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Tax Disclosure Transparency and Corporate Financing Costs: Evidence From U.S. Public Companies

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Abstract

Income-tax information is among the most complex components of corporate financial reports, yet creditors rely on it to evaluate cash-flow capacity and exposure to tax-related risk. This paper examines whether the transparency of tax disclosure is associated with the cost of debt financing of U.S. public companies. Using machine-readable XBRL data from the SEC Financial Statement Data Sets, we construct a tax disclosure transparency (TDT) measure that captures the granularity of income-tax line items presented in the primary financial statements of fiscal-year 2020 Form 10-K filings, complemented by a seven-component disclosure index. Cross-sectional regressions for 986 non-financial firms with industry fixed effects show that TDT is negatively and significantly associated with the cost of debt after controlling for firm size, leverage, profitability, asset tangibility, cash flow, liquidity, growth, filer status and general reporting granularity. A one-standard-deviation increase in TDT corresponds to a 1.21-percentage-point lower interest rate on debt, about 14% of the sample mean. The association is robust to alternative transparency measures, a cash-based cost of debt, taxpayer and profitable subsamples that control for the effective tax rate, trimming and median regression, and it is present across filer-status, leverage and profitability subsamples. The evidence indicates that granular tax reporting is priced by debt providers and informs ongoing initiatives to enhance income-tax disclosure.

Keywords

Tax disclosure, transparency, cost of debt, XBRL, disaggregation, information asymmetry.

1. Introduction

Information asymmetry between firms and capital providers is a fundamental source of financing frictions. When outside investors cannot fully observe a firm's prospects and actions, they demand compensation for adverse selection and agency risks [1–3]. Disclosure theory predicts that richer public information mitigates these frictions and lowers the cost of capital [4–6]. Creditors are particularly sensitive to accounting information because their payoffs are concave in firm value: structural models price corporate debt from the distribution of asset values [7], and incomplete accounting information widens credit spreads [8, 9]. Consistent with these arguments, firms with higher disclosure and accounting quality obtain cheaper debt financing [10–13].

Income taxes constitute a distinctive and economically important part of this information set. Tax payments are a first-order cash outflow that competes with debt service, and tax positions embed uncertainty about future audits, settlements and the realizability of deferred tax assets [14, 15]. At the same time, tax reporting is notoriously complex: tax planning can rely on structures that obscure the economics of the firm [16], and tax-aggressive firms exhibit lower

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corporate transparency [17]. Lenders price these features, as tax avoidance is associated with higher bank loan spreads and bond yields [18–20], with the relation shaped by institutional and governance conditions [21]. Research on tax disclosure has examined uncertain tax benefits [22, 23], geographic earnings disclosure [24], the public release of tax-return information [25], [26], country-by-country reporting [27, 28] and the readability of tax footnotes [29]. Much less is known about whether the transparency of routine tax reporting itself, as distinct from the level of tax avoidance, is reflected in the price that firms pay for debt.

This paper addresses that question using structured XBRL data. Building on the disaggregation approach of Chen et al. [30] and the XBRL tag-count approach of Hoitash and Hoitash [31], we measure tax disclosure transparency (TDT) as the granularity of income-tax line items that a firm separately presents in its primary financial statements, such as current and deferred tax expense, income taxes paid, deferred tax balances, current tax payables and receivables, uncertain tax positions and the tax effects of other comprehensive income (OCI). We complement this count-based measure with a seven-component disclosure index. Using the fiscal-year 2020 Form 10-K filings of 986 U.S. non-financial companies, we find that higher TDT is associated with a significantly lower cost of debt after controlling for standard determinants of borrowing costs and for the general granularity of the financial statements. The association is economically meaningful and robust across alternative measures, samples and estimators.

The study makes three contributions. First, it links the transparency of tax reporting to the pricing of corporate debt, complementing research that relates tax avoidance to borrowing costs. Second, it offers a replicable, XBRL-based measure of tax disclosure transparency that can be computed for the population of SEC registrants. Third, it provides timely evidence for standard setters and regulators that are expanding income-tax disclosure requirements. The remainder of the paper is organized as follows. Section II reviews the literature and develops the hypothesis, Section III describes the research design, Section IV reports the empirical results, Section V discusses the implications, and Section VI concludes.

