Financing Intangibles *

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Abstract

Intangible assets, such as brands, software, customer relationships, and technologies, account for a growing share of firm capital, yet their role in debt financing remains unclear. Using a large sample of detailed asset valuations from acquisition transactions, I show that each dollar of intangible assets acquired is associated with a $0.24 increase in long-term debt, compared to $0.44 for tangibles. I find intangibles are financed primarily through cash flow–based rather than asset-based lending. Consistent with this finding, redeployability increases debt usage for tangible assets but has no effect on intangible assets. I document that demand-shifter intangibles, such as brands and customer relationships, exhibit a stronger association with debt financing than production-based intangibles, such as patents and technology, consistent with their role in reducing cash flow volatility. To provide causal evidence, I exploit the 2014 Marblegate court ruling, which impaired the pledgeability of intangibles, and show that the ability of intangibles to support borrowing depends critically on the legal environment.

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Intangible assets, such as brands, software, customer relationships, and technologies, have become central to firm value in the modern economy. Although they lack physical form, these assets play a critical role in how firms operate, compete, and grow. Consider, for example, Amazon Prime membership, the Starbucks rewards app, Google's search algorithm, or Tesla's self-driving software. While none is tangible like factories or machines, each is essential to the firm's value. Recent estimates suggest that intangibles account for more than one-third of firms' capital input (Corrado and Hulten, 2010). They are commonly grouped into three categories: innovative property, computerized information, and economic competencies (Corrado et al., 2005). Empirical studies find that these assets are strongly associated with firm productivity, profitability, and financial soundness (Chappell and Jaffe, 2018; Crouzet and Eberly, 2018; Eisfeldt et al., 2020).

A growing body of macro-finance research has raised concerns that the increasing reliance on intangible capital may weaken firms' debt capacity (e.g., Caggese and Pérez-Orive, 2022; Döttling and Ratnovski, 2023; Falato et al., 2022; Giglio and Severo, 2012; Howes et al., 2022; Li, 2025). The prevailing assumption in theory is that intangible assets, because they lack physical form, are difficult to redeploy and offer limited collateral value. In fact, a common modeling assumption is that intangibles cannot support debt, while tangibles can back debt up to their value (e.g., Li, 2025).

This study examines that assumption. I empirically explore whether, how, and to what extent different types of intangible assets can be financed with debt. I document that, while tangible assets are more closely associated with debt financing, the gap is substantially smaller than theoretical models assume. In short, intangible assets can support debt, just in a different way.

To overcome measurement challenges related to intangible assets, I use detailed asset-level valuations from acquisition transactions, specifically Purchase Price Allocations (PPA), to construct precise measures of intangible assets. These data allow me to observe the market value of specific intangible categories, such as customer relationships, technology, brands, and software, at the time of acquisition.[1] This approach avoids many of the measurement challenges associated with commonly used proxies such as R&D expense for knowledge capital and SG&A expenses for organizational capital.[2] Since the adoption of

[1] See Figure A1 that shows common types of intangibles.

[2] A widely used approach in the literature estimates intangible capital by capitalizing firm-level expenditures, such as R&D for knowledge capital and a portion of SG&A for organizational capital, using the perpetual inventory method. This methodology has been highly influential and remains central to empirical work on intangibles (e.g., Eisfeldt and Papanikolaou, 2013, 2014; Peters and Taylor, 2017).

However, it relies on strong assumptions about depreciation rates, capitalization shares, and the aggregation of spending into stock measures.

the Statement of Financial Accounting Standards No. 141 (SFAS 141) in 2001, acquirers are required to disclose the fair value of purchased assets, including detailed valuations of intangibles (Ewens et al., 2025; Lim et al., 2020; Masulis et al., 2023). These valuations are market-based, arising from transactions, and are supported by third-party valuation experts and subject to audit and regulatory review. Because they reflect fair value at the time of acquisition and disaggregate different types of intangibles, PPA disclosures offer a more precise and economically meaningful measure of intangible capital than traditional accounting data.

In the first part of this paper, I show that intangible assets can support debt financing. First, I examine acquisition transactions to assess how firms use debt to finance the purchase of intangible versus tangible assets. The acquisition setting offers a clean empirical environment because it isolates new asset purchases and provides market-based valuations at a detailed level. My results show that while firms finance intangible assets with less debt than tangible assets, the extent of debt financing for intangibles is still economically meaningful. Specifically, each dollar of intangible assets acquired is associated with a \$0.24 increase in long-term debt, a coefficient that is statistically significant and distinct from zero. This result challenges the common modeling assumption that intangible assets cannot support debt financing (e.g., Caggese and Pérez-Orive, 2022; Li, 2025). For comparison, a dollar of tangible assets is associated with a \$0.44 increase in long-term debt, and the difference between the two coefficients is also statistically significant. While intangible assets may be associated with somewhat more constrained borrowing relative to tangibles, the magnitude of this constraint is far smaller than theoretical models typically assume.

In the second part of this paper, I examine the underlying mechanism through which intangible assets support debt financing by distinguishing between two primary lending channels: *asset-based lending*, which is secured by the value of specific pledged assets (e.g., Bernanke et al., 1999; Kiyotaki and Moore, 1997; Shleifer and Vishny, 1992), and *cash flow–based lending*, which depends on a firm's ongoing earnings capacity (e.g., Holmstrom and Tirole, 1997). The core distinction whether lending is tied to an asset's value or to the firm's ongoing ability to generate cash flow is often described as the difference between "land" versus "fruit" as in Kiyotaki and Moore (1997). Building on the empirical approaches developed by Lian and Ma (2021) and Ivashina et al. (2022), I classify corporate debt into these two categories to investigate how intangibles relate to each lending base.

This distinction is important because much of the skepticism around the debt capacity of intangible assets assumes that most corporate borrowing is asset-based. Under this

view, intangible assets, which lack physical form and are potentially difficult to redeploy, make poor asset-based collateral and therefore contribute little to borrowing capacity. Consistent with this perspective, the literature often uses asset tangibility as a proxy for pledgeability and, by extension, for a firm's overall debt capacity (Almeida and Campello, 2007), reinforcing the notion that intangibles play a limited role in supporting debt financing.

My empirical results reveal that while intangibles contribute little to asset-based borrowing, they are strongly associated with cash flow–based debt. For each dollar of intangible assets acquired, there is a \$0.25 increase in cash flow–based debt, statistically indistinguishable from the \$0.24 increase per dollar of tangible assets. In contrast, the relationship between intangible assets and asset-based debt is much weaker: only \$0.05 of asset-based debt is associated with each dollar of intangibles, compared to \$0.20 for tangibles. The difference between these coefficients is statistically significant, confirming that intangibles play a minimal role in asset-based borrowing.

To further test whether the asset-based mechanism is truly limited for intangibles, I examine whether redeployability, a core determinant of collateral value in asset-based lending, affects the relationship between asset purchases and debt financing. I construct a measure of redeployability based on the number of mid-sized firms in the target's 3-digit NAICS industry, capturing the breadth of the secondary market for acquired assets. I find that redeployability significantly amplifies the debt financing of tangible assets, consistent with the idea that more redeployable assets provide better collateral. In contrast, redeployability has no significant effect on the debt financing of intangible assets. This result reinforces the conclusion that intangible assets do not support debt through the asset-based channel and instead are financed primarily through lending based on the firm's going-concern value.

These findings call for a reevaluation of how we think about debt financing in the context of intangible assets. The traditional emphasis on specific pledged collateral and liquidation value does not fully capture the financing dynamics of intangibles in the modern economy. Instead, debt associated with intangible assets operates primarily through cash flow–based channels, reflecting lenders' reliance on future earnings rather than asset resale value. Once the cash flow channel exists, limited pledgeability is a weaker constraint on the firm's overall debt financing than many traditional physical collateral-only models assume. This shift challenges existing theoretical assumptions and suggests the need for models that better reflect how firms with intangible capital access credit markets.

In the third part of the paper, I examine whether different types of intangible assets differ

in their ability to support debt financing. Since the earlier analysis shows that intangibles are primarily associated with cash flow–based debt, a natural question is whether some intangibles are better suited to this than others. Conceptually, intangible assets that help reduce cash flow volatility should be especially valuable in supporting debt, given the reliance of this form of lending on stable and predictable earnings.

To empirically test this idea, I classify intangibles into two broad types: production-based intangibles (e.g., patents and technology), which enhance a firm's production capability, and demand-shifter intangibles (e.g., customer relationships and brands), which help sustain and stabilize sales. A broad literature in industrial organization shows that demand-shifter intangibles can create demand persistence through repeated purchases, habit formation, search and switching frictions, or reputation effects (e.g., Bronnenberg et al., 2012; Cabral, 2016; Katz and Shapiro, 1985; Gourio and Rudanko, 2014). Motivated by these insights, I hypothesize that demand-shifter intangibles stabilize cash flows and are therefore better suited to support borrowing.

Consistent with this hypothesis, I find that demand-shifter intangibles are more strongly associated with debt financing. Specifically, a $1 increase in demand-shifter intangibles is associated with a $0.45 increase in long-term debt, compared to just $0.15 for production-based intangibles. Both effects are statistically significant, and the difference between them is also significant, highlighting meaningful heterogeneity in how different types of intangibles support borrowing. Also, the effect is concentrated in cash flow–based debt, aligning with prior findings and supporting the proposed mechanism that demand-shifter intangibles help stabilize cash flows. Dividing the analysis into specific categories within each intangible group reveals a consistent pattern that demand-shifter intangibles are more strongly linked to debt usage than production-based intangibles. As a further check on this mechanism, I show that acquisitions rich in demand-shifter intangibles are associated with lower post-acquisition cash flow volatility.

In the final part of the paper, I provide causal evidence on the role of intangible assets in supporting debt financing using the 2014 Marblegate court ruling as a quasi-exogenous shock to their pledgeability. In this ruling, the U.S. District Court reinterpreted Section 316(b) of the Trust Indenture Act, requiring unanimous bondholder consent for many types of debt restructurings. As a result, firms reliant on bond financing were pushed toward more prolonged and costly formal bankruptcies, rather than being able to restructure debt out of court (Fan, 2025; Kornejew, 2024). This shock is particularly damaging for firms with a high share of intangible assets, such as customer relationships, technology, or brand value, because these assets tend to deteriorate rapidly in financial distress: customers

may lose trust in the firm, key employees with specialized knowledge may leave, and reputation-based assets are harder to preserve (e.g., Antill and Hunter, 2023; Babina, 2020; Baghai et al., 2021; Hortaçsu et al., 2013). Consequently, the indirect costs of distress are higher for intangible-intensive firms, leading to lower expected recovery values.

Importantly, the Marblegate ruling was not driven by firm-specific choices and did not directly affect firms' investment opportunities, making it a clean and plausibly exogenous shock to the pledgeability, and thus the financing capacity, of intangible assets. If intangible assets had been supporting borrowing, then firms with both high bond reliance and high intangible intensity should reduce their debt usage after the shock. I test this hypothesis using a triple-difference design on a panel of high-yield firms from 2013 to 2016. The approach compares changes in leverage before and after the ruling across firms with differing pre-shock exposures to bond financing and intangible intensity.

The results show that leverage declines relative to the counterfactual groups for firms with both high bond reliance and high intangible intensity. This decline is driven entirely by reductions in bond debt, with no evidence of substitution into loans. Event study plots show no evidence of pre-existing trends. Placebo tests using investment-grade firms, which were unaffected by the ruling, further help rule out confounding macroeconomic or regulatory shocks as alternative explanations. Two years after the ruling, firms with high intangibles and high-bond reliance experienced a cumulative 7% decline in residualized debt, relative to their 2014Q3 assets, compared to similar firms with low intangible intensity. No such decline is observed among low-bond firms. Together, these findings suggest that intangible assets had indeed supported borrowing prior to the shock and that their reduced pledgeability after Marblegate constrained firms' debt financing. More broadly, the evidence underscores that the ability to borrow against intangible assets depends critically on a legal infrastructure that preserves firm value and allows for orderly restructuring in distress.

Related literature and contribution. This paper builds on and contributes to several strands of existing literature. First, it relates to research on the measurement of intangible assets. A substantial body of work on intangibles has used the perpetual-inventory method to infer intangible capital from firm-level expenditures such as R&D and SG&A (e.g., Belo et al., 2022; Crouzet and Eberly, 2021; Eisfeldt and Papanikolaou, 2013, 2014; Eisfeldt et al., 2020; Falato et al., 2022; Peters and Taylor, 2017; Xiaolan, 2014). He et al. (2025) capitalized sales and marketing expense to capture customer capital investment. Complementing this approach, I use detailed PPA data from acquisition transactions, which provide direct, market-based valuations of different intangible categories alongside tangible assets. Prior

studies using PPA data typically have focused on public target firms or aggregate intangible values (e.g., Ewens et al., 2025; Kepler et al., 2023; Lim et al., 2020). This paper expands on that work by assembling one of the most comprehensive PPA datasets to date, covering both public and private targets. This broader coverage provides a more representative picture of how firms finance and value different types of intangible assets, especially since public-to-public acquisitions are a highly selected subset of deals, often concentrated in specific sectors, such as healthcare and business equipment.

Second, this paper adds to a growing empirical literature on the debt financing of intangible assets. Loumioti (2012) studies syndicated loans that have intangibles as part of the security. Mann (2018), Hochberg et al. (2018), and Ciaramella et al. (2022) provide evidence on patent and intellectual property–based lending. Gill and Heller (2024) further shows how stronger IP protections can increase access to external finance. Larkin (2013) finds that stronger brands provide additional debt capacity through lowering cash flow volatility. Lim et al. (2020), which is closest to my work, links target asset composition and firm pre-acquisition capital structure using PPA data.[3]

My analysis advances this literature by offering both an empirical quantification of financing magnitudes and a structured perspective on the underlying mechanisms. I not only show that intangibles can support debt financing, but also estimate the dollar amount of long-term debt associated with each dollar of acquired intangible capital. I find that intangibles are primarily associated with cash flow–based lending, where financing decisions rely on the firm's going-concern value rather than asset liquidation. To explore why some intangibles support debt more than others, I classify them into two categories based on the production function: production-based and demand-shifter. Demand-shifter intangibles are more strongly associated with debt usage, consistent with their role in reducing cash flow volatility. Finally, I provide evidence from a quasi-natural experiment setting, using the 2014 Marblegate court ruling, which reduced the pledgeability of intangibles. I show that intangibles' contribution to debt usage depends critically on the legal infrastructure that supports orderly restructuring. Collectively, these findings offer a more structured and nuanced understanding of how, why, and under what conditions intangible assets can support debt financing.

[3]Lim et al. (2020) provides valuable early evidence linking asset composition to firm leverage using PPA data. I extend this analysis in several ways. First, I directly quantify the amount of debt associated with each dollar of acquired intangible capital. Second, I use a broader and more representative sample, including roughly ten times more target firms across both public and private deals, which helps mitigate the selection concerns inherent in public-to-public transactions. Finally, I delve into economic mechanisms focused on cash flow–based debt financing, propose and empirically test an alternative cash flow–volatility channel, and incorporate a quasi-natural experiment. Together, these elements bring richness to the study and shed light on how and why different types of intangible assets support debt financing.

Third, the paper connects to theoretical and macro-finance work on collateral, pledgeability, and monetary transmission. Foundational models such as Hart and Moore (1994), Holmstrom and Tirole (1997), and Rampini and Viswanathan (2010) show how collateral mitigates agency problems and links firms' borrowing capacity to the redeployability of their assets, an attribute often associated with tangible assets. Recent empirical work highlights the coexistence of asset-based and cash flow–based lending (e.g., Benmelech et al., 2025; Hartman-Glaser et al., 2025; Ivashina et al., 2022; Kermani and Ma, 2023; Lian and Ma, 2021), suggesting that financing capacity may depend not only on collateral value but also on future earnings potential. In macro-finance, papers such as Falato et al. (2022), Caggese and Pérez-Orive (2022), and Li (2025) argue that the rise of intangibles weakens debt capacity, with implications for investment, cash holdings, and the effectiveness of monetary policy.

My paper contributes to this broader conversation by showing that while intangible assets are only weakly associated with asset-based debt, they are nonetheless strongly linked to cash flow–based debt. In addition, I find that, unlike with tangible assets, the debt financing of intangibles is not sensitive to asset redeployability, a pattern consistent with lending that relies on going-concern value rather than resale potential. These findings add nuance to prior work that appropriately emphasized the role of tangibility and resale value in traditional lending contexts. In today's economy, where intangible-intensive firms are increasingly central and legal frameworks better support restructuring, cash flow–based lending channels have become especially relevant. My results offer new empirical grounding for theories of debt capacity and highlight the importance of updating existing frameworks to better reflect the evolving nature of firm financing.

1 Data and Measurement

1.1 Purchase Price Allocation Data

A key challenge in measuring intangible assets is the limited availability of data. Most intangible assets are not recorded on a firm's balance sheet because accounting standards prohibit the capitalization of internally developed intangibles.[4] Furthermore, secondary-market transaction data are limited to certain asset types, such as patents, and are not consistently available across firms. As a result, obtaining a comprehensive and comparable

[4]There are some exceptions, such as internally used software or website development costs, but these are only allowed under narrow rules (e.g., ASC 350-40 and ASC 350-50).

valuation of intangible assets is difficult.

To address this problem, I use data from purchase price allocations (PPA) disclosed during acquisitions. A PPA is a standardized accounting procedure required under GAAP ASC 805, in which the acquiring firm must allocate the total purchase price across the fair value of acquired assets and liabilities. This process results in a detailed breakdown of the acquired firm's assets, including both tangible and intangible assets. Under ASC 820, both types of assets are valued using a consistent, market-based fair value standard that reflects the price a market participant would pay, regardless of the buyer's specific intentions.[5] Any value attributable to buyer-specific synergies or unallocated components is captured in the residual category, goodwill.

Since 2001, accounting rules (SFAS 141 and 141R) have required firms to report granular details on identifiable intangibles such as customer relationships, brands, trademarks, and technology. These valuations are conducted by specialized accountants and are subject to audit. Figure A2 and Figure A3 provide two examples.

