.01**
t-stat	(2.3)	(-4.18)	(-1.33)
Size	**0.1*** **	**0.12*** **	**0.12*** **
t-stat	(3.55)	(4.65)	(6.57)
Leverage	**-0.07*** **	**-0.05*** **	**-0.08*** **
t-stat	(-4.23)	(-5.18)	(-7.55)
$\mathbf{R^2}$	0.04	0.03	0.04

*Note: This table reports Fama-MacBeth cross-sectional regressions of standardised buy-and-hold abnormal returns (BHAR) on subsequent Debt Amortisation Intensity (DAI) over 12-, 36-, and 60-month horizons. Reported coefficients are the time-series averages of the underlying monthly cross-sectional regressions: 109 for the 12-month BHAR, 85 for the 36-month BHAR, and 61 for the 60-month BHAR. All variables are winsorised at the 1st and 99th percentiles within each month and z-scored cross-sectionally. Standard errors are Newey-West adjusted using horizon-appropriate lags to correct for return overlap. Coefficients reflect the change in BHAR (in standard deviations) associated with a one-standard-deviation increase in each predictor. *, **, *** denote significance at the 10%, 5%, and 1% levels.*

Table 17: FE Estimates using Subsequent DAI in Industry Unadjusted Growth Firm Sample (2015-2024)

Panel A: FE Regression Estimates using Subsequent DAI in Industry Unadjusted Growth Firm Sample, k = 1							
Expl. V	**Sales (g)**	**Total Assets (g)**	**Op.Income (g)**	**CapEx Intensity**	**Op.ROA (Δ)**	**Op.Margin (Δ)**	**A.Turn (Δ)**
DAI	-0.17**	-0.38**	-0.01	-0.04***	0.08**	0.03	0.17
t-stat	(-2.43)	(-1.90)	(-0.09)	(-4.00)	(2.67)	(1.50)	(1.21)
N	1508	1508	1508	1508	1508	1508	1508
Adj. R^2	0.27	0.15	0.20	0.09	0.30	0.13	0.18
Panel B: FE Regression Estimates using Subsequent DAI Industry Unadjusted Growth Firm Sample, k = 3							
DAI	-0.24	0.09	-0.03	-0.05	0.10	0.12	-0.18
t-stat	(-0.53)	(0.16)	(-0.05)	(-1.67)	(1.11)	(0.80)	(-0.37)
N	949	949	949	949	949	949	949
Adj. R^2	0.25	0.22	0.29	0.13	0.47	0.21	0.28
Panel C: FE Regression Estimates using Subsequent DAI in Industry Unadjusted Growth Firm Sample, k = 5							
DAI	-1.22**	-2.60***	-0.04	-0.02	0.28*	0.09	0.15
t-stat	(-2.44)	(-3.33)	(-0.04)	(-0.50)	(1.87)	(0.35)	(0.31)
N	707	707	707	707	707	707	707
Adj. R^2	0.25	0.30	0.24	0.13	0.36	0.25	0.23

*Note: Firm fixed-effects regressions of operating outcomes on subsequent DAI over horizons k = 1, 3, and 5 years, estimated on the industry-unadjusted growth-firm sample. All models include firm and year fixed effects and the baseline controls (Section 3.3.1). Standard errors are clustered by firm; variables are winsorised at the 1st and 99th percentiles by fiscal year. *, **, *** denote significance at the 10%, 5%, and 1% levels.*

Table 18: CRE Estimates using Subsequent DAI in Industry Unadjusted Growth Firm Sample (2015-2024)

Panel A: CRE Regression Estimates using Subsequent DAI 2015-2024 in Industry Unadjusted Growth Sample, k = 1							
Expl. V	**Sales (g)**	**Total Assets (g)**	**Op.Income (g)**	**CapEx Intensity**	**Op.ROA (Δ)**	**Op.Margin (Δ)**	**A.Turn (Δ)**
DAI (between β^B)	0.16	0.12	0.28	-0.02	-0.01	0.01	0.04
t-stat (β^B)	(1.45)	(0.52)	(0.62)	(-0.50)	(-0.20)	(0.25)	(0.20)
N	1508	1508	1508	1508	1508	1508	1508
Adj. R^2	0.26	0.14	0.20	0.09	0.30	0.12	0.18
Panel B: CRE Regression Estimates using Subsequent DAI 2015-2024 in Industry Unadjusted Growth Sample, k = 3							
DAI (between β^B)	0.01	-0.78	-0.98	-0.01	-0.06	-0.08	0.56
t-stat (β^B)	(0.02)	(-1.30)	(-1.09)	(-0.20)	(-0.50)	(-0.50)	(1.06)
N	949	949	949	949	949	949	949
Adj. R^2	0.24	0.20	0.29	0.13	0.47	0.20	0.29
Panel C: CRE Regression Estimates using Subsequent DAI 2015-2024 in Industry Unadjusted Growth Sample, k = 5							
DAI (between β^B)	1.04	2.18**	-0.50	-0.02	-0.46***	-0.21	-0.14
t-stat (β^B)	(1.21)	(2.20)	(-0.37)	(-0.33)	(-2.56)	(-0.81)	(-0.23)
N	707	707	707	707	707	707	707
Adj. R^2	0.24	0.29	0.24	0.12	0.35	0.24	0.22

