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, 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 reduced the pledgeability of intangibles, and find that leverage declined the most among exposed high-intangible firms, and primarily impacted cash flow–based borrowing.

Keywords: Intangible Assets, Debt Financing, Acquisition

JEL classifications: G32, G34

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1 Introduction

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 are 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 (Falato et al., 2022; Giglio and Severo, 2012; Döttling and Ratnovski, 2023; Caggese and Pérez-Orive, 2022; 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.

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 assumed. 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 acquisition¹. 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 capital². Since the adoption

¹See Figure A1 that shows common types of intangibles.

²A 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

of 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 (e.g., 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 rejects the common modeling assumption that intangible assets cannot support debt financing (e.g., Falato et al. (2020); 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., Shleifer and Vishny (1992); Kiyotaki and Moore (1997); Bernanke et al. (1999)), 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 asset's value or to the firm's ongoing ability to generate cash flows, 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.

work on intangibles (e.g., Eisfeldt and Papanikolaou (2013), Eisfeldt and Papanikolaou (2014), Peters and Taylor (2017)). However, it relies on strong assumptions about depreciation rates, capitalization shares, and the aggregation of spending into stock measures.

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, are poor 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 \$0.23 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. Consistent with theory, 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 expected future cash flows.

These findings call for a reevaluation of how we think about debt financing in the context of intangible assets. The traditional emphasis on 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. 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 capacity to support debt financing. I distinguish between production-based intangibles, such as patents and technology, which enhance production capability, and demand-shifter intangibles, such as customer relationships and brands, which help sustain sales. Motivated by insights in Larkin (2013) that firms with a strong brand perception perform better during recessions³, I develop a model suggesting that customer-related intangibles can stabilize cash flows in business downturns, thereby supporting greater borrowing. I empirically test the assumption of this channel that demand-shifter intangibles reduce cash-flow volatility, and find evidence in support of it.

Turning to debt financing outcomes, I classify intangible assets into demand-shifter intangibles and production-based intangibles and find that demand-shifter intangibles are more strongly associated with debt financing. Specifically, I find a dollar increase in demand-shifter intangibles is associated with a \$0.47 increase in long-term debt, whereas each dollar increase in production-based intangibles is only associated with a \$0.12 increase in long-term debt. Both coefficients are statistically significant. Importantly, there is also a statistically significant difference between these two coefficients, which confirms the existence of the heterogeneous effect in the ability to support debt across types of intangibles. Breaking 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.

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 (e.g., Kornejew (2024), Fan (2025)). 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 employee with specialized knowledge may leave and reputation-based assets are harder to preserve (e.g., Antill and Hunter (2023); Hortaçsu et al. (2013); Baghai et al. (2021); Babina (2020)). 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

³Bronnenberg et al. (2012) and Gourio and Rudanko (2014) provide related insights: persistent brand preferences and switching frictions can stabilize demand, implying lower cash flow volatility for firms with strong brand capital.

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 significantly for firms with both high bond reliance and high intangible intensity, relative to the other groups. 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 capacity.

Related literature and contribution. This paper intersects with several strands of existing literature. First, it contributes to research on the measurement of intangible assets. Many studies rely on the perpetual inventory method to infer intangible capital from firm-level expenditures such as R&D and SG&A (e.g., Crouzet and Eberly (2021); Eisfeldt et al. (2020); Belo et al. (2022); Eisfeldt and Papanikolaou (2013), Falato et al. (2020); Peters and Taylor (2017); Xiaolan (2014); Eisfeldt and Papanikolaou (2014)). He et al. (2024) capitalized sales and marketing expense to capture customer capital investment. I depart from this approach by using detailed PPA data from acquisition transactions, which provide direct, market-based valuations of different intangible categories alongside tangible assets. Prior studies using PPA data has largely focused on public target firms or aggregate intangible values (e.g., Lim et al. (2020); Ewens et al. (2025); Kepler et al. (2023)). By contrast, this paper uses one of the most comprehensive PPA datasets assembled to date, covering both public and private targets. Broadening the sample is important, as acquisitions of public targets by public acquirers represent a highly selected group, concentrated in the healthcare and business equipment sectors. Including private targets provides a much broader and more representative view of how firms finance and value intangible assets.

Second, this work closely relates to empirical studies on the debt financing of intangibles.

Loumioti (2012) studies the use of intangibles as collateral in syndicated loans, while Lim et al. (2020) explores the relationship between intangible asset acquisitions and preacquisition leverage. 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. Together, these studies offer important insights into how specific intangible assets interact with lending markets, particularly in settings where they can be directly pledged or legally protected.

I complement this literature by taking a broader perspective. Rather than focusing narrowly on patents or the loan market, I study a wide range of intangible assets and consider all forms of debt. I draw an explicit distinction between asset-based and cash flow-based lending. I show that intangible assets are indeed poor collateral and do not support asset-based borrowing, but they are nonetheless strongly associated with cash flow-based debt—a distinction not clearly made in prior work. I also explore heterogeneity across intangible types to shed light on the underlying mechanism. Demand-shifter intangibles, such as brands and customer relationships, reduce cash-flow volatility, while production-based intangibles, such as technology and patents, increase the level of cash flows. Consistent with this distinction, I find that demand-shifter intangibles are more strongly associated with borrowing. While Lim et al. (2020) examines heterogeneity, the economic mechanism behind these differences has not been articulated in the literature. Finally, I use the 2014 Marblegate ruling as an exogenous shock to show the causal effect of intangibles on debt capacity, which is something that has been difficult to establish in prior work.

Third, this paper engages with the broader theoretical literature on pledgeability, collateral, and enforcement. 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. However, recent work highlights the coexistence of asset-based and cash flow-based lending (e.g., Lian and Ma (2021); Kermani and Ma (2023); Hartman-Glaser et al. (2025); Ivashina et al. (2022); Benmelech et al. (2025)), suggesting that financing capacity may depend not only on collateral value but also on future earnings potential. My paper extends this line of inquiry. I show that in the presence of intangible assets, borrowing capacity is less tied to redeployability, since intangibles are nonetheless strongly associated with cash flow-based debt. This finding indicates that the emphasis on tangibility and liquidation value may be less central in economies where intangible assets dominate, and it offers new

empirical grounding for theories of debt capacity.

Fourth, this paper also contributes to a growing macro-finance literature that examines how intangible capital impacts firm financing and monetary transmission mechanisms. For example, Falato et al. (2022) and Li (2025) find that the rise of intangibles reduces debt capacity and drives firms to hold more cash. Giglio and Severo (2012) develops a model that tightened borrowing constraints and can give rise to asset bubbles. Döttling and Ratnovski (2023) find that firms with more intangible capital are less responsive to monetary policy shocks. Caggese and Pérez-Orive (2022) argue that intangibles weaken the stimulative power of low interest rates. These papers typically build on the assumption that intangible assets cannot support debt and emphasize the asset-based lending channel, leading to reduced debt capacity, lower debt usage, and higher cash reserves. Such dynamics have important macro-finance and monetary policy implications in the corporate savings glut, weakening the credit channel of monetary policy transmission and financial stability.

Through empirical analysis, I test these model assumptions against real-world data. My findings confirm that intangibles are minimally associated with asset-based debt financing. However, this does not mean that intangibles cannot support lending. I show that they are primarily associated with cash flow-based lending. In the context of cash flow-based debt financing, the issue of limited pledgeability is far less restrictive than many models suggest, where future earnings, rather than resale value, underpin lending decisions. My results highlight the unique nature of intangible assets and the importance of revisiting existing assumptions to address critical questions in the knowledge economy.

2 Data and Measurement

2.1 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 valuation of intangible assets is difficult.

⁴There 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).

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. 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. Funding for the acquisition, whether through cash, stock, or debt, is typically arranged before closing, and the total purchase price is then allocated across the acquired assets and liabilities as part of the PPA process.

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)).

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. These intangible assets are valued separately from goodwill. 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.

My analysis focuses on identifiable intangible assets. These include customer relationships, brands, patents, technology, etc. In contrast, I exclude unidentifiable intangibles such as goodwill, which reflects residual value after accounting for identifiable assets. Goodwill

often embeds synergies, overpayment, or organizational capital, 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. Lastly, there are limited incentives to inflate intangible values in this context, especially given tax neutrality (as discussed in Section 8).

Additional information on the specific intangible categories is provided in Appendix A.⁵

2.2 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, 8-K(A), S-1, S-4(A), SC 14D1/A, SC TO-T/A, and others. 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 (which details 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 provide the purchase price allocation in textual form in the "note" variable. I use natural language processing (NLP) technique to extract those terms. A detailed discussion of intangible asset categorization can be found in Appendix A, Table A2. The 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. They also indicate any portion of the payment is contingent on future performance. I flag deals that involve stock

⁵Related studies include Masulis et al. (2023) and Guo et al. (2019), who use PPAs to study intangibles. Ewens et al. (2025) analyzed the estimated aggregate intangible value of the firm and Lim et al. (2020) focus on public-to-public deals. This paper compiles the most comprehensive database to date with detailed intangible breakdowns.

payments or assumed debt, and I use this information in the sample splits 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.

2.3 Debt Measures 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). In the Appendix, I also report results using total debt (dltt + dlc) as the dependent variable.

Capital IQ Capital Structure Debt includes the capital debt structure of a public company, compiled from SEC filings. The debt structure is classified into categories 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 follows Lian and Ma (2021)⁶. 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. A debt contract is classified as asset-based if one of the following conditions holds: (i) 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 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

⁶Replication package from Kermani and Ma (2022) contains the code for classification, accessed through The Quarterly Journal of Economics Dataverse.

as asset-based; or (iii) it is explicitly labeled as cash flow-based. To be conservative, I classify all secured debt that cannot be assigned with certainty as asset-based.

2.4 Sample Construction

The data focus on acquisition transactions conducted by U.S. public companies from 1995 to 2022⁷.

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 and DealScan. 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 A11 presents the summary statistics for the outcome variables, purchase price allocation variables, and control variables used in the main analysis and the robustness 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. Rajan and Zingales (1995); Frank and Goyal (2009); Martynova

⁷Although detailed purchase price allocations (PPA) became mandatory with SFAS 141 in 2001, the sample contains some transactions from earlier years; particular transactions involving public target firms, had already adopted the practice of reporting detailed asset valuations.

and Renneboog (2009)). I do not exclude observation from the overall sample because of missing accounting variables.

Table A12 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 firm's intangible assets intensity.

Table A13 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 by these factors.

3 Baseline Empirical Strategy and Results (PPA Sample)

Firms can finance acquisitions using a range of sources: issuing new debt, raising equity, or drawing on existing cash reserves. In practice, even when a deal is labeled a "cash transaction", acquirers frequently issue new debt to fund the payment, since most firms do not hold enough liquid assets to fully cover the purchase price (e.g., Faccio and Masulis (2005); Bharadwaj and Shivdasani (2003)).

My empirical analysis focuses on actual changes in the acquirer's balance sheet to identify how the acquisition was ultimately financed, regardless of how the transaction is labeled as either a cash or stock transaction.

In addition to financing the purchase itself, 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. In the baseline regressions, I assume that acquirers have sufficient discretion to make financing and liability decisions that reflect the characteristics of the acquired assets. However, this flexibility may be limited by constraints imposed by the target's

existing 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 account for potential limitations on this flexibility, I later relax the assumption in a series of robustness checks. These include distinguishing acquisitions in which the acquirer assumes the target's debt from those in which it does not, and adding additional control for the target's pre-acquisition unused debt capacity.

3.1 Regression Specification

This project explores the change in debt and its relationship with the types of assets acquired, including tangible assets and intangible assets. The ideal experiment would involve tracking firms with similar characteristics as they invest in varying amounts of intangible assets (or tangible assets), to observe the corresponding change in the amount of debt used to finance the transaction.

My baseline analysis involves two steps. First, I uncover the value of different categories of assets of the target firm with PPA data. Then, I track the associate financing decision of the acquirer by tracking its usage of debt before and after the acquisition.