The PPA valuation is initiated and paid for by the acquiring firm, often in consultation with external auditors or accounting advisors. Although planning may begin earlier, the formal valuation work typically starts after the deal has closed, once the buyer has full access to the target's financial records. Accounting rules (ASC 805) allow up to one year after the closing date to complete the valuation, but most companies finish within the first quarter to meet reporting deadlines. Initial estimates may appear in the Form 8-K shortly after the deal, with final numbers included in the next 10-Q or 10-K. Importantly, financing arrangements are secured pre-closing and draw on the same asset information reviewed during due diligence. Although the PPA is completed post-closing, it reflects the same inputs that lenders and acquirers use to structure debt commitments. Thus, the PPA valuations are effectively contemporaneous with the financing terms observed in the data. The PPA process formally allocates the total purchase price across acquired tangible and identifiable intangible assets, liabilities, and the residual category, goodwill.

Identifiable intangibles are intangibles that meet the identifiability criteria outlined in ASC 805, requiring that they are either separable from the business or arise from contractual or legal rights: identifiable intangibles exist on a standalone basis. Additionally, firms are required to estimate the remaining useful life of each amortizable intangible, based on expected economic benefit, contractual duration, or technological obsolescence. These estimates are disclosed along with the identifiable intangible valuation in financial statements and determine the asset's amortization schedule post-acquisition.

[5]For more discussion on fair value, see Appendix A.1.

Valuation firms follow a structured process when determining the fair value of intangible assets during a purchase price allocation. They rely on internal financial records, management forecasts, customer contracts, and interviews with both the buyer and seller to assess the economic contribution of each asset. Common valuation methods are the income, market, or cost approach (Crouzet and Ma, 2023).

My analysis focuses on identifiable intangible assets. These include customer relationships, brands, patents, technology, etc.[6] I exclude goodwill because it embeds synergies and overpayment, making it difficult to interpret economically. While excluded from the main analysis, I include goodwill in robustness checks to confirm the consistency of the results.

The PPA data have several key advantages. First, they offer comprehensive coverage of all identifiable intangibles acquired from target firms in a transaction. Second, because the valuations are conducted near the deal closing date, they reflect up-to-date market conditions and avoid distortions associated with outdated book values. Third, the process is governed by standardized accounting rules and subject to audit, ensuring consistency and reliability. Finally, there are limited incentives to inflate intangible values in this context, especially given tax neutrality (as discussed in Section 7.6) and offsetting financial accounting incentives, the net bias is likely small (as discussed in Appendix A.3).

1.2 Business Valuation Resources' DealStats

Business Valuation Resources (BVR) collects comprehensive M&A transaction details. For public firms, the transaction data is sourced from SEC filings, including 10-K, 10-Q, and 8-K filings. The database provides a wealth of information, including balance sheet and income statement data for target firms, purchase price allocations, valuation multiples, and details about both target and acquirer firms.

Key data items retrieved include the Central Index Key (CIK), acquirer name, the notes section (detailing the purchase price allocation), deal terms, and the target's pre-acquisition balance sheet information.

The purchase price allocation provides details on both intangible and tangible assets at fair value. DealStats provides the purchase price allocation in text form in the "note" variable. I use the natural language processing (NLP) technique to extract those terms. A detailed discussion of intangible asset categorization can be found in Appendix A.4. The

[6] Additional information on the specific intangible categories is provided in Appendix A.2.

categorization of tangible assets is more straightforward and includes categories like real estate and property, plant and equipment.

Deal terms specify how the purchase price is paid, typically including forms of payment such as cash, stock, promissory notes, or a combination of these. I flag deals that involve stock payments or assumed debt and use this information in the sample split analysis within the robustness section.

The acquirer's CIK is the primary identifier used to link DealStats with Compustat. When the CIK is missing, I supplement it with the acquirer's name and use a string-matching algorithm to facilitate the matching process between DealStats and Compustat.

1.3 Debt Instrument Classification and Matching

The Compustat sample includes all firm-year observations with non-missing data on total assets. The main measure of debt is long-term debt ($dltt$).

Capital IQ Capital Structure Debt includes the capital debt structure of a public company, compiled from SEC filings. The debt structure is categorized using descriptions in text format. I exclude observations where the debt is described as a "bridge loan" or "bridge notes," as these types of debt are intended to provide temporary financing and are typically settled or replaced with longer-term financing.

The classification into asset-based and cash flow–based debt follows Lian and Ma (2021).[7] Asset-based debt is defined as borrowing secured by specific assets. These assets include tangible items such as real estate, equipment, and inventory, as well as separable intangible assets such as patents and trademarks. A debt contract is classified as asset-based if one of the following conditions holds: (i) one can directly observe key features of asset-based lending, such as security against specific assets or borrowing limits tied to them; (ii) the debt belongs to a contract type that is typically asset-based, such as small business loans, finance company loans, secured revolving credit lines, and capital leases; or (iii) the contract is explicitly labeled as asset-based. Cash flow–based debt is not secured by specific assets. Such debt can be unsecured or secured by the corporate entity as a whole (for example, through blanket liens), which grants priority over the firm's going-concern value after deducting the value of any assets pledged separately. This category includes most corporate bonds and a large share of corporate loans, such as syndicated loans. A debt contract is classified as cash flow–based if: (i) it is unsecured or secured only by the

[7]The replication package from Kermani and Ma (2022) contains the code for classification, accessed through The Quarterly Journal of Economics Dataverse.

corporate entity, and does not display any features of asset-based lending; (ii) it belongs to a contract type that is typically cash flow–based, such as corporate bonds other than asset-backed bonds and industrial revenue bonds, or term loans in syndicated loans, and is not otherwise classified as asset-based; or (iii) it is explicitly labeled as cash flow–based. If none of those conditions is met, the fallback rule is to classify all secured debt that cannot be assigned with certainty as asset-based.

1.4 Sample Construction

The data focus on acquisition transactions conducted by U.S. public companies from 1995 to 2022.[8]

I begin with all mergers and acquisitions recorded in DealStats. I then restrict the sample to acquisition transactions classified as business combinations by public firms, which ensures access to textual purchase price allocation (PPA) data. The resulting dataset contains PPA information from 5,137 deals over two decades. For cases in which a firm acquires multiple targets within the same year, I aggregate deal-level data to the acquirer–year level, resulting in 4,789 firm-year observations.

Next, I merge these transactions with Compustat and restrict the sample to non-financial firms. I exclude finance and insurance firms (2-digit NAICS code 52) because their assets (such as securities and loans) and liabilities (such as deposits) are not comparable to those of non-financial firms.

The analysis combines three main sources: annual balance sheet data from Compustat, detailed acquisition data from DealStats, and debt-level data from Capital IQ. Compustat provides firm-level changes in debt usage, while Capital IQ's Capital Structure Debt database supplies detailed information on individual debt instruments.

After merging DealStats, Compustat, and Capital IQ, the final dataset includes approximately 3,800 firm-year observations. To mitigate the influence of outliers and reporting errors, all variables are winsorized at the 1st and 99th percentiles.

Table A1 shows that the acquirers in the sample represent approximately 14% of Compustat firms, with broad coverage across all major industry groups.

Table A2 presents the summary statistics for the outcome variables, purchase price allocation variables, and control variables used in the main analysis and the robustness

[8]Although detailed purchase price allocations (PPA) became mandatory with SFAS 141 in 2001, the sample contains some transactions from earlier years; particularly transactions involving public target firms that already had adopted the practice of reporting detailed asset valuations.

checks. The main outcome variable is the change in long-term debt ($dltt$) from the balance sheet. The control variables include variables that may correlate with both the decision to acquire the target firm with specific assets and debt usage. Additionally, I incorporate additional variables suggested by empirical literature examining the capital structure and debt financing (e.g., Frank and Goyal, 2009; Martynova and Renneboog, 2009; Rajan and Zingales, 1995).

Table A3 provides the summary statistics for intangible assets acquired, categorized in detail. The intangible assets are scaled by the target firm's total assets minus cash, offering a clearer picture of the intensity of the target firm's intangible assets.

Table A4 compares acquirers that acquired targets with low and high intangible asset shares across key financial variables relevant to financing. Firms that acquire firms with higher intangible shares exhibit significantly greater market-to-book ratios, Q, and cumulative market valuation relative to assets, reflecting stronger market performance. Firms that acquire firms with lower intangible shares tend to have higher book leverage, more physical assets, and a larger credit spread. The significant differences in book leverage and cash holdings suggest that firms that acquire targets with low intangible ratios rely more on debt, while high intangible firms hold more cash relative to their assets. In the regression analysis, the variables compared in the table are used as control variables to mitigate the bias from these factors.

2 Baseline Empirical Strategy and Results (PPA Sample)

The main empirical setting is acquisition transactions. Acquisitions offer a unique opportunity to examine how debt financing decisions respond to the composition of assets being acquired. They also generate detailed valuations of both intangible and tangible assets through PPA, data that are typically unavailable from firms' balance sheets. I exploit this setting to study how acquirers adjust their debt holdings around the transaction and relate these changes to the target's asset composition. This allows me to estimate, on average, how much debt firms choose to raise per dollar of intangible versus tangible assets acquired.

Acquirers can finance deals using new debt, equity issuance, or internal cash reserves. In practice, even when a deal is labeled a "cash transaction," acquirers frequently issue new debt to fund the payment, as few firms hold sufficient liquid assets to cover the full purchase price (e.g., Bharadwaj and Shivdasani, 2003; Faccio and Masulis, 2005). My analysis focuses on actual changes in the acquirer's balance sheet to identify how the

acquisition was ultimately financed, regardless of the stated deal form.

Beyond financing the purchase, acquirers must also determine how to treat the target's existing liabilities. They may retire (i.e., pay off) the debt at closing, assume and refinance it, or assume it without modification. In my baseline analysis, I treat these decisions as flexible: acquirers choose how to structure post-acquisition liabilities based on the financial characteristics of the acquired firm and the composition of the assets acquired.

There is the possibility that this discretion is constrained by the target's preexisting debt contracts. For instance, if the target has high levels of existing debt with restrictive covenants (e.g., prepayment prohibitions), the acquirer's observed financing structure may be driven more by historical capital structure than by the new asset base. To address this, I conduct robustness checks that distinguish acquisitions in which the acquirer assumes the target's debt from those in which it does not, thereby testing whether the main results hold under varying degrees of financing flexibility.

2.1 Regression Specification

The core empirical strategy links the composition of assets acquired in a deal to the acquirer's change in long-term debt. The ideal experiment would compare the same firms' debt usage before and after acquisition, differing in the mix of intangible versus tangible assets acquired. While such variation is rare, acquisition transactions approximate this design by producing discrete, observable changes in asset composition, particularly between tangible and intangible capital. This setting enables a cleaner identification of how firms finance incremental investment.

A key advantage of this design is that it mitigates simultaneity bias common in cross-sectional regressions of capital structure on asset composition. In those settings, a firm's capital structure influences investment decisions, and vice versa (e.g., Jensen and Meckling, 1976; Myers, 1977). Here, the timing and granularity of acquisitions allow me to observe a marginal financing response to asset purchases, which is closer to the core economic object of interest: how firms finance an additional dollar of tangible or intangible investment.

The empirical analysis proceeds in two steps. First, I use PPA data to identify the composition and dollar value of assets acquired. Second, I relate these purchases to changes in the acquirer's long-term debt. The following regression summarizes the baseline specification:

$$\frac{\Delta \text{LT Debt}_{i,t}}{A_{i,t-1}} = \alpha + \beta_1 \frac{\Delta \text{intangibles}_{i,t}}{A_{i,t-1}} + \beta_2 \frac{\Delta \text{tangibles}_{i,t}}{A_{i,t-1}} + \beta_3 \frac{\Delta \text{wc}_{i,t}}{A_{i,t-1}} + \mathbf{X}_{i,t-1}\xi + \nu_{\text{industry}\times t} + \varepsilon_{i,t}. \tag{1}$$

This is a pooled panel of firm-year observations. Here, the dependent variable is the change in long-term debt scaled by lagged assets.[9] The key independent variables are the amounts of intangibles, tangibles, and working capital acquired, all scaled by the acquirer's assets before the acquisition. The regression is estimated at the firm-year level, since acquirers may complete multiple transactions in a given year; asset and financing data are aggregated accordingly. Standard errors are clustered at the industry and year level.

The coefficients of interest are β_1 and β_2, which capture how much long-term debt is associated with acquiring an additional dollar of intangibles or tangibles, respectively. An F-test compares the two coefficients to assess whether the debt usage associated with intangibles differs statistically from that supported by tangibles.

One key identification concern is omitted variable bias, particularly the acquirer's unused debt capacity. If firms with greater spare capacity are both more likely to acquire intangibles and to issue debt, the estimates could conflate asset composition with financial flexibility. To mitigate this concern with existing spare debt capacity, I control for the acquirer's pre-acquisition book leverage ratio. Several other pre-acquisition control variables are added to further isolate the effect of interests, including rating-specific credit spread, firm profitability, cash on hand, tangible assets, operating cash flow, earnings, market-to-book ratio, cumulative stock return in the past year, firm size, acquired cash from the acquisition, and total Q from Peters and Taylor (2017). All balance sheet control variables other than firm size, are scaled by total assets of the acquirer before the acquisition. All control variables, other than acquired cash from the acquisition enter into the regression with a one-period lag. Additionally, the analysis also includes industry-by-year fixed effects for unobserved heterogeneity across industries over time.

To further assess the potential impact of omitted variable bias, I use the method proposed by Oster (2019), which extrapolates the bias-adjusted treatment effect under assumptions about selection on unobservable. The bias-adjusted coefficients remain similar in magnitude to the baseline estimates, suggesting that omitted variable bias is unlikely to

[9] I focus on long-term debt as the primary outcome variable, because it better captures durable financing responses beyond immediate transaction financing. In practice, firms may use short-term bridge loans or temporary financing to close acquisitions, but these are often repaid shortly afterward using cash on hand, proceeds from equity issuance, or refinancing. Results are robust with total debt, which yield slightly larger but noisier coefficients.

materially affect the interpretation of the results.

Taken together, these controls and the bias-adjusted estimates provide strong evidence that omitted variable bias is unlikely to drive the main results. While the regression design is descriptive in nature, the empirical setting and robustness checks support an interpretation of the coefficients as reflecting firms' marginal financing responses to different types of acquired assets. This moves the analysis closer to identifying the underlying economic mechanism: how firms finance incremental investment in tangible versus intangible capital.

A further potential complication is that acquirers do not always have full flexibility in structuring post-acquisition debt. My baseline assumption is that as long as the acquirer has the option to refinance or pay off the debt, any financing decisions will be made based on the type of assets acquired, allowing the acquirer to choose the most suitable financing method. In this case, I am not concerned about the target's existing debt. However, in reality, the acquirer may not always have full control over the target's existing debt, as it can be a legacy issue with existing debt contracts. I later conduct robustness checks that separate deals where target debt is assumed from those where it is not (see Section 7.1).

A final concern is unrelated investment. Because the analysis is conducted at the firm-year level, it is possible that observed changes in debt are affected by concurrent investments unrelated to the acquisition. This setup has the benefit of capturing all the debt changes that are possibly related to the acquisitions, but at the cost of certain measurement issues, such as acquirer firms engaging in additional PP&E purchases or R&D development on the side, which would bias my estimates. In Section 7.2, I show that there is no significant concurrent investment in additional tangible and intangible assets.

3 Debt Financing of Intangible Assets: Main Findings

First, I find that intangible assets support debt financing, though to a lesser extent than tangible assets. Column (4) of Table 1 shows the preferred specification. Each additional \$1 of intangibles acquired is associated with a \$0.24 increase in long-term debt. This coefficient is statistically significant and economically meaningful, showing that firms use debt to finance intangible assets.

For comparison, each \$1 of tangible assets acquired is associated with a \$0.44 increase in long-term debt. The F-statistic and p-value reported in the bottom row test whether these two coefficients differ. The difference is statistically significant, confirming that tangible assets support more debt than intangibles.

Table 1. Regression Results on the Impact of Intangibles on Long-term Debt

LHS Variable is Δ in Long-term Debt	(1)	(2)	(3)	(4)
Δ Intangibles	0.19***	0.17***	0.26***	0.24***
	(0.04)	(0.04)	(0.04)	(0.04)
Δ Tangibles	0.36***	0.33***	0.46***	0.44***
	(0.04)	(0.04)	(0.05)	(0.06)
Δ Working capital		0.24***	0.23***	0.25***
		(0.05)	(0.08)	(0.08)
Controls			X	X
Industry × year FE				X
Observations	3800	3800	2575	2529
R^2	0.126	0.135	0.243	0.322
F-stats: intan=tan	14.07	13.09	13.73	11.68
F-stats: p-val	.001	.001	.001	.002

Notes: This table reports regression results on the impact of intangibles on long-term debt. Columns (1) to (4) use long-term debt, defined as $(dltt - l.dltt)/l.at$, as the dependent variable. Variable definitions are provided in Appendix B. Standard errors are reported in parentheses and are clustered at the industry and year level. Significance levels are denoted by asterisks (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

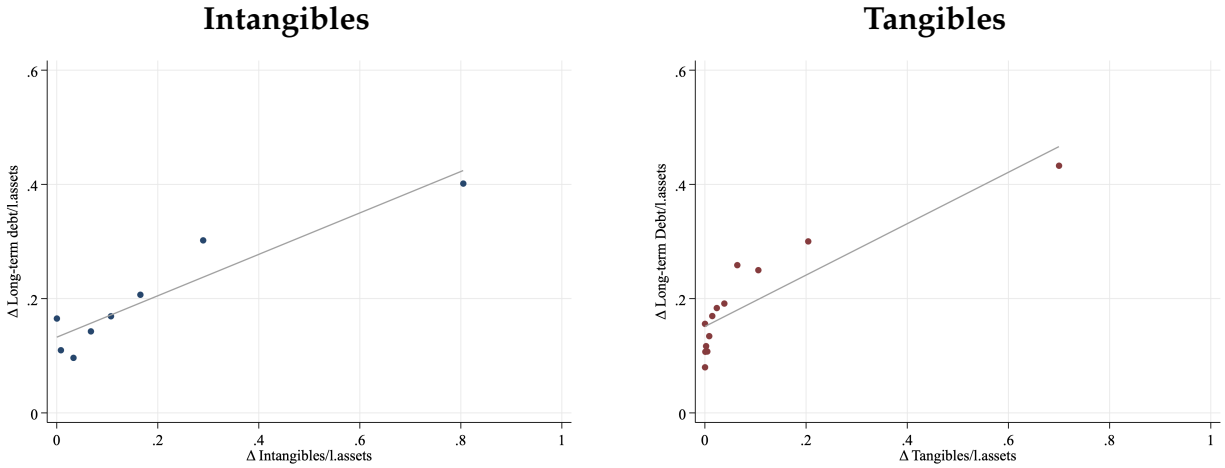
The coefficients remain stable across columns (1) to (4), even as more control variables are added and the R^2 increases substantially. This stability suggests that omitted variable bias is unlikely to be driving the results. To formally assess this concern, I apply the method developed by Oster (2019), which builds on the insight from Altonji et al. (2005) by comparing selection on observables to selection on unobservable. Under standard assumptions, the bias-adjusted coefficient for intangibles is \$0.26, which is very close to the baseline estimate of \$0.24.[10] This suggests that omitted variable bias would have to be implausibly strong to eliminate the effect.