*Note: Correlated random-effects (Mundlak) regressions of operating outcomes on subsequent DAI over horizons k = 1, 3, and 5 years, estimated on the industry-unadjusted growth-firm sample. Reported coefficients are between-firm (β^B) with t-statistics in parentheses. All models include firm and year effects and the baseline controls (Section 3.3.1). Standard errors are clustered by firm; variables are winsorised at the 1st and 99th percentiles by fiscal year. *, **, *** denote significance at the 10%, 5%, and 1% levels.*

Table 19: Risk-Adjusted Returns on High-Minus-Low DAI Portfolios (Fama-French Five-Factor Model) with Unadjusted Tobin's Q

Panel A: Equal-Weighted High-Minus-Low DAI Portfolio in Industry Unadjusted Growth Firm Sample							
	Int	**R_M-R_F**	**SMB**	**HML**	**RMW**	**CMA**	**R^2**
Coef	0.00	-0.02	0.16***	0.06	0.05	-0.03	0.22
t-stat	(1.35)	(-0.72)	(4.15)	(1.65)	(0.90)	(-0.42)	
Panel B: Value-Weighted High-Minus-Low DAI Portfolio in Industry Unadjusted Growth Firms							
Coef	0.00	0.00	0.09	-0.08	-0.11	-0.04	0.34
t-stat	(0.29)	(0.11)	(1.19)	(-1.19)	(-1.09)	(-0.36)	

*Note: This table reports Fama-French five-factor (FF5) regressions for the High-minus-Low (H-L) DAI portfolio return spread, using both equal-weighted (EW) and value-weighted (VW) returns on 121 monthly observations. All variables used in portfolio construction and returns are winsorised at the 1st and 99th percentiles within each month. Factors (MKT, SMB, HML, RMW, CMA) follow Fama & French (2015). Alphas measure abnormal returns relative to the FF5 model. Newey-West standard errors with 3 lags are applied. *, **, *** denote significance at the 10%, 5%, and 1% levels.*

Table 20: Cross-Sectional Relation Between DAI and Future Abnormal Returns with Unadjusted Tobin's Q

Panel A: Fama-MacBeth Estimates at 12-, 36-, and 60-Month Horizons in Industry Unadjusted Growth Firm Sample

Indep. Vars.	**12m**	**36m**	**60m**
Const	**-1.3*****	**-1.26*****	**-1.43*****
t-stat	(-4.55)	(-2.95)	(-8.72)
DAI	**-0.04*****	**-0.04**	**-0.01**
t-stat	(-4.1)	(-1.54)	(-0.81)
BM	**-0.01**	**-0.04**	**0**
t-stat	(-0.48)	(-0.89)	(0.02)
Size	**0.22*****	**0.24*****	**0.26*****
t-stat	(6.13)	(4.88)	(8.35)
Leverage	**0**	**0**	**-0.05**
t-stat	(-0.06)	(0)	(-1.14)
$\mathbf{R^2}$	0.11	0.11	0.12

*Note: This table reports Fama-MacBeth cross-sectional regressions of standardised buy-and-hold abnormal returns (BHAR) on subsequent Debt Amortisation Intensity (DAI) over 12-, 36-, and 60-month horizons. Reported coefficients are the time-series averages of the underlying monthly cross-sectional regressions: 109 for the 12-month BHAR, 85 for the 36-month BHAR, and 61 for the 60-month BHAR. All variables are winsorised at the 1st and 99th percentiles within each month and z-scored cross-sectionally. Standard errors are Newey-West adjusted using horizon-appropriate lags to correct for return overlap. Coefficients reflect the change in BHAR (in standard deviations) associated with a one-standard-deviation increase in each predictor. *, **, *** denote significance at the 10%, 5%, and 1% levels.*

Table 21: FE Estimates using Subsequent DAI in Non-growth Firms Sample (2015-2024)

