Accounting Comparability and Customer Concentration

Abstract

This study examines the relationship between accounting comparability and customer concentration. Higher accounting comparability enhances customers' ability to evaluate suppliers' performance against their industry peers. This allows suppliers to attract more customers, hence reducing their customer concentration. We find a negative association between accounting comparability and customer concentration. This relation is stronger for firms with better profitability, higher information asymmetry, and more innovations. By establishing a link between accounting comparability and customer concentration, our study provides additional evidence about the consequences of accounting comparability and is helpful to both academics and practitioners.

JEL: M41; L25; O30

Keywords: accounting comparability; customer concentration

1. Introduction

One general purpose of financial reporting is to help stakeholders better evaluate firms' past, current, and future performance. To achieve this, financial statement users must be able to compare accounting information across firms. Comparability is thus a critical enhancing qualitative characteristic of financial reporting (FASB, 2018; IASB, 2018).[1] Accordingly, "for information to be comparable, like things must look alike and different things must look different" (FASB, QC23, p.5; IASB, §2.27, p.A29).

Accounting research conventionally defines accounting comparability[2] as the similarity with which the accounting system "maps economic events to financial statements" (De Franco et al., 2023, p.127). De Franco et al. (2011) propose that "for a given set of economic events, two firms have comparable accounting systems if they produce similar financial statements" (p.896). The De Franco et al. (2011) measure is output-based and captures the similarity with which economics events, proxied by returns, are mapped into accounting numbers, proxied by earnings. This measure has become the standard in comparability research.[3]

Prior research documents several benefits of accounting comparability, including better analyst forecasts (De Franco et al., 2011), lower expected share price crash risk (Kim et al., 2016), better syndicated loans (Fang et al., 2016), more profitable merger activities (Chen et al., 2018), higher internal capital market efficiency (Cheng and Wu, 2018), greater corporate innovative efficiency (Chircop et al., 2020), better marginal value of cash holdings (Ahn et al., 2020), enhanced managers' use of corporate resources (Kim et al., 2021), lower tendency of accounting

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[1] FASB Concepts Statement No. 8, Chapter 3, QC20 – QC25; IASB Conceptual Framework for Financial Reporting, Chapter 2, §2.24 – §2.29.
[2] Past literature uses "financial statement comparability," "accounting comparability," and "comparability" interchangeably. In our paper, we tend use "comparability" for brevity.
[3] Most comparability studies use the De Franco et al. (2011) measure.

fraud (Blanco et al., 2023), improved corporate tax strategy (Hong et al., 2023), reduced analysts' accruals-related bias (Lee and Lee, 2024), and improved global supply-chain relations (Peng et al., 2024).[4] One common theme among these studies is that these benefits of accounting comparability stem from its ability to allow users of financial reports to better compare firms against their peers.

In this study, we focus on customers, an often-overlooked group of financial statement users in past comparability research.[5] This is surprising given that customers are among the most important stakeholders as they drive firms' sales revenues. The FASB highlights the importance of this customers by requiring suppliers to disclose in their notes to the financial statements' information about major corporate customers that individually account for at least 10% of their sales revenues along with the sales associated with each major customer.[6] Prior research refers to customer concentration as the extent to which suppliers depend on major customers for their sales.

Customer concentration has a rich and growing literature.[7] While some studies document that high concentration helps suppliers improve operational efficiency (Cowley, 1988; Irvine et al., 2016; Kalwani and Narayandas, 1995; Krishnan et al., 2019; Patatoukas, 2012; Wang et al., 2023), many agree that high concentration strengthens customers' bargaining power at the expense of suppliers (Porter, 1974). Suppliers with higher concentration have lower profit margins (Balakrishnan et al., 1996; Hui et al., 2019; Lustgarten, 1975; Ravenscraft, 1983), higher costs of capital (Dhaliwal et al., 2016), more rigid cost structure (Chang et al., 2021), lower speed of

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[4] A smaller literature examines the determinants of comparability, e.g., auditor style (Francis et al., 2014), proprietary costs (Imhof et al., 2018), economic policy uncertainty (Dhole et al., 2021), and demand for legitimacy (De Franco et al., 2023). Our study belongs to research on the consequences of comparability.

[5] Peng et al. (2024) link comparability to the supplier-customer relationship. However, while Peng et al. (2024) find that non-U.S. firms tend to establish supply-chain relationships with U.S. firms when non-U.S. firms and U.S. firms have more comparability, our study examines customers' choice of U.S. suppliers when these suppliers have more comparability *with one another*. Thus, our study is distinct from Peng et al. (2024).

[6] The FASB requires firms to disclose major customers by the Statement of Financial Accounting Standards (SFAS) No. 131 (paragraph 39, p.15) in 1997. Later on, the FASB codified this requirement into the Accounting Standards Codification (ASC) (ASC 280-10-50-42).

[7] Hereafter, we tend to use "concentration" in place of "customer concentration" for brevity.

leverage adjustment (Rehman et al., 2023), worse debt characteristics (Campello and Gao, 2017), higher likelihood of withholding bad news (Chen et al., 2022), and are more risky targets in mergers and acquisitions (Cheng et al., 2022). Some studies are more neutral, showing that the relationship between concentration and supplier performance depends on suppliers' structural decisions versus executional skills (Matsumura and Schloetzer, 2018) and corporate versus government customers (Cohen and Li, 2020; Yun et al., 2023). Despise this rich literature, no study has examined the relationship between accounting comparability and customer concentration. We seek to fill this gap.

To the extent that potential customers use suppliers' accounting disclosures to decide whether to form a supply-chain relationship with suppliers, higher supplier comparability reduces acquisition and processing costs for customers, facilitating their ability to compare financial performance among suppliers. This helps suppliers with better comparability attract more customers, reducing their reliance on any single customer.

