

The Effect of Firms' Technology Levels on Selling, General, and Administrative Cost Behavior

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ABSTRACT

This study examines the impact of digital technology intensity on firms' cost behavior across industries with different technology levels. Our sample consists of 49,275 firm-year observations for the period from 2010 to 2023. We classify firms into digital, stable, and low-technology groups and examine variations in the selling, general, and administrative (SG&A) costs. The results indicate that SG&A costs are stickier in digital-technology firms, whereas this pattern is not observed for the cost of goods sold (COGS). These findings suggest that digital technologies could change cost composition and behavior, thereby contributing to the literature and discussion on technological advancement and business performance.

Keywords: Cost Behavior, Digital Technology, SG&A cost

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1. Introduction

Over the past few decades, rapid advancements in digital or smart technologies have profoundly transformed the business world. Innovations such as big data, artificial intelligence (AI), machine learning, deep learning, blockchain, the Internet of Things (IoT), and cloud computing have not only created many new business opportunities and fueled the rapid growth of digital technology firms but also reconfigured business models in traditional businesses. While many businesses are embracing this wave of technological change, the extent to which digital transformation contributes to a firm's financial performance remains an open question. This study examines how digital technology affects firms' costs and how the effects vary across firms.

Many firms have integrated digital technologies into their core operations, enabling digital transformation that makes core business functions more efficient and value-creating. For example, the digitalization of retailers, financial technology (FinTech) in financial services, and Industry 4.0 in manufacturing and industrial processes. Although firms in some traditional industries, such as hotels and restaurants (which rely mainly on human interaction), experience less digital transformation in their operations, supporting functions ranging from human resources, accounting, and customer service can still benefit significantly from these technologies. Hence, the extent of technological adoption and incorporation naturally vary across firms and industries. Additionally, this variation in digital technology adoption, is affected by many factors, including high implementation costs, organizational resistance to change, and a shortage of technical expertise among company leaders (Faiz et al., 2024). Therefore, this wave of digital technology transformation affects firm operations and costs across the board, but these effects are likely to vary across firms.

Following prior research (Rajgopal et al., 2023), we partition our sample firms into three sub-samples based on technology levels: digital, stable, and low technology industries. Our final sample comprises 49,275 firm-year observations from 2010 to 2023: 15,055 in digital technology industries, 16,569 in stable industries, and 17,651 in low-technology industries. This study examines and compares cost stickiness in firms in industries with different levels of technology. We focus on selling, general, and administrative (SG&A) costs, and show that SG&A costs vary significantly across technology levels and are stickier in digital technology firm than the other firms. In contrast, such a stickiness pattern is not observed for cost of goods sold (COGS), another important operating cost. The results suggest that technological intensity affects different cost components in distinct ways.

This study contributes to the growing literature on the effects of technological disruption on corporate governance, accounting systems, and firm performance. Several accounting researchers highlight that limited attention has been paid to how new technologies reshape governance and accounting structures (Brennan et al., 2019) and call for further accounting research in the digital era (Ke, 2024). Our study adds to the current discussion on the potential benefits of digital technology by providing empirical evidence on how differences in technological adoption influence firms' cost dynamics, particularly reflected in SG&A cost behavior. Our study helps understand whether digital technology benefits the financial outcome. First, we observe that firms in digital technology industries demonstrate significantly higher SG&A intensity compared to low and stable technology industries. Second, we show that SG&A cost stickiness is strongest among digital technology firms. Third, we find that this pattern is not as prominent for COGS, suggesting that digital technology primarily affects discretionary operating costs rather than production expenses.

2. Literature Review and Hypotheses

2.1. Digital Transformation and Accounting

Accounting has evolved alongside technological advancements. Since the invention of computers, accounting has increasingly become a computer-driven information system, with the widespread adoption of information technologies such as accounting information systems, databases, and enterprise resource planning (ERP) systems. These technologies have transformed accounting from manual processing of accounting information to computer-based processing. Recently, digital transformation has gone beyond simple automation and systemization to encompass the entire organization and its business processes. The emergence of digital technologies is even more groundbreaking in this regard.

Digital technology, also known as smart technology, encompasses recent developments such as big data, artificial intelligence, machine learning, deep learning, blockchain, the Internet of Things (IoT), and cloud computing. These technologies are beginning to shape accounting and other business functions in fundamentally transformative and revolutionary ways. Brennan et al. (2019) provide an overview of disruptive technology and innovations in corporate governance and predict that the entire system of production, management, and governance will be changed by this “fourth industrial revolution.” Building on this perspective, Ke (2024) argues that digital transformation gives rise to intelligent business management, which transforms traditional accounting practices into intelligent accounting methodologies. With the help of digital transformation, complex managerial tasks can now become more autonomous, enabling accounting systems to move beyond recording and reporting to prediction, optimization, and decision support.