Panel A: FE Regression using Subsequent DAI in Non-growth Industry-adjusted Sample, k = 1							
Expl. V	**Sales (g)**	**Total Assets (g)**	**Op.Income (g)**	**CapEx Intensity**	**Op.ROA (Δ)**	**Op.Margin (Δ)**	**A.Turn (Δ)**
DAI	-0.14***	-0.44***	-0.01	-0.04***	0.06***	0.03***	0.26***
t-stat	(-4.67)	(-14.67)	(-0.13)	(-4.00)	(6.00)	(3.00)	(8.67)
N	8556	8556	8556	8556	8556	8556	8556
Adj. R^2	0.30	0.21	0.27	0.07	0.37	0.19	0.19
Panel B: FE Regression using Subsequent DAI in Non-growth Industry-adjusted Sample, k = 3							
DAI	-0.54***	-1.07***	-0.01	-0.05***	0.11***	0.09**	0.40***
t-stat	(-4.15)	(-8.23)	(-0.04)	(-5.00)	(5.50)	(3.00)	(5.00)
N	6093	6093	6093	6093	6093	6093	6093
Adj. R^2	0.30	0.28	0.32	0.07	0.46	0.23	0.22
Panel C: FE Regression using Subsequent DAI in Non-growth Industry-adjusted Sample, k = 5							
DAI	-0.78***	-1.83***	-0.01	-0.06***	0.19***	0.18***	0.68***
t-stat	(-3.00)	(-7.04)	(-0.02)	(-6.00)	(4.75)	(2.57)	(4.25)
N	4111	4111	4111	4111	4111	4111	4111
Adj. R^2	0.30	0.26	0.26	0.06	0.36	0.18	0.19

*Note: Firm fixed-effects regressions of operating outcomes on subsequent DAI over horizons k = 1, 3, and 5 years, estimated on the non-growth, industry-adjusted sample. All models include firm and year fixed effects and the baseline controls (Section 3.3.1). Standard errors are clustered by firm; variables are winsorised at the 1st and 99th percentiles by fiscal year. *, **, *** indicate significance at the 10%, 5%, and 1% levels.*

Table 22: CRE Estimates using Subsequent DAI in Non-growth Firms Sample (2015-2024)

Panel A: CRE Regression using Subsequent DAI in Non-growth Industry-adjusted Sample, k = 1							
Expl. V	**Sales (g)**	**Total Assets (g)**	**Op.Income (g)**	**CapEx Intensity**	**Op.ROA (Δ)**	**Op.Margin (Δ)**	**A.Turn (Δ)**
DAI (between β^B)	0.18***	0.30***	0.19*	0.02	-0.02*	-0.01	-0.11***
t-stat (β^B)	(3.60)	(5.00)	(1.73)	(2.00)	(-2.00)	(-1.00)	(-2.75)
N	8556	8556	8556	8556	8556	8556	8556
Adj. R^2	0.30	0.21	0.27	0.07	0.37	0.19	0.19
Panel B: CRE Regression using Subsequent DAI in Non-growth Industry-adjusted Sample, k = 3							
DAI (between β^B)	-0.04	0.06	-0.05	0.00	0.00	-0.04	-0.07
t-stat (β^B)	(-0.24)	(0.32)	(-0.16)	(0.00)	(0.00)	(-0.80)	(-0.64)
N	6093	6093	6093	6093	6093	6093	6093
Adj. R^2	0.30	0.28	0.32	0.07	0.46	0.23	0.22
Panel C: CRE Regression using Subsequent DAI in Non-growth Industry-adjusted Sample, k = 5							
DAI (between β^B)	-0.54*	0.05	-0.61	-0.01	-0.07	-0.07	-0.32
t-stat (β^B)	(-1.64)	(0.15)	(-1.02)	(-0.50)	(-1.40)	(-0.78)	(-1.60)
N	4111	4111	4111	4111	4111	4111	4111
Adj. R^2	0.30	0.26	0.26	0.06	0.36	0.18	0.19

*Note: Correlated random-effects (Mundlak) regressions of operating outcomes on subsequent DAI over horizons k = 1, 3, and 5 years, estimated on the non-growth, industry-adjusted sample. Reported coefficients are between-firm (β^B) with t-statistics in parentheses. All models include firm and year effects and the baseline controls (Section 3.3.1). Standard errors are clustered by firm; variables are winsorised at the 1st and 99th percentiles by fiscal year. *, **, *** denote significance at the 10%, 5%, and 1% levels.*

Table 23: Risk-Adjusted Returns on High-Minus-Low DAI Portfolios (Fama-French Five-Factor Model) in Non-Growth Sample