Overall, the results show that firms do use debt to finance intangibles. While they borrow slightly less for intangibles than for tangibles, the difference is smaller than what many theories or prior assumptions would assert.

To visually confirm this result, Figure 1, panels (a) and (b), present bin-scatter plots based on the column (4) specification. I residualize both the dependent and independent

[10]Following Oster (2019), I compute β^* using the adjustment $\beta^* = \beta_1 - \frac{(\beta_0 - \beta_1)(R_{\max} - R_1^2)}{R_1^2 - R_0^2}$, where β_0 and R_0^2 are from the specification with minimal controls and β_1 and R_1^2 from the full specification. Assuming $R_{\max} = 1.3R_1^2$, the implied β^* is 0.26, compared with the fully controlled estimate of 0.24. Thus, even if unobservables were to explain as much additional variation as 30% more than observables, the adjusted coefficient would remain similar in magnitude, indicating limited sensitivity to omitted variables.

Figure 1. Acquired Asset and Δ Long-term Debt



Notes: Binned scatter plots of the relation between changes in long-term debt and changes in asset components. The left panel plots debt changes against changes in intangible assets, and the right panel plots debt changes against changes in tangible assets. The specification follows the baseline regression in Table 1, column (4). Dots represent conditional means and solid lines represent fitted values.

variables using the full set of controls and fixed effects, then plot the change in long-term debt against the acquired intangibles and tangibles. The relationship is strong and linear, with no outliers driving the result, providing a clear visual confirmation of the main regression findings.

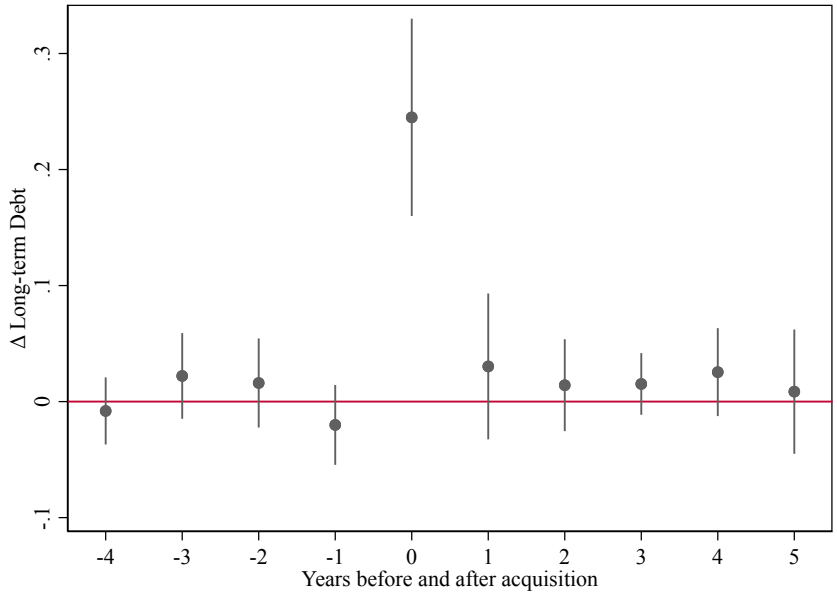
To verify that the effect arises precisely around the acquisition, and not before or after due to unrelated factors, I estimate a dynamic version of the baseline regression. Figure 2 plots the estimated coefficients from regressing four years' lag to five years' lead of the change in long-term debt on the value of intangibles acquired.

The results reveal a sharp and significant increase in debt in the acquisition year, with no evidence of elevated borrowing in the years prior and no further increase in the years following. This pattern rules out both pre-trends and delayed adjustments, suggesting that the estimated coefficient captures the full effect of intangible acquisitions on debt usage in the year of the deal.

Moreover, the timing helps rule out alternative explanations based on firm-level financing capacity. If the effect were driven simply by acquirers being financially unconstrained, one would expect a more gradual increase in debt over time. Instead, the discrete jump in debt at the time of the transaction points to the acquisition itself, and the composition of assets acquired, as the central drivers of the financing response.

In Section 7, I conduct several robustness tests to validate the results.

Figure 2. No Pre-existing Trends or Delayed Effects



Notes: This chart plots the regression coefficients from regressing 4-year lag and 5-year lead of the changes in long-term debt on intangibles acquired during acquisitions while controlling for all the controls and fixed effects as in the baseline regression in Table 1, column (4).

Section 7.1 considers the role of the target's existing debt. Table A15 splits the sample into transactions with and without assumed debt and shows that intangibles continue to support debt, with a stronger effect when no debt is assumed. Table A16 controls for the target's pre-existing asset-to-debt ratios and includes the acquirer's pre-acquisition tangible assets scaled by total debt to capture pledged unused debt capacity. Both checks confirm the baseline findings.

Section 7.2 addresses potential confounding from concurrent investments in PP&E or R&D and finds no evidence of overestimation. Section 7.3 explores deal terms and shows that the intangible–debt relationship is stronger in cash transactions than in stock deals, consistent with the baseline. Section 7.4 adds Tobin's Q as a proxy for investment opportunities instead of total Q from Peters and Taylor (2017), again supporting the results.

Section 7.5 examines whether the inclusion of goodwill affects the core results. The findings remain robust. The coefficient on goodwill is weakly significant and different from zero in the baseline specification, which is not surprising, as some financing is indeed associated with goodwill. To the extent that goodwill captures hard-to-separate intangibles like organizational capital, the weaker relationship with debt may suggest that non-separable intangibles, those that cannot exist independently, are less likely to support debt financing. It's also important to note that the coefficient on goodwill is close to zero in

several alternative specifications, highlighting its instability. In the baseline specification, the sample leans toward active publicly traded acquirers that tend to have better access to financing. This may partly explain the small positive effect observed.

Section 7.6 evaluates possible valuation manipulation from tax considerations. For the majority of the sample, PPA is irrelevant for taxation, because the tax basis is carried over.

Finally, Section 7.7 considers how measurement error affects the results. Despite accountants' best efforts, measuring intangibles is inherently challenging. The estimated effect is likely a lower bound of the true relationship between intangibles and debt financing.

Lastly, these findings provide insight into the relative debt capacity supported by intangible assets compared to tangible assets and are likely a lower bound. First, observed debt usage illustrates how the acquirer's borrowing adjusts in response to acquired tangible and intangible assets while controlling for firm characteristics. Since firms typically preserve financial flexibility, the actual amount borrowed serves as a lower bound on their potential borrowing capacity.

4 Mechanism: How Are Intangibles Financed with Debt?

Corporate borrowing can be broadly classified into two categories, depending on the basis upon which credit is extended: asset-based debt and cash flow–based debt.

Asset-based debt relies on the *liquidation value* of pledged assets. Lenders in this channel extend credit against assets that can be readily transferred to alternative users so that value can be recovered in the event of default. Redeployability is critical: the easier an asset can be sold or put to productive use by another party, the more useful it is as collateral. Seminal contributions including Shleifer and Vishny (1992), Kiyotaki and Moore (1997), and Bernanke et al. (1999) emphasize how physical assets that firms can pledge as collateral shape borrowing capacity. In contrast, cash flow–based debt relies on a firm's *operational cash flow* to meet debt obligations. In this channel, repayment capacity, not collateral resale value, is the key constraint, as in Holmstrom and Tirole (1997).

Much of the theoretical literature assumes that intangible assets cannot sustain debt financing. This view implicitly rests on the dominance of asset-based lending and the idea that intangibles cannot serve as effective collateral in asset-based lending due to their limited resale potential. Consequently, firms with intangible-heavy balance sheets are often viewed as constrained in debt markets.

However, this perspective may miss an important alternative channel. If creditors also

Table 2. Intangibles Are Primarily Associated with cash flow–Based Debt

	Δ Cash flow-based Debt				Δ Asset-based Debt			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Intangibles	0.19***	0.17***	0.27***	0.25***	0.07***	0.04**	0.05*	0.05*
	(0.04)	(0.05)	(0.05)	(0.05)	(0.02)	(0.02)	(0.03)	(0.02)
Δ Tangibles	0.16***	0.14***	0.28***	0.24***	0.20***	0.17***	0.18***	0.20***
	(0.04)	(0.04)	(0.06)	(0.07)	(0.02)	(0.03)	(0.03)	(0.03)
Δ Working capital		0.13*	0.11	0.18		0.26***	0.17**	0.13
		(0.07)	(0.11)	(0.11)		(0.05)	(0.07)	(0.08)
Controls			X	X			X	X
Industry × year FE				X				X
Observations	2874	2874	2041	2012	2874	2874	2041	2012
R^2	0.075	0.078	0.161	0.241	0.055	0.073	0.102	0.187
F-stat: intan=tan	.6	.58	.01	.07	16.71	18.91	8.69	11.98
F-stat: p-value	.445	.452	.913	.799	0	0	.008	.002

Notes: This table presents the results of the regression analysis investigating the impact of intangibles on changes in debt by lending basis. Columns (1) to (4) present the outcome variable of cash flow–based debt, and columns (5) to (8) present the outcome variable of asset-based debt. The debt is classified as cash flow–based if it is backed by blanket lien or unsecured, and is classified as asset-based if it is backed by real estate, fixed asset, receivable, etc. The classification is based on Lian and Ma (2021). Standard errors are reported in parentheses and are clustered at the industry and year level. Significance levels are denoted by asterisks (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

lend against a firm's going-concern value, then intangible assets, while difficult to pledge, may still support debt through the cash flow–based lending channel.

My evidence shows that this alternative channel is not only viable but dominant. Using detailed contract descriptions to classify debt instruments into asset-based and cash flow–based categories (following Lian and Ma (2021)), I find that intangible assets are only weakly associated with asset-based debt, but strongly and consistently associated with cash flow–based debt. This pattern suggests that cash flow–based lending is the primary mechanism through which intangibles support borrowing. Moreover, I show that, unlike tangible assets, the debt financing of intangibles is largely unaffected by asset redeployability. This evidence further supports that the debt financing is not tied to collateral value but to the firm's ability to generate future cash flows.

In today's knowledge economy, borrowing hinges less on asset redeployability and more on the strength and reliability of future cash flows.

4.1 Evidence from Classifying Debt

Following Lian and Ma (2021), I classify each debt instrument as asset-based or cash flow–based using descriptions from the Capital IQ Debt Detail database. This classification mirrors the terminology and categories commonly used by practitioners. Asset-based debt includes loans and bonds secured by specific collateral, such as receivables, inventory, real estate, equipment, or other identifiable assets, and facilities structured around borrowing bases. Cash flow–based debt includes loans and bonds whose repayment is based primarily on the borrower's overall cash-generating capacity, such as unsecured term loans, broadly liened credit facilities, and most unsecured bonds. Capital leases are grouped with asset-based debt, and convertible instruments with cash flow–based debt.

To analyze how intangibles map into each category, I re-estimate the baseline regression framework, replacing the dependent variable with either asset-based debt or cash flow–based debt.

Results are reported in Table 2. The preferred specification in column (4) shows that each additional dollar of identifiable intangible assets is associated with a \$0.25 increase in cash flow–based debt, very similar in magnitude to the \$0.24 increase associated with tangible assets. A formal F-test does not reject equality between the two coefficients, suggesting that intangibles are nearly as effective as tangibles in supporting cash flow–based borrowing.

By contrast, columns (5) to (8) report results for asset-based debt, where the distinction emphasized in the literature becomes evident. In the preferred specification in column (8), a \$1 increase in intangibles is linked to only a \$0.05 increase in asset-based debt, which is small in magnitude and only weakly significant. In contrast, tangible assets are associated with a \$0.20 increase. The difference is statistically significant. Across specifications, the inclusion of additional controls and fixed effects substantially raises the R^2, while leaving the coefficients stable, further suggesting that omitted variable bias is unlikely to be driving the results.[11]

These findings confirm the conventional wisdom that intangible assets play little role in asset-based lending, where pledgeability, redeployability, and standalone collateral valuation are critical (e.g., Crouzet and Eberly, 2019; Giglio and Severo, 2012; Caggese and Pérez-Orive, 2022). However, when the full picture is considered, intangibles do sustain cash flow–based debt.

[11] Following Oster (2019) with $R_{\max} = 1.3R_1^2$, the adjusted coefficient on intangibles in the asset-based debt regression is 0.04, and the corresponding coefficient in the cash-flow–based debt regression is 0.28. Both values remain close to their observed coefficients.

4.2 Evidence from Asset Redeployability

Redeployability, the extent to which an asset can be repurposed by alternative users, has long been recognized as a key determinant of debt capacity, particularly in asset-based lending (e.g., Williamson, 1988). Assets with higher redeployability provide greater liquidation value and are thus more effective as collateral.

The intangible assets in this study are all identifiable intangibles, which means they can be separated from the firm and possess some standalone value. This implies a degree of redeployability. However, as shown earlier, these assets are primarily associated with cash flow–based debt, where borrowing capacity depends on the asset's going-concern value, not resale value. This contrast raises a natural question: does redeployability matter less for intangibles than for tangibles?

To test this idea, I construct a measure of asset redeployability using data from the U.S. Census Bureau's Business Dynamics Statistics (BDS), which reports the number of firms in each industry by size and year. I focus on the target's 3-digit NAICS industry code and count the number of firms with more than 500 employees, which are large enough to plausibly serve as buyers in a secondary market. This measure, calculated as the median over the three years prior to the acquisition, proxies for the pool of potential alternative users for the assets of the target. I merge the redeployability measure into the acquisition sample and classify the acquirer-year level transaction as `High RDPL` if its target industry's value falls above the 25th percentile.[12]

I then extend the baseline regression by interacting each asset type with the high-redeployability indicator. This setup allows for a direct comparison of how redeployability affects debt usage for tangible versus intangible assets. The regression specification is:

$$\begin{aligned}\frac{\Delta LT\ Debt_{i,t}}{A_{i,t-1}} = \alpha &+ \beta_1 \frac{\Delta \text{intangibles}_{i,t}}{A_{i,t-1}} + \beta_2 \frac{\Delta \text{tangibles}_{i,t}}{A_{i,t-1}} + \beta_3 \frac{\Delta \text{wc}_{i,t}}{A_{i,t-1}} + \delta\, \mathbb{1}\{\text{High RDPL}\}_i \\ &+ \beta_4 \left(\frac{\Delta \text{intangibles}_{i,t}}{A_{i,t-1}} \times \mathbb{1}\{\text{High RDPL}\}_i \right) \\ &+ \beta_5 \left(\frac{\Delta \text{tangibles}_{i,t}}{A_{i,t-1}} \times \mathbb{1}\{\text{High RDPL}\}_i \right) \\ &+ \beta_6 \left(\frac{\Delta \text{wc}_{i,t}}{A_{i,t-1}} \times \mathbb{1}\{\text{High RDPL}\}_i \right) \\ &+ \mathbf{X}'_{i,t-1}\boldsymbol{\xi} + \nu_{\text{industry}\times t} + \varepsilon_{i,t}.\end{aligned} \tag{2}$$

[12] For multiple transactions by the same acquirer in the same year, I use the target industry code of the largest deal.

The results, presented in Figure 3, show a sharp contrast in how redeployability affects debt usage for tangibles versus intangibles. See regression results in Table A5.[13] For tangible assets, redeployability matters: in industries with many potential alternative users, each dollar of tangibles acquired supports significantly more debt. This aligns with the view that tangible assets implicitly back borrowing through their resale value: creditors expect to recover more in distress when assets can be easily sold or reused. Even outside of fire-sale scenarios, redeployability shapes expectations about recoverable value in reorganization. Thus, tangibles retain more value under financial distress when they are broadly usable by other firms.

For intangibles, by contrast, redeployability has little effect. The marginal effect of intangibles on long-term debt is similar across both high- and low-redeployability industries. This suggests a different financing mechanism, one not reliant on resale value.

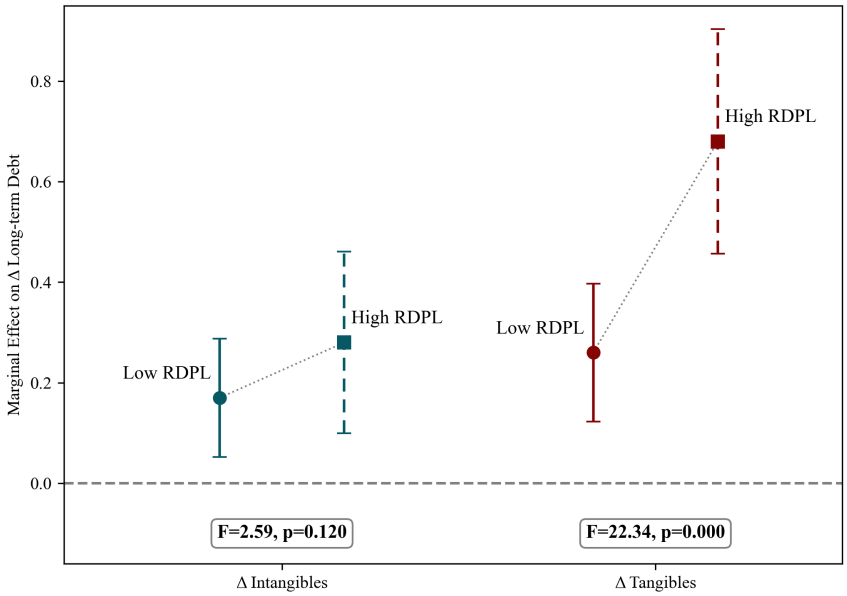
These results invite a reconsideration of how redeployability should be understood in the context of intangible assets. While the conventional view links redeployability to an asset's resale value and usefulness to alternative users, the empirical results suggest that this notion may not fully capture how intangibles function in debt financing.