Assume suppliers A and B are similar in all aspects (including economic fundamentals as well as disclosure quantity and quality), except that supplier A (B) reports accounting numbers that are more (less) comparable to industry peers. Potential customers are likely to find the information of supplier A *more* value-relevant because it is easier to compare supplier A with the rest of the industry.[8] In financial statement analysis where the goal is to evaluate a firm based on its performance, it is important to have reliable benchmarks.[9] As such, potential customers are more likely to do business with supplier A. Thus, supplier A may find it easier than supplier B to diversify

[8] "Value-relevant" refers to the ability of potential customers to price/evaluate suppliers based on suppliers' past, current, and future operating cash flows. Thus, this term is consistent with the value relevance literature (Barth et al., 2001a, 2023).
[9] E.g., a 30% return on asset (ROA) appears attractive (unattractive) if the industry ROA is 20% (40%). Customers can compare various financial ratios of suppliers to the industry benchmarks only if suppliers' financial statements are comparable to industry peers. These comparisons allow customers to evaluate the ability of suppliers to remain in business in the future.

its customer base and reduce its reliance on any single customer. Therefore, we expect a negative association between accounting comparability and customer concentration.

The above reasoning applies only to customers that rely on public disclosures of suppliers' accounting information to make supply-chain decisions. Major customers already in relationships with suppliers may have private information channels that mitigate the need for public disclosures (Crawford et al., 2020). If so, comparability may not have any association with concentration. The relation between these constructs is, therefore, an empirical question.

To test our conjecture, we measure comparability using the De Franco et al. (2011) approach and concentration using the Herfindahl-Hirschman Index following Patatoukas (2012) and Dhaliwal et al. (2016). Using a 1990-2019 sample of U.S. firms, we find a negative association between comparability and concentration. This result is robust to alternative research design choices and to endogeneity tests. It is stronger for firms with better performance, higher information asymmetry, and more innovations.

These results suggest that despite having private information channels with existing customers, suppliers with better comparability can better diversify their customer base, reducing their reliance on any major customer. To the extent that higher concentration is detrimental to suppliers, our study extends research on the benefits of comparability. While both comparability and concentration are important, no prior study has examined their relationship. Our study seeks to fill this gap. By showing that firms with more comparability are less exposed to the negative impacts of high concentration, our study is useful for both academics and practitioners (e.g., customers, suppliers, and financial analysts).

2. Research Design

2.1. Accounting Comparability

Following De Franco et al. (2011), we measure comparability among industry peers using the closeness of their mapping functions of economic news, proxied by stock returns, into accounting outcomes, proxied by earnings. Specifically, we estimate the following time-series regression using the firms' 16 previous quarters of data.

$$EARNINGS_{iq} = \alpha_i + \beta_i RETURN_{iq} + \varepsilon_{iq} \quad (1)$$

In this equation, $EARNINGS_{iq}$ is firm i's net income in quarter q scaled by market value at the end of quarter q-1. $RETURN_{iq}$ is stock return during quarter q. The estimated coefficients $\hat{\alpha}_i$ and $\hat{\beta}_i$ represent the accounting system of firm i in mapping economic events into earnings. Similarly, using time series data for peer firm j, where a peer firm is any firm operating in the same two-digit SIC code as firm i, we obtain $\hat{\alpha}_j$ and $\hat{\beta}_j$ that represent the accounting system of firm j. To estimate the mapping function of economic news into accounting numbers, we estimate the accounting responses of firm i and firm j to economic events of firm i using equations (2a) and (2b).

$$E(EARNINGS)_{iiq} = \hat{\alpha}_i + \hat{\beta}_i RETURN_{iq} + \varepsilon_{iq} \quad (2a)$$

$$E(EARNINGS)_{ijq} = \hat{\alpha}_j + \hat{\beta}_j RETURN_{iq} + \varepsilon_{iq} \quad (2b)$$

Where $E(EARNINGS)_{iiq}$ is predicted earnings of firm i, given the firm i's accounting system $\hat{\alpha}_i$ and $\hat{\beta}_i$ and firm i's stock return ($RETURN_{iq}$) in quarter q. $E(EARNINGS)_{ijq}$ is the predicted earnings of the peer firm j, given the firm j's accounting system $\hat{\alpha}_j$ and $\hat{\beta}_j$ and firm i's stock return ($RETURN_{iq}$) in quarter q. As shown in equation (3), we define the pairwise comparability ($COMP_{ijt}$) of firm i and peer firm j in fiscal year t as the mean absolute difference between the expected earnings of firm i and firm j over the 16 preceding quarters, multiplied by -1.

$$COMP_{ijt} = -\frac{1}{16}\sum_{t-15}^{t}\left|E(EARNINGS)_{iit} - E(EARNINGS)_{ijt}\right| \qquad (3)$$

Where $COMP_{ijt}$ is a non-positive number capturing comparability between firms *i* and *j* in year *t* that increases as the difference in their expected earnings decreases. We then compute the annual firm-level measure of firm *i*'s comparability with its industry peers ($COMP_{it}$) by taking the average of firm *i*'s pairwise comparability scores. We then multiply this by 100 for ease of interpretation and use it as our main comparability measure.[10]

2.2. Customer Concentration

We follow Patatoukas (2012) and Dhaliwal et al. (2016) and use the Herfindahl-Hirschman Index to measure customer concentration (CC_{it}). This measure accounts for the number of major customers identified by suppliers *and* the relative importance of those major customers to suppliers' annual sales.

$$CC_{it} = \sum_{j=1}^{k}\left(\frac{SALE\_C_{ijt}}{SALES_{it}}\right)^2 \qquad (4)$$

$SALES_{it}$ is total sales of firm *i* in year *t*, $SALE\_C_{ijt}$ is sales of firm *i* to major customer *j* in year *t*, and *k* is the number of major corporate customers reported by firm *i* in year *t*. Customer *j* is a major customer if sales to this customer are at least 10% of the total annual sales. CC_{it} equals zero when there is no major customer and one when firm *i* sells all products/services to one customer. We multiply CC_{it} by 100 for ease of interpretation.