2. Literature Review and Hypothesis Development

2.1. Disclosure, Information Asymmetry and the Cost of Debt

A large literature examines the economic consequences of corporate disclosure [32–35]. Theory shows that disclosure reduces information asymmetry, improves liquidity and lowers the information risk premium [4–6], whereas proprietary costs explain why firms do not always disclose fully [36]. On the equity side, the level of disclosure has been associated with a lower cost of equity capital [37, 38], the cost-of-capital effects of voluntary disclosure interact with earnings quality [39], and stronger disclosure and enforcement regimes reduce the cost of equity internationally [40].

Creditors face distinct information problems. Banks and other private lenders mitigate information asymmetry through monitoring and reputation building [41], and debt contracts rely on accounting-based covenants to control conflicts between shareholders and creditors [42], which makes the reliability and granularity of reported numbers central to debt contracting [13]. Empirically, analyst-rated disclosure quality is associated with lower effective interest costs on new debt [10] and lower spreads on private loans [11], and transparency ratings are associated with lower credit spreads, especially at short maturities [9]. Credible financial reporting also matters: auditor choice [43], board and audit committee independence [44] and audit assurance [45] are associated with lower borrowing costs, while restatements are followed by higher loan spreads and tighter terms [46], and lenders restructure contract terms after internal control weakness reports [47]. Lower accounting quality is likewise associated with higher spreads and more restrictive terms [12].

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Structured XBRL reporting offers a new lens on these questions. XBRL adoption has been linked to the cost of debt [48] and to a more level information playing field among investors [49]. Disaggregated reporting conveys finer information: the number of non-missing line items, a measure of disaggregation quality, is associated with lower analyst forecast dispersion, bid-ask spreads and cost of equity [30], and XBRL tag counts capture the complexity of accounting reports [31]. Firms with complex financial statements also provide more voluntary disclosure to mitigate the resulting information problems [50].

2.2. Tax Reporting, Tax Risk and Debt Pricing

Taxes interact with financing decisions through the deductibility of interest [51], and non-debt tax shields such as tax shelters substitute for interest deductions [52]. Reported tax amounts are informative but difficult to interpret. Long-run cash effective tax rates vary widely across firms [53], book-tax differences predict tax authority adjustments [54], and the tax expense is used to meet earnings targets [55]. Tax avoidance can facilitate managerial rent extraction through obfuscation [16], and its valuation consequences depend on governance [56]. Tax avoidance has been associated with greater stock price crash risk, consistent with opacity that allows bad news to accumulate [57], and investors react negatively to news of tax shelter involvement [58]. Tax planning also creates tax uncertainty [59], which concerns creditors because adverse tax settlements reduce the cash available for debt service. In line with these risks, tax avoidance is associated with higher loan spreads and more stringent non-price terms [18], higher bond yields operating partly through future cash flow and information quality channels [19], and loan pricing that reflects loan-specific risk mitigation [20], whereas it is associated with a lower cost of equity [60].

A parallel stream examines tax disclosure. The uncertain tax benefit disclosures mandated by FIN 48 have been studied for their market consequences [23] and their implications for tax compliance [61]; reported tax reserves are informative about private shelter activity [62], and the quality of these disclosures declines with proprietary costs [22]. Firms engaged in tax avoidance aggregate geographic disclosures [24, 63] and provide less readable tax footnotes [29], while public scrutiny and mandated public tax reporting alter corporate tax behavior and capital market valuations [25–28]. Managers of tax-aggressive firms also increase tax-related disclosure to mitigate transparency problems [17].

2.3. Hypothesis

Taken together, these studies suggest that the transparency of tax reporting is relevant to creditors. Granular tax line items allow lenders to separate current from deferred tax charges, to compare tax expense with taxes actually paid, to evaluate deferred tax assets and liabilities, and to identify accrued and uncertain tax obligations that compete with debt claims for the firm's cash flows. Such information reduces uncertainty about after-tax cash flows and tax risk, lowers monitoring costs and facilitates the design of accounting-based covenants [13, 41, 42]. Fig. 1 summarizes these channels and leads to the following hypothesis.