Panel A: Equal-Weighted High-Minus-Low DAI Portfolio in Non-Growth Sample							
	Int	**R_M-R_F**	**SMB**	**HML**	**RMW**	**CMA**	**R^2**
Coef	0.00	0.04	0.17**	0.12**	-0.01	0.03	0.24
t-stat	(-0.36)	(0.98)	(2.46)	(2.52)	(-0.12)	(0.38)	
Panel B: Value-Weighted High-Minus-Low DAI Portfolio in Non-Growth Sample							
Coef	0.00	0.08	0.28**	0.15**	-0.02	0.08	0.35
t-stat	(-0.68)	(1.3)	(2.31)	(2.54)	(-0.16)	(0.95)	

*Note: This table reports Fama-French five-factor (FF5) regressions for the High-minus-Low (H-L) DAI portfolio return spread, using both equal-weighted (EW) and value-weighted (VW) returns on 121 monthly observations. All variables used in portfolio construction and returns are winsorised at the 1st and 99th percentiles within each month. Factors (MKT, SMB, HML, RMW, CMA) follow Fama & French (2015). Alphas measure abnormal returns relative to the FF5 model. Newey-West standard errors with 3 lags are applied. *, **, *** denote significance at the 10%, 5%, and 1% levels.*

Table 24: Cross-Sectional Relation Between DAI and Future Abnormal Returns in Non-Growth Sample

Panel A: Fama-MacBeth Estimates at 12-, 36-, and 60-Month Horizons in Non-Growth Sample			
Indep. Vars.	**12m**	**36m**	**60m**
Const	**-1.26*** **	**-1.31*** **	**-1.23*** **
t-stat	(-4.41)	(-9.91)	(-11.91)
DAI	**-0.03***	**-0.09*** **	**-0.1*** **
t-stat	(-1.82)	(-16.64)	(-39.77)
BM	**-0.06*** **	**-0.11*** **	**-0.11*** **
t-stat	(-3.28)	(-13.87)	(-22.07)
Size	**0.19*** **	**0.21*** **	**0.2*** **
t-stat	(5.83)	(9.91)	(9.56)
Leverage	**-0.04*** **	**-0.05*** **	**-0.07*** **
t-stat	(-4.54)	(-5.26)	(-36.2)
R^2	0.08	0.11	0.11

*Note: This table reports Fama-MacBeth cross-sectional regressions of standardised buy-and-hold abnormal returns (BHAR) on subsequent Debt Amortisation Intensity (DAI) over 12-, 36-, and 60-month horizons. Reported coefficients are the time-series averages of the underlying monthly cross-sectional regressions: 109 for the 12-month BHAR, 85 for the 36-month BHAR, and 61 for the 60-month BHAR. All variables are winsorised at the 1st and 99th percentiles within each month and z-scored cross-sectionally. Standard errors are Newey-West adjusted using horizon-appropriate lags to correct for return overlap. Coefficients reflect the change in BHAR (in standard deviations) associated with a one-standard-deviation increase in each predictor. *, **, *** denote significance at the 10%, 5%, and 1% levels.*

Table 25: FE Estimates using Subsequent DAI with Non-overlapping Horizons (2015-2024)

Panel A: FE Regression using Subsequent DAI and Non-Overlapping Horizons, k = 1							
Expl. V	**Sales (g)**	**Total Assets (g)**	**Op.Income (g)**	**CapEx Intensity**	**Op.ROA (Δ)**	**Op.Margin (Δ)**	**A.Turn (Δ)**
DAI	-0.12	-0.39***	-0.01	-0.05***	0.09***	0.03	0.29**
t-stat	(-1.5)	(-2.79)	(-0.06)	(-5.00)	(3.00)	(1.00)	(2.42)
N	2339	2339	2339	2339	2339	2339	2339
Adj. R^2	0.29	0.15	0.23	0.09	0.33	0.13	0.21
Panel B: FE Regression using Subsequent DAI and Non-Overlapping Horizons, k = 3							
DAI	-1.15*	-1.76**	-0.07	-0.17**	0.57***	0.57*	0.48
t-stat	(-1.67)	(-2.00)	(-0.05)	(-2.43)	(3.8)	(1.97)	(0.56)
N	463	463	463	463	463	463	463
Adj. R^2	0.26	0.44	0.40	0.27	0.58	0.37	0.19

*Note: Firm fixed-effects regressions of operating outcomes on subsequent DAI using non-overlapping horizons (k = 1 and k = 3 years). All models include firm and year fixed effects and the baseline controls (Section 3.3.1). Standard errors are clustered by firm; variables are winsorised at the 1st and 99th percentiles by fiscal year. *, **, *** denote significance at the 10%, 5%, and 1% levels.*

Table 26: CRE Estimates with Non-overlapping Horizons (2015-2024)