2.3. Baseline Model

We test the comparability-concentration relationship using the following model:

$$CC_{it+1} = \beta_0 + \beta_1\, COMP_{it} + \beta\, CONTROLS_t + FE + \varepsilon_{it} \qquad (5)$$

[10] We also compute the measures based on the ten ($COMP10_{it}$) and the four ($COMP4_{it}$) largest pairwise comparability scores to check for robustness.

CC_{it+1} and $COMP_{it}$ are defined above. $CONTROLS_t$ represents firm- and market-level characteristics. The Appendix provides details about all variables. We include industry and year fixed effects (*FE*) to control for industry time-invariant characteristics and time trends, respectively. We cluster standard errors at the firm level to adjust for within-firm correlation of residuals.

2.4. Sample Selection

Our data primarily come from Compustat and CRSP. Following De Franco et al. (2011), we retain firms with fiscal year ends in March, June, September, and December. We exclude firms in the financial and utilities sectors because they are subject to unique regulations. To compute comparability, we require at least 10 peer firms each year. We eliminate firms with market values less than $10 million and winsorize all continuous variables at the 1st and 99th percentiles to reduce the effect of outliers. Our final sample includes 41,292 firm-year observations from 1990 to 2019.[11]

3. Empirical Results

3.1. Summary Statistics

CC_{it+1} averages at 4.932% with a maximum of 56.557% (Table 1), which is comparable to Patatoukas (2012, p.369) and Dhaliwal et al. (2016, p.26). Meanwhile, $COMP_{it}$ averages at -3.01% with a median of -2.438%, which is comparable to De Franco et al. (2011, p.905). Other variables are consistent with prior studies. Comparability shows significant negative correlation with concentration (Table 2), providing preliminary evidence of their negative relationship.

3.2. Baseline Results

We run equation (5) as an ordinary least square regression. $COMP_{it}$ is significantly negative at the 1% level without (Table 3, column [1]) or with (column [2]) all controls. With all controls,

[11] The sample ends in 2019 to avoid COVID-19.

the coefficient on $COMP_{it}$ is -0.159. A one standard deviation (2.016) increase in comparability is associated with a 0.320[12] reduction in concentration, representing a decrease of 6.50%.[13] This association is thus significant both statistically and economically. Other comparability variants ($COMP10_{it}$ and $COMP4_{it}$) provide qualitatively similar results (columns [3] to [6]).

4. Robustness Checks

4.1. Alternative Measures

To ensure our baseline result is not driven by our measurement choices of comparability, we run equation (5) while replacing $COMP_{it}$ with an alternative measure based on eight previous quarters ($COMP\_8Q_{it}$) and its variants based on the average of the ten ($COMP10\_8Q_{it}$) and the four ($COMP4\_8Q_{it}$) largest pairwise comparablity scores. Our results remain robust to these alternative measures (Table 4, Panel A).

We further subject our results to two alternative concentration measures used in prior research (Banerjee et al., 2008; Dhaliwal et al., 2016); the percentage of sales to all major customers ($MajorSales_{it+1}$) and the log of one plus the number of major customers ($MajorCus_{it+1}$). Our results also remain robust to these alternative measures (Table 4, Panel B).

4.2. Entropy Balancing

Because comparability is endogenous, we address the concerns of correlated omitted variables using entropy balancing to isolate the treatment effect from the potential confounding effects (Francis and Wang, 2021; Hainmueller, 2012; Hainmueller and Xu, 2013). In our setting, treatment (control) firms are those with comparability greater (less) than the industry median. We match the treatment and control firms based on firm-level fundamental characteristics.

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[12] 0.159 x 2.016 [standard deviation of $COMP_{it}$ (Table 1)] = 0.320.
[13] (0.320 / 4.932 [mean of CC_{it+1} (Table 1)]) x 100 = 6.50%.

After entropy balancing, the fundamentals between the treatment group and the control group are statistically similar (Table 5, Panel A), as indicated by the standardized difference of zero and the variance ratio of one (Austin, 2011; Rubin, 2001). Based on the entropy-balanced sample, the baseline association remains significant at the 1% level for both $COMP_{it}$ (Table 5, Panel B, column [1]) and $COMP\_8Q_{it}$ (columns [2]). This finding remains robust to $MajorSales_{it+1}$ (column [3] and [4]) and $MajorCus_{it+1}$ (column [5] and [6]). These findings provide some evidence that endogeneity does not drive our results.

5. Cross-Sectional Tests

5.1. Profitability

Entering a supply-chain relationship requires significant up-front costs, making it undesirable for customers to form relationships with poorly performing suppliers (Huang et al., 2016; Itzkowitz, 2013; Raman and Shahrur, 2008). If comparability facilitates customers' evaluation of suppliers, then suppliers with better earnings are likely to attract more customers.[14] Thus, we expect the comparability-concentration association to be stronger for suppliers with better earnings. We measure earnings using return on assets (ROA) – earnings scaled by total assets – and partition the sample based on the annual industry median of suppliers' ROA. We then run equation (5) in each subsample. $COMP_{it}$ is more negative for firms with high ROA (Table 6, Panel A), which supports our prediction.

5.2. Information Asymmetry

If comparability reduces information costs for customers, then suppliers with higher information asymmetry can benefit more from comparability in reducing concentration. We thus predict that the comparability-concentration association is stronger for suppliers with higher

[14] Current earnings can predict future cash flows (Barth et al., 2001b; Dechow et al., 1998), making it a reliable proxy for firm performance.

information asymmetry. We test this by measuring information asymmetry using monthly bid-ask spread (Corwin and Schultz, 2012; Drake et al., 2012), with higher bid-ask spread indicating more information asymmetry. We partition the sample based on the annual industry median of suppliers' bid-ask spread and find that $COMP_{it}$ is more negative for firms with high bid-ask spread (Table 6, Panel B). This supports our information channel.