H1: Firms with greater tax disclosure transparency incur a lower cost of debt, ceteris paribus.

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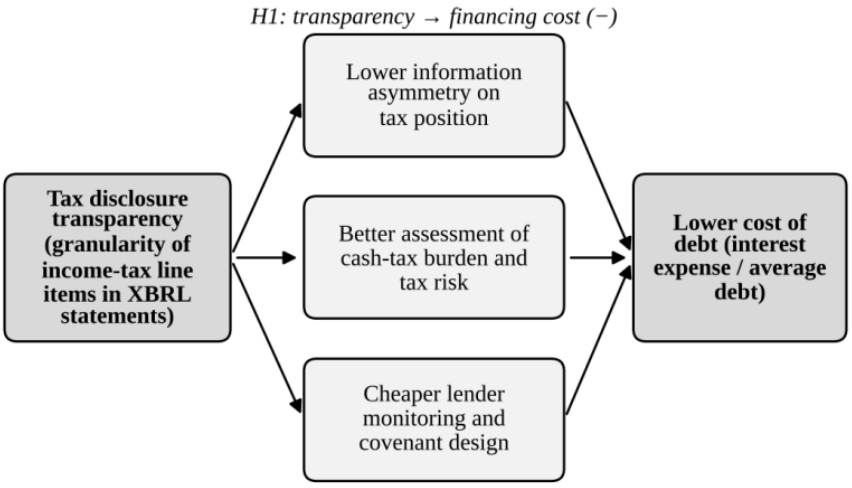


Figure 1. Conceptual framework linking tax disclosure transparency to the cost of debt.

3. Research Design

3.1. Data and Sample

The data are drawn from the SEC Financial Statement Data Sets, which provide the numeric facts, submission information and statement presentation extracted from the XBRL exhibits of all filings. We use the 2021Q1 release, which contains the annual reports filed between January and March 2021, predominantly by December fiscal-year-end registrants for fiscal year 2020. Starting from 2,851 Form 10-K filings of firms outside financial services (SIC 6000–6999) and regulated utilities (SIC 4900–4999), with one filing per registrant, we require positive interest expense, average interest-bearing debt of at least 1% of total assets, a cost of debt between zero and one and non-missing core accounting variables, which yields 1,132 firms. Excluding firms with total assets below $10 million and requiring complete data for all control variables produces a final sample of 986 firms in 56 two-digit SIC industries. The largest industries are chemicals and pharmaceuticals (SIC 28, 167 firms), business services (SIC 73, 133 firms) and measuring instruments (SIC 38, 81 firms), and the sample comprises 501 large accelerated filers, 192 accelerated filers and 293 non-accelerated filers. Continuous variables other than the disclosure measures are winsorized at the 1st and 99th percentiles.

3.2. Measuring Tax Disclosure Transparency

The presentation data identify every XBRL element that a registrant presents in its balance sheet, income statement, cash flow statement, statement of comprehensive income and statement of equity. We classify US-GAAP taxonomy elements as income-tax items when they report income tax expense or its components, deferred tax assets and liabilities, current income taxes payable or receivable, liabilities for uncertain tax positions, income tax cash flows and changes in tax accruals, or the tax effects of OCI components. Elements that report amounts net of tax or before tax, non-income taxes such as sales, excise, property and payroll taxes, and employee tax withholding are excluded. The sample firms use 105 distinct income-tax elements. Following the disaggregation logic of [30] and [31], the primary measure is

$$TDT_i = \ln(1 + NTAX_i) \quad (1)$$

Where $NTAX_i$ is the number of distinct income-tax elements presented by firm i. A higher value indicates that the firm separately reports more dimensions of its tax position instead of aggregating them into broader captions. As an alternative, TDT_INDEX is the average of seven indicators for presenting (i) a current/deferred tax split, (ii) income taxes paid, (iii) deferred

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tax balances, (iv) current tax payables or receivables, (v) noncurrent or uncertain tax liabilities, (vi) changes in tax accruals in operating cash flows and (vii) the tax effects of OCI components. Fig. 2 shows the distribution of the tax item count and the prevalence of each component.