A growing volume of empirical accounting research has examined the perceived benefits of digital transformation in managing and controlling business activities. Some notable and perceivable benefits are that digital value chains and digitally enabled business models speed up information processing, improve operational efficiency, and create new revenue opportunities (Kraus et al., 2022). For instance, Li et al. 2025 (2025) find that digital technology significantly improves a firm’s financing conditions by lowering the cost of capital and expanding access to external funds and suggest that digital technology can mitigate financial frictions and improve capital allocation efficiency. A survey study shows that digitalization, particularly big data analytics, improve a firm’s decision-making, operational efficiency, and competitive advantage (Wamba et al., 2017).

However, empirical evidence on digitalization’s financial performance benefit is generally inconclusive (Chen & Srinivasan, 2024; Rajgopal et al., 2023; Yavuz et al., 2025). Yavuz et al. (2025) show, in a small sample, that a digitalization return measure based on net sales and number of employees is positively related to financial performance measures, such as return on assets. Chen and Srinivasan (2024) examine non-tech digital adopters and find no significant improvement in return on assets. Rajgopal et al. (2023) show that, compared to non-digital industry firms, digital industry firms appear to earn excess profits only when performance is measured using the internal rate of return, rather than traditional accounting-based measures, such as return on assets or return on invested capital. Moreover, Rajgopal et al. (2023) are unable to determine whether these higher returns stem from digital innovation or from increased market power.

While these studies may find it challenging to consistently capture the financial benefits of digital transformation, they all either directly point out or allude to the fact that understanding how digitalization reshapes firms’ cost structures is critical for evaluating the overall financial consequences. Both Yavuz et al. (2005) and Rajgopal et al. (2003) point out that the cost of

investments contribute to the uncertainty of digitalization's benefits on the firm financial performance. Indirectly, Chen and Srinivasan (2024) find that there is a significant decline in margins, which suggest that digital technology adopters may face increased costs.

2.2. Digitalization and Firm Cost Structures

Businesses worldwide are investing substantial financial resources in digitalization. However, the extent of digital technology adoption varies widely across firms, leading to significant differences in digitalization-related spending. For firms that are ready on the technology front, the shift can be drastic, as evidenced by the rising and substantial capital expenditures on digital technology by tech giants. The four major firms, Amazon, Google, Meta, and Microsoft, expect to spend nearly \$670 billion in AI infrastructure and data centers in 2026 ("The Cost of AI Efforts Tops Moon Landing -- WSJ," 2026). Moreover, digital firms are more likely than others to invest in developing proprietary technologies that enable other businesses to scale up technology adoption. For example, Amazon provides Amazon Web Services, and Microsoft offers Azure, allowing firms to digitalize without making large direct investments in data infrastructure.

In contrast, more traditional firms are less likely to invest heavily in developing technologies directly. Instead, they often take a more holistic approach to revamping how their businesses operate in a digital environment. This process typically begins with smaller investments in the digitalization of specific business functions, such as manufacturing or sales, or in certain transaction cycles, and then scales up over time. These costs are often concentrated more on technology consulting and implementation, and less on investments in internal digital capabilities, including labor training (Brynjolfsson et al., 2017).

Digital investment does not always produce the expected revenue growth or productivity in the short run, and this phenomenon is called the digital paradox (Brynjolfsson et al., 2017; Zeng et al., 2022). The paradox of digitalization is different for digital and non-digital firms, as costs are different. Digital technologies change the cost structure of running a business by shifting from physical inputs to intangible and technology-driven inputs, and from relatively linear business operations expenditures toward higher upfront costs for data infrastructure and organizational transformation. Moreover, digital firms are more likely to spend high fixed costs and low variable costs (Chen & Srinivasan, 2024). According to Chen and Srinivasan (2023), new technology adoption entails high implementation costs, and the benefits are often delayed. Some research further indicates that cost reductions may not improve productivity (Li et al., 2025). Actually, some suggest that the digital investment benefits are a function of technology fit; for example, the study by Wang et al. (2025) show that savings from implementing robotic process automation or enterprise systems depend on the transaction volume and business complexity. Such cost differences and benefit disparities are more pronounced in digital firms, as they face higher initial costs and potentially a longer period to implement the technology system.