5.3. Innovation

More innovative firms can better cater to customers' needs (Allen and Phillips, 2000; Leung and Sun, 2021). Thus, more innovative suppliers are more likely to form new relationships with potential customers. Therefore, we expect the comparability-concentration association to be stronger for more innovative suppliers. We test this conjecture by partitioning the sample based on suppliers' innovation, proxied by an input-based measure and an output-based measure (Krolikowski and Yuan, 2017; Leung and Sun, 2021). The input-based measure captures whether a firm has R&D expenditures in a given year, and the output-based measure whether a firm has at least one patent filled and granted in a given year.[15] For the input-based measure, comparability is only negative for firms with R&D (Table 6, Panel C, columns [1] and [2]). Meanwhile, it is more negative for firms with at least one granted patent than for firms without (columns [3] and [4]). These findings are consistent with our expectations.

6. Conclusion

This study examines the comparability–concentration relationship. High comparability enhances customers' ability to evaluate suppliers' performance against their peers, allowing suppliers with better comparability to attract more customers and diversify their customer base. We find a negative comparability–concentration association that is stronger for firms with better

[15] We treat missing R&D as zero R&D. We use an output-based measure because some firms have R&D activities without reporting any R&D expenditures on their income statement (Koh and Reeb, 2015).

profitability, higher information asymmetry, and more innovations. Our study extends the benefits of comparability and is useful for both academics and practitioners (e.g., customers, suppliers, and financial analysts).

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Table 1
Descriptive Statistics

Table 1 displays descriptive statistics for a sample of firm-year data from 1990 to 2019, including MEAN (mean), MEDIAN (median), STD (standard deviation), MIN (minimum), and MAX (maximum). The Appendix contains variable definitions and data sources. All continuous variables are winsorized at the 1^{st} and 99^{th} percentiles to mitigate the impact of outliers.

Variables	Observations	MEAN	MEDIAN	STD	MIN	MAX
CC_{it+1}	41,292	4.932	0.000	9.926	0.000	56.557
$COMP_{it}$	41,292	-3.010	-2.438	2.016	-12.836	-0.854
$COMP10_{it}$	41,292	-1.007	-0.454	1.471	-8.780	-0.060
$COMP4_{it}$	41,292	-0.697	-0.289	1.127	-6.981	-0.033
$SIZE_{it}$	41,292	5.996	5.885	1.938	2.530	10.907
AGE_{it}	41,292	2.914	2.890	0.670	1.609	4.190
LEV_{it}	41,292	0.219	0.191	0.199	0.000	0.889
$R\&D_{it}$	41,292	0.043	0.010	0.069	0.000	0.355
ROA_{it}	41,292	0.014	0.040	0.133	-0.630	0.250
$TOBINQ_{it}$	41,292	1.912	1.498	1.291	0.622	8.118
PPE_{it}	41,292	0.539	0.429	0.405	0.029	1.977
$SG\&A_{it}$	41,292	0.289	0.232	0.231	0.013	1.205
STD_CFO_{it}	41,292	46.550	6.915	137.599	0.287	1,030.647
STD_SALE_{it}	41,292	94.979	15.395	258.667	0.516	1,861.225
STD_EARN_{it}	41,292	44.311	5.797	133.730	0.163	1,002.633
EPU_t	41,292	4.640	4.677	0.248	4.267	5.149
$GDPGR_t$	41,292	1.780	1.923	1.462	-3.786	3.863

Table 2
Pearson Correlations

Table 2 shows the Pearson pairwise correlation coefficients for all variables included in the main regressions. *, **, and *** indicates that the coefficients are statistically significant at the 10%, 5% and 1% levels of significance.

		[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]	[15]	[16]	[17]
[1]	CC_{it+1}	1.00																
[2]	$COMP_{it}$	-0.11***	1.00															
[3]	$COMP10_{it}$	-0.05***	0.83***	1.00														
[4]	$COMP4_{it}$	-0.05***	0.82***	0.98***	1.00													
[5]	$SIZE_{it}$	-0.19***	0.20***	0.12***	0.12***	1.00												
[6]	AGE_{it}	-0.09***	0.13***	0.07***	0.06***	0.42***	1.00											
[7]	LEV_{it}	-0.07***	-0.12***	-0.20***	-0.19***	0.21***	0.03***	1.00										
[8]	$R\&D_{it}$	0.14***	-0.15***	0.06***	0.05***	-0.26***	-0.18***	-0.24***	1.00									
[9]	ROA_{it}	-0.11***	0.42***	0.31***	0.29***	0.29***	0.17***	-0.11***	-0.38***	1.00								
[10]	$TOBINQ_{it}$	0.04***	0.09***	0.16***	0.16***	-0.00	-0.09***	-0.16***	0.31***	0.11***	1.00							
[11]	PPE_{it}	0.02***	-0.06***	-0.14***	-0.13***	0.05***	0.15***	0.22***	-0.23***	-0.02***	-0.18***	1.00						
[12]	$SG\&A_{it}$	-0.02***	-0.13***	-0.04***	-0.04***	-0.31***	-0.19***	-0.25***	0.51***	-0.30***	0.24***	-0.25***	1.00					
[13]	STD_CFO_{it}	-0.07***	0.03***	0.02***	0.02***	0.53***	0.27***	0.09***	-0.06***	0.08***	0.02***	0.12***	-0.19***	1.00				
[14]	STD_SALE_{it}	-0.09***	0.08***	0.05***	0.05***	0.60***	0.28***	0.08***	-0.09***	0.10***	-0.00	0.03***	-0.18***	0.79***	1.00			
[15]	STD_EARN_{it}	-0.06***	-0.05***	-0.04***	-0.05***	0.50***	0.24***	0.10***	-0.04***	0.02***	-0.00	0.09***	-0.18***	0.87***	0.69***	1.00		
[16]	EPU_{t}	0.02***	-0.18***	-0.11***	-0.10***	0.11***	0.11***	0.00	0.00	-0.04***	-0.05***	0.01*	-0.01***	0.08***	0.07***	0.09***	1.00	
[17]	$GDPGR_{t}$	-0.01*	0.02***	0.02***	0.02***	-0.08***	-0.07***	-0.01*	-0.01	0.05***	0.08***	0.01***	0.00	-0.05***	-0.05***	-0.05***	-0.40***	1.00