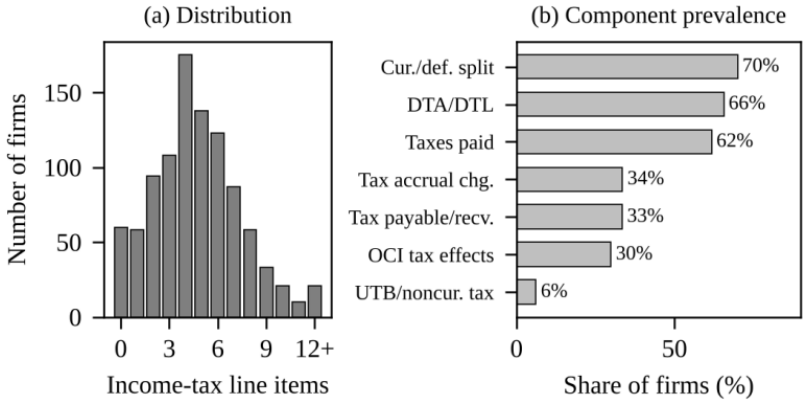


Figure 2. Tax disclosure in the primary statements of FY2020 Form 10-K filings: (a) distribution of the number of income-tax line items; (b) share of firms presenting each disclosure component (N = 986).

Table I. Variable Definitions

Variable	Definition
COD	Interest expense / average of beginning- and end-of-year interest-bearing debt
COD_CASH	Interest paid / average interest-bearing debt
TDT	ln(1 + number of distinct US-GAAP income-tax elements presented in the primary financial statements)
TDT_INDEX	Mean of seven indicators: current/deferred split, taxes paid, deferred tax balances, current tax payables/receivables, noncurrent or uncertain tax liabilities, tax accrual changes in operating cash flows, OCI tax effects
SIZE	ln(total assets)
LEV	Interest-bearing debt / total assets
ROA	Net income / total assets
LOSS	1 if net income is negative, 0 otherwise
TANG	Net property, plant and equipment / total assets
CFO	Net cash from operating activities / total assets
CR	Current assets / current liabilities
GROWTH	Revenue growth relative to the prior fiscal year
LAF	1 for large accelerated filers, 0 otherwise
NITEMS	ln(1 + number of distinct non-tax line items in the balance sheet, income statement and cash flow statement)
ETR	Income tax expense / pre-tax income for firms with positive pre-tax income, bounded to [0, 1]

Note: All variables are computed from the SEC Financial Statement Data Sets (2021Q1 release).

3.3. Cost of Debt and Control Variables

Following [43], the cost of debt (COD) is interest expense divided by the average of beginning- and end-of-year interest-bearing debt. Interest-bearing debt is the sum of all debt captions presented on the balance sheet, including short-term borrowings, commercial paper, current and noncurrent long-term debt, notes payable, lines of credit, convertible debt and finance lease

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liabilities, with totals and their components never counted twice. The alternative measure COD_CASH replaces interest expense with interest paid reported in the cash flow statement.

The control variables capture determinants of default risk and information asymmetry used in prior cost-of-debt research [10, 12, 43]: firm size (SIZE), leverage (LEV), profitability (ROA), a loss indicator (LOSS), asset tangibility (TANG), operating cash flow (CFO), the current ratio (CR), revenue growth (GROWTH) and an indicator for large accelerated filers (LAF), which reflects visibility and the strength of the information environment. To ensure that TDT does not simply proxy for the overall level of detail in the financial statements, NITEMS controls for the general granularity of the primary statements, measured as the logarithm of one plus the number of distinct non-tax line items. Table I defines all variables.