Panel A: CRE Regression using Subsequent DAI and Non-Overlapping Horizons, k = 1							
Expl. V	**Sales (g)**	**Total Assets (g)**	**Op.Income (g)**	**CapEx Intensity**	**Op.ROA (Δ)**	**Op.Margin (Δ)**	**A.Turn (Δ)**
DAI (between β^B)	-0.01	0.04	0.03	-0.06	-0.02	-0.03	-0.06
t-stat (β^B)	(-0.08)	(0.21)	(0.07)	(-1.50)	(-0.40)	(-0.75)	(-0.33)
N	2339	2339	2339	2339	2339	2339	2339
Adj. R^2	0.29	0.14	0.22	0.09	0.33	0.13	0.21
Panel B: CRE Regression using Subsequent DAI and Non-Overlapping Horizons, k = 3							
DAI (between β^B)	1.09	1.22	-0.12	0.10	-0.33*	-0.23	-0.63
t-stat (β^B)	(1.54)	(1.31)	(-0.09)	(1.25)	(-1.94)	(-0.72)	(-0.79)
N	463	463	463	463	463	463	463
Adj. R^2	0.23	0.41	0.34	0.22	0.55	0.26	0.15

*Note: Correlated random-effects (Mundlak) regressions of operating outcomes on subsequent DAI using non-overlapping horizons (k = 1 and k = 3 years). Reported coefficients are between-firm (β^B) with t-statistics in parentheses. All models include firm and year effects and the baseline controls (Section 3.3.1). Standard errors are clustered by firm; variables are winsorised at the 1st and 99th percentiles by fiscal year. *, **, *** denote significance at the 10%, 5%, and 1% levels.*

A.3.2 Alternative Variable Definitions

Table 27: FE Estimate using Alternative Profit Measure (EBIT; 2015-2024)

Expl. V	**Sales (g)**	**Total Assets (g)**	**Op.Income (g)**	**CapEx Intensity**	**Op.ROA (Δ)**	**Op.Margin (Δ)**	**A.Turn (Δ)**
Panel A: FE Regression using Subsequent DAI and EBIT in profit measures, k = 1							
DAI	-0.15*	-0.38***	-0.01	-0.05***	0.07**	0.00	0.29**
t-stat	(-1.88)	(-2.71)	(-0.03)	(-5.00)	(2.33)	(0.00)	(2.42)
N	2175	2175	2175	2175	2175	2175	2175
Adj. R^2	0.28	0.14	0.26	0.10	0.26	0.16	0.23
Panel B: FE Regression using Subsequent DAI and EBIT in profit measures, k = 3							
DAI	-0.78**	-0.52	-0.03	-0.10***	0.08	0.02	0.06
t-stat	(-2.00)	(-0.98)	(-0.04)	(-3.33)	(1.14)	(0.25)	(0.14)
N	1485	1485	1485	1485	1485	1485	1485
Adj. R^2	0.23	0.18	0.35	0.14	0.40	0.26	0.26
Panel C: FE Regression using Subsequent DAI and EBIT in profit measures, k = 5							
DAI	-1.50**	-1.84**	-0.03	-0.09***	0.17	0.09	0.45
t-stat	(-2.27)	(-2.59)	(-0.02)	(-3.00)	(1.31)	(0.60)	(0.56)
N	1064	1064	1064	1064	1064	1064	1064
Adj. R^2	0.19	0.26	0.23	0.13	0.30	0.22	0.21

*Note: Firm fixed-effects regressions of operating outcomes on subsequent DAI using EBIT-based profitability measures over horizons k = 1, 3, and 5 years. All models include firm and year fixed effects and the baseline controls (Section 3.3.1). Standard errors are clustered by firm; variables are winsorised at the 1st and 99th percentiles by fiscal year. *, **, *** denote significance at the 10%, 5%, and 1% levels.*

Table 28: CRE Estimate using Alternative Profit Measure (EBIT; 2015-2024)