Table 3
Baseline Results

This table reports the OLS results for the following equation during the 1990-2019 period.

$$CC_{it+1} = \beta_0 + \beta_1 COMP_{it} + \beta\ CONTROLS_t + FE + \varepsilon_{it} \qquad (5)$$

CC_{it+1} stands for the Herfindahl-Hirschman Index-based measure of customer concentration of firm i in year t+1 (Dhaliwal et al., 2016; Patatoukas, 2012). $COMP_{it}$ is the accounting comparability measure (De Franco et al., 2011), computed as the mean of comparability scores between firm i and all its industry peers (two-digit SIC code) in year t, with the score measured over 16 preceding quarters. For robustness, we substitute $COMP_{it}$ (column [1] and [2]) with $COMP10_{it}$ (column [3] and [4]) and $COMP4_{it}$ (column [5] and [6]). $COMP10_{it}$ ($COMP4_{it}$) is the mean of comparability scores between firm i and its 10 (4) most comparable industry peers. $CONTROLS_t$ stands for firm size ($SIZE_{it}$), firm age (AGE_{it}), research and development expenditures ($R\&D_{it}$), return on assets (ROA_{it}), Tobin's Q ($TOBINQ_{it}$), tangible assets (PPE_{it}), selling, general and administrative expenses ($SG\&A_{it}$), standard deviation of cash from operations (STD_CFO_{it}), standard deviation of sales (STD_SALE_{it}), and standard deviation of net income (STD_EARN_{it}), economic policy uncertainty (EPU_t), and GDP growth rate ($GDPGR_t$). The Appendix provides detailed variable definitions. *FE* stands for year and industry fixed effects. Standard errors are robust and clustered at the firm level in all regressions. Figures in parentheses are t-statistics. ***, **, and * indicate that the coefficients are statistically significant at the 1%, 5%, and 10% levels of significance, respectively.

	CC_{it+1}					
	[1]	**[2]**	**[3]**	**[4]**	**[5]**	**[6]**
$COMP_{it}$	-0.406***	-0.159***				
	(-7.62)	(-3.17)				
$COMP10_{it}$			-0.424***	-0.141**		
			(-6.09)	(-2.19)		
$COMP4_{it}$					-0.497***	-0.173**
					(-5.69)	(-2.16)
$SIZE_{it}$		-1.107***		-1.117***		-1.118***
		(-11.35)		(-11.43)		(-11.45)
AGE_{it}		-0.846***		-0.856***		-0.857***
		(-4.19)		(-4.23)		(-4.24)
LEV_{it}		-1.781***		-1.712***		-1.703***
		(-3.15)		(-3.03)		(-3.02)
$R\&D_{it}$		16.379***		16.417***		16.421***
		(6.03)		(6.03)		(6.03)
ROA_{it}		-2.054**		-2.390***		-2.434***
		(-2.40)		(-2.83)		(-2.89)
$TOBINQ_{it}$		0.289***		0.287***		0.287***
		(3.19)		(3.17)		(3.17)
PPE_{it}		0.370		0.392		0.398
		(0.83)		(0.88)		(0.89)

$SG\&A_{it}$		-5.907^{***}		-5.859^{***}		-5.854^{***}
		(-7.77)		(-7.70)		(-7.69)
STD_CFO_{it}		-0.001		-0.001		-0.001
		(-0.85)		(-0.89)		(-0.90)
STD_SALE_{it}		0.001		0.001		0.001
		(1.10)		(1.10)		(1.10)
STD_EARN_{it}		0.000		0.001		0.001
		(0.53)		(0.69)		(0.71)
EPU_t		0.201		0.210		0.218
		(0.24)		(0.25)		(0.26)
$GDPGR_t$		-0.050		-0.049		-0.049
		(-0.82)		(-0.81)		(-0.81)
Constant	3.711^{***}	13.341^{***}	4.505^{***}	13.683^{***}	4.585^{***}	13.674^{***}
	(18.46)	(3.36)	(30.69)	(3.45)	(32.09)	(3.45)
Industry and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	41,292	41,292	41,292	41,292	41,292	41,292
Adjusted R^2	0.084	0.142	0.082	0.141	0.081	0.141

Table 4
Robustness Tests: Alternative Measures

This table reports the OLS results for the following equation during the 1990-2019 period.

$$CC_{it+1} = \beta_0 + \beta_1 COMP_{it} + \beta_2 CONTROLS_t + FE + \varepsilon_{it} \quad (5)$$

In Panel A, CC_{it+1}, which is the Herfindahl-Hirschman Index-based measure of customer concentration of firm i in year t+1 (Dhaliwal et al., 2016; Patatoukas, 2012). We replace $COMP_{it}$ with $COMP\_8Q_{it}$, which is similar to $COMP_{it}$ except that the comparability scores are measured over 8 preceding quarters. For robustness, we substitute $COMP\_8Q_{it}$ (column [1]) with $COMP10\_8Q_{it}$ (column [3]) and $COMP4\_8Q_{it}$ (column [4]). $COMP10\_8Q_{it}$ ($COMP4\_8Q_{it}$) is the mean of comparability scores between firm i and its 10 (4) most comparable industry peers.