3.4. Empirical Model

We estimate the following cross-sectional model by ordinary least squares:

$$COD_i = \beta_0 + \beta_1 TDT_i + \Sigma_k \gamma_k X_{k,i} + \Sigma_j \delta_j IND_{j,i} + \varepsilon_i \quad (2)$$

Where X denotes the control variables and IND denotes two-digit SIC industry fixed effects. Standard errors are clustered by industry to allow for correlated residuals within industries [64]. H1 predicts $\beta_1 < 0$.

4. Empirical Results

4.1. Descriptive Statistics and Correlations

Table II. Descriptive Statistics

Variable	N	Mean	SD	P25	Median	P75
COD	986	0.086	0.096	0.040	0.058	0.090
COD_CASH	724	0.059	0.053	0.032	0.045	0.067
TDT	986	1.599	0.597	1.386	1.609	1.946
N_TAX	986	4.733	2.796	3.000	4.000	6.000
TDT_INDEX	986	0.429	0.250	0.286	0.429	0.571
SIZE	986	20.812	2.082	19.366	20.984	22.309
LEV	986	0.311	0.240	0.137	0.273	0.418
ROA	986	−0.100	0.271	−0.154	−0.018	0.048
LOSS	986	0.569	0.495	0.000	1.000	1.000
TANG	986	0.199	0.224	0.042	0.105	0.273
CFO	986	0.003	0.215	−0.028	0.063	0.117
CR	986	2.680	2.757	1.223	1.814	3.047
GROWTH	986	0.238	1.758	−0.151	−0.013	0.137
LAF	986	0.508	0.500	0.000	1.000	1.000
NITEMS	986	4.478	0.124	4.394	4.477	4.554

Note: N_TAX is the number of income-tax line items underlying TDT. Variables are defined in Table I.

Table II reports descriptive statistics. The mean (median) cost of debt is 8.6% (5.8%), and the interquartile range from 4.0% to 9.0% indicates substantial cross-sectional dispersion in borrowing costs. Firms present on average 4.7 income-tax line items (median 4), and the mean TDT_INDEX of 0.43 implies that a typical firm presents three of the seven tax disclosure components. As shown in Fig. 2(b), the current/deferred split (70%), deferred tax balances

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(66%) and income taxes paid (62%) are common, whereas noncurrent or uncertain tax liabilities are presented separately by only 6% of firms. Loss firms account for 57% of the sample, reflecting the large share of research-intensive companies and the economic conditions of fiscal year 2020.

Table III presents Pearson correlations. COD is negatively correlated with TDT (−0.31) and TDT_INDEX (−0.30). TDT is positively correlated with SIZE (0.44), ROA (0.46) and CFO (0.52), indicating that larger and more profitable firms present more detailed tax information and underscoring the need for multivariate controls. The correlation between TDT and NITEMS is moderate (0.29), confirming that tax disclosure granularity is distinct from general reporting granularity, while the two transparency measures are highly correlated (0.89).

Table III. Pearson Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) COD	1									
(2) TDT	−0.31	1								
(3) TDT_INDEX	−0.30	0.89	1							
(4) SIZE	−0.34	0.44	0.41	1						
(5) LEV	−0.14	0.07	0.04	0.15	1					
(6) ROA	−0.39	0.46	0.46	0.44	−0.04	1				
(7) LOSS	0.27	−0.31	−0.31	−0.32	0.05	−0.57	1			
(8) CFO	−0.37	0.52	0.49	0.47	0.06	0.76	−0.46	1		
(9) LAF	−0.28	0.29	0.26	0.67	0.06	0.34	−0.33	0.31	1	
(10) NITEMS	−0.06	0.29	0.27	0.22	0.02	0.15	−0.02	0.16	0.18	1

Note: N = 986. Correlations with absolute values of 0.07 or greater are significant at the 5% level (two-tailed).