A nuanced interpretation is that identifiable intangible assets, while legally separable, may not be economically redeployable in the conventional sense. Their value is often deeply embedded in the acquiring firm's internal ecosystem—customer relationships, brand reputation, proprietary processes, or internally developed technologies—that do not easily transfer across firms. Although examples of brand or patent sales exist, these markets remain relatively thin and uncertain. As a result, lenders are reluctant to rely on the liquidation value of such assets and instead focus on the future cash flows these intangibles help generate within the firm. While intangibles may not expand asset-based borrowing, they still play a role in impacting the way lenders establish priority in getting the payment in default resolution (Benmelech et al., 2024).

Viewed differently, redeployability for intangibles may operate at the level of the firm, not the asset. Instead of referring to the transferability of a standalone asset, the relevant concept may be the transferability of the firm as a going concern. From this perspective, what is "redeployable" is not the asset per se, but the ongoing enterprise that can continue to generate value from it. This interpretation shifts attention away from asset resale value and toward the firm's ability to sustain cash flows under new ownership or control.

[13]Results are robust to alternative definitions, including a finer firm-size classification of 1,000–5,000 employee (Table A6) and using the median cutoff for redeployability (Table A7). Note that BDS applies data masking for confidentiality, the 500+ employee categorization is preferred because it is coarser and thus not affected by this.

Figure 3. Marginal Effects of Asset Changes on Long-Term Debt by Redeployability.



Notes: The bars plot the marginal effects of changes in intangible and tangible assets on long-term debt. Estimates are from the baseline specification in Table A5, column (4), augmented with interaction terms as in Equation 2. Effects are shown separately for industries with low RDPL (below the 25th percentile) and high RDPL (above the 25th percentile), where RDPL is measured using the U.S. Census Bureau's BDS as the average number of 500+ employees in the industry over the three years prior to acquisition. Whiskers denote 95% confidence intervals with standard errors clustered by industry and year.

Together, these insights suggest that the conventional notion of redeployability, centered on tangible assets and secondary markets, may be too narrow. In a modern, intangible-driven economy, debt financing increasingly hinges on a firm's ability to generate and sustain cash flows, not on the resale potential of individual assets. Rethinking redeployability in this broader context is essential to understanding how financial capacity is determined for today's firms.

5 Heterogeneity: Not All Intangibles Are the Same

Intangible assets are typically defined as "assets that lack physical substance." Beyond this definition, they are far from homogeneous. Intangibles differ in how they create value for firms, and this heterogeneity may shape how they support debt financing.

In this section, I explore one meaningful dimension of this variation by classifying intangible assets into two broad categories: *production-based* and *demand-shifter* intangibles. I hypothesize that these categories differ in their relationship with debt usage because

they associate with firm cash flows in different ways. In particular, demand-shifter intangibles tend to stabilize operating cash flows, a feature that is especially valuable for cash flow–based lending.

Production-based intangibles, such as patents, proprietary technology, and know-how, enhance the firm's operational efficiency or productivity. In contrast, *demand-shifter intangibles*, such as brands and customer relationships, primarily shape the demand curve a firm faces. These assets help stabilize revenue over time by reducing the *volatility of cash flows*.[14] These differences are especially relevant given my earlier findings that intangible assets are primarily financed with *cash flow–based debt*, a type of lending that is more sensitive to the stability of future earnings than to collateral value.

Stabilizing cash flows, particularly in downturns, may enhance a firm's ability to borrow. Larkin (2013), for instance, shows that firms with stronger brands exhibit greater resilience during recessions, suggesting a key channel through which demand-shifter intangibles could support more borrowing. I formalize this mechanism with a model in Appendix Section C and test its predictions empirically below.

Based on this framework, I use the PPA to classify major types of intangible assets into production-based and demand-shifter categories. Table A8 summarizes the classification. Each asset is assigned to a category based on its primary economic role.[15]

Production-based intangibles are capital that a firm uses in production and affect the firm's marginal cost or production efficiency, holding demand constant. Production-based intangibles are assets that directly contribute to the firm's productive capacity. This group includes legally protected innovations (e.g., patents, proprietary software, and in-process R&D), embedded technical knowledge (e.g., know-how, blueprints, and licenses), and rights to use productive inputs (e.g., copyrighted materials and contractual rights of use).

Demand-shifter intangibles, in contrast, do not enhance production directly but influence the quantity or price at which output is sold. Demand-shifter intangibles are variables that affect the demand curve firms face directly, holding production technology constant. These include customer-related assets (e.g., customer lists, relationships, and proprietary data), market-facing assets (e.g., brands, trademarks, and domain names), and contractual

[14] Any mechanism that creates demand persistence would have this implication, which appears across a range of models in industrial organization. Demand-shifter intangibles, through reputation, advertising, or customer relationship, create demand persistence through habit formation, search and switching frictions, consumer inertia, and limited attention, thus stabilizing cash flows (e.g., Bronnenberg et al., 2012; Cabral, 2016; Katz and Shapiro, 1985; Gourio and Rudanko, 2014).

[15] Some assets may influence both production and demand; my classification reflects their primary function in practice rather than enforcing a strict dichotomy.

Table 3. Regression Results on the Impact of Intangibles on Debt Usage by Type of Intangibles

LHS Variable is Δ in Long-term Debt	(1)	(2)	(3)
Δ Intangibles (demand-shifter)	0.35***	0.44***	0.45***
	(0.05)	(0.07)	(0.07)
Δ Intangibles (production-based)	0.05	0.17**	0.15**
	(0.05)	(0.06)	(0.07)
Δ Tangibles	0.34***	0.45***	0.44***
	(0.04)	(0.05)	(0.05)
Δ Working capital	0.21***	0.22***	0.25***
	(0.05)	(0.06)	(0.07)
Controls		X	X
Industry × year FE			X
Observations	3800	2575	2529
R^2	0.145	0.251	0.332
F-stat: ds-intan=pb-intan			10.03
F-stat: p-value			.004

Notes: This table presents the results of the regression analysis investigating the impact of intangibles on debt usage by type of intangibles. Columns (1) to (3) present the outcome variable of change in long-term debt, which is defined as (dltt-l.dltt)/l.at. Intangibles are classified into production intangibles and demand-based intangibles, see Table A8 for details. Significance levels are denoted by asterisks (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

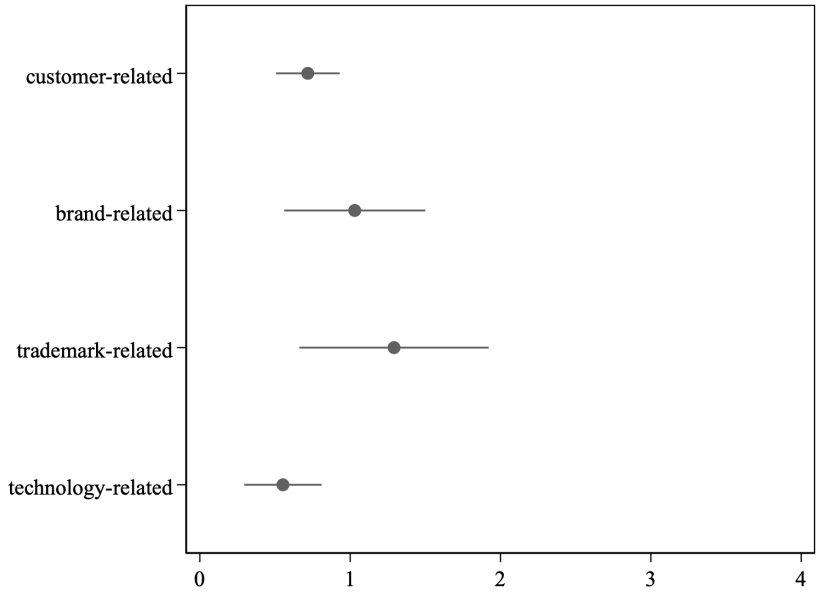
demand commitments (e.g., customer contracts and backlogs). This category also includes assets that preserve demand continuity post-acquisition, such as franchise agreements, supplier and distributor ties, and non-compete clauses.

I re-estimate the baseline regression from Table 1, now distinguishing between production-based and demand-shifter intangibles. Results are reported in Table 3. Column (3) shows that a $1 increase in demand-shifter intangibles is associated with a $0.45 increase in debt financing, whereas a $1 increase in production-based intangibles is associated with only a $0.15 increase. An *F*-test confirms that the difference is statistically significant.

Figure 4 visualizes the regression coefficients for the major subcategories. The coefficients for the major categories of demand-shifter intangibles consistently lie to the right of the major production-based intangibles, technology-related, which further support the finding that demand-shifter intangibles are more strongly associated with debt financing.

In Table A9, I examine whether these intangible types differ in how they affect post-acquisition cash flow volatility, to provide direct evidence on the proposed mechanism.

Figure 4. Debt Financing by Types of Intangibles



Notes: This chart plots the regression coefficients from regressing changes in long-term debt on various categories of intangibles while controlling for all the controls and fixed effects as in the baseline regression.

I find that acquisitions involving high levels of demand-shifter intangibles are followed by a significant decline in cash flow volatility, consistent with the idea that these assets help stabilize firm performance. In contrast, acquisitions with a lot of production-based intangibles do not exhibit the same pattern. In fact, higher levels of these assets are associated with increased post-deal volatility, suggesting that while they may enhance productivity or upside potential, they do not reduce earnings risk.

Table A10 further supports this interpretation by showing that the observed effects are concentrated in cash flow–based debt. This reinforces earlier findings in the paper that intangibles primarily support borrowing through cash flow–based channels, and it aligns with the proposed mechanism that demand-shifter intangibles facilitate borrowing by stabilizing a firm's cash flows.

I acknowledge that this classification is stylized. In practice, some intangible assets may play both roles. Still, the distinction offers a useful framework for understanding how different types of intangibles contribute to debt financing. Empirically, the most important demand-shifter categories driving the results are brands, trademarks, customer lists, and customer relationships, while the key production-based category is technology.

6 Complementary Evidence: Marblegate Ruling

The acquisition setting provides compelling evidence that firms raise debt to finance intangible assets, suggesting that intangibles are, in practice, pledgeable. However, these results are based on cross-sectional variation and may still be subject to endogeneity concerns, despite the best efforts. For example, firms with more unused debt capacity may be more likely to acquire intangibles and use debt financing, not because the intangibles themselves support borrowing, but because these firms are less financially constrained overall.

To further examine whether intangibles support debt and to test the institutional underpinnings of their pledgeability, I turn to a quasi-natural experiment: the Marblegate legal ruling. This shock provides plausibly exogenous variation in the expected recovery of intangible assets, and thus their pledgeability.

This setting allows me to assess whether intangible assets had truly supported debt financing by observing how firms' leverage responded when the legal infrastructure backing such debt was suddenly weakened. A decline in borrowing among intangible-intensive firms after the ruling would provide direct evidence that intangibles had been pledgeable and that their pledgeability depends critically on the legal infrastructure that supports debt contracting.

6.1 Institutional Background

Institutional Context: The EDMC Restructuring. In 2014, Education Management Corporation (EDMC), one of the largest U.S. for-profit education providers, entered financial distress and sought to restructure its debt out of court. Like many distressed firms, EDMC hoped to avoid formal bankruptcy proceedings by negotiating directly with bondholders. But it ran into a legal obstacle: under Section 316(b) of the Trust Indenture Act of 1939 (TIA), changes to bond payment terms required unanimous bondholder consent. While designed to protect investors, this provision made it difficult to restructure debt, since a single holdout creditor could block the deal.[16]

Over time, the market developed a workaround to sidestep this requirement. Distressed firms began using exchange offers with exit consents, in which participating bondholders agreed to swap their old bonds for new ones while stripping key protective covenants from the old bonds. Because these changes did not formally alter core payment terms, courts

[16]For related work by legal scholars, see, e.g., Kahan (2018).

had long treated the strategy as compliant with Section 316(b), and it became standard practice in the distressed debt market.

EDMC followed this established playbook. In its restructuring plan, EDMC moved assets into a new subsidiary and offered new securities only to consenting bondholders. Dissenting creditors, including Marblegate Asset Management, were stripped of meaningful enforcement rights. The expectation was that the court would uphold the deal.

But this time, the court ruled against EDMC's exchange when Marblegate Asset Management challenged the plan. In a surprise move, on December 30, 2014, the U.S. District Court for the Southern District of New York reinterpreted Section 316(b) much more broadly: not only literal payment terms, but also practical recovery rights could not be impaired without unanimous consent.[17]

The Marblegate Lawsuit and Legal Shock. This ruling strengthened the bondholder's right to payment but made out-of-court restructurings much harder by intensifying the holdout problem.[18] As a result, firms with outstanding bonds now faced a greater risk of being pushed into formal bankruptcy rather than restructuring privately. Before Marblegate, firms could restructure out of court with majority creditor support, which was fast and cost-effective. After Marblegate, the greater bargaining power of holdout creditors made such workouts harder, forcing firms more often into costly and time-consuming bankruptcy proceedings. Bankruptcy filings rose sharply after the ruling, close to doubling relative to the baseline.[19]

Differential Impact on Intangible- versus Tangible-Intensive Firms. Prolonged bankruptcy court procedures are particularly damaging to intangible-intensive firms. In financial distress, intangible assets such as brand, customer relationships, software, and customer lists lose value more quickly than tangible assets, as customer relationships deteriorate, reputation tarnishes, key employees leave, and technology becomes outdated (e.g., Antill and Hunter, 2023; Babina, 2020; Baghai et al., 2021; Hortaçsu et al., 2013). This erosion reduces the expected recovery of intangibles, affecting both the asset value that

[17] In fact, case law on this part of Section 316(b) had been sparse. The prior decision was in 1999, Federated Strategic Income Fund v. Mechala Group Jamaica Ltd. ("Mechala"), which had briefly held that certain asset transfers impaired bondholders' right to payment. The case drew little attention at the time, and Marblegate was the first to revive and expand this interpretation.

[18] Here, I build on recent work by Kornejew (2024), which finds that the Marblegate ruling increased restructuring frictions, leading distressed firms to restructure in court, and excessive creditor protection can weaken public credit markets and investment.

[19] After Marblegate, high-bond firms are 0.72 percentage points more likely to file for bankruptcy in a given quarter. Since the unconditional quarterly bankruptcy probability in this sample is only 0.38%, this effect corresponds to an increase of close to 200%. See Appendix Table A11. Kornejew (2024) documents a similar magnitude using an alternative sample.

creditors could recover directly from pledged intangibles and the cash flow value that the firm could generate if kept as a going concern. By contrast, firms with more tangible assets experience far less erosion. Land does not disappear, and buildings and machinery generally hold their value even during prolonged distress. Because Marblegate pushed firms toward formal bankruptcy, it effectively reduced expected recoveries on intangible assets while leaving tangible assets largely unaffected.

Empirical Implications. This differential effect creates a natural experiment setting. The Marblegate ruling introduced an exogenous shock that reduced the effective pledgeability of intangible assets. It did so suddenly, through an unrelated court case, and with clear timing in 2014Q4, making it particularly well-suited for causal identification. The empirical strategy, therefore, compares changes in debt financing for (i) intangible versus tangible-intensive firms and (ii) firms with high versus low reliance on bond financing, since the ruling directly altered bondholder rights. The prediction is that intangible-intensive firms, especially those dependent on bond markets, experienced sharper reductions in debt financing because the higher "indirect cost of bankruptcy" after the Marblegate ruling lowered creditor recoveries.

In January 2017, the Second Circuit Court of Appeals overturned the district court's Marblegate decision. This reversal was more anticipated and less of a surprise to markets. For this reason, my analysis stops in 2016Q4. Consistent with this interpretation, the event-study plot shows that effects appear more muted toward the end of the sample.

6.2 Identification Strategy: Triple Difference

To estimate the effect of the Marblegate ruling on leverage, I use a triple-difference (DDD) specification using panel data from Compustat non-financial firms from 2013Q1 to 2016Q4. The sample is restricted to high-yield firms, those with an S&P rating of BB+ or below during the period preceding the Marblegate ruling, because these firms have greater exposure to restructuring risk and thus are most impacted by the ruling.

The estimation equation is:

$$\begin{aligned} Y_{i,t} = \alpha + \lambda_i + \theta_t \\ + \beta_1\big(\text{Marblegate}_t \times \text{HighBond}_i\big) + \beta_2\big(\text{Marblegate}_t \times \text{HighIntan}_i\big) \\ + \beta_3\big(\text{Marblegate}_t \times \text{HighBond}_i \times \text{HighIntan}_i\big) + \mathbf{X}'_{j,t-1}\boldsymbol{\xi} + \varepsilon_{i,t}. \end{aligned} \tag{3}$$

The outcome variable Y_{it} is a measure of leverage: total debt (shortened to debt),

bonds, or loans scaled by total assets. Firm fixed effects (λ_i) control for time-invariant firm characteristics, and quarter fixed effects (θ_t) absorb aggregate macroeconomic shocks. Thus, identification comes from within-firm variation in leverage after netting out both time-invariant firm factors and time-varying economy-wide trends. The variable $\texttt{Marblegate}_t$ is an indicator that equals one in the post-ruling period (2015Q1–2016Q4). To avoid endogenous selection in response to the ruling, both treatment variables, $\texttt{HighBond}_i$ and $\texttt{HighIntan}_i$, are measured prior to the ruling. Specifically, $\texttt{HighBond}_i$ identifies firms with above-median bond share in 2014Q3, and $\texttt{HighIntan}_i$ identifies firms with above-median intangible asset intensity in 2013, calculated as intangible assets over total assets using data from Peters and Taylor (2017).

The vector $\mathbf{X}_{jt-1}$ is lagged industry-level controls: asset growth and value-weighted stock returns at the 2-digit NAICS level. These variables capture real-side conditions and financial market trends but are less likely to introduce post-treatment bias because most of the variation stems from large, unaffected firms. I do not include industry-by-quarter fixed effects, because a substantial share of the variation in intangible intensity occurs at the industry level, and including such fixed effects would absorb much of the identifying variation. This is especially problematic for estimating interactions that involve `HighIntan`.