In Panel B, we replace CC_{it+1} with $MajorSales_{it+1}$, which is the total percentage of sales to all major customers of firm i in year t+1, and $MajorCus_{it+1}$, which is the log of 1 plus the number of major customers reported by firm i in year t+1. We also alternate $COMP_{it}$ with $COMP\_8Q_{it}$ for robustness. Under the $COMP\_8Q_{it}$ specification, the measures based on standard deviations are computed over 8 preceding quarters.

For both panels, $CONTROLS_t$ stands for firm size ($SIZE_{it}$), firm age (AGE_{it}), research and development expenditures ($R\&D_{it}$), return on assets (ROA_{it}), Tobin's Q ($TOBINQ_{it}$), tangible assets (PPE_{it}), selling, general and administrative expenses ($SG\&A_{it}$), standard deviation of cash from operations (STD_CFO_{it}), standard deviation of sales (STD_SALE_{it}), and standard deviation of net income (STD_EARN_{it}), economic policy uncertainty (EPU_t), and GDP growth rate ($GDPGR_t$). When the comparability measure is based on 16 (8) preceding quarters, all measures based on standard deviation are computed over 16 (8) preceding quarters for consistency. The Appendix provides detailed variable definitions. *FE* stands for year and industry fixed effects. Standard errors are robust and clustered at the firm level in all regressions. Figures in parentheses are t-statistics. ***, **, and * indicate that the coefficients are statistically significant at the 1%, 5%, and 10% levels of significance, respectively.

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Panel A: Alternative Measures of Accounting Comparability

	CC_{t+1}		
	[1]	**[2]**	**[3]**
$COMP\_8Q_{it}$	-0.118***		
	(-3.19)		
$COMP10\_8Q_{it}$		-0.081*	
		(-1.68)	
$COMP4\_8Q_{it}$			-0.103*
			(-1.73)
Constant	13.563***	13.779***	13.759***
	(3.41)	(3.47)	(3.47)
Controls	Yes	Yes	Yes
Industry and Year FE	Yes	Yes	Yes
Observations	41,292	41,292	41,292
Adjusted R^2	0.141	0.141	0.141

Panel B: Alternative Measures of Customer Concentration

	$MajorSales_{it+1}$		$MajorCus_{it+1}$	
	[1]	**[2]**	**[3]**	**[4]**
$COMP_{it}$	-0.379***		-0.006**	
	(-3.10)		(-2.48)	
$COMP\_8Q_{it}$		-0.300***		-0.006***
		(-3.40)		(-3.09)
Constant	41.504***	41.946***	0.899***	0.903***
	(4.62)	(4.67)	(4.64)	(4.66)
Controls	Yes	Yes	Yes	Yes
Industry and Year FE	Yes	Yes	Yes	Yes
Observations	41,292	41,292	41,292	41,292
Adjusted R^2	0.206	0.206	0.209	0.209

Table 5
Robustness Test: Entropy Balancing

For the entropy balancing method (Francis and Wang, 2021; Hainmueller, 2012; Hainmueller and Xu, 2013), treatment (control) firms have $COMP_{it}$ greater (less) than the industry median (based on two-digit SIC). Treatment and control firms are matched based on firm-level fundamental characteristics.

Panel A reports firm-level fundamentals (mean, variance, and skewness) of the treatment firms (columns [2]-[4]) and the control firms (columns [5]-[7]), along with the standardized difference (column [8]) and the variance ratio (column [9]). The standardized difference is calculated by dividing the mean differences between the treatment and control firms by the standard deviation of the treatment firms for each covariate. The variance ratio is calculated by dividing each covariate's variance for the treatment firms by its variance for the control firms. Consistent with previous studies (Austin, 2011; Rubin, 2001), the standardized differences are close to one while the variance ratios are close to zero.

Panel B reports the OLS results of the following equation using the entropy-balancing sample during the 1990-2019 period.

$$CC_{it+1} = \beta_0 + \beta_1 COMP_{it} + \beta_2 CONTROLS_t + FE + \varepsilon_{it} \qquad (5)$$

CC_{it+1} stands for the Herfindahl-Hirschman Index-based measure of customer concentration of firm i in year t+1 (Dhaliwal et al., 2016; Patatoukas, 2012). In some specifications, we replace CC_{it+1} with $MajorSales_{it+1}$, which is the total percentage of sales to all major customers of firm i in year t+1, and $MajorCus_{it+1}$, which is the log of 1 plus the number of major customers reported by firm i in year t+1. $COMP_{it}$ is the accounting comparability measure (De Franco et al., 2011), computed as the mean of comparability scores between firm i and all its industry peers (two-digit SIC code) in year t, with the score measured over 16 preceding quarters. In some specifications, we substitute $COMP_{it}$ with $COMP\_8Q_{it}$, which is similar to $COMP_{it}$ except that the comparability scores are measured over 8 preceding quarters. $CONTROLS_t$ stands for firm size ($SIZE_{it}$), firm age (AGE_{it}), research and development expenditures ($R\&D_{it}$), return on assets (ROA_{it}), Tobin's Q ($TOBINQ_{it}$), tangible assets (PPE_{it}), selling, general and administrative expenses ($SG\&A_{it}$), standard deviation of cash from operations (STD_CFO_{it}), standard deviation of sales (STD_SALE_{it}), and standard deviation of net income (STD_EARN_{it}), economic policy uncertainty (EPU_t), and GDP growth rate ($GDPGR_t$). For specifications using $COMP\_8Q_{it}$, all measures based on standard deviation are computed over 8 preceding quarters. The Appendix provides detailed variable definitions. *FE* stands for year and industry fixed effects. Standard errors are robust and clustered at the firm level in all regressions. Figures in parentheses are t-statistics. ***, **, and * indicate that the coefficients are statistically significant at the 1%, 5%, and 10% levels of significance, respectively.