2.3. Accounting Treatment of Digital Costs in SG&A and Hypotheses

Given these changes in cost structure, an important and related question is how financial accounting captures digitalization-related expenditures. Because technology evolves much faster than accounting rules, current financial accounting systems struggle to measure accurately the costs of digital technology, as many technology-related investments are treated as period expenses rather than capitalized assets. This accounting treatment further exacerbates differences in digitalization costs across firms, particularly as reflected in SG&A expenses.

Under the current U.S. GAAP framework, the primary accounting standards governing technology-related costs are ASC 350 - 40 (Intangibles - Goodwill and Other - Internal-Use Software) and ASC 350 - 50 (Intangibles - Goodwill and Other - Website Development Costs). On September 18, 2025, the Financial Accounting Standards Board (FASB) issued ASU 2025 - 06 to modernize ASC 350 - 40 and ASC 350 - 50, which are no longer current for technology accounting. The ASU 2025 - 06 is effective for annual periods beginning after December 15, 2027. Under ASC 350, software development costs for internal-use software can be capitalized once the preliminary project stage is completed. Under ASU 2025-06, such costs may be capitalized earlier, once management authorizes and commits to funding a software project. Costs incurred during the preliminary planning and the post-implementation stage are expensed as SG&A. Determining whether costs should be capitalized or expensed requires significant managerial judgment. Moreover, for the technology firms that develop and sell software externally, ASC 985-20 Software- Costs of Software to Be Sold, Leased, or Marketed (External Use Software) also requires the software maintenance costs to be expensed in SG&A.

Rajgopal et al. (2023) argue that assessing the profitability of digital firms is inherently challenging due to the accounting treatment of intangible investments. Under U.S. GAAP, expenditures on internally developed intangibles, such as R&D, software, data analytics, and organizational capabilities, are largely expensed as incurred, distorting the matching of expenses and revenues, and biasing reported earnings downward. Consequently, conventional performance measures (e.g., return on assets and profit margins) tend to understate economic profitability while overstating cost intensity. This treatment also widens the gap between book and market values for firms reliant on intangible capital.

In digital firms, SG&A increasingly incorporates investments in technology, data infrastructure, and human capital in the operational process rather than routine overhead (Rajgopal et al., 2022). At the same time, digital technologies reshape administrative functions by automating routine tasks and shifting costs toward technology-enabled accounting systems and corporate governance infrastructures (Brennan et al., 2019). Together, these changes blur the traditional distinction between SG&A and production costs, suggesting that cost classifications may systematically differ between digital and non-digital firms. We therefore expect that digital technology firms will have a systematically different cost structure compared to non-digital firms, i.e., a higher proportion of SG&A expenses relative to COGS.

Hypothesis 1. Digital technology firms exhibit a higher ratio of SG&A expenses to COGS than non-digital firms.

Digital and non-digital firms differ in how they adopt and deploy digital technologies, which affects their ability to adjust costs. Digital technology firms rely more heavily on digital resources, such as software, data infrastructure, and data analytics tools, which are typically reflected in SG&A expenses rather than in physical assets recorded as cost of sales. These investments often involve higher adjustment costs and are less easily scaled down in the short run. In contrast, non-digital firms are more likely to purchase digital services without making substantial infrastructure investments, resulting in costs that are more variable and closely tied to current business activity. As a result, SG&A expenses are expected to be stickier in digital firms.

Unlike SG&A expenses, COGS primarily reflects variable production inputs such as direct materials, direct labor, and other costs of providing services and goods, which are more closely tied to contemporaneous sales volume. Even in digital technology firms, these costs are probably

less affected by digital transformation. Therefore, the degree of cost stickiness in COGS is not expected to differ systematically between digital technology firms and non-digital firms.

Hypothesis 2a. The cost stickiness of SG&A differs between digital technology and non-digital firms.

Hypothesis 2b. The cost stickiness of COGS is similar between digital technology and non-digital firms.

3. Sample and Results

We first obtain initial data from Compustat for the period from 2010 to 2023, including six-digit GICS industry (GIND) codes. Following Rajgopal et al. (2023), we used these codes to classify industries into three firm types: low technology, stable technology, and digital technology. The detailed mapping of GICS industries to each type is presented in Appendix A. This classification leverages the Global Industry Classification Standard (GICS), which prior research shows improved identification of technology-oriented firms (Kile & Phillips, 2009). Low technology firms include industries such as food, beverages, retail, hospitality, and household-related products. Stable technology firms primarily operate in sectors related to energy and natural resources, chemicals, transportation, equipment, and machinery. Digital technology firms consist of industries such as internet services, software, information technology, semiconductors, and communication services. Further, we deleted the top and bottom 1 percent of the extreme variables used in the empirical regression models.

