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"Does Digital Transformation Pay Off? Disentangling Customer-Facing and Back-Office Digitalization Effects on Bank Financial Performance in Saudi Arabia"

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Abstract:

This study investigates whether digital transformation improves bank financial performance in Saudi Arabia, distinguishing between customer-facing digitalization (POS_SHARE) and back-office technology investment (TECH_INV). Using a balanced panel of ten listed banks over sixty quarters (2010Q1–2024Q4) with fixed effects regression, wild cluster bootstrap, Driscoll–Kraay standard errors, and IV-2SLS, results show that both dimensions significantly improve equity-based returns. Customer-facing digitalization generates substantially larger effects on return on equity ($\beta = 46.315$, $p < 0.001$) than back-office investment ($\beta = 14.607$, $p < 0.01$), confirmed in a combined model. Saudi Vision 2030 is associated with amplified back-office returns (institutional complementarity) and diminished customer-facing returns (competitive convergence). The study contributes to resolving the IT productivity paradox by demonstrating that disaggregating digital transformation reveals mechanism-specific, institution-contingent financial returns amplified by banking leverage. Additional analysis shows that the post-2016 period—coinciding with Saudi Vision 2030 implementation—correlates with larger back-office returns through institutional complementarity, while customer-facing returns appear to diminish as adoption became widespread. These findings offer actionable guidance for bank executives allocating digital transformation budgets and for policymakers designing institutional reforms to maximise the financial returns from digital investment in emerging markets.

Keywords: Digital transformation, Bank financial performance, transaction cost economics, Disruptive innovation, Saudi Vision 2030, IT productivity paradox

JEL Classification: G21; O33; L25; O16; O53

ملخص البحث:

تبحث هذه الدراسة في مدى تأثير التحول الرقمي على الأداء المالي للبنوك في المملكة العربية السعودية، مع التمييز بين بُعدين رئيسيين: الرقمنة الموجَّهة نحو العميل (POS_SHARE)، والاستثمار في التقنية الداخلية (TECH_INV). واستناداً إلى بيانات بانل متوازن يشمل عشرة بنوك مدرجة في بورصة تداول على مدى ستين ربعاً (Q1–2024Q42010)، وباستخدام نموذج التأثيرات الثابتة، وإعادة التحقق بأسلوب Wild Cluster Bootstrap، ومعياري خطأ Driscoll-Kraay، وتقنية المتغيرات الأداتية IV-2SLS؛ تكشف النتائج أن كلا البُعدين يُحسِّنان العوائد القائمة على حقوق الملكية تحسيناً ذا دلالة إحصائية. وتُولِّد الرقمنة الموجَّهة نحو العميل آثاراً أكبر بكثير على العائد على حقوق الملكية ($\beta = 46.315$، $p < 0.001$) مقارنةً بالاستثمار في التقنية الداخلية ($\beta = 14.607$، $p < 0.01$)، وهو ما أكّده النموذج الجامع. ويرتبط برنامج رؤية السعودية 2030 بتضخيم عوائد الاستثمار في التقنية الداخلية (التكامل المؤسسي)، وتراجع عوائد الرقمنة الموجَّهة نحو العميل (تقارب تنافسي). وتُسهم الدراسة في حلّ مفارقة إنتاجية تقنية المعلومات، إذ تُبيِّن أن تفكيك مؤشر التحول الرقمي يكشف عن عوائد مالية خاصة بكل آلية، مشروطة بالسياق المؤسسي، ومُضخَّمة بأثر الرافعة المالية المصرفية. وتقدّم هذه النتائج توجيهات عملية لمديري البنوك في تخصيص ميزانيات التحول الرقمي، وللجهات الرقابية في تصميم إصلاحات مؤسسية تُعظِّم العوائد المالية من الاستثمار الرقمي في الأسواق الناشئة.

الكلمات المفتاحية: التحول الرقمي، الأداء المالي للبنوك، اقتصاديات تكاليف المعاملات، الابتكار التخريبي، رؤية السعودية 2030، مفارقة إنتاجية تقنية المعلومات.

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Public Interest Statement

Banks across the Gulf Cooperation Council and the broader emerging-market world are investing billions of dollars annually in digital technologies, yet it remains unclear whether these investments genuinely improve financial performance or merely keep pace with competitors. This study examines all ten Saudi Arabian banks listed on the Tadawul stock exchange over fifteen years—from the early days of electronic payments in 2010 through the transformative years of Saudi Vision 2030 to 2024—to answer a deceptively simple question: does going digital pay off?