Panel A: CRE Regression using Subsequent DAI and EBIT in profit measures, k = 1							
Expl. V	**Sales (g)**	**Total Assets (g)**	**Op.Income (g)**	**CapEx Intensity**	**Op.ROA (Δ)**	**Op.Margin (Δ)**	**A.Turn (Δ)**
DAI (between β^B)	0.00	-0.23	0.36	-0.09**	0.00	0.04	0.05
t-stat (β^B)	(0.00)	(-1.35)	(0.92)	(-3.00)	(0.00)	(1.00)	(0.31)
N	2175	2175	2175	2175	2175	2175	2175
Adj. R^2	0.18	0.26	0.22	0.12	0.29	0.20	0.20
Panel B: CRE Regression using Subsequent DAI and EBIT in profit measures, k = 3							
DAI (between β^B)	0.61	-0.58	0.89	0.04	0.05	0.12	0.43
t-stat (β^B)	(1.24)	(-1.07)	(0.92)	(1.00)	(0.56)	(1.09)	(0.96)
N	1485	1485	1485	1485	1485	1485	1485
Adj. R^2	0.23	0.17	0.34	0.14	0.40	0.25	0.26
Panel C: CRE Regression using Subsequent DAI and EBIT in profit measures, k = 5							
DAI (between β^B)	1.30	0.99	1.40	0.02	-0.10	-0.03	-0.08
t-stat (β^B)	(1.57)	(1.19)	(0.95)	(0.40)	(-0.71)	(-0.18)	(-0.10)
N	1064	1064	1064	1064	1064	1064	1064
Adj. R^2	0.27	0.13	0.26	0.09	0.25	0.16	0.23

*Note: Correlated random-effects (Mundlak) regressions of operating outcomes on subsequent DAI using EBIT-based profitability measures over horizons k = 1, 3, and 5 years. Reported coefficients are between-firm (β^B) with t-statistics in parentheses. All models include firm and year effects and the baseline controls (Section 3.3.1). Standard errors are clustered by firm; variables are winsorised at the 1st and 99th percentiles by fiscal year. *, **, *** denote significance at the 10%, 5%, and 1% levels.*

A.3.3 Alternative Estimation Choices

Table 29: FE Estimates with 5/95 Winsorisation (2015-2024)

Panel A: FE Regression using Subsequent DAI and at 5/95 winsorisation, k = 1							
Expl. V	**Sales (g)**	**Total Assets (g)**	**Op.Income (g)**	**CapEx Intensity**	**Op.ROA (Δ)**	**Op.Margin (Δ)**	**A.Turn (Δ)**
DAI	-0.11	-0.43***	-0.01	-0.04***	0.09***	0.03	0.29***
t-stat	(-1.38)	(-5.38)	(-0.08)	(-4.00)	(3.00)	(1.00)	(3.63)
N	2339	2339	2339	2339	2339	2339	2339
Adj. R^2	0.29	0.14	0.25	0.12	0.26	0.11	0.27
Panel B: FE Regression using Subsequent DAI and at 5/95 winsorisation, k = 3							
DAI	-0.49	-0.49	-0.02	-0.08***	0.19***	0.21**	0.23
t-stat	(-1.63)	(-1.17)	(-0.04)	(-4.00)	(2.71)	(2.33)	(0.82)
N	1614	1614	1614	1614	1614	1614	1614
Adj. R^2	0.24	0.18	0.29	0.14	0.42	0.18	0.30
Panel C: FE Regression using Subsequent DAI and at 5/95 winsorisation, k = 5							
DAI	-1.14**	-1.40**	-0.03	-0.10***	0.27**	0.05	0.56
t-stat	(-2.00)	(-2.33)	(-0.03)	(-3.33)	(2.08)	(0.21)	(1.08)
N	1151	1151	1151	1151	1151	1151	1151
Adj. R^2	0.23	0.27	0.19	0.13	0.26	0.13	0.23

*Note: Firm fixed-effects regressions of operating outcomes on subsequent DAI using 5/95 winsorisation, estimated over horizons k = 1, 3, and 5 years. All models include firm and year fixed effects and the baseline controls (Section 3.3.1). Standard errors are clustered by firm. *, **, *** denote significance at the 10%, 5%, and 1% levels.*

Table 30: CRE Estimates with 5/95 Winsorisation (2015-2024)

Panel A: CRE Regression using Subsequent DAI and with 5/95 Winsorisation, k = 1							
Expl. V	**Sales (g)**	**Total Assets (g)**	**Op.Income (g)**	**CapEx Intensity**	**Op.ROA (Δ)**	**Op.Margin (Δ)**	**A.Turn (Δ)**
DAI (between β^B)	-0.03	0.02	0.01	-0.05**	-0.01	-0.02	-0.05
t-stat (β^B)	(-0.25)	(0.17)	(0.04)	(-2.50)	(-0.20)	(-0.50)	(-0.45)
N	2339	2339	2339	2339	2339	2339	2339
Adj. R^2	0.29	0.14	0.25	0.11	0.25	0.10	0.27
Panel B: CRE Regression using Subsequent DAI and with 5/95 Winsorisation, k = 3							
DAI (between β^B)	0.99	0.22	0.59	0.02	-0.16	0.00	-0.14
t-stat (β^B)	(1.32)	(0.30)	(0.55)	(0.50)	(-1.07)	(0.00)	(-0.26)
N	1614	1614	1614	1614	1614	1614	1614
Adj. R^2	0.24	0.18	0.29	0.14	0.42	0.17	0.30
Panel C: CRE Regression using Subsequent DAI and with 5/95 Winsorisation, k = 5							
DAI (between β^B)	1.30	0.99	1.40	0.02	-0.10	-0.03	-0.08
t-stat (β^B)	(1.57)	(1.19)	(0.95)	(0.40)	(-0.71)	(-0.18)	(-0.10)
N	1151	1151	1151	1151	1151	1151	1151
Adj. R^2	0.22	0.27	0.19	0.12	0.26	0.12	0.22