Table 1 presents descriptive statistics of the key financial measures of the firms in the three technology types. The final sample consists of 49,275 firm-year observations for the period from 2010 to 2023. There are 17,651 observations from the low technology industries, 16,569 from the stable technology industries, and 15,055 from the digital technology industry. Of the three types of technology levels, stable technology firms tend to be the largest in terms of average assets and average sales. Stable technology firms also exhibit higher asset intensity (AINT = 0.54), whereas low technology firms have much lower asset intensity (AINT = -0.02). This suggests that low technology firms operate with higher asset turnover.

Table 1 Sample Descriptives

Tech Level	N	Mean	Standard Deviation	25 th Percentile	Median	75 th Percentile
Low						
Assets	17,651	4,987.92	16,247.87	205.07	879.86	3,388.97
Sales	17,651	5,083.16	20,672.76	206.50	966.11	3,512.10
SG&A	17,651	1,055.93	5,027.52	40.36	181.50	633.22
COGS	17,651	3,401.14	14,528.07	118.03	599.92	2,192.05
XOPR	17,651	4,457.00	18,958.32	186.33	834.96	2,998.00
Operating Income	17,651	456.64	1,621.51	3.02	58.74	292.38
Net Income	17,651	262.88	1,205.57	-1.99	22.00	147.80
AINT	17,651	-0.02	0.71	-0.50	-0.11	0.39
EINT	17,651	-5.53	0.97	-6.15	-5.56	-4.94
Stable						
Assets	16,569	10,399.22	40,604.70	198.79	1,078.12	4,515.70

Sales	16,569	7,124.72	29,492.49	110.23	616.07	2,837.19
SG&A	16,569	692.61	2,625.86	16.30	64.20	286.98
COGS	16,569	5,335.28	23,666.43	69.87	396.48	1,935.20
XOPR	16,569	6,027.89	25,648.02	93.85	476.77	2,327.00
Operating Income	16,569	607.56	2,895.12	-2.92	35.61	285.00
Net Income	16,569	350.02	2,333.45	-12.48	10.18	142.79
AINT	16,569	0.54	0.84	-0.04	0.41	1.06
EINT	16,569	-6.09	1.08	-6.68	-5.90	-5.43
Digital						
Assets	15,055	6,124.07	26,476.77	75.04	403.03	2,141.44
Sales	15,055	3,538.14	14,650.91	60.73	287.92	1,314.10
SG&A	15,055	886.22	3,488.73	25.33	109.88	416.98
COGS	15,055	1,776.80	7,437.46	25.62	118.47	584.37
XOPR	15,055	2,663.02	10,340.00	61.33	260.31	1,096.21
Operating Income	15,055	551.70	3,579.74	-5.29	6.80	116.92
Net Income	15,055	352.52	2,900.28	-13.74	1.20	57.87
AINT	15,055	0.35	0.69	-0.06	0.35	0.73
EINT	15,055	-5.58	0.80	-6.05	-5.58	-5.13

The final sample comprises 49,275 firm-year observations from 2010–2023: 17,651 in low-technology industries, 16,569 in stable industries, and 15,055 in digital-technology industries.

Variable definitions (Compustat items in parentheses and in \$ millions):

Assets (AT): total assets.

Sales (SALE): net sales.

SG&A (XSGA): selling, general, and administrative expense.

COGS (COGS): cost of goods sold.

XOPR (XOPR): total operating expenses.

Operating income (OIADP): operating income after depreciation.

Net income (IB): income before extraordinary items.

AINT: asset intensity, computed as the log-ratio of total assets to sales.

EINT: employee intensity, calculated as the log-ratio of the number of employees to sales.