The findings reveal that the answer depends critically on the type of digital investment. Technologies that customers interact with directly, such as point-of-sale payment systems and digital transaction channels, generate substantially larger financial returns than internal back-office upgrades. Moreover, the Vision 2030 policy programme amplified the returns from back-office investment while narrowing the advantage of early digital adopters in customer-facing channels. For bank executives, the practical implication is clear: the allocation of the digital technology budget matters as much as its total size. For policymakers in emerging markets, the results demonstrate that institutional reforms designed to accelerate digital adoption can meaningfully increase the financial returns that banks capture from technology investment.

1. Introduction

The global banking sector is undergoing a profound digital transformation that is reshaping the production, distribution, and consumption of financial services (Gomber et al., 2018; Thakor, 2020). Saudi Arabia, the largest banking sector in the Gulf Cooperation Council in terms of total assets (Alqahtani & Mayes, 2018), has seen this change accelerated by Saudi Vision 2030, which specifically targets a cashless society and a digitally enabled financial industry (Saudi Vision 2030, 2016). By 2023, electronic payment transactions increased to more than 62 percent of total transactions, whereas technology spending reached over SAR 12 billion per annum compared to less than 20 percent of total transactions in 2015 (SAMA, 2023). Although such investments have been made, research on the effect of digital transformation on bank financial performance remains fragmented, underdeveloped, and largely confined to developed-market contexts (Vial, 2019; Boot et al., 2021).

The information technology and bank performance studies have produced inconclusive results, a phenomenon formalised as the productivity paradox by Brynjolfsson (1993). Beccalli (2007) found no significant relationship between IT investment and European bank performance. According to Scott et al. (2017), efficiency improvements were recorded following SWIFT adoption, but the analysis was limited to a single technology. Fuster et al. (2019) established cost savings in fintech mortgage banking in the US. DeYoung et al. (2007) documented cost advantages for internet-active banks. A critical limitation of the existing literature is its treatment of digital transformation as unidimensional, which obscures the possibility that different dimensions operate through distinct mechanisms and yield different returns.

This study fills these gaps by separating customer-facing digitalization (POS_SHARE: POS terminal transactions as a share of overall bank transactions) and investment in back-office technologies (TECH_INV: IT expenditure as a share of operating expenses). Its theoretical basis is grounded in transaction cost economics (Williamson, 1985; Coase, 1937) and disruptive innovation theory (Christensen, 1997) supplemented by the resource-based perspective, which holds that different technology investments generate value through distinct pathways (Mata et al., 1995; Bharadwaj, 2000) and by evidence that IT requires complementary organisational changes before its effects materialise in performance (Brynjolfsson & Hitt, 2003).

The research has four contributions to the literature. First, it shows that the two digital transformation dimensions drive vastly different financial returns, with customer-facing digitalization delivering returns that are far larger than is the case with back-office technology investment in point estimate magnitude, a finding that holds in both separate and combined specifications where both proxies enter simultaneously. The combined model addresses the concern that single-proxy specifications may overstate effects through omitted-variable bias, and a formal Wald test is employed to test coefficient equality. Second, it provides the first long-panel empirical study of the digital transformation–financial performance correlation of Saudi banking spanning the full period from early digitalization (2010) to the introduction of Vision 2030 and the COVID-19 pandemic (2024). Saudi banking offers an especially instructive laboratory since Vision 2030 is an institutional shock that happened through policy, which accelerated digital adoption across the entire sector, thereby creating a structural break that enables the separation of technology effects from institutional complementarity effects—an analysis not easily achievable in cross-country or market-driven contexts only.

Third, the structural break analysis of Vision 2030 shows that the post-reform period is associated with two complementary dynamics: substantially larger returns to investment in back-office technology, and diminishing returns to investment in customer-facing digitalization as widespread adoption created convergent relationships among competitors. This provides evidence for the institutional complementarity hypothesis (Brynjolfsson & Hitt, 2003; North, 1990) and the competitive convergence mechanism (Lieberman & Montgomery, 1988; Barney, 1991). Fourth, the leverage amplification mechanism, evident across all specifications, explains why digital transformation returns are most pronounced in equity-based indicators, with direct implications for the evaluation frameworks used by bank managers, regulators, and equity analysts. Beyond its theoretical contributions, the study offers practical guidance for bank executives allocating technology budgets across customer-facing and back-office initiatives, and for policymakers in emerging markets designing institutional reforms to maximise the financial returns of digital transformation. The rest of the paper is structured as follows. Section 2 formulates the hypotheses and theoretical framework. Section 3 examines the available empirical literature. Section 4 describes the research design. Section 5 presents results. Section 6 discusses findings. Section 7 concludes.