I begin my analysis by illustrating the relationship between various acquired assets in acquisition and debt financing. I use the following regression specification:

$$\frac{\Delta Y_{i,t}}{A_{i,t-1}} = \alpha + \beta_1 \frac{\Delta \text{intangibles}_{i,t}}{A_{i,t-1}} + \beta_2 \frac{\Delta \text{tangibles}_{i,t}}{A_{i,t-1}} + \beta_3 \frac{\Delta wc_{i,t}}{A_{i,t-1}} + \mathbf{X}_{i,t-1}\xi + \nu_{\text{industry}\times t} + \varepsilon_{i,t}$$
 (1)

This is a cross-sectional regression. The focus is on tracking acquired assets ⁸ and the corresponding changes in debt usage. The dependent variables of focus are the changes in debt usage: long-term debt and total debt. Occasionally, companies use a bridge loan for short-term financing during transactions, but promptly settle it using cash from the target balance sheet or proceeds from other financing methods such as additional debt financing or equity issuance. By using the long-term debt changes, I specifically focus on the portion of debt that firms do not offset immediately following a transaction. I examine the acquisitions at the acquirer firm-year level instead of at the deal level because sometimes acquirers conduct more than one acquisition in a year. In these cases, I sum all

⁸I run regressions on all three types of assets but only focus on interpreting the coefficients for intangibles and tangibles.

the assets acquired from acquisitions in a given year. The standard errors are clustered at the industry and year level.

The study focuses on debt usage differences for firms that, through an acquisition deal, acquire an additional dollar of intangibles compared to those that do not, all else being equal. The regression coefficient β_1 represents the change in debt in dollars correlated with acquiring an additional dollar of intangible assets. Similarly, β_2 represents the change in debt in dollars correlated with acquiring an additional dollar of tangible assets. I compare the two coefficients with a F-test. If there is no statistically significant difference between the two coefficients, it suggests intangible assets and tangible assets support debt comparably.

The regression strategy mitigates the common problem of simultaneity in regressing capital structure on intangibles as the capital structure also impacts the types of investment the firm chooses (e.g., Myers (1977); Jensen and Meckling (1976)) and thus the assets acquired.

The challenge in identifying this correlation is the potential omitted variables. The most important concern here is the acquirer firms' unused debt capacity. If firms with high unused debt capacity are more likely to acquire intangibles, but that capacity is not controlled for in the model, the regression could attribute the increased debt usage to intangibles when in reality, it might be driven by the firm's ability to borrow more. To help 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, an industry-year fixed effect is incorporated to account for unobserved heterogeneity across industries over time.

Regarding the target firm's existing debt, in my basic framework, I assume 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. In Section 8.1, I further address

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			Х	Х
Industry × year FE				X
Observations	3800	3800	2575	2529
R^2	0.126	0.135	0.243	0.322
<i>F</i> -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)–(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).

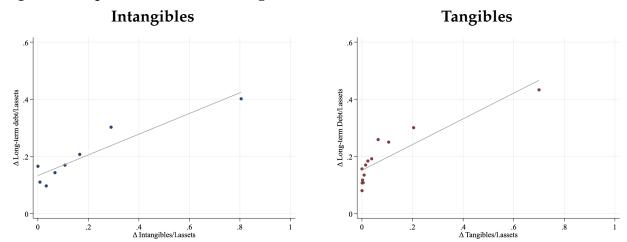
the concern with two robustness checks.

Due to the difficulty of isolating the exact debt changes associated with multiple deals within one year, my analysis is at firm-year level. This way, I capture 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 the robustness check, I show there is no significant concurrent investment in additional tangible and intangible assets in Section 8.2.

4 Debt Financing of Intangible Assets: Main Findings

First, I show that intangibles can support debt to an extent comparable to tangibles. The regression results in Table 1 columns (1) to (4), reveal the impact of identifiable intangibles and tangible assets on net debt issuance. In column (4), the preferred specification, each dollar increase in identifiable intangibles is associated with a 0.24-dollar increase in long-term debt, while each dollar rise in tangible assets corresponds to a 0.44-dollar increase. These coefficients are statistically significant individually, but there is no significant difference between them. Additionally, as more controls are added from column (2) to

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.

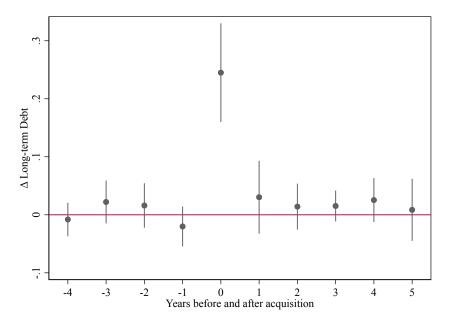
(4), the coefficient values remain relatively stable, suggesting limited concern regarding omitted-variable bias. In Figure 1 panel (a) and (b), I also present the results in bin-scatter graphs.

Even though intangibles do not impact the amount of debt firms have, they do impact the way lenders establish priority in getting the payment in default resolution (Benmelech et al. (2024)). The results show the differences between intangibles and tangible assets in their roles as collateral. The high proportion of cases where intangible assets are paired with tangible assets in serving as collateral suggests some complementary between the two. Moreover, the data may suggest great uncertainty as to the extent to which intangibles can be resold on a standalone basis in a liquidation, even for identifiable intangibles that are, by definition, separable from the firm⁹.

To test whether the increase in debt financing around intangible acquisitions reflects pre-existing or delayed effects, I plot the dynamic response in Figure 2, which uses the baseline regression framework to relate changes in net long-term book debt issuance from four years before to five years after the deal to the value of intangibles acquired. The results show a sharp and significant increase in debt in the acquisition year, with no evidence of borrowing in advance and no reversion in the following years. This pattern rules out

⁹Kermani and Ma (2023) documents high liquidation recovery rates of book intangibles in specific industries such as airlines, mining, and recreation apparel for transferable licenses and usage rights, patents, and data. However, according to industry experts and reports, the market for intangible collateralized debt, asset-based lending, is currently primarily served by specialty lenders and has not yet become mainstream.

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).

pre-trends or delayed adjustments and suggests that the coefficient captured the full effect of intangibles on debt financing during the acquisition and the rise in debt usage linked to intangible acquisitions is persistent.

In Section 8, I conduct several robustness tests to validate the results.

Section 8.1 considers the role of the target's existing debt. Table A18 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 A19 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 8.2, addresses potential confounding from concurrent investments in PP&E or R&D, and finds no evidence of overestimation. Section 8.3 explores deal terms and shows that the intangible–debt relationship is stronger in cash transactions than in stock deals, consistent with the baseline. Section 8.4 adds Tobin's Q as a proxy for investment opportunities instead of total q from Peters and Taylor (2017), again supporting the results.

Section 8.5 evaluates the inclusion of goodwill in the analysis. While tangible assets consistently show stronger support for long-term debt, intangible assets, including goodwill,

remain significant contributors. Section 8.6 evaluates possible valuation manipulation from tax considerations. Because most transactions are tax-deferred, incentive to manipulation PPA valuations for tax benefit is limited, and even in taxable transactions the findings remain robust.

Finally, Section 8.7 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 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.

5 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 or markets—assets with well-defined secondary markets so that value can be recovered in the event of default. Redeployability is therefore central: the more easily an asset can be sold or put to productive use by another party, the greater its usefulness as collateral. Seminal contributions include Shleifer and Vishny (1992), Kiyotaki and Moore (1997), and Bernanke et al. (1999) emphasize how collateral values 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 discussion on debt financing for intangible assets has focused narrowly on the asset-based lending channel. This emphasis rests on two implicit assumptions. First, asset-based debt dominates in corporate borrowing. Second, intangible assets cannot be used effectively as collateral and therefore cannot meaningfully support asset-based debt.

Under these assumptions, asset tangibility is often used as a proxy for pledgeability, with the logic that the more tangible, and thus pledgeable, assets a firm has, the more it

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			Х	Х			Х	Х
Industry \times 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
<i>F-</i> 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. Column (1) to (4) present the outcome variable of cash flow-based debt, and Column (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).

can borrow. In this framing, intangible-heavy firms are viewed as disadvantaged in debt markets.

While this view is correct in one dimension, my evidence confirms that intangible assets have only a weak association with asset-based debt; it overlooks the broader structure of corporate borrowing. When we consider cash flow-based lending, a different pattern emerges. Using evidence from the acquisition context, I show that intangible assets are primarily associated with cash flow-based debt. Moreover, unlike tangible assets, the financing of intangibles is largely unaffected by redeployability. In an economy increasingly driven by intangible capital, focusing exclusively on asset-based debt understates the borrowing capacity of intangible-intensive firms and misses a key channel through which these assets are financed.

5.1 Evidence from Classifying Debt

Following Lian and Ma (2021), I classify each debt instrument as asset-based or cash-flow-based using detailed contract descriptions from Capital IQ Debt Detail database.

Asset-based debt includes loans and bonds secured by specific, monitorable 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. This classification follows the economic distinction between lending against collateral value and lending against repayment capacity.

Table 2 columns (1)–(4) show that a one-dollar increase in 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 cannot reject the null that these two coefficients are equal, indicating that intangibles support cash flow-based borrowing almost as effectively as tangibles. Intangibles, therefore, appear to support cash flow-based borrowing almost as effectively as tangible assets. By contrast, columns (5)–(8) report results for asset-based debt, where the distinction emphasized in the literature becomes evident. In the preferred specification in column (8), a one-dollar increase in intangibles is linked to only a \$0.05 increase in asset-based debt, compared with a \$0.20 increase for tangible assets. Here, the coefficient on intangibles is small and only weakly significant, while the coefficient on tangibles is large and highly significant; an F-test rejects equality of the two coefficients. These findings confirm that in asset-based lending, where pledgeability, redeployability, and standalone collateral valuation are critical, intangibles play little role, consistent with existing views (e.g., Crouzet and Eberly (2019); Giglio and Severo (2012); Caggese and Pérez-Orive (2022)). Yet, when the full debt structure is considered, they form an important foundation for cash flow-based borrowing.

5.2 Evidence from Asset Redeployability

Redeployability is a key determinant of an asset's ability to support debt, particularly in asset-based lending (e.g., Williamson (1988)). The intangible assets in this study are identifiable intangibles—assets that, by definition, can be separated from the firm and have standalone value, implying a degree of redeployability. However, the earlier analysis shows that intangibles are primarily associated with cash flow—based debt, where financing depends on the asset's contribution to future earnings rather than its resale value. This raises the question: does asset redeployability matter less for intangibles than for tangible assets?

To test this, I extend the main specification by interacting each asset type with an indicator for high redeployability, allowing for a direct comparison of its role across asset classes.

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

Redeployability refers to the degree to which acquired assets can be repurposed by alternative users. For tangible assets, a common approach¹⁰ relies on industry-level input–output linkages: assets used across many industries are more redeployable because they have a broader secondary market, whereas assets tied to specialized outputs are less redeployable.

For intangible assets, no input—output matrix exists, but the same logic applies. Redeployability depends on the breadth of potential users. For intangibles, that potential market is often narrow and industry-specific. For example, the Levi's brand and designs are valuable to a clothing company but not to United Airlines, despite both being consumer-facing firms. Similarly, NVIDIA's chip designs are valuable to Huawei, a Chinese competitor, but not to Meta, despite both companies operating in the broader tech sector. Thus, for intangible assets, a reasonable proxy for redeployability is the number of similar firms operating in the same narrowly defined industry segment.

I therefore measure redeployability using firm counts from the U.S. Census Bureau's Business Dynamics Statistics (BDS), focusing on the number of firms in the target's 3-digit NAICS industry. Conceptually, each firm is a bundle of assets, so this count reflects the pool of potential alternative users. This measure likely underestimates redeployability for tangibles – industrial trucks, for instance, can be used across many unrelated industries.

I count the number of firms in that industry large enough to plausibly purchase the

 $^{^{10}}$ For example, Kim and Kung (2017) constructs a redeployability index using the BEA Input–Output Use Tables.

asset in a secondary market, and average this count over the three years preceding the acquisition year to smooth out transitory fluctuations. These mid-sized to large firms are the most likely potential buyers in a secondary market. As a robustness check, I use a finer measure based on the number of firms with 1,000–5,000 employees¹¹. Finally, 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 lies above the 25th percentile¹².

The results, presented in Figure 3¹³, show a striking asymmetry between intangibles and tangibles. For intangibles, the marginal effect on long-term debt is similar across high- and low-redeployability firms: an increase in intangible assets is associated with a comparable increase in borrowing regardless of redeployability. This suggests that redeployability, a core determinant of asset-based lending, is largely irrelevant for the debt financing of intangible assets. In contrast, the relationship between tangible assets and long-term debt is much stronger among high-redeployability firms than among low-redeployability firms. Tangible assets that can be easily redeployed provide significantly greater borrowing capacity, consistent with their use as collateral in asset-based lending. These patterns reinforce the earlier finding that intangibles play a minimal role in asset-based borrowing but are important for cash-flow-based borrowing, while tangibles benefit directly from the redeployability channel emphasized in the asset-based lending literature.