In Table 2 Panel A, to compare SG&A intensity across the low, stable, and digital technology samples, we present the ANOVA results of testing three SG&A ratios across the three technology level samples. The ratio of SG&A to XOPR (which is total operating expenses, the sum of COGS and SG&A) is significantly different across the three samples with F value = 6808.76 and p-value <0.0001, and 21.65% of the variance of the ratio can be explained by the different technological levels. The SG&A to Sales revenue ratio is also significant with F value = 124.78 and p-value <0.0001, but a low R-square suggests that only 0.53% of variance can be explained by the different technological levels. The SG&A to OAI DP (which is operating income) ratio is not significantly different with F value = 1.67 and p-value = 0.1884, and the R-square is low. Overall, these results suggest that digital firms exhibit higher SG&A intensity relative to both sales and total operating costs, while profitability-adjusted measures show no significant group differences. Panel B reports similar comparisons of the cost of goods (COGS) based ratios. Both

the COGS to XOPR ratio and the COGS to Sales ratio differ significantly across technology groups ($p < 0.0001$), whereas the COGS to Operating Income ratio shows no significant difference ($F = 0.57$, $p\text{-value} = 0.5658$). These patterns mirror those of SG&A: cost structure differences across technology levels are evident when costs are scaled by operating activity but not when scaled by operating income.

Table 2 SG&A and COGS Ratios of the Low, Stable, and Digital Technology Samples – ANOVA Test

Panel A SG&A ratios

Ratios	Tech Level	N	Mean	R-Square	F-Test	Prob.
SG&A to XOPR ratio	Low	17,651	0.2933	0.2165	6,808.76***	<0.0001
	Stable	16,569	0.2132			
	Digital	15,055	0.4768			
SG&A to Sales ratio	Low	17,651	0.3610	0.0053	124.78***	<0.0001
	Stable	16,569	0.3548			
	Digital	15,055	0.6050			
SG&A to OIADP ratio	Low	17,651	1.8512	0.0001	1.67	0.1884
	Stable	16,569	0.9533			
	Digital	15,055	3.6170			

Panel B COGS Ratios

Ratios	Tech Level	N	Mean	R-Square	F-Test	Prob.
COGS to XOPR ratio	Low	17,651	0.7081	0.1938	5,920.79***	<0.0001
	Stable	16,569	0.7867			
	Digital	15,055	0.5231			
COGS to Sales ratio	Low	17,651	0.6474	0.0316	803.82***	<0.0001
	Stable	16,569	0.7440			
	Digital	15,055	0.3754			
COGS to OIADP ratio	Low	17,651	9.2911	0.0000	0.57	0.5658
	Stable	16,569	6.0889			
	Digital	15,055	6.2679			

SG&A to XOPR, SG&A to Sales, and SG&A to OIADP ratios are the selling, general, and administrative expenses relative to total operating expenses, total sales, and total operating income.

COGS to XOPR, COGS to Sales, and COGS to OIADP ratios are the cost of goods sold relative to total operating expenses, total sales, and total operating income.

We use the two models in Anderson et al. (2003) to examine the cost behavior. The two models, simple ABJ model and the extended ABJ model, are specified as follows:

$$\Delta \ln COST_{i,t} = \beta_0 + \beta_1 \Delta \ln SALES_{i,t} + \beta_2 DEC_{i,t} \Delta \ln SALES_{i,t} + \varepsilon_{i,t} \quad (1)$$

$$\Delta \ln COST_{i,t} = \beta_0 + \beta_1 \Delta \ln SALES_{i,t} + (\beta_2 + \gamma_1 SUCCDEC_{i,t} + \gamma_2 \Delta GDP_t + \gamma_3 AINT_{i,t} + \gamma_4 EINT_{i,t}) DEC_{i,t} \Delta \ln SALES_{i,t} + \varepsilon_{i,t} \quad (2)$$

In both models, $\Delta \ln COST_{i,t}$ is the log change in costs (i.e., SG&A or COGS) of firm i in year t ; $\Delta \ln SALES_{i,t}$ is the log change in sales revenue; $DEC_{i,t}$ is a sales decrease dummy, equal to 1 if $\Delta \ln SALES_{i,t} < 0$ and 0 otherwise; and $\varepsilon_{i,t}$ is an error term. In the extended model, $SUCCDEC_{i,t}$ is a dummy variable for successive sales decreases, equal to 1 if sales decreased both in period t and in period $t-1$ (i.e., $DEC_{i,t} = DEC_{i,t-1} = 1$), and 0 otherwise; ΔGDP_t is the GDP growth rate; $AINT_{i,t}$ is asset intensity, computed as the log ratio of total assets to sales; $EINT_{i,t}$ is employee intensity, computed as the log ratio of the number of employees to sales. Table 3 presents the correlation matrix of the variables used in the cost stickiness regression.