We expect β_1 to be positive. This captures the ex-ante commitment effect, emphasized in Donaldson et al. (2022): stronger bondholder rights improve enforcement and reduce expropriation risk, which reassures creditors.

The key coefficient of interest is β_3, which captures a pledgeability erosion effect for intangible-intensive firms. This reflects the flip side: for intangible-heavy firms, if distress does occur, the value of their assets collapses more sharply. If intangibles are more fragile in bankruptcy, as suggested by the mechanism, then firms that rely heavily on both bonds and intangibles should face the largest decline in leverage. In this case, β_3 should be negative.

The triple-difference design helps isolate this effect from confounding trends. Specifically, it compares the change in leverage for high-intangible versus low-intangible firms within the high-bond group, relative to the same difference within the low-bond group.

Identification relies on the parallel-trends assumption: absent the Marblegate ruling, the relative debt usage between high- and low-intangible firms in the high-bond groups is to trend in the same way as the relative outcome of debt usage between high- and low-intangible firms in the low-bond group (Olden and Møen, 2022).

Table 4. Effect of the Marblegate Ruling on Leverage in High-Bond, High-Intangible Firms

	(1) Debt/Assets	(2) Debt/Assets	(3) Bonds/Assets	(4) Loans/Assets
Marblegate × High bond	0.044***	0.071***	0.081***	0.014
	(0.014)	(0.021)	(0.024)	(0.014)
Marblegate × High intan		-0.006	-0.005	-0.006
		(0.013)	(0.012)	(0.013)
Marblegate × High bond × High intan		-0.073***	-0.104***	0.011
		(0.027)	(0.031)	(0.022)
Controls	X	X	X	X
Firm FE	X	X	X	X
Quarter FE	X	X	X	X
Observations	7588	7584	7895	7895
R^2	0.756	0.759	0.707	0.837

Notes: The table reports estimates of Equation 3 using Compustat data on non-financial firms. The sample covers 2013Q1–2016Q4 and is restricted to high-yield firms with an S&P rating of BB+ or worse. The dependent variable is total debt, bonds, or loans scaled by total assets in columns (1)–(4). Firm fixed effects control for time-invariant firm characteristics, and quarter fixed effects capture aggregate shocks. $\texttt{Marblegate}_t$ equals one in the post-ruling period (2015Q1–2016Q4). $\texttt{HighBond}_i$ indicates firms with above-median bond share in 2014Q3, and $\texttt{HighIntan}_i$ indicates firms with above-median intangible intensity in 2013, based on data from Peters and Taylor (2017). Controls include lagged industry-level asset growth and stock returns at the 2-digit NAICS level. Standard errors are reported in parentheses and are clustered at the firm level. Significance levels are denoted by asterisks (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

6.3 Results and Interpretation

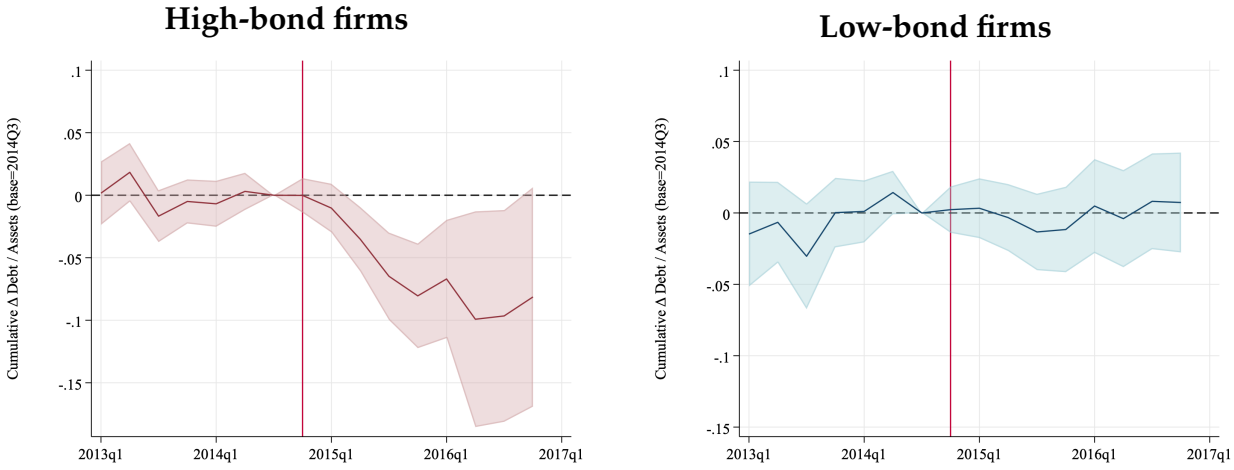
Table 4 column (1) shows a positive effect of the Marblegate ruling on leverage, consistent with bondholders extending more credit after creditor rights were strengthened, in line with Donaldson et al. (2022).[20] This coefficient captures an ex-ante creditor-rights commitment effect that is separate from the intangible-pledgeability mechanism.

The main question, whether intangible assets support debt, is addressed by the differential effect: the triple-difference coefficient that compares high-intangible firms to low-intangible firms.

Column (2) shows that while $\texttt{Marblegate}_t \times \texttt{HighBond}_i$ is positive, the interaction with high-intangible firms ($\texttt{Marblegate}_t \times \texttt{HighBond}_i \times \texttt{HighIntan}_i$) is strongly negative. This indicates that intangibles had been supporting leverage: once the Marblegate ruling reduced expected recovery values for intangibles, debt usage fell. The negative effect is large enough to fully offset the positive commitment effect from strengthened creditor

[20] Table A12 shows that this effect is driven by increased bond usage.

Figure 5. Intangible Asset Effect on Leverage After Marblegate



Notes: The figure plots cumulative differences in debt between high- and low-intangible firms, normalized to 2014Q3 assets, using Compustat data on non-financial firms. The sample covers 2013Q1–2016Q4 and is restricted to high-yield firms with an S&P rating of BB+ or worse. The left panel shows the difference within the high-bond group, and the right panel shows the difference within the low-bond group. Leverage residuals are obtained from regressions with firm and quarter fixed effects and lagged industry controls, converted back to levels, and scaled by pre-ruling (2014Q3) assets. The vertical line marks the Marblegate ruling (2014Q4). The shaded area denotes 95% confidence intervals.

rights.

Columns (3) to (4) separate total debt into bonds and loans. In column (3), the positive effect on bonds of $\texttt{Marblegate}_t \times \texttt{HighBond}_i$ again reflects the ex-ante commitment channel. Notably, the triple-difference term is sharply negative in bond financing but absent in loans. Since bonds are the primary instrument for cash flow–based borrowing, this finding is consistent with earlier evidence (Section 4) that intangibles mainly associate with such debt.

An alternative interpretation is that firms reduced bond usage to avoid legal uncertainty and holdout risk. However, if that were the case, one would expect no decline in total leverage and a shift toward loan financing. I find a decline in leverage in column (2), and column (4) shows no such substitution into loans. This pattern supports the interpretation that the ruling constrained borrowing of intangible-intensive firms by eroding the pledgeability of their assets, rather than reflecting a voluntary shift in debt mix.[21]

Figure 5 shows event-study estimates. Among high-bond firms, leverage in high-intangible firms declines sharply relative to low-intangible firms after the Marblegate

[21]Table A13 shows that results are robust to a DiD specification without the $\texttt{HighBond}_i$ interaction.

ruling, with no evidence of pre-trend differences. Two years after the ruling, intangible-intensive firms in the high-bond group, compared to firms with low intangible intensity, show a cumulative 7% decline in residualized debt, measured relative to 2014Q3 assets. Toward the end of the sample, the effect becomes muted, consistent with anticipation of the 2017Q1 court decision that rolled back the initial Marblegate ruling. No decline is observed among low-bond reliance firms, which serve as the control group.

One potential concern is that the results could be driven by confounding shocks, such as other macroeconomic or regulatory shocks, rather than the Marblegate ruling itself. To address this, I conduct a placebo test using investment-grade firms (rated BBB– or above), which faced little restructuring risk and were therefore largely unaffected by the ruling. If the main results are truly driven by the legal shock, there should be no effect in this sample.

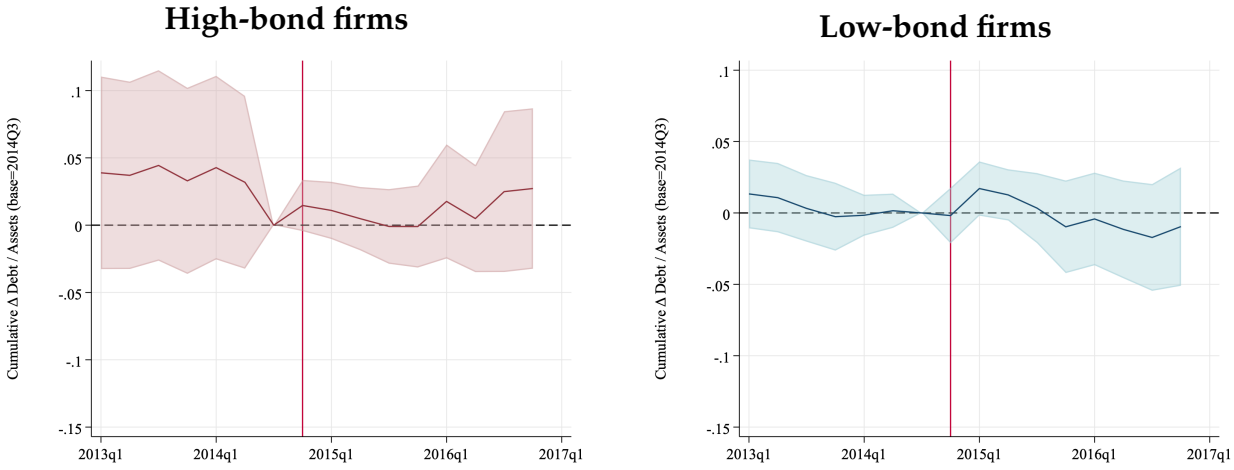
This is indeed what I find. As shown in Figure 6, there is no differential effect of the Marblegate ruling on leverage between high- and low-intangible firms among investment-grade firms. Table A14 presents the corresponding regression results, which show no significant effects across any specification: no ex-ante commitment effect and no differential effect for intangibles as observed in the main sample. These null results support the interpretation that the main results reflect the legal shock to restructuring feasibility rather than broader macroeconomic forces.

Taken together, these findings reinforce the core insight of the paper: intangible assets do support debt financing, but their ability to do so is fragile. The pledgeability of intangibles depends not only on the going-concern value of the firm, but also on the strength of the legal and institutional systems that protect and preserve that value in times of distress.

7 Robustness and Alternative Explanations

In this section, I conduct a series of robustness checks to shed light on potential concerns related to omitted variables and intangible accounting. While these issues cannot be fully ruled out, the analyses suggest they are unlikely to drive the core empirical findings from the acquisition setting.

Figure 6. Intangible Asset Effect on Leverage After Marblegate (Placebo)



Notes: The figure plots cumulative differences in debt between high- and low-intangible firms, normalized to 2014Q3 assets, using Compustat data on non-financial firms. The sample covers 2013Q1–2016Q4 and is restricted to investment-grade firms with an S&P rating of BBB- or above. The left panel shows the difference within the high-bond group, and the right panel shows the difference within the low-bond group. Leverage residuals are obtained from regressions with firm and quarter fixed effects and lagged industry controls, converted back to levels, and scaled by pre-ruling (2014Q3) assets. The vertical line marks the Marblegate ruling (2014Q4). The shaded area denotes 95% confidence intervals.

7.1 Target's Existing Debt and Pre-Acquisition Leverage Constraints

A key premise of the baseline analysis is that the acquiring firm chooses debt financing in response to the assets it acquires. However, this interpretation could be complicated when the target firm already carries substantial debt. In such cases, some of the acquired assets, tangible or intangible, may already be pledged, limiting the acquirer's flexibility to use debt financing. In addition, existing covenants, such as change-of-control clauses, may constrain post-acquisition borrowing decisions, making the observed debt response less reflective of the acquired asset mix.

To shed light on this issue, I conduct two complementary robustness tests.

One potential concern is that part of the observed increase in debt may reflect assumed liabilities from the target, rather than a financing decision by the acquirer in response to asset composition. Although such assumed debt is already captured in the post-transaction consolidated balance sheet of the acquirer, it could obscure the interpretation of the financing response if the increase in leverage is driven primarily by legacy obligations.

To address this, I use the information on whether the acquirer assumed the target's debt. I classify firm-year observations based on whether any of the transactions in that year involved assumed debt. This restricts attention to cases where all observed post-acquisition

debt is newly issued by the acquirer. Table A15 shows that the results remain consistent. In transactions with assumed debt, \$1 of intangible assets is associated with an additional \$0.22 of debt, compared to \$0.43 for tangibles. In deals without assumed debt, \$1 of intangible assets corresponds to \$0.28 more debt, and \$0.45 for tangibles. The findings from the sample without assumed debt are unaffected by the target's pre-existing debt, reinforcing the core result that intangible assets can support debt.

Second, to further address the concern that some acquired assets may already be encumbered by pre-existing debt, I examine a subsample for which I observe the pre-acquisition balance sheet of the target. This allows me to directly control for the extent to which the target's tangible and intangible assets were already backed by long-term debt at the time of acquisition. Specifically, I include additional controls for the target's pre-acquisition ratios of intangibles to long-term debt and tangibles to long-term debt, as well as the acquirer's own tangible assets scaled by debt prior to the transaction. These variables proxy for the degree to which acquired assets may have already been pledged and help isolate the incremental effect of newly acquired assets on post-acquisition financing decisions.

As shown in Table A16, the results remain consistent with the baseline: \$1 of intangible assets is associated with a \$0.24 increase in debt, and \$1 of tangible assets with a \$0.43 increase. These point estimates are closely aligned with the original findings, reinforcing that the observed financing patterns are not driven by unused debt capacity but reflect the financing response to asset composition.

7.2 Simultaneous Investment in Tangible or Intangible Assets

A potential identification concern is that observed changes in debt might reflect not only the acquired assets themselves but also other capital investments made around the same time. For example, acquirers might simultaneously expand PP&E or R&D while purchasing intangible or tangible assets, financing all activities with debt. If so, the estimated effect of asset acquisitions on leverage could be biased upward, overstating the direct financing response to acquired assets.

I address this concern in two steps. First, I revisit the event-time plot in Figure 2 that shows that the increase in debt is sharply concentrated around the acquisition quarter, with little movement before or after. This pattern suggests that unrelated investments are unlikely to be driving the results. If other capital expenditures were contributing materially to the increase in debt, they would likely leave a broader temporal footprint. The fact that

no such lead or lag pattern appears suggests that any potential confounding investment would have to be narrowly concentrated in the acquisition year itself.

Second, I test directly for concurrent changes in Figure A4 that examine changes in other types of investment around the acquisition. I include a timeline to show many years before and after the acquisition, beyond just focusing on the acquisition year. Panel (a) examines changes in SG&A expenses. There is no significant pattern at the time of acquisition, suggesting no concurrent expansion in operating expenditures. Panel (b) analyzes R&D spending. Firms acquiring intangibles show a small decline in R&D in the acquisition year, with a modest post-acquisition increase; neither change is statistically significant. Panel (c) evaluates PP&E purchases and similarly finds no significant change during the acquisition year, nor any meaningful shifts before or after.

7.3 Heterogeneity by Deal Structure: Cash vs. Stock Consideration

The primary goal of this paper is to explore the connection between the assets acquired and the financing methods used in acquisition transactions. A key consideration is the structure of the deal, whether it involves payment in cash or payment in stock, as this may reveal heterogeneous effects. Cash deals typically require debt financing, and one should expect more intangible paid with debt. For stock deals, leverage generally goes down, and the borrowing effect is less obvious.

I split the sample based on the type of deal. I classify a transaction as a stock deal if any portion of the payment is made in stock. For firm-years with multiple stock transactions, the observation is classified as a stock deal, while the remaining firm-year observations are categorized as cash deals.

Table A17 shows that for cash deals, each \$1 of intangible assets is associated with a \$0.38 increase in debt, while each \$1 of tangible assets is linked to a \$0.44 increase in debt. In stock deals, the coefficient for intangible assets is lower, at 0.20, and the coefficient for tangible assets is essentially unchanged. The results suggest that when equity is used, borrowing tied to intangible assets is smaller than in transactions fully financed by cash, which typically involves debt financing in the background.

7.4 Alternative Investment Opportunity Controls: Using Tobin's Q

In my baseline specifications, I control for total Q as proposed by Peters and Taylor (2017), which introduces a new proxy for Tobin's Q that accounts for intangible capital.

They argue that this proxy more accurately reflects a firm's investment opportunities. In case one is curious about the results with Tobin's Q, in Table A18, I re-run the baseline regression using Tobin's Q instead of total Q. The results remain consistent with my original findings.

7.5 Distinguishing the Role of Goodwill

Table A19 examines the relationship between changes in intangible assets, tangible assets, goodwill, and working capital on long-term debt. The findings reveal that both intangible and tangible assets have a positive effect on long-term debt, with tangible assets exerting a stronger influence. Each $1 increase in intangible assets corresponds to an approximate $0.19 rise in debt, while each $1 of tangible assets leads to a $0.42 increase. Goodwill has a smaller and weakly statistically significant impact on debt, with coefficients ranging from $0.01 to $0.11 per dollar across specifications when additional controls are applied. The coefficient captures how much of the purchase (goodwill) is financed with debt. Goodwill captures intangible components like organizational and human capital not fully reflected in other identifiable intangible valuations, as well as synergies and potential overpayment. The results reinforced the conclusion that although tangible assets provide greater support for long-term debt, firms use debt to finance intangible assets.

7.6 Tax-Driven Valuation Distortions in PPA

The deal structure and taxation incentive in the acquisition are important topics (Erickson (1996)). Tax incentives may distort the PPA, for example, by assigning disproportionately high value to intangible assets for tax advantages—even when the target's asset base is more heavily weighted toward tangibles. Because tangible assets generally support debt better than intangibles, such distortions could upwardly bias the estimated effect of intangible assets on leverage. I show, however, that my main findings are robust to this concern.

There are two main tax treatments for acquisitions.

In a tax-deferred (carryover basis) transaction, the target's original tax basis in the assets is transferred to the acquirer. In these cases, the PPA valuation has no effect on the acquirer's taxes and thus provides little incentive to misreport intangible valuations. Practitioners often describe this as "the fair value adjustment in PPA is not taxable".