6 Heterogeneity: Not All Intangibles Are the Same

Intangible assets are commonly defined as "assets that lack physical substance." But intangible assets are not a homogeneous category; they differ in the ways they create value for firms. I classify them into two groups. Production-based intangibles (such as patents, technology, and know-how) enhance operational efficiency or productivity and primarily affect the level of cash flows a firm can produce. Demand-shifter intangibles (such as brands and customer relationships) increase the firm's ability to sustain demand or charge higher prices. Their central contribution is to reduce the volatility of cash flows by stabilizing revenue over time rather than by entering the production process.

¹¹Results are robust to this alternative measure; see Table A4. BDS applies noise infusion or data masking to protect confidentiality, which can cause totals not to match perfectly. The coarser 500+ employee category is less affected by suppression.

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

¹³See regression results in Table A3

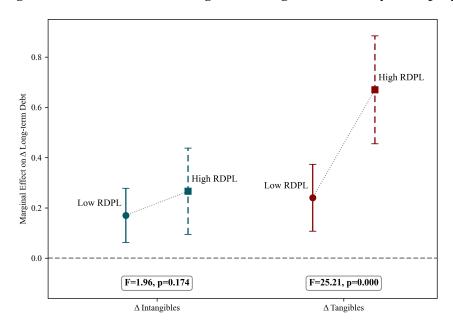


Figure 3. Marginal Effects of Asset Changes on Long-Term Debt by Redeployability.

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 A4, 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.

6.1 Model: Demand-Shifter Intangibles and Optimal Debt

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:

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

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:

Repayment to debtholders =
$$min{F, pq - C}$$
 (3)

Payout to shareholders =
$$\max\{(1 - \tau)pq - F, 0\}$$
 (4)

where τ is the corporate income tax rate.

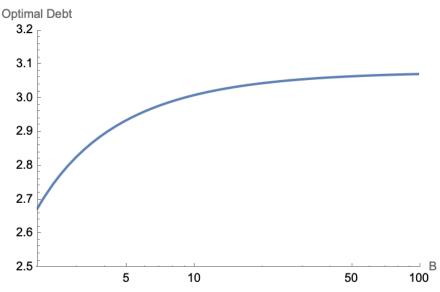
We assume that lenders are risk-neutral, so the expected repayment must equal the debt proceeds:

$$\mathbb{E}[D(F)] = D \tag{5}$$

Firm's Objective Function The firm chooses its debt usage to maximize initial equity value¹⁴.

 $[\]overline{\ }^{14}$ For simplification purposes, here, I do not discount the t=1 payment.

Figure 4. Comparative Statics from Model



Notes: This chart plots the comparative statics results generated from the model. See Appendix E for more details of the model solution and parameters used.

$$V = \max_{F \ge 0} \{ D(F) + \mathbb{E} [\max ((1 - \tau) pq - F + \tau F, 0)] \}$$

subject to:

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

Model implications

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

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

Details on the derivation can be found in Appendix E.

Figure 4 shows 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.

6.2 Empirical Evidence

Based on this framework, I go to the purchase price allocation data and categorize major categories of intangibles into production-based intangibles and demand-shifter intangibles. In Table A15, I list my classification. Kindly be aware that there exists a disparity between the economic meaning researchers attribute to specific intangible categories and the empirical measurement. My categorization is founded on empirical measurement, and I explain the definition of selected categories and my reasoning for classification below.

Production-based intangibles.

- General definition: Production intangibles directly contribute to the firm's production.
- Important categories:
 - Patent, software, technology, IP R&D: patents are legal protections granted for inventions. Software refers to computer programs and applications, including both off-the-shelf software and proprietary software developed by the company. Technology means the proprietary technology, process, or methodology developed, such as innovative manufacturing processes, research techniques, or proprietary algorithms. IP R&D is the in-process research and development.
 - Know-how, blueprints, license: know-how refers to the expertise, skills, and technical knowledge possessed by the acquired company's employees or management which includes trade secrets, best practices, and proprietary techniques. Blueprints are detailed technical drawings or plans used in the design and construction of products, machinery, or infrastructure. license, such as broadcast license, and operation license; these are materials that enable production.
 - Right of use and copyrighted material: the right of use represents the lessee's right to use a leased asset for the lease term. The underlying assets can be PP&E and intangible assets such as technology. Copyrighted material includes original works of authorship, such as literary works, artistic creations, music compositions, and software code. These are intangibles that can be used in production directly and help firms produce more products.
 - Organizational capital: business practices that facilitate production. ¹⁵

Demand-shifter intangibles.

 $^{^{15}\}mathrm{As}$ explained in the data section I do not capture this intangible very well empirically using PPA data.

• General definition: Demand-shifter intangibles do not directly contribute to production but help firms sell more products at larger quantities or higher prices.

• Important categories:

- Customer relationship, customer list: customer relationship is the established connections and interactions between the company and its customers. The relationship can include various aspects, such as the loyalty of customers and the potential for repeat business. The customer list contains details about the company's customers, such as contact information and purchasing history.
- Brands, trademark, domain name: brands represent the overall perception and reputation of a company or its products/services in the marketplace. Trademarks distinguish a company's products or services from those of competitors with legal protection. Domain names are unique addresses that identify specific websites on the internet. They play a crucial role in establishing an online presence and facilitating customer access to a company's website. Domain names may reflect the company's brand name, product name, or key terms relevant to its business.
- Customer contract, backlog: Customer contracts represent formal agreements between the acquired company and its customers. These contracts outline the terms and conditions of the products or services to be provided, including pricing, duration, and any specific obligations or commitments. Customer contracts can be valuable assets because they often represent future revenue streams and provide visibility into the company's customer base. Backlog refers to the unfulfilled orders or contractual commitments that the acquired company has already secured but has not yet delivered or recognized as revenue.
- Business relationship: relationship with downstream and upstream firms, such as relationship with distributors, vendors, and suppliers.
- Data: In purchase price allocation (PPA), "data" typically refers to the value associated with data assets acquired as part of a business acquisition. Data assets can include various types of information collected and stored by the acquired company, most importantly customer data, sales data, and in some cases market research data, operational data, and proprietary datasets. This category is where the conceptual gap between current research and this empirical work is the largest. Some recent work on data economy (Begenau et al. (2018); Farboodi et al. (2019); Farboodi and Veldkamp (2023)) is extremely interesting. The essence

of a "data" economy is where firms gather information and essentially use data to reduce uncertainty is very interesting. From an empirical perspective, data is more similar to a customer list where a database contains information about valuable customer and their preferences. The more advanced analytical potential of data will be part of technology or organizational capital which is outside of my current study.

- Franchise agreement: a franchise agreement allows a franchisee to operate a business associated with the franchisor's trademark.
- Non-compete agreement: a non-compete agreement is a contractual arrangement
 that restricts the employee from the seller from engaging in competitive activities
 within a specified geographic area or industry sector for a certain period after
 the acquisition. Non-compete agreements do not impact the firms' production
 but protect the demand the firm faces¹⁶.

Next, I conduct the same regression as in Table 1, but splitting intangibles into the aforementioned two categories to test if there is a differential effect on debt financing associated with production-based intangibles and demand-shifter intangibles. The results in Table 3 column (3) show one one-dollar increase in demand-shifter intangibles leads to a \$0.45 increase in debt financing, while one dollar increase in production-based intangibles leads to a \$0.15 increase in debt financing. The results suggest that demand-shifter intangibles induce more debt than production-based intangibles. I use a *F*-test to confirm that the difference in the two coefficients is statistically significant.

In Figure 5, I show the regression results from individual categories from the production-based intangibles and demand-shifter intangibles. In general, demand-shifter intangibles are on the right side of production-based intangibles. Indeed, demand-shifter intangibles correlate with more debt financing than production-based intangibles.

6.3 Discussion

I do acknowledge that this classification is a bold attempt. In the real world, the classification may not be as clear-cut as one would like. For my result, the most important types of demandshifter intangibles are brand trademarks, customer lists, and customer relationships, and the most important types of production-based intangibles are patents, software, and technology.

¹⁶Another interpretation of the non-compete agreement is that it represents the value of employees retained by the firm, thereby partially reflecting the value of its human capital.

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

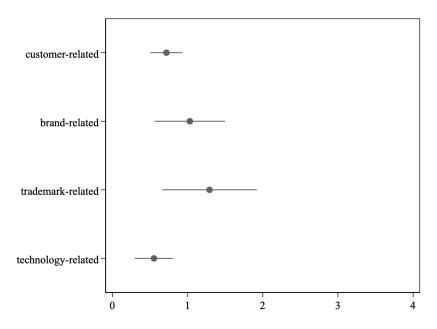
LHS Variable is Δ in Long-term Debt			
	(1)	(2)	(3)
Δ Intangibles (demand-shifter)	0.35***	0.44***	0.45***
	(0.05)	(0.07)	(0.07)
Δ Intangibles (production-based)	0.05	0.17**	0.15**
	(0.05)	(0.06)	(0.07)
Δ Tangibles	0.34***	0.45***	0.44***
	(0.04)	(0.05)	(0.05)
Δ Working capital	0.21***	0.22***	0.25***
	(0.05)	(0.06)	(0.07)
Controls		Х	Х
Industry \times 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) through (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 A15 for details. Significance levels are denoted by asterisks (*** p < 0.01, ** p < 0.05, * p < 0.1).

I empirically test the actual relationship between different types of intangibles and cash-flow volatility. In Table A16, I show results from the regression analysis that confirm demand-shifter intangibles reduce cash flow volatility, while production-based intangibles increase it. Specifically, I find that acquirer firms that acquired one standard deviation higher demand-shifter intangibles are associated with a reduction of 0.017 in post-acquisition cash-flow volatility, representing a decrease of 12% compared to the unconditional mean. In contrast, the acquirer firms that acquired one standard deviation higher production-based intangibles are associated with an increase of 0.021 in post-acquisition cash-flow volatility, representing an increase of 15% compared to the unconditional mean.

A prediction from this model is the effect of demand-shifter intangibles keeps diminishing as the market environment becomes more stable in terms of fewer negative shocks. Figure A4 illustrates this by plotting the difference between the optimal debt level between firms with high versus low demand-shifter intangibles across ϕ . The figure shows that firms with higher demand-shifter intangibles always have higher optimal debt in a given

Figure 5. 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.

market environment, and this gap keeps diminishing as the market has less frequent negative shocks. I empirically test this prediction in Table A17. It confirms during bad times one more unit of demand-shifter intangibles correlates with \$0.43 of long-term debt. The coefficient is smaller in magnitude during good times – this number is \$0.42.

7 Complementary Evidence: Marblegate Ruling

The acquisition setting provides direct evidence that intangibles can be financed with debt. However, due to the limitations of the setting, we cannot completely rule out the endogeneity issue, in particular, unused debt capacity. It may be the case that firms with unused debt capacity are more willing to purchase intangibles, and those acquirers also tend to issue more debt not because intangibles are pledgeable, but because they are unconstrained. To strengthen identification, I turn to the Marblegate ruling shock as a natural experiment to provide additional evidence.

7.1 Institutional Background

Institutional Context: The EDMC Restructuring Education Management Corporation (EDMC), one of the largest U.S. for-profit colleges, fell into distress in 2014. The firm wanted to restructure its debt out of court, but 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. This act was designed to protect investors, but the unintended consequence is that it may make restructurings difficult because a single holdout creditor could block the deal¹⁷.

Over time, the market had developed a workaround. Firms would use exchange offers with exit consents: consenting bondholders agreed to swap into new securities while simultaneously stripping restrictive covenants from the old bonds. Since this did not alter the core payment terms, courts had long treated such exchanges as compliant with the TIA, even if they left holdouts worse off. Everyone knew the workaround was aggressive, but judges generally allowed it.

That is what EDMC tried. The restructuring plan stripped dissenting creditors of meaningful enforcement rights by moving assets into a new subsidiary and distributing securities only to consenting bondholders. The expectation was that the court, as usual, would permit it.

The Marblegate Lawsuit and Legal Shock But in late 2014, a dissenting bondholder, Marblegate Asset Management, challenged the plan in court. 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.¹⁸

This ruling strengthened the bondholder's right to payment, but altered restructuring dynamics by intensifying the holdout problem – when individual creditors refuse concessions in the hope of free riding on others, thereby blocking a collective agreement¹⁹.

The shift had important implications for firms with high intangible asset intensity.

¹⁷For related work by legal scholars, see, e.g., Kahan (2018)

¹⁸In 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.

¹⁹Here, 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.

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 baseline²⁰.