Table 3 Correlation Matrix of the Variables in the ABJ Models

Coefficients with p-values in parentheses

Variable	$\Delta \ln SG\&A$	$\Delta \ln COGS$	$\Delta \ln SALES$	DEC	AINT	EINT	SUCCDEC	ΔGDP	Industry D
$\Delta \ln SG\&A$	1	0.428	0.528	-0.383	0.06	-0.014	-0.268	0.175	0.02
		(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.000)	(0.000)	(0.000)
$\Delta \ln COGS$	0.428	1	0.7	-0.461	0.035	-0.051	-0.308	0.168	0.015
	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
$\Delta \ln SALES$	0.528	0.7	1	-0.633	0.006	-0.06	-0.382	0.233	0.015
	(0.000)	(0.000)		(0.000)	(0.190)	(0.000)	(0.000)	(0.000)	(0.001)
DEC	-0.383	-0.461	-0.633	1	0.043	0.031	0.585	-0.245	0.018
	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
AINT	0.06	0.035	0.006	0.043	1	-0.01	0.028	-0.011	0.201
	(0.000)	(0.000)	(0.190)	(0.000)		(0.026)	(0.000)	(0.013)	(0.000)
EINT	-0.014	-0.051	-0.06	0.031	-0.01	1	0.059	-0.036	-0.031
	(0.003)	(0.000)	(0.000)	(0.000)	(0.026)		(0.000)	(0.000)	(0.000)
SUCCDEC	-0.268	-0.308	-0.382	0.585	0.028	0.059	1	-0.113	0.015
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.001)
ΔGDP	0.175	0.168	0.233	-0.245	-0.011	-0.036	-0.113	1	-0.004

	(0.000)	(0.000)	(0.000)	(0.000)	(0.013)	(0.000)	(0.000)		(0.347)
Industry D	0.02	0.015	0.015	0.018	0.201	-0.031	0.015	-0.004	1
	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.347)	

Variable definitions: $\Delta \ln \text{SG\&A}$ ($\Delta \ln \text{COGS}$) is the log-change in SG&A (COGS); $\Delta \ln \text{SALES}$ is the log-change in sales revenue; DEC is a sales decrease dummy, equal to 1 if $\Delta \ln \text{SALES} < 0$ and 0 otherwise; SUCCDEC is a dummy variable for successive sales decreases, equal to 1 if sales decreased both in period t and in period $t-1$ (i.e., $\text{DEC}_{i,t} = \text{DEC}_{i,t-1} = 1$), and 0 otherwise; ΔGDP is the GDP growth rate; AINT is asset intensity, computed as the log-ratio of total assets to sales; EINT is employee intensity, calculated as the log-ratio of the number of employees to sales; IndustryD is a categorical variable, where 1 denotes low-tech firms, 2 denotes stable firms, and 3 denotes digital technology firms.

Table 4 presents the regression results of the cost stickiness of SG&A. Panel A presents the results of estimating the simple Anderson et al. (2003) cost stickiness model for the full and different subsamples. For the full sample, the coefficient on sales increases ($\Delta \ln \text{SALES}$) is 0.4707, indicating that SG&A costs rise by about 0.46% for every 1% increase in sales. The negative coefficient on the interaction term ($\Delta \ln \text{SALES} \times \text{DEC} = -0.1113$, $t = 7.62$) confirms the presence of cost stickiness - costs decrease less when sales fall than they increase when sales rise. This cost stickiness exists in all subsamples with varying magnitudes: the digital technology subsample shows the strongest stickiness (-0.2126), while the stable technology subsample exhibits the weakest (-0.0419).

Table 4 Panel B presents the SG&A cost stickiness results for estimating the extended Anderson et al. (2003) model. Panel B adds firm- and macro-level moderators to the ABJ framework. For the full sample, the interaction term ($\Delta \ln \text{SALES} \times \text{DEC}$) is small and only marginally significant (-0.0886, $t = -1.86$), indicating that stickiness is largely conditional on firm characteristics and conditions. The digital subsample continues to show the strongest stickiness (-0.6779, $t = -6.03$), the stable technology subsample does not show stickiness with a positive coefficient instead (0.1249), and the low technology subsample shows stickiness (-0.3514, $t = 2.93$). Relative to Panel A, cross-subsample differences in stickiness are amplified in Panel B.