2. Theoretical Framework and Hypotheses

2.1. Transaction Cost Economics and Digital Banking

Transaction cost economics (Coase, 1937; Williamson, 1985) posits that economic activity is organised so as to minimise the sum of production and transaction costs. In banking, transaction costs arise from processing deposits, originating loans, executing payments, and maintaining branch networks to serve customers (Sealey & Lindley, 1977). Digital transformation reduces these costs through two channels. Front-office channels—POS terminals, mobile banking, internet platforms—replace expensive branch interfaces, thereby reducing labour, real-estate, and processing costs. According to Fuster et al. (2019), fintech platforms shortened mortgage processing times by 20 percent, and DeYoung et al. (2007) recorded that internet-active banks had operating cost ratios 1.5–2.0 percentage points lower than their competitors. The cost reductions from customer-facing channels are immediate and externally visible, directly lowering the bank's cost-to-income ratio.

Back-office investments include upgrades to core banking, process automation, and data analytics, reducing internal coordination costs, error rates, and processing redundancies (Martins et al., 2014). Back-office investments have longer gestation periods and require complementary organisational restructuring before financial returns materialise, as new systems must be integrated with existing procedures and staff retrained (Brynjolfsson & Hitt, 2003). Both channels are expected to improve performance through cost reduction, yet the magnitude and timing of returns are likely to differ systematically: customer-facing channels yield larger short-term gains, whereas back-office investments take longer to pay off.

2.2. Disruptive Innovation and Market Capture

The theory behind the digital transformation is the disruptive innovation theory (Christensen, 1997), which describes how competitive landscapes are being transformed. Digital platforms shift competition away from physical branches toward environments characterised by lower customer-acquisition costs, greater scalability, and stronger lock-in effects (Gomber et al., 2018; Thakor, 2020). Although the framework proposed by Christensen focused on entrant disruption, incumbent banks that embrace digital channels can obtain analogous benefits through platform competition and network effects (Boot et al., 2021; Philippon, 2016). Boot et al. (2021) differentiated between scalable and non-scalable banking functions, predicting that technology yields the greatest returns in scalable activities such as payments and transaction processing—a distinction that is directly parallel to the customer-facing versus back-office split in the current study. Philippon (2016) documented the striking paradox that despite massive technology investment, the unit cost of financial intermediation in the United States has remained remarkably stable, suggesting that aggregate IT spending measures mask substantial heterogeneity in how different technologies create value. More digitally engaged banks capture a disproportionate share of transaction revenues and generate network externalities (Katz & Shapiro, 1985). These effects are most readily observed in customer-facing digitalization (POS_SHARE), whereas back-office investment operates primarily through the TCE channel of cost reduction.

2.3. Resource-Based View, Dynamic Capabilities, and Implementation Lags

The resource-based view (Barney, 1991; Wernerfelt, 1984) holds that sustained competitive advantage derives from resources that are valuable, rare, inimitable, and non-substitutable (VRIN). Digital capabilities, particularly customer-facing infrastructure, satisfy these criteria when adoption is uneven across firms. The resource-based view further emphasises that IT resources generate competitive advantage only when firms possess complementary organisational capabilities (Mata et al., 1995; Bharadwaj, 2000). Teece (2007) extends this through the dynamic capabilities framework, which highlights that firms must reconfigure internal processes to capture value from technological investments. This perspective illuminates why back-office technology investment (TECH_INV) exhibits delayed returns relative to customer-facing digitalization (POS_SHARE).

Back-office investments require substantial organisational restructuring: legacy system integration, workflow redesign, staff retraining, and data governance implementation (Brynjolfsson & Hitt, 2003). These complementary changes unfold over multiple quarters, creating a productivity J-curve where initial disruption precedes eventual efficiency gains. Customer-facing digitalization, by contrast, interfaces directly with external customers and can generate transaction revenues immediately upon deployment, without requiring extensive internal reconfiguration. This distinction predicts not only differential return magnitudes but also distinct temporal patterns: customer-facing effects should appear within one quarter, while back-office effects may require four or more quarters to materialise. The dynamic capabilities framework thus provides theoretical grounding for the lag structure employed in the empirical specification.