Prolonged court bankruptcy procedure is particularly damaging to firms with high intangible assets. Because in financial distress, intangible assets such as brand, customer relationships, software, and customer lists lose value more quickly than tangible assets, for example, customer relationships deteriorate, reputation tarnishes, key employees leave, and technology becomes outdated (e.g., Antill and Hunter (2023); Hortaçsu et al. (2013); Baghai et al. (2021); Babina (2020)). This erosion reduces the expected recovery of intangibles; both the asset value that 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.

This mechanism motivates my empirical design to compare changes in debt financing between intangible-intensive and tangible-intensive firms, before and after Marblegate, and across firms with high versus low levels of bond financing reliance, since the ruling directly strengthened bondholders' 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.

The Marblegate ruling is an unusually clean setting to study this question. It provides an exogenous shock to the pledgeability of intangible assets: the legal change was not initiated by firms, arrived suddenly through an unrelated court case, and had sharp timing in 2014Q4, making it well-suited for a natural experiment design.

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.

²⁰After 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 A6. Kornejew (2024) documents a similar magnitude using an alternative sample.

7.2 Identification Strategy: Triple Difference

The sample for this analysis is Compustat non-financial firms, and the sample period is from 2013Q1 to 2016Q4. I further focus on high-yield firms 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. To estimate the effect of the Marblegate ruling on leverage, I use a triple difference (DDD) specification of the form:

$$Y_{i,t} = \alpha + \lambda_i + \theta_t$$

$$+ \beta_1 (\text{Marblegate}_t \times \text{HighBond}_i) + \beta_2 (\text{Marblegate}_t \times \text{HighIntan}_i)$$

$$+ \beta_3 (\text{Marblegate}_t \times \text{HighBond}_i \times \text{HighIntan}_i) + \mathbf{X}'_{j,t-1} \boldsymbol{\xi} + \varepsilon_{i,t}$$
(6)

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, so we are looking at within-firm, over-time deviations that are not explained by quarter-specific common shocks. The indicator Marblegate_t equals one in the post-ruling period (2015Q1–2016Q4). To avoid endogenous selection in response to the ruling, both treatment variables, HighBond_i and HighIntan_i, are measured prior to the ruling. Specifically, HighBond_i identifies firms with above-median bond share in 2014Q3, and 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 control vector \mathbf{X}_{jt-1} includes lagged industry-level variables at the 2-digit NAICS level. These variables are industry asset growth and value-weighted stock returns, which are intended to capture real-side demand conditions and financial market trends, respectively. Although these controls reflect average behavior across all firms, they are less likely to introduce post-treatment bias because most of the variation comes from large and investment-grade firms that are not directly affected by the treatment. The common approach of including industry-by-quarter fixed effects does not apply well in this setting, 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.

Lastly, because the specification includes firm fixed effects, there is no need to control separately for time-invariant or pre-treatment firm characteristics; these are already absorbed. In contrast to the baseline acquisition regressions, I also exclude lagged firm-

level controls (such as market-to-book ratio or cash holdings) in this setting, as they may themselves be affected by the Marblegate ruling. Including such variables could introduce bias through post-treatment (or "bad") controls.

The coefficient β_3 captures the additional effect of the Marblegate ruling on leverage for firms that are both high-bond reliant and high-intangible relative to the other three groups, including high-bond firms with low-intangibles, low-bond firms with high-intangibles, and low-bond firms with low-intangibles. If firms rely on intangible assets to support borrowing, then given the shock to intangible pledgability, firms with high intangible assets and high bond reliance should experience the largest reduction in leverage post-Marbegate. That is, the β_3 should be negative.

The identification assumption is the parallel trend assumption. 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 in the absence of treatment (Olden and Møen, 2022).

7.3 Results and Interpretation

Table 4 column (1) shows a positive effect of Marblegate on leverage, consistent with bondholders extending more credit after creditor rights were strengthened, in line with Donaldson et al. (2022)²¹. This reflects an ex-ante commitment effect, independent of intangibility.

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

Column (2) shows that while $Marblegate_t \times HighBond_i$ is positive overall, the interaction with high-intangible firms is strongly negative. This indicates that intangibles had been supporting leverage: once Marblegate 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 rights.

Columns (3) to (4) split total debt into bonds and loans. The positive effect of $Marblegate_t \times HighBond_i$ again reflects stronger creditor rights, but the key result is the large negative effect of the triple difference effect. It appears entirely in bonds, which is a form of cash flow–based borrowing, consistent with earlier evidence in Section 5 that

²¹Table A8 shows that this effect is driven by increased bond usage.

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*** (0.014)	0.071*** (0.021)	0.081*** (0.024)	0.014 (0.014)
Marblegate × High intan		-0.006 (0.013)	-0.005 (0.012)	-0.006 (0.013)
Marblegate \times High bond \times High intan		-0.073*** (0.027)	-0.104*** (0.031)	0.011 (0.022)
Controls	X	X	X	X
Firm FE	X	X	Χ	Χ
Quarter FE	X	X	X	Χ
Observations	7588	7584	7895	7895
R^2	0.756	0.759	0.707	0.837

Notes: The table reports estimates of Equation 6 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. Marblegate_t equals one in the post-ruling period (2015Q1-2016Q4). HighBond_i indicates firms with above-median bond share in 2014Q3, and 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).

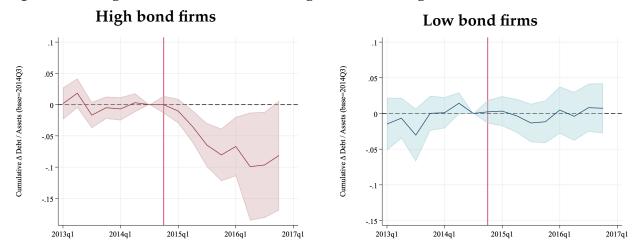
intangibles primarily support cash flow–based debt. Column (4) indicates no effect in loans²².

Figure 6 shows event-study estimates. Among high-bond firms, leverage in high-intangible firms declines sharply relative to low-intangible firms after Marblegate, with no evidence of pre-trend differences. Two years after the ruling, high intangible 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..

The Marblegate ruling mainly affected high yield firms that were more exposed to restructuring risk. This motivates a placebo test using firms rated BBB– or above, which faced little risk of restructuring. In Figure 7, I show that there is no significant effect of Marblegate on leverage for this group. The result supports the interpretation that

²²Table A9 shows that results are robust in a DiD framework without the HighBond_i interaction.

Figure 6. 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.

the main results reflect the legal shock to restructuring feasibility rather than broader macroeconomic forces.

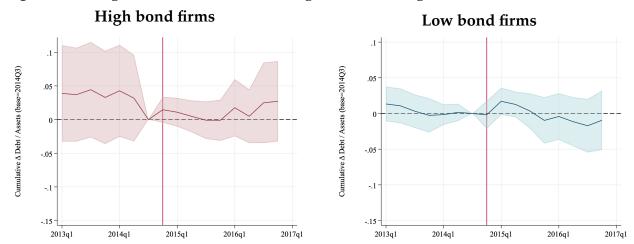
8 Robustness and Alternative Explanations

In this section, I conduct several robustness checks for my core empirical finding that intangibles can support debt to address potential remaining omitted variables issues and intangibles accounting challenges.

8.1 Impact of Existing Debt of the Target

In my baseline specification, I attribute changes in debt during acquisitions to the assets acquired, controlling for various factors. The capital structure adjustment of the acquiring firm is primarily a choice made by the acquirer and is influenced by the target's assets. However, this becomes more complex when the target firm already has existing debt. In such cases, the target's debt holders may have claims on its tangible or intangible assets, meaning that decisions regarding the debt are not solely under the acquirer's control.

Figure 7. 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 denote 95% confidence intervals.

To address this, I conduct two robustness tests. First, I utilize a subsample for which I have access to the deal terms, identifying transactions involving assumed debt. I divide the sample into two groups: transactions with assumed debt and those without. For firm-year observations with multiple transactions, if any involve assumed debt, the firm-year is classified as such. Table A18 shows that in transactions with assumed debt, one dollar of intangible assets is associated with an additional \$0.21 of debt, while one dollar of tangible assets is associated with \$0.42 more debt. For transactions without assumed debt, one dollar of intangible assets corresponds to \$0.28 more debt, and one dollar of tangible assets is linked to \$0.44 more debt. 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, in Table A19, for the subsample where I have pre-acquisition balance sheet data for target firms, I introduce additional controls, including the ratios of intangible assets to long-term debt and tangible assets to long-term debt of the target firm before the acquisition and the acquirer's pre-acquisition tangible assets scaled by total debt. I find one dollar of intangible assets corresponds to \$0.25 more debt, and one dollar of tangible assets is linked to \$0.41 more debt. The results are consistent with the baseline findings, and with point estimates closely aligning with the original results.

8.2 Confounding Investment in Tangible or Intangible Assets

A potential identification concern in my firm-year level regression framework is the possibility that acquirers might simultaneously engage in other capital investments, such as acquiring more PP&E or expanding R&D efforts, alongside their acquisitions of tangible or intangible assets. As a result, the observed changes in intangibles or tangibles from acquisitions may not fully capture the total capital accumulation. If these additional investments are also associated with increased debt usage, it could lead to an overestimation of the effect of asset acquisitions on debt. For example, if a firm purchases intangible assets during an acquisition and simultaneously invests in more PP&E, financing both with debt, the estimated coefficients from the regression might be biased upward.

To explore this, I examine several potential confounders. In Figure A6, panel (a) shows the change in SG&A expenses, where I find no significant pattern before or after acquisitions, suggesting no concurrent SG&A expansion. In panel (b), I analyze changes in in-process R&D expenses. The direction of the coefficient indicates that firms reduce their own in-process R&D spending following intangible acquisitions, but due to large standard errors, this result is not statistically significant. Finally, in panel (c), I assess changes in PP&E purchases and similarly find no discernible pattern before or after the acquisition.

8.3 Deal Terms and Considerations

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 A20 shows that for cash deals, each dollar of intangible assets is associated with a \$0.38 increase in debt, while each dollar of tangible assets is linked to a \$0.42 increase in debt. In stock deals, the coefficient for intangible assets is lower, at 0.18, indicating less borrowing associated with intangible assets when equity is part of the transaction. The

results suggest that when equity is used, the borrowing tied to intangible assets is smaller compared to transactions fully financed by debt.

8.4 Tobins' 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 A21, I re-run the baseline regression using Tobin's Q instead of total Q. The results remain consistent with my original findings.

8.5 Effect with Goodwill

Table A22 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 dollar increase in intangible assets corresponds to an approximate \$0.18 rise in debt, while each dollar of tangible assets leads to a \$0.41 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.

8.6 Taxation Incentive for Misreporting

The deal structure and taxation incentive in the acquisition is an important topic (Erickson (1996)). In my analysis, if tax considerations influence asset valuation, it could introduce bias into my results. For instance, due to tax motivations, the purchase price allocation (PPA) of assets may be skewed, such as intentionally assigning more value to intangible assets when the target firm actually holds more tangible assets. Since tangible assets typically support debt better than intangible assets, this could lead to an overestimation

of the positive coefficient associated with intangibles. However, I demonstrate that my findings are robust to this concern.

There are two primary tax treatments for acquisitions: tax-deferred transactions, where the seller does not recognize any gain or loss on the assets (i.e., "carryover basis"), and taxable transactions, where the seller recognizes a gain or loss (i.e., "stepped-up basis").

In a carryover basis transaction, the seller's original tax basis in the assets is transferred to the acquirer. Since the PPA valuation in these cases does not affect the acquirer's taxation—often described as "the fair value adjustment in PPA is not taxable"—there is little incentive to manipulate intangible valuations for tax purposes.

In a 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 (IRC), intangible assets, including goodwill, must be amortized over 15 years on a straight-line basis. In this case, the fair value assigned to intangible assets during the PPA does affect taxation, creating more potential for manipulation.

I infer the tax structure of acquisitions based on two factors: the primary considerations and the type of acquisition. In my sample, the majority of transactions (85%) are tax-deferred, while only 7.5% are taxable, where the PPA valuation impacts taxation. For the remaining 7.5%, I lack sufficient information to determine the tax structure.

8.7 Measurement Error of Intangibles

In this section, I explore how measurement error impacts my results and how differences in the measurement error for intangible versus tangible assets could bias my findings.

There is evidence that accountants strive to estimate intangible assets accurately, rather than assigning arbitrary values. First, these valuations are subject to audits. Second, in Section C.2, I explain the incentive to deliberately manipulate intangible asset valuations for tax purposes is limited. Furthermore, He et al. (2024) shows that the valuation of customer relationship intangibles is positively correlated with the target firm's prior sales and marketing expenditures. Despite these efforts to ensure accuracy, measurement errors may still occur.