Table 4 SG&A Cost Stickiness Regression

Panel A Simple ABJ Model

	Full Sample	Low	Stable	Digital
Intercept	0.0254 (18.40)	0.0213 (10.09)	0.0282 (11.02)	0.0208 (7.87)
$\Delta \ln \text{SALES}$	0.4707 (48.14)	0.5746 (29.79)	0.3591 (26.41)	0.5557 (29.65)
$\Delta \ln \text{SALES} \times \text{DEC}$	-0.1113 (-7.62)	-0.1112 (-3.85)	-0.0419 (-2.01)	-0.2126 (-7.35)
N	49,275	17,651	16,569	15,055
Adj. R-square	0.2814	0.3709	0.2078	0.3294

Panel B Extended ABJ Model

	Full Sample	Low	Stable	Digital
Intercept	0.0289 (20.31)	0.0247 (11.39)	0.0309 (11.90)	0.0246 (8.86)
$\Delta \ln \text{SALES}$	0.4638 (47.12)	0.5667 (29.09)	0.3542 (25.86)	0.5475 (28.91)
$\Delta \ln \text{SALES} \times \text{DEC}$	-0.0886 (-1.86)	-0.3514 (-2.93)	0.1249 (2.01)	-0.6779 (-6.03)
$\text{AINT} * \Delta \ln \text{SALES} \times \text{DEC}$	-0.1170 (-12.63)	-0.1111 (-5.17)	-0.0873 (-7.41)	-0.1040 (-4.64)
$\text{EINT} * \Delta \ln \text{SALES} \times \text{DEC}$	-0.0101 (-1.30)	-0.0583 (-2.81)	0.0169 (1.78)	-0.0998 (-4.84)
$\text{SUCCDEC} * \Delta \ln \text{SALES} \times \text{DEC}$	0.1185 (7.02)	0.0926 (2.59)	0.1078 (4.83)	0.1657 (5.03)
$\text{GDP} * \Delta \ln \text{SALES} \times \text{DEC}$	-0.0161 (-5.62)	-0.0234 (-4.06)	-0.0089 (-2.33)	-0.0272 (-4.38)
N	49,275	17,651	16,569	15,055
Adj. R-square	0.2924	0.3830	0.2151	0.3474

The variables are as described in Table 3.

COGS and SG&A are two major components of a firm's operating costs (Novy-Marx, 2011), and SG&A is much stickier than COGS since COGS resembles variable costs and changes with sales (Hwang, 2023). Managers have more discretion over SG&A than COGS. Thus, we also examine the stickiness of COGS to contrast with SG&A.

Table 5 presents the results of the COGS stickiness regression. Panel A is the simple ABJ model, and Panel B is the extended ABJ model. In Panel A, the stickiness coefficient for COGS is modest in the full sample ($\Delta \ln \text{Sale} \times \text{DEC} = -0.0632$, $t = -3.29$), the stable technology group shows the largest stickiness (-0.0819 , $t = -2.59$), the low-technology group is slightly negative but not significant (-0.0363 , $t = -1.36$), and the digital group is effectively zero (-0.0061 , $t = -0.16$). In Panel B, the full sample does not show stickiness, i.e., the stickiness coefficient is positive and significant instead ($\Delta \ln \text{Sale} \times \text{DEC} = 0.4999$, $t = 6.00$); the low technology subsample remains significantly sticky (-0.2782 , $t = -2.24$), the stable technology subsample is significantly anti-sticky (0.8274 , $t = 6.90$), and the digital technology subsample is negative but only marginally significant (-0.3118 , $t = -1.67$). Overall, COGS shows limited evidence of cost stickiness. Moreover, whereas SG&A's stickiness is consistent across models (strongest in digital, weakest in stable), the COGS results do not exhibit a similar, consistent pattern across subsamples.

Table 5 COGS Cost Stickiness Regression

Panel A Simple ABJ Model

	Full Sample	Low	Stable	Digital
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Intercept	0.0086 (5.27)	0.0008 (0.44)	0.0160 (4.54)	0.0078 (2.49)
$\Delta \ln \text{SALES}$	0.8402 (79.06)	0.9352 (58.69)	0.7510 (41.66)	0.8871 (49.24)
$\Delta \ln \text{SALES} \times \text{DEC}$	-0.0632 (-3.29)	-0.0363 (-1.36)	-0.0819 (-2.59)	-0.0061 (-0.16)
N	49,275	17,651	16,569	15,055
Adj. R-square	0.4911	0.7476	0.3408	0.6103