In a taxable (stepped-up basis) transaction, the tax basis of the assets is adjusted to reflect

the full purchase price. Under Section 197 of the Internal Revenue Code, intangible assets, including goodwill, must be amortized over 15 years on a straight-line basis. This structure can, in principle, create an incentive to shift basis from long-lived tangible assets (e.g., buildings) to Section 197 intangibles to accelerate deductions. Such reclassification would mechanically raise reported intangible values and could inflate the estimated coefficient on intangibles. In practice, however, this incentive is limited: most tangible PP&E already qualifies for 5- or 7-year accelerated MACRS (Modified Accelerated Cost Recovery System) schedules often with bonus depreciation, so shifting value to intangibles would actually slow deductions. Moreover, identifiable intangibles must meet strict ASC 805 criteria and are subject to third-party appraisal and audit.

I infer the likely tax treatment using deal attributes and acquirer disclosures. In my sample, 85% of transactions are tax-deferred, meaning that the fair value assigned in the PPA has no tax impact. Only 7.5% of deals appear to be taxable, where PPA valuations affect amortization. The remaining 7.5% lack sufficient information to classify.

Given the overwhelming share of tax-deferred transactions and the robustness of results across subsamples, tax-motivated distortions in asset valuation are unlikely to drive my main findings.

7.7 Impact of Measurement Error of Intangibles

In this section, I assess how measurement error in asset valuations might affect the estimated relationship between debt financing and intangible versus tangible assets.

There is good reason to believe that accountants make a genuine effort to value intangible assets accurately. These valuations are subject to external audit review, and as discussed in Section 7.6 and Appendix A.3, the incentive to deliberately manipulate intangible valuations for tax or financial accounting is limited.

Of course, valuation is inherently difficult, and some error is inevitable. As long as accountants make unbiased, best-effort estimates so that the reported value equals the true value plus random noise, the measurement error can be considered classical. In that case, the resulting bias is well understood: the estimated coefficient is attenuated toward zero.

When measurement error departs from the classical form, however, the biases become harder to characterize. Fortunately, Abel (2018) offers insights into this issue, highlighting two primary channels through which bias arises.

The first channel is the multivariate attenuation factor, a generalization of the standard

attenuation factor. This factor uniformly attenuates the OLS estimates of all coefficients by the same proportion. The extent of multivariate attenuation increases with the product of the measurement error multiplier and the variances of the measurement errors across all regressors. The second channel, known as weight shifting, redistributes weight among the regressors. This further attenuates the OLS coefficient of the mismeasured regressor and can also impact the coefficients of other variables, either attenuating or inflating them, depending on the interplay between the measurement errors and their correlations.

I estimate how debt responds to changes in acquired intangible and tangible assets. In this two-regressor setting with both variables measured with error, Bound et al. (2001) provides an approximate expression for the bias.[22] The bias in the estimated coefficient for intangible assets, denoted as $\hat{\beta}_{\text{intan}}$, is given by the formula:[23]

$$\text{bias}(\hat{\beta}_{\text{intan}}) \approx \frac{-\beta_{\text{intan}}\lambda_{\text{intan}} + \beta_{\text{tan}}\lambda_{\text{tan}}\rho}{1-\rho^2}$$

where ρ is the correlation between the true values of the regressors (Δintan* and Δtan*), and the λ's represent the error to total variance ratios for the two variables ($\lambda_j \equiv \sigma^2_{\mu_j}/\sigma^2_{x_i^*}$).

To interpret the bias, suppose the true coefficients β_{intan} and β_{tan} are equal, and $\lambda_{\text{intan}} > \lambda_{\text{tan}}$ which corresponds to intangibles having more error variance relative to tangibles, then $\hat{\beta}_{\text{intan}}$ is biased downward, underestimating the true effect of intangibles, while the bias on $\hat{\beta}_{\text{tan}}$ is ambiguous because it depends on the interaction between error variances and correlation.

This analysis indicates that my estimate of β_{intan} is likely a lower bound, thereby strengthening the argument that intangible assets can be financed with debt.

8 Conclusion

This paper examines how intangible assets are financed with debt. Using detailed PPA data from acquisition transactions, I obtain precise valuations of both tangible and intangible assets. The acquisition setting provides a particularly informative context: acquirers are large public firms spanning a wide range of industries, representing roughly 14% of all public firms and thus a substantial portion of the economy. By comparing

[22] Chapter 59, equation 12 gives a nice approximation for the bias. Originally derived in Theil (1961).

[23] Let the observed valuation of intangibles and tangibles be Δintan ($\Delta\text{intan} = \Delta\text{intan}^* + \mu_{\text{intan}}$) and Δtan ($\Delta\text{tan} = \Delta\text{tan}^* + \mu_{\text{tan}}$), where the starred variables denote the true (unobserved) values. The errors (the μ's) are assumed to be independent of each other and are small. Here, the measurement errors do not need to be classical.

acquirers with similar pre-acquisition characteristics that differ in the types of assets acquired, I identify how debt financing responds to increases in tangible versus intangible capital.

The analysis yields several key findings.

First, contrary to the common view that intangibles cannot support borrowing, I show that firms do use debt to finance them. One dollar of identifiable intangible assets is associated with a \$0.24 increase in long-term debt, compared to \$0.44 for tangible assets. Although smaller, this effect is economically meaningful, demonstrating that intangibles can support debt financing, although through different channels than tangible assets.

Second, the financing mechanism for intangibles differs fundamentally from that for tangibles. Intangibles are closely associated with cash flow–based debt, rather than asset-based debt. Asset-based lending relies on collateral that can be liquidated in default, while cash flow–based lending depends on the borrower's ongoing ability to generate earnings. Moreover, debt financing of intangibles is unaffected by asset redeployability, reinforcing that their borrowing capacity is tied to the stability of cash flows, not resale value. In the modern economy, where intangible capital plays an increasingly central role, these findings highlight a broader shift: financing capacity is less about collateral and more about reliable, durable cash flows.

Third, the PPA data allow me to examine different types of intangible assets. I classify intangibles according to their function in the firm, distinguishing between production-based and demand-shifting assets. Demand-shifter intangibles, such as brands and customer relationships, do not enter the production function directly but shift the demand curve the firm faces, while production-based intangibles directly enhance production. Demand-shifter intangibles are special because they help firms stabilize cash flow, particularly during downturns, as customers are likely to continue purchasing from them during bad times. Demand-shifter intangibles are more strongly associated with debt financing than production-based intangibles.

Finally, to complement the main findings, I exploit the 2014 Marblegate legal ruling as a quasi-natural experiment in a triple-difference framework. The ruling strengthened bondholder protections, but made it harder to restructure firms in distress. The expected recovery of intangible-intensive firms is more exposed to the shock. Consistent with the paper's mechanism, the leverage of intangible-intensive firms declined after the ruling. These results confirm that intangibles support debt financing but also underscore that their pledgeability depends critically on legal infrastructure. Unlike tangible assets, which retain value through resale, the value of intangibles is more fragile and depends on preserving

firm value through orderly restructuring.

Taken together, the results show a clear pattern: intangible assets do support debt financing, but not in the way traditional assets do. Intangible assets do not back borrowing through their piecemeal resale value; in contrast, they sustain borrowing by supporting stable, durable operating cash flows. Their economic value is highest when the firm continues as a going concern rather than when the assets are separated and sold.

A key insight from the analysis is the macroeconomic relevance of demand-shifter intangibles, such as brand capital and customer relationships. These assets allow firms to smooth cash flows and maintain earnings even during downturns, enabling greater access to debt. Investment in customer-related intangibles has been rising steadily, and the sectors most intensively investing in them are among the fastest-growing in the U.S. economy (He et al., 2025). Their dual role, enhancing resilience and expanding financing capacity, makes them central to understanding the relationship between intangible capital, debt markets, and long-term growth. Ensuring that such assets remain financeable will be critical for sustaining innovation and economic dynamism in an increasingly intangible-driven world.

From a policy perspective, the findings offer both reassurance and urgency. The continued ability of intangible-intensive firms to access credit suggests that the monetary policy transmission channel remains active, even in an economy increasingly dominated by intangibles. At the same time, the weakening of the traditional collateral channel, long central to financial accelerator models, calls for rethinking how monetary policy operates in this context. Because intangibles are more fragile in distress and depend on preserving firm value through orderly restructuring, access to debt will increasingly hinge on the strength of the legal and institutional infrastructure. Strengthening bankruptcy and restructuring regimes will be critical to safeguarding creditor recoveries and supporting credit flows to the firms driving modern innovation and growth.

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APPENDIX

A Additional Details on Purchase Price Allocation

A.1 Fair Value

What does "fair value" mean? Under ASC 820, fair value is defined as the price that would be received to sell an asset or paid to transfer a liability in an orderly transaction between market participants on the measurement date. The concept is *market-based*, focusing on the assumptions and pricing of market participants, not those of the specific company preparing the financial statements.

Whose assumptions are used? Fair value reflects how a typical market participant would value the asset. It does *not* reflect the acquirer's unique expectations or internal plans. Any buyer-specific value created through expected synergies, integration, or special use is excluded from individual asset fair values and instead captured as goodwill.

What if an asset's value depends on being used with other assets? If the highest and best use of an asset is in combination with others, ASC 820 requires first determining the combined fair value of the asset group, then allocating that amount to the individual components based on their units of account. For example, if a technology derives value only when embedded in a specific device, the combined fair value of the technology and device must be estimated and then distributed between the two.

How does fair value differ from useful life? ASC 350-30-35-3(a) distinguishes between these two ideas. The *useful life* of an asset depends on entity-specific assumptions, how long the firm expects to use the asset, whereas the *fair value* is determined from the perspective of market participants at the measurement date.

See PwC, "Fair Value Measurements," *Viewpoint Guide*, March 2022, available at https://viewpoint.pwc.com.

A.2 List of Identifiable Intangibles

Table of List of Identifiable Intangibles

This table shows examples of identifiable intangibles from various categories defined by US GAAP ASC 805-20-55.

Category	Examples of identifiable intangibles
Marketing-related intangible assets	Newspaper mastheads; Trademarks, service marks, trade names, collective marks, certification marks; Trade dress; Internet domain names; Noncompetition agreements
Customer-related intangible assets	Customer lists; Customer contracts and related customer relationships; Noncontractual customer relationships; Order or production backlogs
Artistic-related intangible assets	Plays, operas, ballets; Books, magazines, newspapers, and other literary works; Musical works such as compositions, song lyrics, and advertising jingles; Photographs, drawings, and clip art; Audiovisual material including motion pictures, music videos, television programs
Contract-based intangible assets	License, royalty, and standstill agreements; Advertising contracts; Lease agreements; Construction permits; Construction contracts; Management, service, or supply contracts; Broadcast rights; Franchise rights; Operating rights; Use rights; Servicing contracts; Employment contracts
Technology-based intangible assets	Patent technology; Computer software and mask works; Unpatented technology; Databases; Trade secrets

A.3 Financial Accounting Incentive

Section 7.6 discusses how tax incentives may affect asset valuation in acquisitions. A natural follow-up question is whether financial accounting incentives might also distort purchase price allocations (PPA). For readers less familiar with accounting, it is important to note that financial reporting (e.g., for SEC filings) and tax reporting follow different rules and serve different purposes.

The key concern on the financial accounting side is earnings management, specifically, how the allocation of the purchase price across asset categories affects earnings per share (EPS) after the transaction. Managers might face trade-offs depending on how much value they assign to: Identifiable intangibles with definite useful lives (e.g., customer

relationships, software), which are amortized over time, creating predictable non-cash expenses that reduce reported EPS; versus indefinite-lived intangibles (e.g., goodwill, certain IP R&D), which are not amortized but instead subject to periodic impairment testing.

The incentives here are conflicting. On one hand, allocating more value to indefinite-lived intangibles avoids recurring amortization charges, thus improving reported EPS. On the other hand, inflating goodwill or indefinite-lived IP can lead to future impairment charges, which are lumpy and unpredictable, and expose management to scrutiny or criticism for overpayment. In particular, high goodwill may be seen as a signal of weak bargaining or value overstatement.

This conflicting set of incentives reduces the likelihood of systematic manipulation in one direction. Empirical evidence supports this: even within the same asset category, such as customer relationships, I observe substantial heterogeneity in reported useful life estimates—ranging from 1 to 32 years, with a median of 10 years. If managers were solely motivated to minimize amortization expense, one would expect uniformly long useful lives. Instead, this variation suggests that accountants are making situation-specific, good-faith estimates.

Further reducing the scope for manipulation is the fact that purchase price allocations are prepared by third-party valuation experts and subject to audit scrutiny. Moreover, acquisition accounting standards under ASC 805 require a thorough, arm's-length identification and classification of intangible assets, leaving little room for arbitrary allocation.

Finally, even if managers had strong incentives to manipulate accounting EPS, sophisticated investors often rely on alternative earnings metrics, such as adjusted EPS or "cash EPS," which add back amortization and other non-cash charges to better reflect operating performance. These practices further dilute any incentive to shift value between amortizable and non-amortizable intangibles for cosmetic reporting purposes.

In sum, while financial accounting incentives do exist, they are conflicted, mitigated by procedural safeguards, and further weakened by investor focus on adjusted earnings, making it unlikely that they meaningfully bias the intangible valuations used in my analysis.

Table of Identifiable Intangibles Categorization

The 24 categories of identifiable intangibles are based on the US GAAP framework, with adjustments made to align more closely with economic interpretations.

A.4 Categories of Intangibles

Category	Description
Customer relationship	customer, client, loyalty program, user base, customer base, membership
Customer list	customer list, phone number
Customer contract	customer contract, customer agreement
Trademark / trade name	trademark, masthead
Brand	name, brand, marketing related
Business relationship	business relationship, record, network, deposit intangibles
IP R&D	in process research, research
Technology	core technology, existing technology, technology; *excl. in-process technology*
Business know-how	knowhow, recipe, mold, formula, business process, algorithm
Patent	patent; *excl. patent license*
Software	software; *excl. software license*
Trade secrets	trade secrets
Database	database
IP	intellectual property
Backlog	backlog, order
R.O.U	mineral right, other right of use, rental agreement; *excl. operating lease, lease agreement, rents, lease in place*
Franchise	franchise agreement
License	permit, license, approval
Non-compete agreement	non-compete agreement
Employee relation	employment contract, workforce, employee relation
Other contract	contract, agreement, arrangement; *excl. with customer, non-compete, lease, backlog*
Design	design, art, music library, drawing
Domain	website, domain
Publication	publication, copyright

B Variable definitions

Control variables	Definition
Spread	firm-level rating specific credit spread
Total q	Peters and Taylor 17 from WRDS
Market to book	mkval/ceq
Stock return	past 12 month cumulative return
Tobin's Q	(mkval+dlc+dltt)/l.at
Size	ln(at)
Cash on-hand	che/at
Operating earnings	ebitda/l.at
Cash flow	(oancf+xint)/l.at
Tangible (acquirer)	ppent/at
Book leverage	(dlc+dltt)/at

C Model: Demand-Shifter Intangibles and Debt Financing

This section presents a model to illustrate how different types of intangible assets, focusing on demand-shifter and production-based intangibles, can have heterogeneous effects on firms' optimal debt usage. The key mechanism is that demand-shifter intangibles reduce the volatility of cash flows, especially in adverse market conditions, thereby increasing firms' debt capacity.

Model setup and assumptions. The model has two time periods, $t = 0, 1$. There is a single firm with three capital components: tangible capital (k_T), production-based intangible capital (k_N), and demand-shifter intangibles (B). We treat the capital stocks k_T, k_N, and B as exogenously given, and only k_T, k_N enter the production function.

Output is determined by a standard production function:

$$q \equiv f(k_N, k_T).$$

The firm faces a stochastic linear demand curve affected by both market conditions and the stock of customer-related intangibles:

$$p(q, B, z) \equiv p^* - \frac{z}{B}q + \varepsilon = \begin{cases} p^* + \varepsilon, & z = 0 \text{ with prob } \phi, \\ p^* - \frac{1}{B}q + \varepsilon, & z = 1 \text{ with prob } 1 - \phi. \end{cases} \tag{4}$$

where p^* is the prevailing price in the absence of any shocks, z is a demand shock that reflects the market condition, q is the production quantity, B is the demand-shifter intangibles, ε is an idiosyncratic shock the firm experiences and follows a uniform distribution $U[0, 1]$.

A negative market shock occurs with a probability $1 - \phi$, and a higher B shelters the firm from the negative market condition by partially offsetting the shock: a larger amount of customer relationships reduces the price impact of a large number of outputs when the market condition is tight.

This formulation captures the empirical observation that customer-related intangibles (e.g., brand, customer loyalty) help stabilize revenue during downturns (Larkin, 2013).

Financing Environment. In period $t = 0$, the firm issues debt with face value F and pays out the proceeds, denoted $D(F)$, as dividends to shareholders. In period $t = 1$, the firm generates cash flow equal to pq and repays the debt. If cash flow is insufficient, the

firm defaults and incurs bankruptcy costs C.

The payouts are given by:

$$\text{Repayment to debtholders} = \min\{F, pq - C\}, \tag{5}$$

$$\text{Payout to shareholders} = \max\{(1-\tau)pq - F, 0\}. \tag{6}$$

where τ is the corporate income tax rate.