First, suppose the measurement errors associated with asset valuation are classical measurement errors. In a univariate regression setting, classical measurement error introduces attenuation bias, which biases the estimated coefficient toward zero. This result is well-known. However, in a multivariate regression setting, the implications of

classical measurement error are more complex. 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.

In my analysis, I examine how debt is related to intangible and tangible assets. Bound et al. $(2001)^{23}$ derives an approximation of bias in regression with two regressors where two variables are measured with error. The bias in the estimated coefficient for intangible assets, denoted as $\hat{\beta}_1$, is given by the formula²⁴:

bias(
$$\hat{\beta}_1$$
) $\approx \frac{-\beta_1 \lambda_1 + \beta_2 \lambda_2 \rho}{1 - \rho^2}$

where ρ is the correlation between the true values of the regressors (Δ intan* and Δ tan*), and the λ 's represent the error to total variance ratios for the two variables ($\lambda_j \equiv \sigma_{\mu_i}^2/\sigma_{\chi_i^2}^2$).

To interpret the bias, suppose the true coefficients β_1 and β_2 are equal, and $\lambda_1 > \lambda_2$ which corresponds to intangibles have more error variance relative to tangibles, then $\hat{\beta}_1$ is biased downward underestimates the true effect of intangibles, while the bias on $\hat{\beta}_2$ is ambiguous because it depends on the interaction between error variances and correlation.

This analysis indicates that my estimate of β_1 is likely a lower bound, thereby strengthening the argument that intangible assets can be financed with debt.

9 Conclusion

In this paper, I investigate the impact of intangible capital on firms' debt usage. Utilizing purchase price allocation data from acquisition transactions, I obtain the most precise measure of asset valuation, including detailed categories of intangible assets and tangible assets.

²³Chapter 59, equation 12 gives a nice approximation for the bias. Originally derived in Theil (1961).

 $^{^{24}}$ Δintan (Δintan = Δintan* + μ_1) and Δtan (Δtan = Δtan* + μ_2). 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.

By examining the setting of acquisition events, I analyze how the increase in intangible and tangible assets from the target firm influences the debt usage of the acquirer firm. Specifically, I compare changes in long-term debt usage of acquirers with similar characteristics before the acquisition but acquired additional units of tangible (or intangible assets).

The study reveals several key findings. First, contrary to common belief, firms do use debt to finance intangible assets. In other words, intangible assets can support debt. Even though to an extent weaker than tangible assets, the economic magnitude is still significant. Second, intangibles are strongly associated with firms having a higher proportion of cash flow-based debt rather than asset-based debt. Further analysis of bank loans issued after acquisitions and collateral utilization reveals that intangibles are predominantly used in cash flow-based debt and are rarely employed as sole collaterals but rather paired with other tangible assets.

One unique feature of my data is the ability to explore the various types of intangibles. I highlight the heterogeneous nature of intangible assets despite some common characteristics. To understand their impact, I categorize intangibles based on their role in the production function. This categorization allows me to differentiate between intangibles that directly contribute to production and those that act as demand-shifters, affecting cash flows without directly influencing production quantities. Interestingly, demand-shifter intangibles exhibit a positive correlation with higher levels of debt, while production intangibles do not.

To provide insight into the relationship between cash flow-based intangibles and higher debt capacity, I develop a simple model. The model suggests that an increase in demand-shifter intangibles protects against negative market demand shocks, partially offsetting the impact of these shocks and reducing the price impact of larger production quantities. Consequently, firms with higher levels of demand-shifter intangibles experience more stable cash flows during market downturns, leading to higher debt capacity. Furthermore, this effect is strengthened in the presence of more frequent negative shocks in the market.

This paper reveals several policy implications. For example, the findings indicate that the transmission of monetary policy operates in a broadly similar way, regardless of whether firms have tangible or intangible assets. However, the study also highlights that intangibles are financed in distinct and unconventional ways. As intangible assets continue to play an increasingly central role in the economy, their growing significance calls for targeted efforts to improve their financeability. Policymakers and legal frameworks may need to address existing challenges by implementing measures that reduce financing

barriers. Moreover, if the rise of intangibles leads to more asset-based debt, their rise could reduce the strength of the financial accelerator channel (Öztürk (2022)) and thereby reshape the business cycle, and monetary policy transmission channel. The results underscore the need to adapt economic policies and strategies to better support an economy driven by intangible capital.

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APPENDIX

A Categories of Intangibles

Table A1. 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

Table A2. Categorization of Identifiable Intangibles

The 25 categories of identifiable intangibles are based on the US GAAP framework, with adjustments made to align more closely with economic interpretations.

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

Variable	Definition
Δ long-term debt	(dltt-l.dltt))/lat
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
Tobinś Q	(mkval+dlc+dltt)/at
Size	ln(at)
Cash on-hand	ch_lat = che/lat
Operating earnings	ebitda/lat
Cashflow	(oancf+xint)/lat
PPE/lat	ppent/lat
Leverage	book leverage
Cash from target	cash from PPA/lat

B Variable definitions

C Purchase Price Allocation

Purchase price allocation is the allocation of the purchase price of the business into assets and liabilities during business combinations. Accounting rules of the business combination process necessitate the acquirer to recognize the tangible assets and identifiable intangible assets acquired separately from goodwill and to properly classify and measure them (ASC 805 Business Combinations).

Generally, after allocating the purchase price to each identifiable asset and liabilities category, the residual unidentifiable intangibles are goodwill. Organizational capital and human capital that are not related to the non-compete agreement and workforce contracts are included in goodwill.

After the business combination takes place, the assets and liabilities from the purchase price allocation are recorded on a consolidated balance sheet to reflect the combined business. The detailed purchase price allocation breakdown then shows us a comprehensive picture of intangible assets.

The assets are evaluated at fair value during business combinations. Fair value is "the price that would be received to sell an asset or paid to transfer a liability in an orderly transaction between market participants at the measurement date." Thus, the fair value of

the intangibles is not about recording the cost of acquiring the intangible assets. The core concern lies in understanding the economic value to the firm, or to put it in another way, to project counterfactual cash flow in a state of the world where the company does not own the intangible asset.

Under this rule, the identifiable intangibles asset price in the purchase price allocation is closer to market value rather than the book value (Ewens et al. (2025)). The fair value valuation requirement for business combinations for the asset is different from what is done for typical book assets reported on the balance sheet, such as the book value for property, plants, and equipment. These are evaluated at historical costs.

Both private firms and public firms are subject to the accounting rules in the business combination process. Private firms are eligible to adopt a "private company alternative," which simplifies some accounting procedures. In both cases, third-party valuation and accounting professionals conduct the valuation work.

The main advantages of retrieving the intangible data from purchase price allocation are threefold. First, it covers all the identifiable intangibles the firm owns as well as the unidentifiable intangibles rather than just selected categories. Second, all the appraisal work is done at around the acquisition time, thus avoiding the stale value problem. Third, the valuation at M&A provides a market price for intangibles.

C.1 Intangibles Accounting Background

The definition of intangible assets is very broad. Before understanding intangible assets, we should discuss the definition of assets because the meaning of intangible assets boils down to assets that lack tangibility. According to US GAAP, an asset is the present right of an entity to an economic benefit. Intangible assets lack physicality but nevertheless benefit the organization²⁵. The general definitions for assets and intangible assets and are why items such as backlogs, non-compete agreements, and right of use are also considered intangible assets beyond assets such as patents, trademarks, and technology.

There are two main categories of intangible assets: identifiable intangibles and unidentifiable intangibles. The identifiable intangibles are intangibles that are separable from the entity that holds them or results of contractual or legal rights (ASC 805-20-55). Some examples are customer relationships, brands, patents, trademarks, technology, and various use rights. Unidentifiable intangibles are intangibles that cannot be identified in practice.

²⁵Except for financial assets which are tangible assets.

In particular, these intangibles cannot be easily separated from the business, and examples include organizational capital and human capital. In this study, they are part of goodwill.

C.2 Tax Incentive

In the sample under consideration, the influence of tax incentives is relatively weak.

Primarily, the tax basis deriving from Mergers and Acquisitions (M&As) is classified into two types: carry-over basis and stepped-up basis. The carry-over basis signifies the continuation of the target's original tax base. Hence, if the transaction tax basis adopts a carry-over format, tax accounting is unaffected by the purchase price allocation. The majority of the sample in this study operates on a carry-over basis. A mere 10% or less of my sample employs the stepped-up basis, which mirrors the valuation of the purchase price.

One might conjecture that tax incentives could provoke a manipulation in the distribution of intangibles across different categories. This arises from the fact that distinct types of assets follow diverse amortization schedules. Consequently, firms may prefer to channel a higher valuation into intangibles with shorter useful lives, leading to booking a higher upfront amortization expense and consequent tax savings. However, this concern is mitigated by the tax treatment of intangibles, which imposes a compulsory straight-line 15-year amortization on all intangibles, including goodwill (in compliance with Section 197 of the Internal Revenue Code - IRC). Therefore, no tax incentive exists to distort the amount of intangibles across categories.

C.3 Financial Accounting Incentive

Given the interplay of contradictory incentives, it is unlikely that a systematic bias, either downward or upward, would occur in the valuation of unidentifiable intangibles due to managerial concerns regarding the value of goodwill. Firstly, managers might show a proclivity to attribute a larger value to goodwill compared to other intangibles. In financial statements, goodwill undergoes impairment testing, while other identifiable intangibles follow a regular amortization schedule. Assigning a larger portion to goodwill can curtail the amortization expense and augment net income after the acquisition, which results in increased earnings per share. Conversely, managers might also be incentivized to assign less value to goodwill and emphasize identifiable intangibles to evade criticism for overpayment. Thus, financial accounting incentives push managers in conflicting

directions with regard to intangible valuation.

It is crucial to note that the procedure for intangible valuation occurs at arm's length and is fortified with mechanisms to prevent manipulation. It is conducted by third-party acquisition accountants and the resulting report is subjected to audit supervision. Moreover, specific acquisition accounting rules exist to identify a comprehensive range of intangible assets.

C.4 Valuation of Intangibles

Three widely adopted approaches for intangibles valuation are market price, discounted cash flow (DCF) analysis, and replacement cost. The objective is to utilize actual transaction data in order to achieve a measure of market value. Despite this, the process remains complex, ambiguous, subjective, and labor-intensive. Classical measurement error may induce attenuation bias, which contradicts the findings of this study.

C.5 Measures of Redeployability

Table A3. 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 average 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, 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 versus tangible assets. 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	0.13**	0.099*	0.22***	0.17***
	(0.056)	(0.057)	(0.056)	(0.055)
High RDPL	-0.031*	-0.029*	-0.0078	0.012
	(0.017)	(0.017)	(0.015)	(0.020)
High RDPL \times Δ Intangibles	0.065	0.085	0.048	0.096
	(0.052)	(0.057)	(0.071)	(0.068)
Δ Tangibles	0.24***	0.22***	0.27***	0.24***
	(0.047)	(0.044)	(0.065)	(0.068)
High RDPL \times Δ Tangibles	0.27***	0.26***	0.40***	0.43***
	(0.082)	(0.087)	(0.089)	(0.086)
Δ Working capital		0.27**	0.36**	0.46***
		(0.11)	(0.14)	(0.14)
High RDPL \times Δ Working capital		-0.068	-0.20	-0.31
		(0.12)	(0.18)	(0.19)
L.Book leverage			0.060**	0.031
			(0.026)	(0.028)
Controls			Х	Х
Industry \times year FE				X
Observations	3775	3775	2557	2511
R^2	0.138	0.145	0.242	0.329
F-stat: intan(Redeploy)	1.55	2.22	.45	1.96
p-value: intan(Redeploy)	.224	.148	.507	.174
F-stat: tan(Redeploy)	11.14	8.87	19.92	25.21
p-value:tan(Redeploy)	.003	.006	0	0
<u> </u>				

Table A4. Marginal Effects of Asset Changes on Long-Term Debt by Redeployability (Alternative Measure)