4.2. Baseline Results

Table IV reports the estimates of (2). In column (1), which includes only TDT and industry fixed effects, the coefficient on TDT is −0.0516 (t = −7.99). After the control variables are added in column (2), the coefficient remains negative and significant at −0.0184 (t = −3.55). Column (3) further controls for NITEMS, and the TDT coefficient is −0.0203 (t = −3.52). Holding other factors constant, a one-standard-deviation increase in TDT (0.597) is associated with a 1.21-percentage-point lower cost of debt, or 14.2% of the sample mean of 8.57%. Column (4) replaces TDT with TDT_INDEX and yields a coefficient of −0.0455 (t = −3.89), so that a one-standard-deviation increase in the index corresponds to a 1.14-percentage-point lower cost of debt. These results support H1.

The control variables behave as expected. Larger firms borrow at lower rates, and profitability is negatively related to the cost of debt. The negative coefficient on LEV is typical of interest-expense-based measures, because firms with greater debt capacity tend to access lower-cost instruments, whereas small balances of high-rate debt raise the ratio for firms with little leverage. NITEMS is positive and only marginally significant, indicating that general reporting granularity does not carry the same pricing implication as tax-specific transparency; the TDT coefficient is therefore not a mechanical reflection of overall statement detail.

Fig. 3 illustrates the relation using mean COD across TDT quintiles. Firms in the lowest quintile, which present 1.1 tax items on average, pay 14.7% on their debt, compared with 7.4% to 7.9% in the middle quintiles and 5.4% in the highest quintile, where firms present 8.8 items on average.

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Table IV. Tax Disclosure Transparency and the Cost of Debt

Variable	(1)	(2)	(3)	(4)
TDT	−0.0516***	−0.0184***	−0.0203***	
	(−7.99)	(−3.55)	(−3.52)	
TDT_INDEX				−0.0455***
				(−3.89)
SIZE		−0.0052**	−0.0055**	−0.0057**
		(−2.15)	(−2.39)	(−2.57)
LEV		−0.0477***	−0.0472***	−0.0488***
		(−4.87)	(−4.93)	(−4.94)
ROA		−0.0627	−0.0633*	−0.0625
		(−1.64)	(−1.66)	(−1.64)
LOSS		0.0086	0.0073	0.0071
		(1.33)	(1.15)	(1.10)
TANG		0.0086	0.0084	0.0087
		(0.59)	(0.58)	(0.60)
CFO		−0.0370	−0.0369	−0.0390
		(−1.09)	(−1.11)	(−1.17)
CR		0.0002	0.0002	0.0004
		(0.12)	(0.13)	(0.21)
GROWTH		0.0008	0.0007	0.0007
		(0.93)	(0.84)	(0.80)
LAF		−0.0115	−0.0120	−0.0123
		(−1.08)	(−1.13)	(−1.14)
NITEMS			0.0389*	0.0383*
			(1.87)	(1.90)
Industry FE	Yes	Yes	Yes	Yes
N	986	986	986	986
Adj. R^2	0.100	0.202	0.203	0.203

Note: The dependent variable is COD. t-statistics based on standard errors clustered by two-digit SIC industry are in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels. Intercepts are included but not reported.

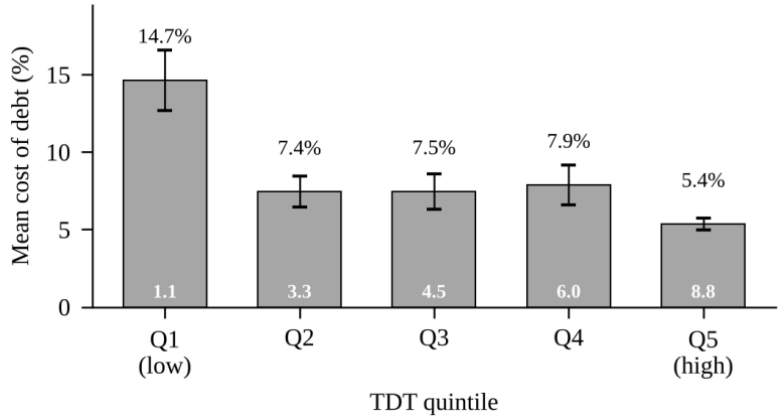


Figure 3. Mean cost of debt by TDT quintile with 95% confidence intervals. Numbers inside the bars denote the mean number of income-tax line items in each quintile.