Panel B Extended ABJ Model

	Full Sample	Low	Stable	Digital
Intercept	0.0123 (7.24)	0.0033 (1.85)	0.0209 (5.73)	0.0103 (3.28)
$\Delta \ln \text{SALES}$	0.8328 (77.46)	0.9292 (56.98)	0.7424 (40.64)	0.8819 (48.82)
$\Delta \ln \text{SALES} \times \text{DEC}$	0.4999 (6.00)	-0.2782 (-2.24)	0.8274 (6.90)	-0.3118 (-1.67)
$\text{AINT} * \Delta \ln \text{SALES} \times \text{DEC}$	-0.1608 (-10.42)	-0.0631 (-2.72)	-0.1918 (-7.89)	-0.0657 (-2.00)
$\text{EINT} * \Delta \ln \text{SALES} \times \text{DEC}$	0.0859 (6.29)	-0.0510 (-2.47)	0.1330 (6.91)	-0.0671 (-2.13)
$\text{SUCCDEC} * \Delta \ln \text{SALES} \times \text{DEC}$	0.1559 (5.42)	0.0400 (1.21)	0.2492 (5.33)	0.0924 (1.74)
$\text{GDP} * \Delta \ln \text{SALES} \times \text{DEC}$	-0.0048 (-1.12)	0.0075 (1.27)	-0.0040 (-0.57)	-0.0190 (-2.62)
N	49,275	17,651	16,569	15,055
Adj. R-square	0.5015	0.7476	0.3652	0.6103

The variables in Table 5 are as described in Table 3.

4. Conclusions

This study uses a relatively large sample over an extended period to examine the relationship between digital technology and firm cost structures and behaviors. The results show that digital technology firms exhibit higher SG&A cost intensity and greater SG&A cost stickiness than traditional firms. These findings contribute to a better understanding of technology's impact on business operations and provide insight into how profits are reflected in accounting systems. In the digital era, when firms continue to invest substantial capital in digital technology to remain competitive, our evidence on SG&A cost differences across firms with varying levels of digitalization is therefore timely and relevant for both practitioners and researchers.

A limitation of this study is that it relies on industry-based classifications as proxies for firms' levels of digital technology, rather than using firm-level measures of technology adoption. Firms within the same industry classification could potentially differ substantially in their actual level of digital transformation, attenuating the observed relationships between digitalization and cost behavior. Future research could address this limitation by employing approaches such as textual analysis to capture firm-specific digital technology adoption. In addition, future studies could examine the impact of recent accounting standard updates, such as ASU 2025-06, on firms' cost structures.

Appendix A

Tech level	Industry	GIND
Low Technology	Construction Materials	151020
Low Technology	Containers & Packaging	151030
Low Technology	Paper & Forest Products	151050
Low Technology	Building Products	201020
Low Technology	Construction & Engineering	201030
Low Technology	Trading Companies & Distributors	201070
Low Technology	Commercial Services & Supplies	202010
Low Technology	Professional Services	202020
Low Technology	Household Durables	252010
Low Technology	Leisure Products	252020
Low Technology	Textiles, Apparel & Luxury Goods	252030
Low Technology	Hotels, Restaurants & Leisure	253010
Low Technology	Diversified Consumer Services	253020
Low Technology	Distributors	255010
Low Technology	Multiline Retail	255030
Low Technology	Specialty Retail	255040
Low Technology	Food & Staples Retailing	301010
Low Technology	Beverages	302010
Low Technology	Food Products	302020
Low Technology	Tobacco	302030
Low Technology	Household Products	303010
Low Technology	Personal Products	303020
Stable Technology	Energy Equipment & Services	101010
Stable Technology	Oil, Gas & Consumable Fuels	101020
Stable Technology	Chemicals	151010
Stable Technology	Metals & Mining	151040
Stable Technology	Aerospace & Defense	201010
Stable Technology	Electrical Equipment	201040
Stable Technology	Industrial Conglomerates	201050
Stable Technology	Machinery	201060
Stable Technology	Air Freight & Logistics	203010
Stable Technology	Airlines	203020
Stable Technology	Marine	203030
Stable Technology	Road & Rail	203040
Stable Technology	Transportation Infrastructure	203050
Stable Technology	Auto Components	251010
Stable Technology	Automobiles	251020
Digital Technology	Internet & Direct Marketing Retail	255020
Digital Technology	Internet Software & Services	451010
Digital Technology	Information Technology Services	451020
Digital Technology	Software	451030
Digital Technology	Communications Equipment	452010

Digital Technology	Technology Hardware, Storage & Peripherals	452020
Digital Technology	Electronic Equipment, Instruments & Components	452030
Digital Technology	Semiconductor Equipment & Products	453010
Digital Technology	Diversified Telecommunication Services	501010
Digital Technology	Wireless Telecommunication Services	501020
Digital Technology	Media	502010
Digital Technology	Entertainment	502020
Digital Technology	Interactive Media & Services	502030

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