This table reports estimates from Table ??, 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 average number of mid-sized firms (1,000-5,000 employees) in the 3-digit NAICS industry over the three years prior to acquisition. 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 versus tangible assets. 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	0.13**	0.093	0.19***	0.15***
	(0.055)	(0.057)	(0.044)	(0.040)
High RDPL	-0.022	-0.019	0.0023	0.016
	(0.017)	(0.017)	(0.015)	(0.019)
High RDPL \times Δ Intangibles	0.071	0.093	0.093	0.14**
	(0.052)	(0.057)	(0.065)	(0.059)
Δ Tangibles	0.25***	0.23***	0.28***	0.25***
	(0.046)	(0.044)	(0.069)	(0.074)
High RDPL \times Δ Tangibles	0.26***	0.25***	0.37***	0.41***
	(0.080)	(0.086)	(0.094)	(0.095)
Δ Working capital		0.29**	0.46***	0.54***
		(0.11)	(0.15)	(0.14)
High RDPL \times Δ Working capital		-0.10	-0.34**	-0.41**
		(0.13)	(0.16)	(0.16)
L.Book leverage			0.062**	0.030
			(0.026)	(0.029)
Controls			Х	Х
Industry × year FE				X
Observations	3773	3773	2555	2509
R^2	0.138	0.145	0.243	0.331
F-stat: intan(Redeploy)	1.85	2.64	2.06	5.37
<i>p</i> -value: intan(Redeploy)	.185	.116	.164	.029
F-stat: tan(Redeploy)	10.47	8.39	15.43	18.56
p-value:tan(Redeploy)	.003	.008	.001	0

C.6 Explore the Impact of Relative Size of Acquirer and Target

Table A5. Regression Results with Relative Size Interaction

This table presents the results of the regression analysis results investigating the impact of intangibles on long-term debt. Large relative size is a binary indicator equal to 1 if the acquired firm's total assets, scaled by the acquirer's pre-acquisition total assets, fall in the top 50th percentile of all transactions, and 0 otherwise. 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	0.097	0.11*	0.17***	0.16***
	(0.070)	(0.064)	(0.058)	(0.054)
Δ Tangibles	0.24**	0.30**	0.39**	0.47**
	(0.10)	(0.11)	(0.18)	(0.20)
Large relative size $\times \Delta$ Intangibles	0.10*	0.052	0.082	0.082
	(0.059)	(0.052)	(0.062)	(0.065)
Large relative size \times Δ Tangibles	0.13	0.036	0.028	-0.054
	(0.11)	(0.12)	(0.17)	(0.18)
Δ Working capital		-0.59***	-0.44**	-0.66**
		(0.20)	(0.20)	(0.25)
Large relative size \times Δ Working capital		0.85***	0.73***	0.97***
		(0.21)	(0.20)	(0.25)
L.Book leverage			0.073**	0.045
			(0.028)	(0.028)
Controls			Х	Х
Industry \times year FE				X
Observations	3797	3797	2576	2530
R ²	0.130	0.142	0.233	0.318

D Marblegate: Additional Results

Table A6. 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 the post-Marblegate period (2014Q4 to 2016Q3) and an indicator for High Bond, defined as firms with bond financing above 25 percent of assets as of 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 \times Quarter FE		X
Observations	9093	9089
R^2	0.011	0.060

Table A7. Marblegate Ruling Result With Alternative Total Debt Specification

The table reports estimates of Equation 6 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)–(4). Total debt defined as dltt + dlc, with dlc set to zero if missing. Firm fixed effects control for time-invariant firm characteristics, and quarter fixed effects capture aggregate shocks. Marblegate_t equals one in the post-ruling period (2015Q1–2016Q4). HighBond_i indicates firms with above-median bond share in 2014Q3, and 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) Debt/Assets	(3) Bonds/Assets	(4) Loans/Assets
Marblegate × High bond	0.040*** (0.014)	0.061***	0.081***	0.014
Marblegate × High intan	(0.014)	(0.020) -0.010 (0.013)	(0.024) -0.005 (0.012)	(0.014) -0.006 (0.013)
$Marblegate \times High \ bond \times High \ intan$		-0.062** (0.026)	-0.104*** (0.031)	0.011 (0.022)
Controls	Х	Х	Х	Х
Firm FE	Χ	Χ	Χ	Χ
Quarter FE	X	Χ	X	X
Observations	7927	7923	7895	7895
R^2	0.759	0.761	0.707	0.837

Table A8. Marblegate Ruling For High-Bond Firms

The table reports estimates of Equation 6 but modified to include only one interaction term Marblegate $_t$ × 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)–(4). Firm fixed effects control for time-invariant firm characteristics, and quarter fixed effects capture aggregate shocks. Marblegate $_t$ equals one in the post-ruling period (2015Q1–2016Q4). 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) Debt/Assets	(2) Bonds/Assets	(3) Loans/Assets
Marblegate × High bond	0.044***	0.043**	0.019*
	(0.014)	(0.017)	(0.010)
Controls	Χ	X	Х
Firm FE	Χ	X	Χ
Quarter FE	Χ	X	X
Observations	7588	7899	7899
R^2	0.756	0.702	0.837

Table A9. Marblegate Ruling For High-Intangible Firms

The table reports estimates of Equation 6 but modified to include only one interaction term $\mathtt{Marblegate}_t \times \mathtt{HighIntan}_i$ 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)–(4). Firm fixed effects control for time-invariant firm characteristics, and quarter fixed effects capture aggregate shocks. $\mathtt{Marblegate}_t$ equals one in the post-ruling period (2015Q1–2016Q4). $\mathtt{HighIntan}_i$ 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	Χ	X	X
Firm FE	Χ	X	X
Quarter FE	Χ	X	X
Observations	7738	7980	7980
R^2	0.755	0.708	0.834

E Details on the Model

Three steps:

1. Solve explicitly for D(F)

2. Then solve for r such that the condition

$$\mathbb{E}\left[D\left(F\right)\right] = \frac{1}{1+r}F$$

holds

3. Solve the maximization problem of the firm, taking into account the endogeneity of r

Let's say the debt holder is always paid in full when z = 0, and occasionally not paid in full if z = 0 and bad ε shock.

I first solve for D(F) using independence of z and ϵ .

$$\begin{split} &D\left(F\right) = \mathbb{E}\left[\min\left(F,pq-C\right)\right] \\ &= \mathbb{E}\left[\min\left\{F,\left(p^* - \frac{z}{B}q + \varepsilon\right)q - C\right\}\right] \\ &= \mathbb{P}\left(z = 0\right) \mathbb{E}\left[\min\left\{F,\left(p^* + \varepsilon\right)q - C\right\} \mid z = 0\right] \\ &\quad + \mathbb{P}\left(z = 1\right) \mathbb{E}\left[\min\left\{F,\left(p^* - \frac{z}{B}q + \varepsilon\right)q - C\right\} \mid z = 1\right] \\ &= \phi \mathbb{E}\left[\min\left\{F,\left(p^* + \varepsilon\right)q - C\right\}\right] \\ &\quad + \left(1 - \phi\right) \mathbb{E}\left[\min\left\{F,\left(p^* - \frac{1}{B}q + \varepsilon\right)q - C\right\}\right] \\ &= \phi\left[\mathbb{P}\left(\varepsilon > \varepsilon_1\right)\int_{\varepsilon_1}^1 F df\left(\varepsilon \mid \varepsilon > \varepsilon_1\right) + \mathbb{P}\left(\varepsilon < \varepsilon_1\right)\int_0^{\varepsilon_1} \left(\left(p^* + \varepsilon\right)q - C\right) df\left(\varepsilon \mid \varepsilon < \varepsilon_1\right)\right] \\ &\quad + \left(1 - \phi\right)\left[\mathbb{P}\left(\varepsilon > \varepsilon_2\right)\int_{\varepsilon_2}^1 F df\left(\varepsilon \mid \varepsilon > \varepsilon_2\right) + \mathbb{P}\left(\varepsilon < \varepsilon_2\right)\int_0^{\varepsilon_2} \left(\left(p^* - \frac{1}{B}q + \varepsilon\right)q - C\right) df\left(\varepsilon \mid \varepsilon < \varepsilon_2\right)\right] \end{split}$$

Let's analyze this term-by-term.

1. This term corresponds to re-payment conditional on z = 0 (the good state)

$$\int_{\varepsilon_{1}}^{1} F df \left(\varepsilon \mid \varepsilon > \varepsilon_{1}\right) = F \int_{\varepsilon_{1}}^{1} df \left(\varepsilon \mid \varepsilon > \varepsilon_{1}\right) = F \text{ with } \mathbb{P}\left(\varepsilon > \varepsilon_{1}\right) = 1 - \varepsilon_{1}$$

2. Let's do the second term

$$\begin{split} \int_0^{\varepsilon_1} \left((p^* + \varepsilon) \, q - C \right) df \left(\varepsilon \mid \varepsilon < \varepsilon_1 \right) &= p^* q + q \int_0^{\varepsilon_1} \varepsilon df \left(\varepsilon \mid \varepsilon < \varepsilon_1 \right) - C \\ &= p^* q + q \left[\frac{1}{2} \varepsilon^2 \right]_0^{\varepsilon_1} - C \\ &= p^* q + q \frac{1}{2} \varepsilon_1^2 - C \end{split}$$

3. The third term

$$\int_{\varepsilon_2}^1 F df \, (\varepsilon \mid \varepsilon > \varepsilon_2) = F$$

4. The fourth term

$$\int_0^{\varepsilon_2} \left(\left(p^* + \frac{1}{B} q + \varepsilon \right) q - C \right) df \left(\varepsilon \mid \varepsilon < \varepsilon_2 \right) = p^* q + \frac{1}{B} q^2 - C + q \frac{\varepsilon_2^2}{2}$$

Now, I combine these terms to get

$$D(F) = \phi \left[\underbrace{(1 - \varepsilon_1)F}_{\text{No-Default}} + \varepsilon_1 \left(p^* q + q \frac{1}{2} \varepsilon_1^2 - C \right) \right]$$

$$+ \left(1 - \phi \right) \left[\underbrace{(1 - \varepsilon_2)F}_{\text{No-Default}} + \varepsilon_2 \left(p^* q + \frac{1}{B} q^2 - C + q \frac{\varepsilon_2^2}{2} \right) \right]$$
Bad State

The equilibrium condition is that

$$\frac{1}{1+r}F = D\left(F\right)$$

Let's see what it looks like

$$\begin{split} \frac{1}{1+r}F &= \phi \left[(1-\varepsilon_1)F + \varepsilon_1 \left(p^{\star}q + q\frac{1}{2}\varepsilon_1^2 - C \right) \right] + \left(1-\phi \right) \left[(1-\varepsilon_2)F + \varepsilon_2 \left(p^{*}q + \frac{1}{B}q^2 - C + q\frac{\varepsilon_2^2}{2} \right) \right] \\ F &= (1+r) \left(\phi \left[(1-\varepsilon_1)F + \varepsilon_1 \left(p^{\star}q + q\frac{1}{2}\varepsilon_1^2 - C \right) \right] + (1-\phi) \left[(1-\varepsilon_2)F + \varepsilon_2 \left(p^{*}q + \frac{1}{B}q^2 - C + q\frac{\varepsilon_2^2}{2} \right) \right] \right) \\ 1 + r &= \frac{F}{\phi \left[(1-\varepsilon_1)F + \varepsilon_1 \left(p^{\star}q + q\frac{1}{2}\varepsilon_1^2 - C \right) \right] + \left(1-\phi \right) \left[(1-\varepsilon_2)F + \varepsilon_2 \left(p^{*}q + \frac{1}{B}q^2 - C + q\frac{\varepsilon_2^2}{2} \right) \right]} \end{split}$$

Let ε_1 be the solution to the following equation (case where the shock is such that proceeds can just pay face value conditional on z = 0):

$$F = (p^* + \varepsilon_1) q - C$$
$$\varepsilon_1 = \frac{F + C}{q} - p^*$$

let ε_2 be the solution to the following equation (case where the shock is such that the proceeds can just pay face value conditional on z = 1):

$$F = \left(p^* - \frac{1}{B}q + \varepsilon_2\right)q - C$$
$$\varepsilon_2 = \frac{F + C}{q} - p^* + \frac{1}{B}q$$