*Note: Correlated random-effects (Mundlak) regressions of operating outcomes on subsequent DAI using 5/95 winsorisation, estimated over horizons k = 1, 3, and 5 years. Reported coefficients are between-firm (β^B) with t-statistics in parentheses. All models include firm and year effects and the baseline controls (Section 3.3.1). Standard errors are clustered by firm. *, **, *** denote significance at the 10%, 5%, and 1% levels.*

Table 31: Risk-Adjusted Returns on High-Minus-Low DAI Portfolios (Fama-French Five-Factor Model) with Increased Winsorisation

Panel A: Equal-Weighted High-Minus-Low DAI Portfolio with 5/95 Winsorisation							
	Int	**R_M-R_F**	**SMB**	**HML**	**RMW**	**CMA**	**R^2**
Coef	0.00	-0.03	0.14***	0.05*	0.04	-0.04	0.26
t-stat	(0.91)	(-1.24)	(4.06)	(1.73)	(0.83)	(-0.77)	
Panel B: Value-Weighted High-Minus-Low DAI Portfolio with 5/95 Winsorisation							
Coef	0.00	-0.03	0.07	-0.06	-0.12	-0.07	0.38
t-stat	(0.42)	(-0.84)	(1.17)	(-1.11)	(-1.49)	(-0.82)	

*Note: This table reports Fama-French five-factor (FF5) regressions for the High-minus-Low (H-L) DAI portfolio return spread, using both equal-weighted (EW) and value-weighted (VW) returns on 121 monthly observations. All variables used in portfolio construction and returns are winsorised at the 5^{th} and 95^{th} percentiles within each month. Factors (MKT, SMB, HML, RMW, CMA) follow Fama & French (2015). Alphas measure abnormal returns relative to the FF5 model. Newey-West standard errors with 3 lags are applied. *, **, *** denote significance at the 10%, 5%, and 1% levels.*

Table 32: Cross-Sectional Relation Between DAI and Future Abnormal Returns with Increased Winsorisation

Panel A: Fama-MacBeth Estimates at 12-, 36-, and 60-Month Horizons with 5/95 Winsorisation

Indep. Vars.	12m	36m	60m
Const	**-0.64****	**-0.23**	**-0.12**
t-stat	(-2.33)	(-1.51)	(-1.61)
DAI	**-0.02***	**-0.1*****	**-0.1*****
t-stat	(-1.68)	(-3.37)	(-4.1)
BM	**0.05*****	**0.02**	**0.05*****
t-stat	(3.06)	(0.94)	(5.18)
Size	**0.11*****	**0.1*****	**0.08*****
t-stat	(3.56)	(4.01)	(5.42)
Leverage	**-0.13*****	**-0.17*****	**-0.21*****
t-stat	(-6.13)	(-5.74)	(-8.72)
$\mathbf{R^2}$	0.08	0.08	0.08

*Note: This table reports Fama-MacBeth cross-sectional regressions of standardised buy-and-hold abnormal returns (BHAR) on subsequent Debt Amortisation Intensity (DAI) over 12-, 36-, and 60-month horizons. Reported coefficients are the time-series averages of the underlying monthly cross-sectional regressions: 109 for the 12-month BHAR, 85 for the 36-month BHAR, and 61 for the 60-month BHAR. All variables are winsorised at the 5^{th} and 95^{th} percentiles within each month and z-scored cross-sectionally. Standard errors are Newey-West adjusted using horizon-appropriate lags to correct for return overlap. Coefficients reflect the change in BHAR (in standard deviations) associated with a one-standard-deviation increase in each predictor. *, **, *** denote significance at the 10%, 5%, and 1% levels.*

Table 33: Pooled OLS (No Fixed Effects) Estimate using Subsequent DAI (2015-2024)