2.4. Differential Returns: Customer-Facing versus Back-Office

This distinction reflects theoretically meaningful differences in value creation. Mata et al. (1995) demonstrated that different IT resources generate returns through different mechanisms. Bharadwaj (2000) showed that firm-specific IT capability drives superior performance. The multidimensional nature of digital transformation has been confirmed by Vial (2019) and Verhoef et al. (2021). POS_SHARE captures both technology infrastructure and customer adoption outcomes, encompassing network externalities and revenue growth. TECH_INV reflects internal efficiency improvements that are more susceptible to competitive imitation through standardised vendor solutions (Tambe & Hitt, 2012). This predicts larger financial payoffs from customer-facing relative to back-office digitalization.

2.5. Institutional Context: Saudi Vision 2030

North (1990) established that formal institutions shape the incentive structures governing technology investments and their eventual payoff. Vision 2030, announced in April 2016, targeted the expansion of digital financial services and cashless transactions (Saudi Vision 2030, 2016). According to Brynjolfsson and Hitt (2003), IT investments must be accompanied by complementary institutional changes; accordingly, Vision 2030 should serve as an institutional complement that unlocks the productivity benefits of prior technology investments. On the other hand, when digital adoption is widespread, competitive differentiation declines, consistent with advantage erosion as resources become widely diffused (Barney, 1991; Lieberman & Montgomery, 1988; Ethiraj & Zhu, 2008). Digital transformation affects return on equity more strongly than return on assets owing to the amplifying effect of banking leverage (equity-to-asset ratios of 10–15 percent) (Penman, 2013; Berger & Bouwman, 2013).

2.6. Hypotheses

H1: Digital channel penetration (POS_SHARE) has a positive influence on bank financial performance.
H2: The intensity of technology investment (TECH_INV) has a positive impact on the financial performance of banks.
H3: Customer-facing digitalization is linked with higher financial returns as compared to back-office technology investment.
H4a: Vision 2030 is associated with increased returns to investment in back-office technology (institutional complementarity).
H4b: Vision 2030 is associated with reduced returns to customer-facing digitalization (competitive convergence).

3. Literature Review

3.1. The IT Productivity Paradox

The relationship between IT and performance has been debated since Solow (1987) first raised the question and Brynjolfsson (1993) formalised it as the productivity paradox. Brynjolfsson and Hitt (2003) established that IT yields returns when accompanied by complementary organisational investment. Banker et al. (2006) found that effects depend on the type of IT and the competitive environment. Mithas et al. (2012) suggested that IT capabilities influence firm performance in various ways such as revenue growth, cost reduction, and improvement of profitability, and argued that the paradox arises from aggregating heterogeneous effects across these dimensions. In their meta-analysis of 66 studies, Kohli and Devaraj (2003) confirmed that IT effects are contingent on investment type, performance measure, and time horizon. Tambe and Hitt (2012) showed that disaggregating IT by type uncovers heterogeneous productivity effects that are masked in aggregate measures—directly motivating the current approach of the study.

3.2. Digital Transformation and Banking

Using aggregate spending data for European banks, Beccalli (2007) found no significant relationship between IT and performance (Beccalli, 2007). Scott et al. (2017) reported an 8.6 percent improvement in long-run profitability as a result of SWIFT adoption. DeYoung et al. (2007) established that internet-active banks incurred 1.5–2.0 percentage points in reduced operating costs. Thakor (2020) argued that fintech creates value by reducing intermediation costs. Boot et al. (2021) identified scalable and non-scalable banking functions, anticipating the greatest returns in scalable functions such as payments, which is parallel to the current study's customer-facing/back-office divide. Philippon (2016) found that the unit cost of intermediation remained constant despite substantial IT investment, indicating that aggregate measures conceal significant heterogeneity.