Now solve the maximization problem problem of the firm. First, I want to explicitly characterize the following expression:

$$\max_{F \ge 0} \{D(F) + \mathbb{E} [\max ((1 - \tau) pq - F + \tau F, 0)] \}$$

Start with the expectation term

$$\begin{split} &\mathbb{E}\left[\max\left((1-\tau)pq-F+\tau F,0\right)\right] \\ &= \mathbb{P}\left(z=0\right)\mathbb{E}\left[\max\left((1-\tau)pq-F+\tau F,0\right)\mid z=0\right] + \mathbb{P}\left(z=1\right)\mathbb{E}\left[\max\left((1-\tau)pq-F+\tau F,0\right)\mid z=1\right] \\ &= \mathbb{P}\left(z=0\right)\mathbb{E}\left[\max\left((1-\tau)\left(p^*+\varepsilon\right)q-F+\tau F,0\right)\right] + \mathbb{P}\left(z=1\right)\mathbb{E}\left[\max\left((1-\tau)\left(p^*-\frac{1}{B}q+\varepsilon\right)q-F+\tau F,0\right)\right] \\ &= \phi\left[\mathbb{P}\left(\varepsilon>\varepsilon_3\right)\int_{\varepsilon_3}^1\left((1-\tau)\left(p^*+\varepsilon\right)q-F+\tau F\right)df\left(\varepsilon\mid\varepsilon>\varepsilon_3\right)\right] + \left(1-\phi\right)\left[\mathbb{P}\left(\varepsilon>\varepsilon_4\right)\int_{\varepsilon_4}^1\left((1-\tau)\left(p^*-\frac{1}{B}q+\varepsilon\right)q-F+\tau F\right)df\left(\varepsilon\mid\varepsilon>\varepsilon_4\right)\right] \\ &= \phi\left[\mathbb{P}\left(\varepsilon>\varepsilon_3\right)\left((1-\tau)p^*q-F+\tau F+(1-\tau)q\int_{\varepsilon_3}^1\varepsilon df\left(\varepsilon\mid\varepsilon>\varepsilon_3\right)\right)\right] \\ &+ \left(1-\phi\right)\left[\mathbb{P}\left(\varepsilon>\varepsilon_4\right)\left((1-\tau)\left(p^*q-\frac{1}{B}q^2\right)-F+\tau F+(1-\tau)q\int_{\varepsilon_4}^1\varepsilon df\left(\varepsilon\mid\varepsilon>\varepsilon_4\right)\right)\right] \\ &= \phi\left[\left(1-\varepsilon_3\right)\left((1-\tau)p^*q-F+\tau F+(1-\tau)q\frac{1-\varepsilon_3^2}{2}\right)\right] + \left(1-\phi\right)\left[\left(1-\varepsilon_4\right)\left((1-\tau)\left(p^*q-\frac{1}{B}q^2\right)-F+\tau F+(1-\tau)q\frac{1-\varepsilon_4^2}{2}\right)\right] \end{split}$$

Let ε_3 be the solution to the following equation $(1 - \tau)(p^* + \varepsilon_3)q - F + \tau F = 0$

$$(1 - \tau) (p^* + \varepsilon_3) q = F - \tau F$$

$$\varepsilon_3 = \frac{F - \tau F - (1 - \tau) p^* q}{(1 - \tau) q}$$

$$\varepsilon_3 = \frac{(1 - \tau) F - (1 - \tau) p^* q}{(1 - \tau) q}$$

$$\varepsilon_3 = \frac{F}{q} - p^*$$

Let ε_4 be the solution to the following equation: $(1-\tau)\left(p^*-\frac{1}{B}q+\varepsilon_4\right)q-F+\tau F=0$

$$\begin{split} (1-\tau)\left(p^*q-\frac{1}{B}q^2\right) + \varepsilon_4\left(1-\tau\right)q - F + \tau F &= 0 \\ \varepsilon_4\left(1-\tau\right)q &= F - \tau F - (1-\tau)\left(p^*q-\frac{1}{B}q^2\right) \\ \varepsilon_4 &= \frac{(1-\tau)F - (1-\tau)\left(p^*q-\frac{1}{B}q^2\right)}{(1-\tau)q} \\ \varepsilon_4 &= \frac{F}{q} - p^* + \frac{1}{B}q \end{split}$$

Combine all the elements

$$\max_{F>0} \{D(F) + \mathbb{E} [\max ((1-\tau)pq - F + \tau F, 0)] \}$$

$$\begin{aligned} \max_{F \geq 0} \quad \phi \left[(1 - \varepsilon_1) F + \varepsilon_1 \left(p^* q + \frac{1}{2} q \varepsilon_1^2 - C \right) \right] + \left(1 - \phi \right) \left[(1 - \varepsilon_2) F + \varepsilon_2 \left(p^* q + \frac{1}{B} q^2 + \frac{1}{2} q \varepsilon_2^2 - C \right) \right] \\ + \phi \left[(1 - \varepsilon_3) \left((1 - \tau) p^* q - F + \tau F + (1 - \tau) q \frac{1 - \varepsilon_3^2}{2} \right) \right] + \left(1 - \phi \right) \left[(1 - \varepsilon_4) \left((1 - \tau) \left(p^* q - \frac{1}{B} q^2 \right) - F + \tau F + (1 - \tau) q \frac{1 - \varepsilon_4^2}{2} \right) \right] \end{aligned}$$

I then use Mathematica to solve for the closed-form solution for F. The optimal F has the following closed-form solution:

$$\begin{split} F &= \frac{q^2}{3\left(1 + \phi - \tau\phi\right)} \left(\frac{-3 + 3\phi}{B} + \frac{-3C}{q^2} + \frac{3 + 3p - \tau - 2\phi + 3p\phi + 2\tau\phi - 3p\tau\phi}{q}\right) \\ &\pm \sqrt{\left(-4\mathbb{A}\left(\frac{3\left(1 + \phi - \tau\phi\right)}{2q^2}\right) + \left(\frac{3 - 3\phi}{B} + \frac{3C}{q^2} + \frac{-3 - 3p + \tau + 2\phi - 3p\phi - 2\tau\phi + 3p\tau\phi}{q}\right)^2\right)} \end{split}$$

where

$$\mathbb{A} = \left(\frac{3C - 3pq - 3C\phi + 3pq\phi}{B} + \frac{3p^2 - \phi + 3p^2\phi + \tau\phi - 3p^2\tau\phi}{2} + \frac{3C^2}{2q^2} + \frac{-2C - 3Cp}{q} + \frac{3q^2 - 3q^2\phi}{2B^2} + 2p + \tau - p\phi + p\tau\phi\right)$$

I get two solutions for the optimal debt. There are solutions here that get at the local maximum, not the global maximum. I pick the larger root of the two because the firm benefits from a debt tax shield, and the larger root provides more of that. But qualitatively my comparative static results are not sensitive to this choice.

F Additional Figures and Tables

F.1 Figures

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. The figure is a screenshot from the Men's Wearhouse, Inc.'s 8-K/A filing on 2014-09-02 in the report of its acquisition of Jos. A. Bank Clothiers, Inc.

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 (279,196(iv)) Goodwill 722,199(v) Total purchase price (ii) 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 in cinome tax receivable. These increases were partially offset by the elimination of 13.0 million 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 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 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 combine on pumps has a net 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 combine on pumps has a net current deferred tax asset of \$25.4 million for favorable lose. 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 franchies store genemates of \$4.0 million, which the Company recognized an intangible asset related to the Jos. A Bank fr

Purchase price allocation

\$539.1 million
\$53.0 million
\$24.4 million
\$4.7 million
\$621.2 million

Reformatted detailed breakdown of the purchase price allocation to various 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.

Figure A4. Comparative Statics from Model This chart plots the comparative statics results generated from the model. See Appendix E for more details of the model solution and parameters used.

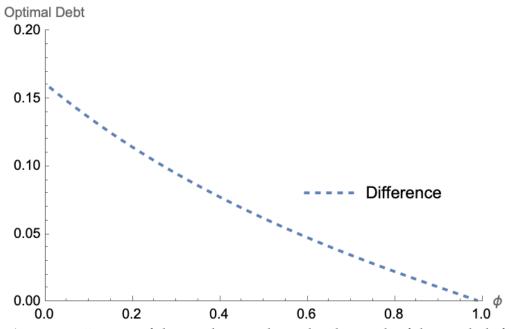
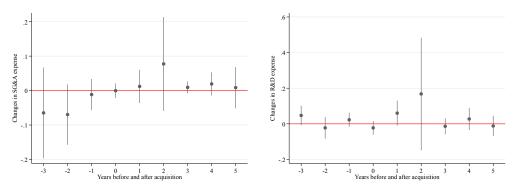
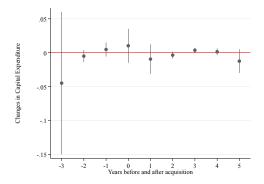


Figure A5. Impact of the market condition by the stock of demand-shifter intangibles on optimal debt

Figure A6. 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 Change in R&D expense scaled by lagged assets



Change in CapEx by lagged assets

F.2 Tables

Table A10. Proportion of Compustat Firms Involved in Acquisition Activities

This figure illustrates the percentage of Compustat firms engaging in acquisition activities that are included in the purchase price allocation sample. The industries presented are the Fama-French 12 industries, excluding the financial industry.

industry	coverage (%)
Consumer NonDurables	10.9
Consumer Durables	11.0
Manufacturing	14.8
Oil, Gas, and Coal Extraction and Products	8.02
Chemicals and Allied Products	8.22
Business Equipment	19.8
Telephone and Television Transmission	11.9
Utilities	6.77
Wholesale, Retail, and Some Services	9.91
Healthcare, Medical Equipment, and Drugs	10.8
Other	10.8

Table A11. Summary Statistics

The presented table displays the summary statistics for the different variables utilized 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).

	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	2875
Δ Cash flow-backed debt/l.assets	0.00	0.00	0.18	0.13	0.30	2875
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	0.08	0.21	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	3122
l.Market to book	1.49	2.51	4.31	3.81	5.43	3137
1.12 month cumulative stock return	0.88	1.14	1.47	1.26	0.65	2885
l.Total q	0.56	1.07	2.07	2.22	3.74	3581
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/l.assets	0.06	0.18	0.44	0.38	0.60	3689
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.PPE/l.assets	0.06	0.13	0.32	0.24	0.29	3664
Cash from target/l.assets	0.00	0.00	0.01	0.03	0.08	3831
l.Tangibles/total debt	0.26	0.79	2.21	6.97	27.23	3105

Table A12. Summary Statistics for Identifiable Intangibles

This table reports transaction-level summary statistics for identifiable intangibles, scaled by target total assets net of 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 A11.

Panel A. Demand-shifter Intangibles and Subcomponents								
	p50	p75	p90	Mean	SD	N		
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								
Panel B. Production-based Intangibles a	nd Subo	compon	ents					
Panel B. Production-based Intangibles a	nd Subo p50	compon p75	ents p90	Mean	SD	N		
Intangibles (production-based)				Mean 0.10	SD 0.36	N 4038		
	p50	p75	p90					
Intangibles (production-based)	p50 0.00	p75	p90 0.30	0.10	0.36	4038		
Intangibles (production-based) Technology intangible	p50 0.00 0.00	p75 0.09 0.00	p90 0.30 0.14	0.10 0.04	0.36 0.12	4038 4038		
Intangibles (production-based) Technology intangible Software intangible	p50 0.00 0.00 0.00	p75 0.09 0.00 0.00	p90 0.30 0.14 0.00	0.10 0.04 0.00	0.36 0.12 0.03	4038 4038 4038		
Intangibles (production-based) Technology intangible Software intangible Patent intangible	p50 0.00 0.00 0.00 0.00	p75 0.09 0.00 0.00 0.00	p90 0.30 0.14 0.00 0.00	0.10 0.04 0.00 0.01	0.36 0.12 0.03 0.27	4038 4038 4038 4038		
Intangibles (production-based) Technology intangible Software intangible Patent intangible Know-how intangible	p50 0.00 0.00 0.00 0.00 0.00	p75 0.09 0.00 0.00 0.00 0.00	p90 0.30 0.14 0.00 0.00 0.00	0.10 0.04 0.00 0.01 0.00	0.36 0.12 0.03 0.27 0.01	4038 4038 4038 4038 4038		
Intangibles (production-based) Technology intangible Software intangible Patent intangible Know-how intangible Trade secrets intangible	p50 0.00 0.00 0.00 0.00 0.00 0.00	p75 0.09 0.00 0.00 0.00 0.00 0.00	p90 0.30 0.14 0.00 0.00 0.00	0.10 0.04 0.00 0.01 0.00 0.00	0.36 0.12 0.03 0.27 0.01 0.01	4038 4038 4038 4038 4038 4038		
Intangibles (production-based) Technology intangible Software intangible Patent intangible Know-how intangible Trade secrets intangible Research intangible	p50 0.00 0.00 0.00 0.00 0.00 0.00	p75 0.09 0.00 0.00 0.00 0.00 0.00	p90 0.30 0.14 0.00 0.00 0.00 0.00	0.10 0.04 0.00 0.01 0.00 0.00 0.02	0.36 0.12 0.03 0.27 0.01 0.01	4038 4038 4038 4038 4038 4038 4038		
Intangibles (production-based) Technology intangible Software intangible Patent intangible Know-how intangible Trade secrets intangible Research intangible Employee intangible	p50 0.00 0.00 0.00 0.00 0.00 0.00 0.00	p75 0.09 0.00 0.00 0.00 0.00 0.00 0.00 0.0	p90 0.30 0.14 0.00 0.00 0.00 0.00 0.00	0.10 0.04 0.00 0.01 0.00 0.00 0.02	0.36 0.12 0.03 0.27 0.01 0.01 0.11	4038 4038 4038 4038 4038 4038 4038		
Intangibles (production-based) Technology intangible Software intangible Patent intangible Know-how intangible Trade secrets intangible Research intangible Employee intangible License intangible	p50 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0	p75 0.09 0.00 0.00 0.00 0.00 0.00 0.00 0.0	p90 0.30 0.14 0.00 0.00 0.00 0.00 0.00 0.00	0.10 0.04 0.00 0.01 0.00 0.00 0.02 0.00 0.01	0.36 0.12 0.03 0.27 0.01 0.01 0.11 0.13	4038 4038 4038 4038 4038 4038 4038 4038		
Intangibles (production-based) Technology intangible Software intangible Patent intangible Know-how intangible Trade secrets intangible Research intangible Employee intangible License intangible Right of use intangible	p50 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0	p75 0.09 0.00 0.00 0.00 0.00 0.00 0.00 0.0	p90 0.30 0.14 0.00 0.00 0.00 0.00 0.00 0.00	0.10 0.04 0.00 0.01 0.00 0.02 0.00 0.01 0.01	0.36 0.12 0.03 0.27 0.01 0.01 0.11 0.13 0.05 0.08	4038 4038 4038 4038 4038 4038 4038 4038		