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4.3. Robustness Tests

Table V summarizes robustness tests based on the specification in column (3) of Table IV. First, with the cash-based cost of debt, available for 724 firms, the coefficient on TDT is −0.0074 and significant at the 10% level. Second, the within-industry percentile rank of TDT has a coefficient of −0.0348 (t = −3.98), so moving from the bottom to the top of an industry's transparency distribution is associated with a 3.5-percentage-point lower cost of debt. Third, excluding the OCI tax-effect lines from the count yields a coefficient of −0.0228 (t = −3.95), showing that the result is driven by income-tax items rather than by the complexity of other comprehensive income. Fourth, restricting the sample to firms that report non-zero income tax expense strengthens the association (−0.0347, t = −3.37), consistent with tax information being most relevant for taxpaying firms. Fifth, among profitable firms, controlling for the GAAP effective tax rate as a proxy for the level of tax avoidance leaves the TDT coefficient at −0.0207 (t = −2.37), while the ETR itself is insignificant. Finally, excluding the top 5% of the COD distribution (−0.0076, t = −3.83) and estimating a median regression [65] (−0.0073, t = −3.62) confirm that the association is not driven by extreme observations; the smaller magnitudes in these two tests reflect the reduced influence of the right tail of the COD distribution.

Table V. Robustness Tests

Test	Coef.	t	N	Adj. R^2
Cash-based cost of debt (COD_CASH)	−0.0074*	−1.70	724	0.156
Within-industry percentile rank of TDT	−0.0348***	−3.98	986	0.203
TDT excluding OCI tax effects	−0.0228***	−3.95	986	0.204
Firms with non-zero tax expense	−0.0347***	−3.37	868	0.165
Profitable firms, controlling for ETR	−0.0207**	−2.37	406	0.109
Excluding top 5% of COD	−0.0076***	−3.83	936	0.256
Median (LAD) regression	−0.0073***	−3.62	986	—

Note: Each row reports the coefficient on the transparency measure from the specification in column (3) of Table IV, modified as described. t-statistics are based on industry-clustered standard errors, except for the median regression, which uses robust quantile-regression standard errors. ***, ** and * denote significance at the 1%, 5% and 10% levels.

Table VI. Component-Level Analysis

Disclosure component	Share	Coef.	t
Current/deferred tax split	0.70	−0.0139**	−2.50
Income taxes paid	0.62	−0.0139**	−2.28
Deferred tax balances	0.66	−0.0155***	−2.70
Current tax payable/receivable	0.33	−0.0133***	−3.52
Noncurrent/uncertain tax liabilities	0.06	−0.0100	−1.26
Tax accrual changes	0.34	−0.0070	−1.46
Tax effects of OCI	0.30	−0.0015	−0.36

Note: Each row reports the coefficient from a separate regression of COD on the component indicator, the controls of Table IV, column (3), and industry fixed effects. Share is the proportion of firms presenting the component. t-statistics are based on industry-clustered standard errors. ***, ** and * denote significance at the 1%, 5% and 10% levels.

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4.4. Component-Level Evidence

To identify which elements of tax reporting are priced, Table VI reports separate regressions of COD on each disclosure component with the full set of controls and industry fixed effects. Four components carry negative and significant coefficients: the current/deferred tax split (−0.0139), income taxes paid (−0.0139), deferred tax balances (−0.0155) and current tax payables or receivables (−0.0133). These items convey the most direct information about the timing of tax cash flows and near-term tax obligations. Noncurrent or uncertain tax liabilities and changes in tax accruals have negative but insignificant coefficients, and OCI tax effects are unrelated to COD. Lenders therefore respond chiefly to disclosures that clarify the cash-flow consequences of income taxes.

4.5. Subsample Analysis

Fig. 4 plots TDT coefficients estimated separately for subsamples formed by filer status, leverage (median split) and profitability. The coefficient is negative in all six subsamples and significant at the 5% level in five of them, with the loss-firm subsample significant at the 10% level. Point estimates are larger for firms other than large accelerated filers (−0.0270) than for large accelerated filers (−0.0153), and for low-leverage firms (−0.0284) than for high-leverage firms (−0.0124). Interaction tests indicate that these differences are not statistically significant (t-statistics between 0.12 and 0.89), so the pricing of tax disclosure transparency is pervasive across firm types rather than confined to a particular group.