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Panel A: Summary statistics of the entropy-balanced samples

	Treatment			Control			Std. Diff	Var Ratio
	Mean	Variance	Skewness	Mean	Variance	Skewness		
$SIZE_{it}$	6.353	3.626	0.193	6.353	3.626	0.193	0.000	1.000
AGE_{it}	2.980	0.461	-0.100	2.980	0.461	-0.100	0.000	1.000
LEV_{it}	0.207	0.033	0.876	0.207	0.033	0.876	0.000	1.000
$R\&D_{it}$	0.036	0.003	2.245	0.036	0.003	2.245	0.000	1.000
ROA_{it}	0.053	0.005	-1.064	0.053	0.005	-1.070	0.000	0.999
$TOBINQ_{it}$	2.063	1.807	2.269	2.063	1.807	2.269	0.000	1.000
PPE_{it}	0.525	0.151	1.128	0.525	0.151	1.128	0.000	1.000
$SG\&A_{it}$	0.264	0.039	1.511	0.264	0.039	1.511	0.000	1.000
STD_CFO_{it}	51.132	19,841.659	5.089	51.132	19,841.532	5.089	0.000	1.000
STD_SALE_{it}	111.700	79,464.360	4.551	111.699	79,463.732	4.551	0.000	1.000
STD_EARN_{it}	42.495	15,990.526	5.511	42.494	15,990.461	5.511	0.000	1.000

Panel B: Baseline Regression Using Entropy Balanced Sample

	CC_{it+1}		$MajorSales_{it+1}$		$MajorCus_{it+1}$	
	[1]	[2]	[3]	[4]	[5]	[6]
$COMP_{it}$	-0.162***		-0.371**		-0.006*	
	(-2.62)		(-2.25)		(-1.72)	
$COMP\_8Q_{it}$		-0.149***		-0.352***		-0.006**
		(-2.92)		(-2.61)		(-2.25)
Constant	13.406***	13.446***	43.106***	43.141***	0.916***	0.914***
	(3.15)	(3.16)	(4.06)	(4.06)	(3.73)	(3.71)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	41,292	41,292	41,292	41,292	41,292	41,292
Adjusted R^2	0.133	0.133	0.200	0.200	0.207	0.207

Table 6
Cross-Sectional Tests

For each test, we partition the sample based on a cross-sectional variable and rerun OLS regression of the following equation within each subsample before comparing β_1 between the two subsamples during the 1990-2019 period.

$$CC_{it+1} = \beta_0 + \beta_1 COMP_{it} + \beta_2 CONTROLS_t + FE + \varepsilon_{it} \quad (5)$$

CC_{it+1} stands for the Herfindahl-Hirschman Index-based measure of customer concentration of firm i in year t+1 (Dhaliwal et al., 2016; Patatoukas, 2012). $COMP_{it}$ is the accounting comparability measure (De Franco et al., 2011), computed as the mean of comparability scores between firm i and all its industry peers (two-digit SIC code) in year t, with the score measured over 16 preceding quarters. $CONTROLS_t$ stands for firm size ($SIZE_{it}$), firm age (AGE_{it}), research and development expenditures ($R\&D_{it}$), return on assets (ROA_{it}), Tobin's Q ($TOBINQ_{it}$), tangible assets (PPE_{it}), selling, general and administrative expenses ($SG\&A_{it}$), standard deviation of cash from operations (STD_CFO_{it}), standard deviation of sales (STD_SALE_{it}), and standard deviation of net income (STD_EARN_{it}), economic policy uncertainty (EPU_t), and GDP growth rate ($GDPGR_t$). The Appendix provides detailed variable definitions. *FE* stands for year and industry fixed effects. Standard errors are robust and clustered at the firm level in all regressions. Figures in parentheses are t-statistics. ***, **, and * indicate that the coefficients are statistically significant at the 1%, 5%, and 10% levels of significance, respectively.

In Panel A, the cross-sectional variable is profitability. We measure profitability using return on asset (ROA_{it}), computed as net income scaled by total assets. $HIGH\_ROA_{it}$ equals 1 when ROA_{it} is greater than industry median in a given year and 0 otherwise.

In Panel B, the cross-sectional variable is information asymmetry. We measure information asymmetry using $SPREAD_{it}$, an annual average of the monthly bid-ask spreads based on daily prices from 9 months before to 3 months after the fiscal year-end (Corwin and Schultz, 2012; Drake et al., 2012). $HIGH\_SPREAD_{it}$ equals 1 when $SPREAD_{it}$ is greater than industry median in a given year and 0 otherwise.

In Panel C, the cross-sectional variable is innovation. We use an input-based innovation measure based on whether firm i has positive R&D expenditures in year t ($R\&D_{it} > 0$). We also use an output-based innovation measure based on whether firm i has at least one patent filed and granted in year t ($PATENT_{it} > 0$).

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Panel A: Profitability

	$HIGH\_ROA_{it} = 1$	$HIGH\_ROA_{it} = 0$
	[1]	**[2]**
$COMP_{it}$	-0.204***	-0.097*
	(-2.62)	(-1.81)
Constant	17.954***	7.268
	(3.34)	(0.98)
Controls	Yes	Yes
Industry and Year FE	Yes	Yes
Observations	20,936	20,356
Adjusted R^2	0.131	0.152
	[1] vs [2]	
F-statistics (P-value)	4.341 (0.037)	

Panel B: Information Asymmetry

	$HIGH\_SPREAD_{it} = 1$	$HIGH\_SPREAD_{it} = 0$
	[1]	**[2]**
$COMP_{it}$	-0.127***	-0.056
	(-2.19)	(-0.84)
Constant	18.989***	6.679
	(2.85)	(1.29)
Controls	Yes	Yes
Industry and Year FE	Yes	Yes
Observations	20,563	20,538
Adjusted R^2	0.141	0.127
	[1] vs [2]	
F-statistics (P-value)	41.720 (0.000)	