Table A13. Balance Test of Acquirers Based on Targets' Low and High Intangible-to-Tangible Asset Ratios

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

	Low Intangible Share		High Inta	High Intangible Share		rence
	Mean	SD	Mean	SD	b	t-stat
1.Log assets	6.08	2.43	6.08	2.26	0.00	(0.01)
l.Total q	1.76	3.47	2.26	3.36	-0.50***	(-3.79)
1.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)
1.12 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***	(5.97)
l.Cash/l.assets	0.26	0.49	0.41	0.61	-0.15***	(-7.20)
l.EBITDA/l.assets	0.02	0.48	-0.00	0.55	0.02	(1.24)
l.Net cash receipts/l.assets	0.06	0.29	0.03	0.35	0.03*	(2.01)
l.PPE/l.assets	0.38	0.34	0.17	0.21	0.21***	(19.17)
Cash from target/l.assets	0.03	0.08	0.03	0.08	-0.01*	(-2.17)
l.Tangibles/total debt	5.90	24.43	6.90	28.02	-1.00	(-0.92)

Table A14. Regression Results on the Impact of Intangibles on Debt Financing by Debt Instrument Type

This table presents the results of the regression analysis investigating the impact of intangibles on changes in debt by debt instrument type. Column (1) to (4) present the outcome variable of changes in bank debt and Column (5) to (8) presents the outcome variable of changes in bond debt. 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).

	Δ Bank debt				Δ Bond debt			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Intangibles	0.12***	0.093***	0.19***	0.18***	0.013	0.014	0.060***	0.058***
	(0.028)	(0.029)	(0.040)	(0.040)	(0.011)	(0.012)	(0.014)	(0.014)
Δ Tangibles	0.22***	0.19***	0.22***	0.22***	0.074***	0.075***	0.098***	0.095***
	(0.038)	(0.039)	(0.050)	(0.053)	(0.015)	(0.015)	(0.026)	(0.026)
Δ Working capital		0.23***	0.19	0.21		-0.015	0.018	0.027
		(0.064)	(0.13)	(0.13)		(0.024)	(0.030)	(0.031)
L.Book leverage			0.0015	-0.020			0.048***	0.064***
			(0.029)	(0.029)			(0.015)	(0.015)
Controls			Х	Х			Х	Х
Industry \times year FE				X				X
Observations	2875	2875	2042	2013	2875	2875	2042	2013
R^2	0.067	0.078	0.139	0.226	0.030	0.031	0.127	0.254
F-stat: intan=tan	4.74	4.98	.45	.49	9.13	9.24	1.66	1.45
F-stat: p-value	.04	.036	.508	.491	.006	.006	.211	.242

Table A15. Intangible Categorization

The various intangible assets are categorized based on the framework presented in Section 6. Production intangible capital refers to the subset of intangible capital that the firm uses in production, such as patents, technology, and organizational capital. Demand-shifter intangibles are intangibles that are important for firms to generate cash flow but do not directly enter into the production function to produce more widgets.

Production-based	Demand-shifter
Patent	Customer relationship
Software	Brand
Technology	Trademark
IP R&D	Customer list
License	Customer contract
Organizational capital	Business relationship
Know-how/ trade secrets	Database
Copyrighted material	Domain
R.O.U	Franchise agreement
Blueprint	Non-compete agreement
Employee relation	Backlog

Table A16. 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) through (4) present the outcome variable of cash flow volatility after the acquisition with different quantities of intangibles acquired. The post-deal cash flow volatility is measured as the standard deviation of income before extraordinary items scaled by lagged assets for 5 years after the acquisition (ib/l.at). The pre-deal cash flow volatility is measured as the standard deviation of income before extraordinary items scaled by lagged assets for 5 years before the acquisition (ib/l.at). Significance levels are denoted by asterisks (*** p < 0.01, ** p < 0.05, * p < 0.1).

	(1)	(2)	(3)
Δ Intangibles (demand-shifter)	-0.010	-0.10**	-0.092*
	(0.052)	(0.048)	(0.049)
Δ Intangibles (production-based)	0.15**	0.097*	0.10*
	(0.069)	(0.050)	(0.058)
Δ Tangibles	0.014	0.087	0.031
	(0.031)	(0.087)	(0.060)
Δ Working capital	-0.0083	-0.012	-0.0091
	(0.063)	(0.072)	(0.080)
Cash flow vol. (pre)	0.17***	0.094**	0.067*
	(0.034)	(0.045)	(0.036)
L.Book leverage		0.073	0.050
		(0.073)	(0.068)
Controls		Χ	Х
Industry \times year FE			X
Observations	2850	2112	2070
R^2	0.105	0.241	0.380

Table A17. Regression Results on the Impact of Demand-shifter Intangibles on Debt Financing during Bad or Good Times

This table presents the results of the regression analysis investigating the impact of intangibles on demand-shifter intangibles on debt financing during bad or good times. I classify transactions as occurring during bad times if they take place between 2000-2003, 2007-2010, or 2020-2021, while all other transactions are considered to have occurred during good times. Significance levels are denoted by asterisks (*** p < 0.01, ** p < 0.05, * p < 0.1).

	Bad times	Good times
	(1)	(2)
Δ Intangibles (demand-shifter)	0.43***	0.42***
	(0.092)	(0.073)
Observations	1225	2575
R^2	0.066	0.065

Table A18. Regression Results with Subsample with 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) through (4) 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).

	Assumed Debt Subsample				The Rest			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Intangibles	0.17***	0.15***	0.24***	0.21***	0.24***	0.23***	0.26***	0.28***
	(0.040)	(0.038)	(0.052)	(0.046)	(0.053)	(0.053)	(0.056)	(0.062)
Δ Tangibles	0.34***	0.30***	0.42***	0.42***	0.35***	0.34***	0.44***	0.44***
	(0.063)	(0.062)	(0.12)	(0.13)	(0.056)	(0.056)	(0.058)	(0.053)
Δ Working capital		0.29***	0.18	0.15		0.11	0.41***	0.59***
		(0.061)	(0.12)	(0.12)		(0.085)	(0.094)	(0.12)
L.Book leverage			0.052	0.012			0.12***	0.098*
			(0.038)	(0.035)			(0.038)	(0.047)
Controls			X	Χ			X	X
Industry \times year FE				X				X
Observations	2822	2822	1911	1848	978	978	665	608
R^2	0.090	0.101	0.182	0.288	0.202	0.204	0.327	0.501
<i>F</i> -stat: intan=tan	7.85	6.64	2.23	2.87	3.32	3.64	6.35	3.25
<i>F-</i> stat: p-value	.009	.016	.148	.103	.081	.069	.019	.086

Table A19. Regression Results with Controls for Target Pre-acquisition Unused Debt Capacity

This table presents the regression analysis results, investigating the impact of intangible assets on long-term debt, with added controls for the target's pre-existing unused debt capacity. The debt capacity is proxied by the long-term debt-to-tangible and long-term debt-to-identifiable intangible ratios. Columns (1) through (4) 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).

	(1)	(2)
Δ Intangibles	0.26***	0.24***
	(0.050)	(0.052)
Δ Tangibles	0.43***	0.41***
	(0.069)	(0.078)
Δ Working capital	0.33***	0.38***
	(0.090)	(0.098)
L.Book leverage	0.100***	0.057
	(0.036)	(0.039)
L.Tangible asset/total debt	0.00027	0.000091
	(0.00029)	(0.00034)
Intangibles/pre-acquisition long-term debt (target)	-0.000021*	-0.000016
	(0.000010)	(0.000012)
Tangibles/pre-acquisition long-term debt (target)	-0.00015	-0.00016
	(0.00015)	(0.00016)
Controls	Χ	X
Industry \times year FE		X
Observations	1874	1822
R^2	0.243	0.333
F-stats: intan=tan	7.65	6
F-stats: p-val	.011	.022

Table A20. 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) through (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).

	Stock Deal Subsample				Cas			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Intangibles	0.16***	0.14***	0.20***	0.18***	0.31***	0.28***	0.37***	0.38***
	(0.043)	(0.040)	(0.044)	(0.046)	(0.048)	(0.050)	(0.11)	(0.100)
Δ Tangibles	0.32***	0.30***	0.40***	0.44***	0.48***	0.45***	0.48***	0.42***
	(0.038)	(0.035)	(0.088)	(0.11)	(0.080)	(0.081)	(0.10)	(0.14)
Δ Working capital		0.21**	0.22**	0.16		0.29**	0.39***	0.37**
		(0.082)	(0.11)	(0.16)		(0.12)	(0.14)	(0.15)
L.Book leverage			0.078*	0.038			0.053	0.027
			(0.042)	(0.047)			(0.032)	(0.037)
Controls			Х	Х			Х	X
Industry \times year FE				X				X
Observations	1664	1664	998	926	2136	2136	1578	1522
R^2	0.129	0.136	0.220	0.341	0.150	0.160	0.273	0.353
F-stat: intan=tan	8.27	7.55	3.89	5.1	3.57	3.39	.67	.06
F-stat: p-value	.008	.011	.06	.033	.07	.077	.42	.81

Table A21. Regression Results on the Impact of Intangibles on Long-term Debt Robustness Check with Total Q

This table presents the results of the regression analysis results investigating the impact of intangibles on long-term debt. Columns (1) through (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).

	(1)	(2)	(3)	(4)
Δ Intangibles	0.19***	0.17***	0.25***	0.24***
	(0.038)	(0.036)	(0.042)	(0.040)
Δ Tangibles	0.36***	0.33***	0.42***	0.42***
	(0.039)	(0.037)	(0.053)	(0.060)
Δ Working capital		0.24***	0.26***	0.26***
		(0.048)	(0.085)	(0.088)
L.Book leverage			0.073**	0.043
			(0.028)	(0.029)
Controls			X	Χ
Industry \times year FE				X
Observations	3800	3800	2588	2543
R^2	0.127	0.135	0.234	0.317
F-stats: intan=tan	14	13.02	10.7	10.41
F-stats: p-val	.001	.001	.003	.003

Table A22. Regression Results with Goodwill

This table presents the results of the regression analysis results investigating the impact of intangibles on long-term debt, with goodwill. Columns (1) through (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***	0.18***
	(0.044)	(0.041)	(0.048)	(0.047)
Δ Tangibles	0.35***	0.33***	0.41***	0.41***
	(0.039)	(0.038)	(0.055)	(0.061)
Δ Goodwill	0.018	0.010	0.10**	0.11**
	(0.014)	(0.015)	(0.042)	(0.042)
Δ Working capital		0.23***	0.23**	0.22**
		(0.052)	(0.087)	(0.090)
L.Book leverage			0.069**	0.038
			(0.029)	(0.031)
Controls			Χ	X
Industry \times year FE				X
Observations	3800	3800	2576	2530
R^2	0.128	0.135	0.248	0.331
F-stats: intan=tan	14.37	12.48	14.35	13.32
<i>F</i> -stats: p-val	.001	.002	.001	.001