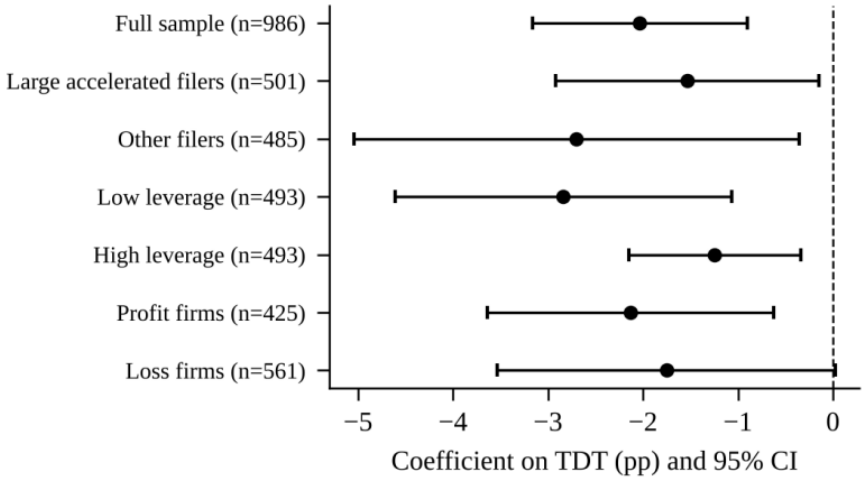


Figure 4. Coefficients on TDT estimated separately by subsample using the specification of Table IV, column (3), with 95% confidence intervals based on industry-clustered standard errors.

5. Discussion

The results have implications for several parties. For managers, presenting tax information at a finer level of detail is associated with a tangible financing benefit. The estimated reduction of about 1.2 percentage points for a one-standard-deviation increase in TDT is large relative to typical borrowing costs, and the component evidence indicates that low-cost presentation choices, namely separating current and deferred taxes, reporting income taxes paid and presenting deferred tax balances and current tax payables or receivables, account for most of this benefit. For lenders and credit analysts, structured XBRL data make tax disclosure transparency observable at scale, so the measure can be incorporated into credit screening and monitoring. For standard setters and regulators, the evidence indicates that disaggregated income-tax information has economic value to capital providers. This is relevant to the FASB's

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Accounting Standards Update 2023-09, which requires public business entities to disaggregate the rate reconciliation and income taxes paid by jurisdiction, and to international initiatives that promote public tax transparency [27, 28].

The findings also complement research on tax avoidance and debt pricing [18–20]. That research shows that lenders charge for the risks of aggressive tax planning; our evidence indicates that the presentation of tax information is priced in addition to the level of tax avoidance, since the TDT coefficient remains of similar magnitude when the effective tax rate is controlled (−0.0207 versus −0.0203). Transparency and avoidance therefore represent distinct dimensions of a firm's tax profile from the perspective of creditors, in line with the argument that firms can mitigate the transparency costs of tax planning through additional disclosure [17].

6. Conclusion

This paper examines whether tax disclosure transparency is associated with the cost of debt of U.S. public companies. Using XBRL data from fiscal-year 2020 Form 10-K filings, we measure transparency as the granularity of income-tax line items presented in the primary financial statements. Firms with more transparent tax disclosure pay significantly lower interest rates on their debt after controlling for size, leverage, profitability, liquidity, growth, filer status and general reporting granularity. The association is economically significant, robust to alternative transparency and financing-cost measures, samples and estimators, and present across firm types. Disclosures of the current/deferred composition of tax expense, income taxes paid, deferred tax balances and current tax obligations are the components most closely associated with borrowing costs. The XBRL-based approach extends naturally to tax footnote elements and multi-year panels, which allows future research to trace how financing costs respond to the expanded income-tax disclosure requirements now being implemented.

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