Recent work by Pierri and Timmer (2022) demonstrates that technology-intensive US banks exhibited greater fragility during stress periods, suggesting that IT returns may vary significantly across market conditions—a heterogeneity masked in aggregate productivity measures. Babina et al. (2022) document how fintech growth has reshaped competitive dynamics in financial intermediation, with implications for incumbent bank strategies that parallel the customer-facing/back-office distinction of the current study. Frame and White (2004, 2014) provide comprehensive surveys of technological change in financial services, consistently finding that IT returns depend critically on regulatory environment and competitive structure—factors that vary substantially across institutional contexts and may explain why Beccalli (2007) found null effects in European banking while the Saudi sample shows significant returns.

3.3. Banking Performance Determinants

According to the preceding research, the profitability of banks is determined by bank-specific, industry-specific, and macroeconomic factors (Athanasoglou et al., 2008; Dietrich & Wanzenried, 2011), and in the GCC settings, oil prices are of particular relevance (Alqahtani & Mayes, 2018). These findings guide the selection of control variables in the present study.

4. Methods

4.1. Sample and Data

All ten commercial banks listed on the Saudi Stock Exchange (Tadawul) in 2010Q1–2024Q4—including Al Rajhi Bank, Saudi National Bank, Saudi Awwal Bank, Riyad Bank, Banque Saudi Fransi, Arab National Bank, Alinma Bank, Bank Aljazira, Bank Albilad, and Saudi Investment Bank—constitute the sample. This census approach avoids sampling bias (Gujarati & Porter, 2009). None of the ten banks experienced mergers, delistings, or government interventions that would introduce survivorship bias, yielding a balanced panel of 600 bank-quarter observations (590 after lagging one quarter). Financial data are sourced from Refinitiv Eikon, digital transformation data from Bloomberg Terminal, and macroeconomic data from the World Bank.

The Saudi banking context offers distinctive institutional features that shape digital transformation returns. Vision 2030, announced in April 2016, represented a state-led economic restructuring programme that explicitly targeted financial sector digitalization and cashless transaction growth (Saudi Vision 2030, 2016; Hertog, 2010). Unlike market-driven digitalization in Western economies, Saudi reform proceeded through coordinated regulatory intervention by the Saudi Central Bank (SAMA), including fintech licensing frameworks, payment infrastructure investment, and mandatory digital adoption timelines. This state-led approach created rapid, sector-wide adoption that differs from the firm-specific, voluntary digitalization typically studied in US and European banking research. Consequently, the findings may reflect institutional complementarity effects that are stronger in coordinated economies than in liberal market contexts—a boundary condition that qualifies generalisation to other institutional settings.

4.2. Variables

Four dependent variables capture financial performance: return on assets (ROA), return on equity (ROE), return on invested capital (ROIC) (Damodaran, 2012), and earnings per share (EPS). Two independent variables are lagged one quarter and scaled 0–1: L1_POS_SHARE (POS transactions / total transactions) and L1_TECH_INV (IT expenditure / operating expenses). The one-quarter lag serves both theoretical and methodological purposes: digital investments require time to affect performance (Brynjolfsson & Hitt, 2003), and the lag establishes temporal precedence, mitigating simultaneity bias (Angrist & Pischke, 2009). Control variables include SIZE (natural logarithm of total assets), GDP growth, inflation, oil price, and SAIBOR (Saudi Arabian Interbank Offered Rate). POST_VISION = 1 for quarters ≥ 2016Q2. A COVID dummy (2020Q1–2021Q4) is included in robustness tests.

Variance decomposition indicates that 89.1 percent of the variation of POS_SHARE is between-bank, and 10.9 percent within-bank temporal variation (ICC = 0.89), indicating persistent, bank-specific digital strategies that are absorbed by fixed effects. The between-bank coefficient of variation (0.87) confirms the heterogeneity of these strategies. In comparison, TECH_INV ICC = 0.24 with 75.6 percent variation within-bank. The macroeconomic controls (GDP growth, inflation, oil price, SAIBOR) absorb economy-wide trends that are common to all banks and therefore cross-sectionally invariant, rendering them functionally equivalent to weighted time dummies. The low bivariate correlation ($r = 0.229$, VIF = 2.202) confirms that the two proxies capture distinct dimensions.

4.3. Econometric Model

The baseline specification is a bank-level fixed effects panel regression (Equation 1):

$FP\_\{it\} = \alpha\_\{i\} + \delta DT\_\{i,t-1\} + \gamma' X\_\{it\} + \varepsilon\_\{it\}$

The Hausman (1978) test ($\chi^2 = 340.808$, $p < 0.001$) confirms fixed effects. Standard errors are clustered at the bank level (Petersen, 2009). A combined model tests H3 by including both DT proxies simultaneously, with a Wald test of $\delta_1 = \delta_2$. Interaction models add DT × POST_VISION for H4a/H4b.