We assume that lenders are risk-neutral, so the expected repayment must equal the debt proceeds:

$$\mathbb{E}[D(F)] = D. \tag{7}$$

Firm's Objective Function The firm chooses its debt usage to maximize initial equity value.[24]

$$V = \max_{F \geq 0} \left\{ D(F) + \mathbb{E}\left[\max\left((1-\tau)pq - F + \tau F, 0 \right) \right] \right\}. \tag{8}$$

subject to:

$$D(F) = \mathbb{E}\left[\min(F, pq - C) \right]. \tag{9}$$

Model implications

Proposition 1. *The optimal debt level F^* is increasing in the stock of customer-related intangibles B. That is,*

$$\frac{dF^*}{dB} > 0.$$

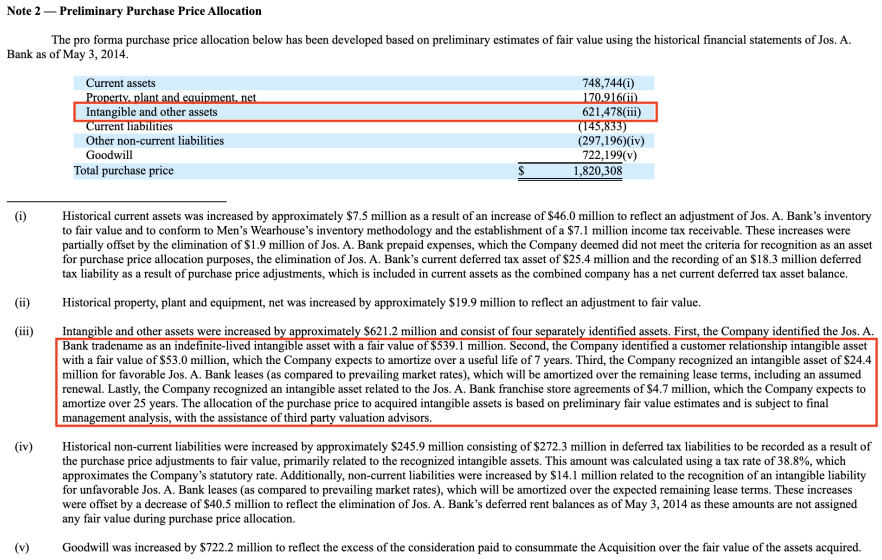
The relationship between B and F^*. As the level of customer-related intangibles increases, the firm's optimal debt also increases. This result illustrates that firms with stronger customer loyalty and brand equity face less revenue volatility and can support higher debt levels.

[24] For simplification purposes, here, I do not discount the $t = 1$ payment.

D Additional Figures and Tables

Figure A1. Various Types of Intangibles This graph illustrates the various major types of intangibles as defined by US GAAP.

Figure A2. Purchase Price Allocation Example. This figure shows a screenshot from Men's Wearhouse Inc.'s 8-K/A filing on 2014-09-02, reporting the acquisition of Jos. A. Bank Clothiers, Inc.



Note 2 — Preliminary Purchase Price Allocation

The pro forma purchase price allocation below has been developed based on preliminary estimates of fair value using the historical financial statements of Jos. A. Bank as of May 3, 2014.

Current assets	748,744(i)
Property, plant and equipment, net	170,916(ii)
Intangible and other assets	621,478(iii)
Current liabilities	(145,833)
Other non-current liabilities	(297,196)(iv)
Goodwill	722,199(v)
Total purchase price	$ 1,820,308

(i) Historical current assets was increased by approximately $7.5 million as a result of an increase of $46.0 million to reflect an adjustment of Jos. A. Bank's inventory to fair value and to conform to Men's Wearhouse's inventory methodology and the establishment of a $7.1 million income tax receivable. These increases were partially offset by the elimination of $1.9 million of Jos. A. Bank prepaid expenses, which the Company deemed did not meet the criteria for recognition as an asset for purchase price allocation purposes, the elimination of Jos. A. Bank's current deferred tax asset of $25.4 million and the recording of an $18.3 million deferred tax liability as a result of purchase price adjustments, which is included in current assets as the combined company has a net current deferred tax asset balance.

(ii) Historical property, plant and equipment, net was increased by approximately $19.9 million to reflect an adjustment to fair value.

(iii) Intangible and other assets were increased by approximately $621.2 million and consist of four separately identified assets. First, the Company identified the Jos. A. Bank tradename as an indefinite-lived intangible asset with a fair value of $539.1 million. Second, the Company identified a customer relationship intangible asset with a fair value of $53.0 million, which the Company expects to amortize over a useful life of 7 years. Third, the Company recognized an intangible asset of $24.4 million for favorable Jos. A. Bank leases (as compared to prevailing market rates), which will be amortized over the remaining lease terms, including an assumed renewal. Lastly, the Company recognized an intangible asset related to the Jos. A. Bank franchise store agreements of $4.7 million, which the Company expects to amortize over 25 years. The allocation of the purchase price to acquired intangible assets is based on preliminary fair value estimates and is subject to final management analysis, with the assistance of third party valuation advisors.

(iv) Historical non-current liabilities were increased by approximately $245.9 million consisting of $272.3 million in deferred tax liabilities to be recorded as a result of the purchase price adjustments to fair value, primarily related to the recognized intangible assets. This amount was calculated using a tax rate of 38.8%, which approximates the Company's statutory rate. Additionally, non-current liabilities were increased by $14.1 million related to the recognition of an intangible liability for unfavorable Jos. A. Bank leases (as compared to prevailing market rates), which will be amortized over the expected remaining lease terms. These increases were offset by a decrease of $40.5 million to reflect the elimination of Jos. A. Bank's deferred rent balances as of May 3, 2014 as these amounts are not assigned any fair value during purchase price allocation.

(v) Goodwill was increased by $722.2 million to reflect the excess of the consideration paid to consummate the Acquisition over the fair value of the assets acquired.

(A) Purchase price allocation summary

Tradename	$539.1 million
Customer relationship	$53.0 million
Favorable leases	$24.4 million
Franchise store agreements	$4.7 million
Total Intangible assets	$621.2 million

(B) Detailed breakdown of identifiable assets in note (iii)

Figure A3. More Example of Identifiable Intangibles Valuation The target is Ploycom, a global corporation that develops video, voice and content collaboration and communication technology.

(in thousands, except for remaining life)	Fair Value
Existing technology	$ 538,600
Customer relationships	245,100
Trade name/Trademarks	115,600
Backlog	28,100
Total amortizable intangible assets acquired	927,400
In-process research and development	58,000
Total acquired intangible assets	$ 985,400

Existing technology relates to products for voice, video and platform products. The Company valued the developed technology using the discounted cash flow method under the income approach. This method reflects the present value of the projected cash flows that are expected to be generated by the developed technology less charges representing the contribution of other assets to those cash flows. The economic useful life was determined based on the technology cycle related to each developed technology, as well as the cash flows over the forecast period.

Customer relationships represent the fair value of future projected revenue that will be derived from sales of products to existing customers of Polycom. Customer relationships were valued using the discounted cash flow method as described above and the distributor method under the income approach. Under the distributor method, the economic profits generated by a distributor are deemed to be attributable to the customer relationships. The economic useful life was determined based on historical customer turnover rates.

Table A1. Proportion of Compustat Firms Involved in Acquisition Activities with PPA Data

This table reports the share of Compustat public firms that engaged in acquisition activities and are included in the purchase price allocation sample. Industries are defined using the Fama–French 12 classification, excluding financial firms. The period is 2001–2022, following the adoption of SFAS 141, which made purchase price allocations mandatory for public acquirers.

Industry	Coverage (%)
Consumer NonDurables	14.6
Consumer Durables	12.6
Manufacturing	16.6
Oil, Gas, and Coal Extraction and Products	11.6
Chemicals and Allied Products	14.1
Business Equipment	20.7
Telephone and Television Transmission	13.5
Utilities	9.3
Wholesale, Retail, and Some Services	13.4
Healthcare, Medical Equipment, and Drugs	13.4
Other	9.2
Total	14.0

Table A2. Summary Statistics

This table shows the summary statistics for the variables used in the regression analysis. See the detailed definitions of the variables in Appendix B and see detailed information on the categorization of debt in Lian and Ma (2021). Prefix "l." indicates the variable is lagged one year.

	p25	p50	p75	Mean	SD	N
Δ Long-term debt/l.assets	0.00	0.06	0.28	0.19	0.32	3800
Δ Asset-backed debt/l.assets	-0.00	0.01	0.16	0.11	0.24	2874
Δ Cash flow-backed debt/l.assets	0.00	0.00	0.18	0.13	0.29	2874
Δ Identifiable intangibles/l.assets	0.00	0.05	0.17	0.17	0.37	3831
Δ Tangibles/l.assets	0.00	0.01	0.06	0.09	0.24	3831
Δ Intangibles (production-based)/l.assets	0.00	0.00	0.04	0.07	0.20	3831
Δ Intangibles (demand-shifter)/l.assets	0.00	0.00	0.08	0.08	0.19	3831
Δ Working capital/l.assets	0.00	0.00	0.05	0.05	0.13	3831
Deal size/l.assets	0.16	0.32	0.68	0.72	1.42	3831
l.Log assets	4.41	5.96	7.52	5.96	2.40	3821
l.Q	1.00	1.51	2.42	2.06	1.76	3121
l.Market to book	1.49	2.51	4.31	3.81	5.43	3136
l.12 month cumulative stock return	0.88	1.14	1.47	1.26	0.65	2884
l.Total q	0.56	1.07	2.07	2.22	3.74	3580
l.Credit-spread	3.27	3.50	5.11	4.16	2.09	3812
l.Book leverage	0.01	0.17	0.36	0.23	0.27	3804
l.Cash/assets	0.05	0.16	0.37	0.24	0.24	3821
l.EBITDA/l.assets	0.03	0.12	0.18	-0.01	0.56	3659
l.Net cash receipts/l.assets	0.04	0.11	0.17	0.04	0.34	3390
l.PPENT/assets	0.04	0.11	0.26	0.20	0.22	3796
Cash from target/l.assets	0.00	0.00	0.01	0.03	0.08	3831

Table A3. Summary Statistics for Identifiable Intangibles

This table reports transaction-level summary statistics for identifiable intangibles. Important to note, they are scaled by target total assets minus cash. The figures are shown prior to winsorization. Winsorization is applied at the acquirer-year level in the regressions. Summary statistics for the regression sample are presented in Table A2.

Panel A. Demand-shifter Intangibles and Subcomponents						
Intangibles (demand-shifter)	0.01	0.20	0.37	0.17	2.43	4038
Customer-relationship intangible	0.00	0.07	0.23	0.06	0.12	4038
Customer list intangible	0.00	0.00	0.00	0.01	0.05	4038
Customer contracts intangible	0.00	0.00	0.00	0.05	2.43	4038
Backlog intangible	0.00	0.00	0.00	0.00	0.02	4038
Brand intangible	0.00	0.00	0.03	0.01	0.06	4038
Trademark intangible	0.00	0.00	0.01	0.01	0.06	4038
Franchise agreement intangible	0.00	0.00	0.00	0.00	0.03	4038
Domain name intangible	0.00	0.00	0.00	0.00	0.02	4038
Non-compete agreement intangible	0.00	0.00	0.00	0.00	0.03	4038
Business relation intangible	0.00	0.00	0.00	0.01	0.05	4038
Contracts intangible	0.00	0.00	0.00	0.01	0.08	4038
Database intangible	0.00	0.00	0.00	0.00	0.02	4038
Panel B. Production-based Intangibles and Subcomponents						
Intangibles (production-based)	0.00	0.09	0.30	0.10	0.36	4038
Technology intangible	0.00	0.00	0.14	0.04	0.12	4038
Software intangible	0.00	0.00	0.00	0.00	0.03	4038
Patent intangible	0.00	0.00	0.00	0.01	0.27	4038
Know-how intangible	0.00	0.00	0.00	0.00	0.01	4038
Trade secrets intangible	0.00	0.00	0.00	0.00	0.01	4038
Research intangible	0.00	0.00	0.00	0.02	0.11	4038
Employee intangible	0.00	0.00	0.00	0.00	0.13	4038
License intangible	0.00	0.00	0.00	0.01	0.05	4038
Right of use intangible	0.00	0.00	0.00	0.01	0.08	4038
Art intangible	0.00	0.00	0.00	0.00	0.04	4038
Intellectual property intangible	0.00	0.00	0.00	0.00	0.03	4038
Publication intangible	0.00	0.00	0.00	0.00	0.01	4038

Table A4. Balance Test of Acquirers Based on Targets' Low and High Intangible-to-Tangible Asset Ratios

Summary statistics for the acquirer sample, split between targets with low intangible-to-tangible asset ratios and those with high intangible-to-tangible asset ratios.

	Low Intangible Share		High Intangible Share		Difference	
	Mean	**SD**	**Mean**	**SD**	**b**	**t-stat**
l.Log assets	6.08	2.43	6.08	2.26	-0.00	(-0.02)
l.Total q	1.76	3.47	2.26	3.36	-0.50***	(-3.79)
l.Q	1.56	1.32	2.25	1.80	-0.69***	(-10.61)
l.Market to book	3.08	5.09	4.19	5.53	-1.10***	(-4.99)
l.12 month cumulative stock return	1.24	0.66	1.25	0.60	-0.01	(-0.34)
l.Credit-spread	4.24	2.17	4.03	1.92	0.21**	(2.73)
l.Book leverage	0.28	0.27	0.22	0.26	0.06***	(5.95)
l.Cash/assets	0.17	0.21	0.26	0.24	-0.09***	(-10.37)
l.EBITDA/l.assets	0.02	0.48	-0.00	0.55	0.02	(1.22)
l.Net cash receipts/l.assets	0.06	0.29	0.03	0.35	0.03*	(1.99)
l.PPENT/assets	0.32	0.27	0.13	0.14	0.19***	(23.01)
Cash from target/l.assets	0.03	0.08	0.03	0.08	-0.01*	(-2.18)

D.1 Results Discussed in Section 4

Table A5. Marginal Effects of Asset Changes on Long-Term Debt by Redeployability

This table reports estimates from Table 1, but augmented with additional interaction terms of `High RDPL` as in Equation 2. RDPL is measured using the U.S. Census Bureau's BDS as the median number of mid-sized and above firms (500+ employees) in the 3-digit NAICS industry over the three years prior to acquisition. Industries above the 25th percentile are classified as High RDPL. Standard errors are clustered by industry and year, and F-statistics test equality of marginal effects across low vs. high RDPL groups for intangible and tangible assets. Significance levels are denoted by asterisks (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

	(1)	(2)	(3)	(4)
Δ Intangibles	0.13**	0.09	0.21***	0.17***
	(0.06)	(0.06)	(0.06)	(0.06)
High RDPL	-0.03*	-0.03*	-0.01	0.01
	(0.02)	(0.02)	(0.02)	(0.02)
High RDPL × Δ Intangibles	0.07	0.09	0.07	0.11
	(0.05)	(0.06)	(0.07)	(0.07)
Δ Tangibles	0.25***	0.23***	0.31***	0.26***
	(0.05)	(0.04)	(0.06)	(0.07)
High RDPL × Δ Tangibles	0.26***	0.26***	0.37***	0.42***
	(0.08)	(0.09)	(0.09)	(0.09)
Δ Working capital		0.30***	0.40***	0.49***
		(0.10)	(0.14)	(0.13)
High RDPL × Δ Working capital		-0.11	-0.31*	-0.39**
		(0.12)	(0.16)	(0.16)
Controls			X	X
Industry × year FE				X
Observations	3775	3775	2557	2511
R^2	0.137	0.145	0.256	0.339
F-stat: intan(Redeploy)	1.67	2.61	1.03	2.59
p-value: intan(Redeploy)	.208	.118	.319	.12
F-stat: tan(Redeploy)	10.34	8.73	16.8	22.34
p-value:tan(Redeploy)	.003	.007	0	0

Table A6. Marginal Effects of Asset Changes on Long-Term Debt by Redeployability (Alternative Measure)

This table reports estimates from Table 1, but augmented with additional interaction terms of `High RDPL` as in Equation 2. RDPL is measured using the U.S. Census Bureau's BDS as the median number of mid-sized firms (1,000–5,000 employees) in the 3-digit NAICS industry over the three years prior to acquisition, to mitigate impact of Industries above the 25th percentile are classified as High RDPL, and those below as Low RDPL. Standard errors are clustered by industry and year, and F-statistics test equality of marginal effects across low vs. high RDPL groups for intangible and tangible assets. Significance levels are denoted by asterisks (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

	(1)	(2)	(3)	(4)
Δ Intangibles	0.14**	0.10	0.20***	0.17***
	(0.06)	(0.06)	(0.05)	(0.05)
High RDPL	-0.02	-0.02	-0.00	0.01
	(0.02)	(0.02)	(0.02)	(0.02)
High RDPL × Δ Intangibles	0.06	0.09	0.08	0.12*
	(0.05)	(0.06)	(0.07)	(0.07)
Δ Tangibles	0.25***	0.23***	0.31***	0.27***
	(0.05)	(0.04)	(0.07)	(0.07)
High RDPL × Δ Tangibles	0.26***	0.25***	0.36***	0.41***
	(0.08)	(0.09)	(0.09)	(0.09)
Δ Working capital		0.29**	0.40***	0.49***
		(0.11)	(0.14)	(0.13)
High RDPL × Δ Working capital		-0.11	-0.30*	-0.39**
		(0.12)	(0.16)	(0.16)
Controls			X	X
Industry × year FE				X
Observations	3773	3773	2555	2509
R^2	0.137	0.145	0.256	0.340
F-stat: intan(Redeploy)	1.41	2.23	1.33	3.22
p-value: intan(Redeploy)	.246	.148	.26	.085
F-stat: tan(Redeploy)	10.55	8.6	14.67	20.28
p-value:tan(Redeploy)	.003	.007	.001	0

Table A7. Marginal Effects of Asset Changes on Long-Term Debt by Redeployability (Alternative Cut off)

This table reports estimates from Table 1, but augmented with additional interaction terms of `High RDPL` as in Equation 2. RDPL is measured using the U.S. Census Bureau's BDS as the median number of mid-sized and above firms (500+ employees) in the 3-digit NAICS industry over the three years prior to acquisition. Industries above the median are classified as High RDPL. Standard errors are clustered by industry and year, and F-statistics test equality of marginal effects across low vs. high RDPL groups for intangible and tangible assets. Significance levels are denoted by asterisks (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

	(1)	(2)	(3)	(4)
Δ Intangibles	0.14***	0.11**	0.25***	0.23***
	(0.04)	(0.04)	(0.05)	(0.05)
High RDPL	-0.01	-0.01	0.00	0.01
	(0.01)	(0.01)	(0.01)	(0.02)
High RDPL × Δ Intangibles	0.08*	0.10*	0.03	0.04
	(0.05)	(0.05)	(0.07)	(0.07)
Δ Tangibles	0.30***	0.27***	0.32***	0.27***
	(0.04)	(0.04)	(0.06)	(0.07)
High RDPL × Δ Tangibles	0.20**	0.20**	0.38***	0.44***
	(0.09)	(0.09)	(0.09)	(0.09)
Δ Working capital		0.27***	0.36**	0.39***
		(0.09)	(0.13)	(0.13)
High RDPL × Δ Working capital		-0.08	-0.26	-0.29*
		(0.14)	(0.16)	(0.16)
Controls			X	X
Industry × year FE				X
Observations	3775	3775	2557	2511
R^2	0.135	0.144	0.256	0.337
F-stat: intan(Redeploy)	3.3	3.39	.15	.43
p-value: intan(Redeploy)	.081	.077	.703	.516
F-stat: tan(Redeploy)	5.1	4.56	19.95	23.68
p-value:tan(Redeploy)	.033	.042	0	0

D.2 Results Discussed in Section 5

Table A8. Intangible Categorization

The various intangible assets are categorized based on the framework introduced in Section 5. Production-based intangibles are capital that a firm uses in production and affect the firm's marginal cost or production efficiency, holding demand constant, such as patents, technology, and organizational capital. Demand-shifter intangibles are variables that affect the demand curve firms face directly, holding production technology constant, such as trademark, brand, customer relationship. They are important for firms to generate cash flow but do not directly enter into the production function to produce more widgets. For clarity, the category "intellectual property (IP)" is omitted because it is too broad and can refer to intangibles, such as patents and trademarks. This ambiguity affects 48 observations in the empirical sample.