Panel C: Corporate Innovation

	Input-based Innovation		**Output-based Innovation**	
	$R\&D_{it} > 0$	$R\&D_{it} = 0$	$PATENT_{it} > 0$	$PATENT_{it} = 0$
	[1]	**[2]**	**[3]**	**[4]**
$COMP_{it}$	-0.224***	-0.077	-0.259**	-0.130**
	(-3.07)	(-1.14)	(-2.57)	(-2.39)
Constant	9.375*	22.513***	10.734	15.042***
	(1.84)	(3.36)	(1.16)	(3.19)
Controls	Yes	Yes	Yes	Yes
Industry and Year FE	Yes	Yes	Yes	Yes
Observations	23,739	17,553	11,452	29,840
Adjusted R^2	0.151	0.161	0.162	0.141
	[1] vs [2]		[3] vs [4]	
F-statistics (P-value)	4.602 (0.032)		9.554 (0.002)	

Appendix

Variable definitions

Variable	Definition	Data source
$COMP_{it}$	De Franco et al. (2011)'s accounting comparability measure based on 16 previous quarters (mean of comparability scores between firm i and *all* of its peers in the same two-digit SIC code).	Compustat. Programming code is available at: https://mitmgmtfaculty.mit.edu/rverdi/publications/
$COMP4_{it}$	De Franco et al. (2011)'s accounting comparability measure based on 16 previous quarters (mean of comparability scores between firm i and its *four* most comparable peers in the same two-digit SIC code).	Compustat. Programming code is available at: https://mitmgmtfaculty.mit.edu/rverdi/publications/
$COMP10_{it}$	De Franco et al. (2011)'s accounting comparability measure based on 16 previous quarters (mean of comparability scores between a firm i and its *10* most comparable peers in the same two-digit SIC code).	Compustat. Programming code is available at: https://mitmgmtfaculty.mit.edu/rverdi/publications/
$COMP\_8Q_{it}$	De Franco et al. (2011)'s accounting comparability measure based on 8 previous quarters (mean of comparability scores between firm i and *all* of its peers in the same two-digit SIC code).	Compustat. Programming code is available at: https://mitmgmtfaculty.mit.edu/rverdi/publications/
$COMP4\_8Q_{it}$	De Franco et al. (2011)'s accounting comparability measure based on 8 previous quarters (mean of comparability scores between firm i and its *four* most comparable peers in the same two-digit SIC code).	Compustat. Programming code is available at: https://mitmgmtfaculty.mit.edu/rverdi/publications/
$COMP10\_8Q_{it}$	De Franco et al. (2011)'s accounting comparability measure based on 8 previous quarters (mean of comparability scores between firm i and its *10* most comparable peers in the same two-digit SIC code).	Compustat. Programming code is available at: https://mitmgmtfaculty.mit.edu/rverdi/publications/
CC_{it}	Herfindahl-Hirschman Index-based customer concentration measure (Dhaliwal et al., 2016; Patatoukas, 2012).	Compustat

	$$CC_{it} = \sum_{j=1}^{k} \left(\frac{SALE\_C_{ijt}}{SALES_{it}} \right)^2$$ $SALES_{it}$ is total sales of firm i in a year t, and $SALE\_C_{ijt}$ is sale to the firm i's the major customer j; and k is the number of major customers reported by firm i in year t. Major customer is defined as a customer to which sale is greater than or equal to 10% of total sales of firm i in year t. Theoretically, *CC* ranges from 0 to 1, with a higher value indicates higher level of customer concentration (*CC* = 1 when firm i sells all products and services to one customer). We multiply *CC* with 100 for ease of interpretation.	
$MajorSales_{it}$	Percentage of sales to all major customers of firm i in year t.	Compustat
$MajorCus_{it}$	Log of one plus the number of major customers reported by firm i in year t.	Compustat
$SIZE_{it}$	Log(sale).	Compustat
LEV_{it}	Short-term debt plus long-term debt divided by total assets	Compustat
AGE_{it}	Firm age, which is log(current year – earliest year listed on Compustat).	Compustat
$R\&D_{it}$	Research and development costs scaled by total assets. Missing values are replaced by 0.	Compustat
ROA_{it}	Return on assets, which is equal to net income divided by total assets.	Compustat
$HIGH\_ROA_{it}$	Indicator equal to 1 if *ROA* is greater than the industry median in a given year, and to 0 otherwise.	
$TOBINQ_{it}$	Market value of equity plus total assets minus book value of equity, scaled by total assets	Compustat
PPE_{it}	Gross property plant and equipment divided by total assets	Compustat
$SG\&A_{it}$	Selling, general and administrative expenses divided by total assets.	Compustat
STD_CFO_{it}	Standard deviation of operating cash flows from 16 preceding quarters used to calculate accounting comparability. We require at least 10 non-missing values for calculation.	Compustat

STD_SALE_{it}	Standard deviation of sales from 16 preceding quarters used to calculate accounting comparability. We require at least 10 non-missing values for calculation.	Compustat
STD_EARN_{it}	Standard deviation of net income from 16 preceding quarters used to calculate accounting comparability. We require at least 10 non-missing values for calculation.	Compustat
EPU_t	Economic policy uncertainty by Baker et al. (2016). We take the log of the average of 12 months preceding to the fiscal year-end.	https://www.policyuncertainty.com/
$GDPGR_t$	Annual GDP growth rate. We take the average GDP growth rate of 16 quarters from q-15 to q.	Data are available at https://fred.stlouisfed.org/series/GDPC1
$PATENT_{it}$	The number of parents filed and granted in a given year.	Patent and citation data are available at https://kelley.iu.edu/nstoffma/
$SPREAD_{it}$	Measure of information asymmetry (Corwin and Schultz, 2012; Drake et al., 2012) based on the annual average of the monthly bid-ask spread from nine months before to three months after the fiscal year-end, with the monthly bid-ask spread being computed from daily share prices.	Compustat
$HIGH\_SPREAD_{it}$	Indicator equal to 1 if *SPREAD* is greater than the industry median in a given year, and to 0 otherwise.	