Expl. V	**Sales (g)**	**Total Assets (g)**	**Op.Income (g)**	**CapEx Intensity**	**Op.ROA (Δ)**	**Op.Margin (Δ)**	**A.Turn (Δ)**
Panel A: Pooled OLS Regression using Subsequent DAI, k = 1							
DAI	-0.07	-0.39***	-0.02	-0.09***	0.09***	0.02	0.29***
t-stat	(-1.17)	(-4.33)	(-0.10)	(-4.50)	(4.50)	(1.00)	(3.63)
N	2339	2339	2339	2339	2339	2339	2339
Adj. R^2	0.29	0.15	0.23	0.10	0.33	0.13	0.22
Panel B: Pooled OLS Regression using Subsequent DAI, k = 3							
DAI	-0.19	-0.91***	-0.03	-0.11***	0.13**	0.09*	0.45***
t-stat	(-0.76)	(-3.37)	(-0.08)	(-3.67)	(2.60)	(1.80)	(3.00)
N	1614	1614	1614	1614	1614	1614	1614
Adj. R^2	0.25	0.23	0.26	0.15	0.46	0.17	0.27
Panel C: Pooled OLS Regression using Subsequent DAI, k = 5							
DAI	-0.30	-1.17**	-0.04	-0.09**	0.08	0.03	0.41*
t-stat	(-0.54)	(-2.09)	(-0.05)	(-2.25)	(1.14)	(0.38)	(1.95)
N	1151	1151	1151	1151	1151	1151	1151
Adj. R^2	0.29	0.33	0.27	0.15	0.41	0.18	0.23

*Note: Pooled OLS regressions of operating outcomes on subsequent DAI over horizons k = 1, 3, and 5 years. All models include the baseline controls (Section 3.3.1) but no firm fixed effects. Standard errors are clustered by firm; variables are winsorised at the 1st and 99th percentiles by fiscal year. *, **, *** denote significance at the 10%, 5%, and 1% levels.*

Table 34: Cross-Sectional (with Fixed Effects) Relation Between DAI and Future Abnormal Returns

Panel A: Fama-MacBeth Estimates at 12-, 36-, and 60-Month Horizons with Fixed Effects

Indep. Vars.	12m	36m	60m
Const	**0.06**	**0**	**-0.1**
t-stat	(0.84)	(-0.05)	(-1.43)
DAI	**0.03**	**-0.02**	**0.01**
t-stat	(1.26)	(-0.66)	(0.31)
BM	**0.01**	**0.05**	**-0.08**
t-stat	(0.25)	(0.73)	(-1.05)
Size	**1.52*** **	**1.77*** **	**1.77*** **
t-stat	(6.83)	(8.48)	(7.42)
Leverage	**-0.04**	**-0.05**	**-0.02**
t-stat	(-0.54)	(-0.7)	(-0.17)
R^2	0.13	0.25	0.38

*Note: This table reports cross-sectional regressions of standardised buy-and-hold abnormal returns (BHAR) on subsequent Debt Amortisation Intensity (DAI) over 12-, 36-, and 60-month horizons. All variables are winsorised at the 1st and 99th percentiles within each month and z-scored cross-sectionally. Standard errors are Newey-West adjusted using horizon-appropriate lags to correct for return overlap. Coefficients reflect the change in BHAR (in standard deviations) associated with a one-standard-deviation increase in each predictor. *, **, *** denote significance at the 10%, 5%, and 1% levels.*

Table 35: Risk-Adjusted Returns on High-Minus-Low DAI (Quintile) Portfolios (Fama-French Five-Factor Model)

Panel A: Equal-Weighted High-Minus-Low DAI Portfolio using Quintiles							
	Int	**R_M-R_F**	**SMB**	**HML**	**RMW**	**CMA**	**R^2**
Coef	0.00	-0.06**	0.22***	0.02	0.06	-0.04	0.25
t-stat	(1.13)	(-1.98)	(4.67)	(0.55)	(1.03)	(-0.54)	
Panel B: Value-Weighted High-Minus-Low DAI Portfolio using Quintiles							
Coef	0.00	-0.01	0.30***	-0.11	-0.05	-0.22	0.36
t-stat	(-0.27)	(-0.15)	(2.78)	(-1.35)	(-0.4)	(-1.44)	

*Note: This table reports Fama-French five-factor (FF5) regressions for the High-minus-Low (H-L) DAI portfolio return spread, using both equal-weighted (EW) and value-weighted (VW) returns on 121 monthly observations. All variables used in portfolio construction and returns are winsorised at the 1st and 99th percentiles within each month. Factors (MKT, SMB, HML, RMW, CMA) follow Fama & French (2015). Alphas measure abnormal returns relative to the FF5 model. Newey-West standard errors with 3 lags are applied. *, **, *** denote significance at the 10%, 5%, and 1% levels.*