Production-based	Demand-shifter
Technology	Customer relationship
Software	Brand
Patent	Trademark
IP R&D	Customer list
Business know-how	Customer/other contract
Trade secrets	Business relationship
Design	Database
License	Domain
R.O.U	Franchise agreement
Publication	Non-compete agreement
Employee relation	Backlog

Table A9. Regression Results on the Impact of Intangibles on Cash Flow Volatility by Type of Intangibles

This table presents the results of the regression analysis investigating the impact of intangibles on cash flow volatility by type of intangibles. Columns (1) to (3) present the outcome variable of cash flow volatility after the acquisition by terciles of demand-shifter or production-based intangibles acquired. Pre- and post-acquisition cash-flow volatility are calculated as the 5-year standard deviation of EBITDA ($oibdp + dp$) scaled by total assets, using the 5 years prior to or following the acquisition year. All volatility measures are reported in logs. Significance levels are denoted by asterisks (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

LHS variable is Post-acquisition Cash-flow Volatility			
	(1)	(2)	(3)
Δ Intangibles (demand-shifter): Med	-0.02	-0.02	-0.02
	(0.01)	(0.01)	(0.01)
Δ Intangibles (demand-shifter): High	-0.02*	-0.02**	-0.02**
	(0.01)	(0.01)	(0.01)
Δ Intangibles (production-based): Med	0.03**	0.02*	0.02
	(0.01)	(0.01)	(0.01)
Δ Intangibles (production-based): High	0.03**	0.03**	0.03**
	(0.01)	(0.01)	(0.01)
Post-acquisition cash-flow volatility	0.98***	1.00***	1.00***
	(0.01)	(0.01)	(0.01)
Controls		X	X
Industry × year FE			X
Observations	3718	2574	2528
R^2	0.946	0.960	0.965

Table A10. Regression Results on the Impact of Intangibles on Cash flow–based Debt

This table presents the results of the regression analysis investigating the impact of intangibles on cash flow–based debt usage by type of intangibles. Intangibles are classified into production intangibles and demand-based intangibles, see Table B for details. Standard errors are reported in parentheses and are clustered at the industry and year level. Significance levels are denoted by asterisks (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

LHS Variable is Δ in Cash flow-based Debt			
	(1)	(2)	(3)
Δ Intangibles (demand-shifter)	0.30***	0.44***	0.45***
	(0.07)	(0.07)	(0.08)
Δ Intangibles (production-based)	0.11**	0.17**	0.13*
	(0.05)	(0.07)	(0.07)
Δ Tangibles	0.15***	0.28***	0.24***
	(0.04)	(0.06)	(0.06)
Δ Working capital	0.11	0.11	0.19*
	(0.07)	(0.10)	(0.10)
Controls		X	X
Industry × year FE			X
Observations	2874	2041	2012
R^2	0.083	0.168	0.250
F-stat: ds-intan=pb-intan			10.23
F-stat: p-value			.005

D.3 Results Discussed in Section 6

Table A11. More Bankruptcy Filings after Marblegate Ruling

Sample consists of non-financial high-yield Compustat firms over the period 2013Q1–2016Q3. The dependent variable is an indicator for bankruptcy filing. The key regressor is the interaction between $\texttt{Marblegate}_t$ and $\texttt{HighBond}_i$. $\texttt{Marblegate}_t$ equals one in the post-ruling period (2015Q1–2016Q4). $\texttt{HighBond}_i$ indicates firms with above-median bond share in 2014Q3. Column (1) includes lagged two-digit industry asset growth and value-weighted returns as controls. Column (2) replaces these controls with two-digit industry × quarter fixed effects to absorb time-varying industry shocks. Standard errors are clustered at the firm level and reported in parentheses. Similar evidence is reported in Kornejew (2024), Table 1, using an alternative sample. Significance levels are denoted by asterisks (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

LHS Variable is Number of Bankruptcy Filings		
	(1)	(2)
Marblegate × High bond	0.0106***	0.0072***
	(0.0027)	(0.0023)
Controls	X	
Industry × Quarter FE		X
Observations	9093	9089
R^2	0.011	0.060

Table A12. Marblegate Ruling For High-Bond Firms

The table reports estimates of Equation 3 but modified to include only one interaction term $\texttt{Marblegate}_t \times \texttt{HighBond}_i$ using Compustat data on non-financial firms. The sample covers 2013Q1–2016Q4 and is restricted to high-yield firms with an S&P rating of BB+ or worse. The dependent variable is total debt, loans, or bonds scaled by total assets in columns (1) to (3). Firm fixed effects control for time-invariant firm characteristics, and quarter fixed effects capture aggregate shocks. $\texttt{Marblegate}_t$ equals one in the post-ruling period (2015Q1–2016Q4). $\texttt{HighBond}_i$ indicates firms with above-median bond share in 2014Q3. Controls include lagged industry-level asset growth and stock returns at the 2-digit NAICS level. Standard errors are reported in parentheses and are clustered at the firm level. Significance levels are denoted by asterisks (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

	(1)	(2)	(3)
	Debt/Assets	Bonds/Assets	Loans/Assets
Marblegate × High bond	0.044***	0.043**	0.019*
	(0.014)	(0.017)	(0.010)
Controls	X	X	X
Firm FE	X	X	X
Quarter FE	X	X	X
Observations	7588	7899	7899
R^2	0.756	0.702	0.837

Table A13. Marblegate Ruling For High-Intangible Firms

The table reports estimates of Equation 3 but modified to include only one interaction term $\texttt{Marblegate}_t \times \texttt{HighIntan}_i$ using Compustat data on non-financial firms. The sample covers 2013Q1–2016Q4 and is restricted to high-yield firms with an S&P rating of BB+ or worse. The dependent variable is total debt, loans, or bonds scaled by total assets in columns (1) to (3). Firm fixed effects control for time-invariant firm characteristics, and quarter fixed effects capture aggregate shocks. $\texttt{Marblegate}_t$ equals one in the post-ruling period (2015Q1–2016Q4). $\texttt{HighIntan}_i$ indicates firms with above-median intangible intensity in 2013, based on data from Peters and Taylor (2017). Controls include lagged industry-level asset growth and stock returns at the 2-digit NAICS level. Standard errors are reported in parentheses and are clustered at the firm level. Significance levels are denoted by asterisks (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

	(1) Debt/Assets	(2) Bonds/Assets	(3) Loans/Assets
Marblegate × High intan	-0.043***	-0.061***	-0.004
	(0.014)	(0.016)	(0.010)
Controls	X	X	X
Firm FE	X	X	X
Quarter FE	X	X	X
Observations	7738	7980	7980
R^2	0.755	0.708	0.834

Table A14. Marblegate Ruling Result With Placebo Sample

The table reports estimates of Equation 3 using Compustat data on non-financial firms. The sample covers 2013Q1–2016Q4 and is restricted to investment grade firms with an S&P rating of BBB- or above. The dependent variable is total debt, loans, or bonds scaled by total assets in columns (1) to (4). Firm fixed effects control for time-invariant firm characteristics, and quarter fixed effects capture aggregate shocks. $\texttt{Marblegate}_t$ equals one in the post-ruling period (2015Q1–2016Q4). $\texttt{HighBond}_i$ indicates firms with above-median bond share in 2014Q3, and $\texttt{HighIntan}_i$ indicates firms with above-median intangible intensity in 2013, based on data from Peters and Taylor (2017). Controls include lagged industry-level asset growth and stock returns at the 2-digit NAICS level. Standard errors are reported in parentheses and are clustered at the firm level. Significance levels are denoted by asterisks (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

	(1)	(2)	(3)	(4)
	Debt/Assets	Debt/Assets	Bonds/Assets	Loans/Assets
Marblegate × High bond	0.005	0.005	0.003	0.003
	(0.011)	(0.024)	(0.024)	(0.010)
Marblegate × High intan		-0.007	-0.013	0.008
		(0.014)	(0.012)	(0.009)
Marblegate × High bond × High intan		-0.001	0.002	-0.007
		(0.026)	(0.026)	(0.011)
Controls	X	X	X	X
Firm FE	X	X	X	X
Quarter FE	X	X	X	X
Observations	4689	4689	4857	4857
R^2	0.846	0.846	0.821	0.782

E Results Discussed in Section 7

Table A15. Regression Results with Subsample with no Assumed Debt

This table presents the results of the regression analysis examining the impact of intangible assets on long-term debt, with a sample split between firm-year transactions that involve assumed debt and those that do not. Columns (1) to (8) show the outcome variable, defined as the change in long-term debt ((dltt - l.dltt)/l.at). Standard errors are reported in parentheses and are clustered at the industry and year level. Significance levels are denoted by asterisks (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

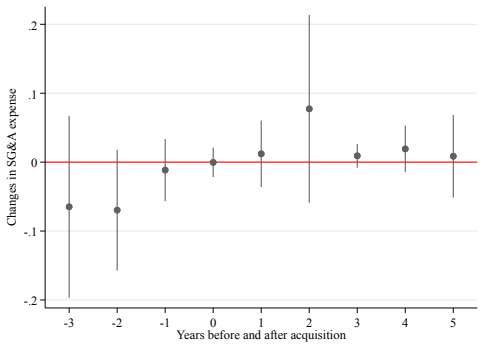
LHS Variable is Δ in Long-term Debt								
	Assumed Debt Subsample				The Rest			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Intangibles	0.17***	0.15***	0.24***	0.22***	0.24***	0.22***	0.27***	0.28***
	(0.04)	(0.04)	(0.05)	(0.04)	(0.05)	(0.05)	(0.06)	(0.06)
Δ Tangibles	0.34***	0.30***	0.46***	0.43***	0.35***	0.34***	0.46***	0.45***
	(0.06)	(0.06)	(0.12)	(0.13)	(0.06)	(0.06)	(0.06)	(0.05)
Δ Working capital		0.29***	0.14	0.13		0.11	0.38***	0.57***
		(0.06)	(0.12)	(0.12)		(0.08)	(0.09)	(0.11)
Controls			X	X			X	X
Industry × year FE				X				X
Observations	2821	2821	1910	1847	979	979	665	608
R^2	0.090	0.101	0.201	0.302	0.202	0.204	0.330	0.504
F-stat: intan=tan	7.86	6.65	3.2	3.08	3.36	3.68	5.72	3.19
F-stat: p-value	.009	.016	.086	.092	.079	.067	.025	.089

Table A16. Regression Results with Controls for Asset-to-Debt Ratios of Target and Acquirer

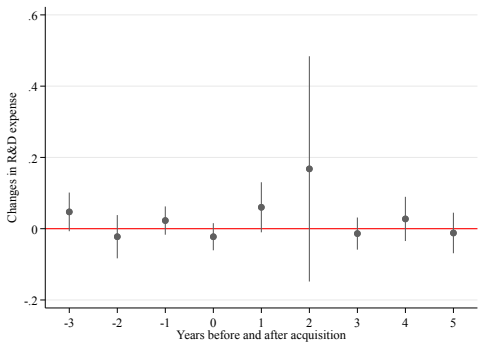
This table reports regression results with additional controls for the target and acquirer's pre-acquisition balance sheet ratios, which proxy for the extent to which assets have already been used to support debt financing. For the target, I use the ratio of tangible assets to long-term debt and identifiable intangible assets to long-term debt, where long-term debt is from the pre-acquisition balance sheet and asset values are based on the PPA. For the acquirer, I include the ratio of tangible assets to long-term debt measured prior to the acquisition. Columns (1) to (4) use the change in long-term debt, defined as (dltt−l.dltt)/l.at, as the outcome variable. Standard errors are clustered at the industry and year level and reported in parentheses. Significance levels are denoted by asterisks (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

LHS Variable is Δ in Long-term Debt				
	(1)	(2)	(3)	(4)
Δ Intangibles	0.19***	0.17***	0.26***	0.24***
	(0.04)	(0.04)	(0.05)	(0.05)
Δ Tangibles	0.36***	0.33***	0.45***	0.43***
	(0.04)	(0.04)	(0.06)	(0.07)
Δ Working capital		0.24***	0.28***	0.34***
		(0.05)	(0.08)	(0.09)
Controls			X	X
Industry × year FE				X
Observations	3800	3800	1873	1821
R^2	0.126	0.135	0.258	0.346
F-stats: intan=tan	14.07	13.09	12.3	8.73
F-stats: p-val	.001	.001	.002	.007

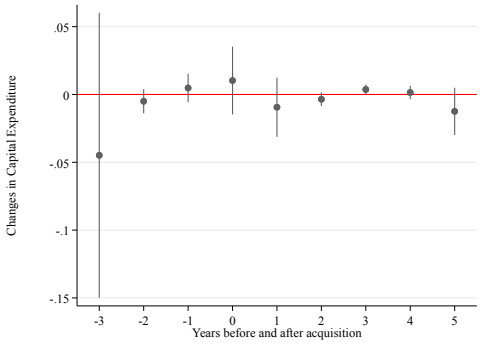
Figure A4. Robustness Test for Confounding Investments These figures plot the regression coefficients from regressing 4-year lag and 5-year lead of the various variables on intangibles acquired during acquisition, while controlling for all the controls and fixed effects as in the baseline regression.



Change in SG&A expense scaled by lagged assets



Change in R&D expense scaled by lagged assets



Change in CapEx by lagged assets

Table A17. Regression Results with Subsample with Stock Deal and Cash Deal

This table presents the results of the regression analysis investigating the impact of intangibles on long-term debt, with a sample split between firm-year transactions that involve stock deals and those that do not. Columns (1) to (8) present the outcome variable of change in long-term debt, which is defined as (dltt-l.dltt)/l.at. Standard errors are reported in parentheses and are clustered at the industry and year level. Significance levels are denoted by asterisks (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

LHS Variable is Δ in Long-term Debt								
	Stock Deal Subsample				Cash Deal Only			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Intangibles	0.16***	0.14***	0.21***	0.20***	0.31***	0.28***	0.37***	0.38***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.11)	(0.10)
Δ Tangibles	0.32***	0.29***	0.42***	0.45***	0.48***	0.45***	0.52***	0.44***
	(0.04)	(0.03)	(0.09)	(0.10)	(0.08)	(0.08)	(0.10)	(0.14)
Δ Working capital		0.21**	0.17*	0.12		0.29**	0.37***	0.37**
		(0.08)	(0.10)	(0.14)		(0.12)	(0.13)	(0.15)
Controls			X	X			X	X
Industry × year FE				X				X
Observations	1664	1664	997	925	2136	2136	1578	1522
R^2	0.128	0.136	0.241	0.354	0.150	0.160	0.281	0.357
F-stat: intan=tan	8.31	7.58	4.52	5.41	3.58	3.41	1.29	.16
F-stat: p-value	.008	.011	.044	.028	.07	.076	.267	.694

Table A18. Regression Results on the Impact of Intangibles on Long-term Debt Robustness Check with Tobin's Q

This table presents the results of the regression analysis investigating the impact of intangibles on long-term debt. Columns (1) to (4) present the outcome variable of change in long-term debt, which is defined as (dltt-l.dltt)/l.at. Beyond the standard controls I used in the baseline regression, Tobin's Q instead of total q from Peters and Taylor (2017). Standard errors are reported in parentheses and are clustered at the industry and year level. Significance levels are denoted by asterisks (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

LHS Variable is Δ in Long-term Debt				
	(1)	(2)	(3)	(4)
Δ Intangibles	0.19***	0.17***	0.25***	0.24***
	(0.04)	(0.04)	(0.04)	(0.04)
Δ Tangibles	0.36***	0.33***	0.45***	0.44***
	(0.04)	(0.04)	(0.05)	(0.06)
Δ Working capital		0.24***	0.23***	0.24***
		(0.05)	(0.08)	(0.08)
Controls			X	X
Industry × year FE				X
Observations	3800	3800	2587	2542
R^2	0.126	0.135	0.249	0.328
F-stats: intan=tan	14.07	13.09	14.79	12.05
F-stats: p-val	.001	.001	.001	.002

Table A19. Regression Results with Goodwill

This table presents the results of the regression analysis investigating the impact of intangibles on long-term debt, with goodwill. Columns (1) to (4) present the outcome variable of change in long-term debt, which is defined as (dltt-l.dltt)/l.at. Beyond the standard controls I used in the baseline regression, Tobin's Q instead of total q from Peters and Taylor (2017). Standard errors are reported in parentheses and are clustered at the industry and year level. Significance levels are denoted by asterisks (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

LHS Variable is Δ in Long-term Debt				
	(1)	(2)	(3)	(4)
Δ Intangibles	0.17***	0.16***	0.20***	0.19***
	(0.04)	(0.04)	(0.05)	(0.05)
Δ Tangibles	0.35***	0.33***	0.43***	0.42***
	(0.04)	(0.04)	(0.05)	(0.06)
Δ Goodwill	0.02	0.01	0.10**	0.11**
	(0.01)	(0.01)	(0.04)	(0.04)
Δ Working capital		0.23***	0.20**	0.20**
		(0.05)	(0.08)	(0.08)
Controls			X	X
Industry × year FE				X
Observations	3800	3800	2575	2529
R^2	0.128	0.135	0.262	0.340
F-stats: intan=tan	14.44	12.53	18.34	14.55
F-stats: p-val	.001	.002	0	.001