4.4. Robustness and Identification

With only ten clusters, asymptotic standard errors may over-reject the null (Cameron et al., 2008). Three supplementary procedures are therefore employed: (a) wild cluster bootstrap-*t* with 9,999 replications (Webb, 2014); (b) Driscoll–Kraay

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(1998) standard errors; (c) IV-2SLS using second lags as instruments (Wooldridge, 2010). Within-bank AR(1) coefficients (POS: 0.953; TECH: 0.881) confirm instrument relevance (first-stage $F > 2{,}400$; Stock & Yogo, 2005). System GMM (Arellano & Bond, 1991) is not employed because $T = 60$, $N = 10$ violates the short-T assumption (Roodman, 2009). Additional robustness checks include drop-one-bank jackknife, winsorisation (1st/99th percentiles), COVID control, year fixed effects, and alternative four-quarter lags.

A further concern involves time-varying omitted variables (e.g., changes in management quality) that may simultaneously drive digital adoption and performance. Bank fixed effects absorb time-invariant confounders; the lag structure and IV partially address time-varying endogeneity. The stability of results across jackknife subsamples, winsorised specifications, and alternative lag structures provides reassurance; nevertheless, estimates should be interpreted as conditional associations rather than definitive causal effects. Despite the multi-method identification strategy, the observational design cannot fully eliminate endogeneity concerns, and readers should exercise appropriate caution in drawing causal inferences.

5. Results

5.1. Descriptive Statistics

Table 1. Descriptive Statistics

Variable	Mean	SD	Min	P25	Median	P75	Max	N
Panel A: Financial Performance Indicators								
ROA (%)	1.700	0.695	−1.170	1.400	1.771	2.093	3.615	600
ROE (%)	12.178	5.425	−6.621	9.310	12.307	15.903	23.736	600
ROIC (%)	9.542	4.110	2.184	6.891	9.149	11.344	23.499	600
EPS (SAR)	0.374	0.235	−0.282	0.221	0.338	0.499	1.047	600
Panel B: Digital Transformation Variables								
TECH_INV	0.105	0.146	0.000	0.004	0.020	0.178	0.778	600
POS_SHARE	0.100	0.087	0.000	0.028	0.072	0.144	0.358	600
Panel C: Control Variables								
SIZE (ln)	11.982	0.802	9.843	11.476	12.064	12.495	13.933	600
GDP Growth	3.014	3.821	−4.340	0.330	2.700	5.040	11.850	600
Inflation	2.203	1.439	−1.170	1.900	2.460	3.440	3.750	600
Oil Price	78.377	23.776	33.360	61.477	76.655	102.202	118.490	600
SAIBOR	2.036	1.700	0.680	0.877	0.990	2.462	6.150	600

Note. $N = 600$ bank-quarter observations. DT = digital transformation; SD = standard deviation; P25 = 25th percentile; P75 = 75th percentile; SAR = Saudi Arabian Riyal. All DT variables scaled 0–1.

ROA averages 1.70 percent (SD = 0.695), ROE 12.18 percent (SD = 5.43), ROIC 9.54 percent (SD = 4.11), and EPS SAR 0.374 (SD = 0.235). TECH_INV averages 10.5 percent of operating expenses (SD = 14.6 percent) and POS_SHARE averages

10.0 percent (SD = 8.7 percent), both with substantial cross-bank heterogeneity. The mean leverage ratio (ROE/ROA) is 7.12, implying an equity-to-asset ratio of 14.1 percent.

Figure 1. Digital Transformation Trends (2010Q1–2024Q4). Individual bank quarterly values (*N* = 10 banks, 60 quarters). Dashed line = Vision 2030 (April 2016).

[Figure 1 should be inserted here: Line graph showing POS_SHARE and TECH_INV trends by bank over time with vertical dashed line at 2016Q2]

Figure 2. Financial Performance Trends (2010Q1–2024Q4). Cross-bank quarterly averages (*N* = 10 banks). Dashed line = Vision 2030.

[Figure 2 should be inserted here: Multi-panel line graph showing ROA, ROE, ROIC, and EPS trends over time with vertical dashed line at 2016Q2]

Table 2. Pearson Correlation Matrix

Variable	TECH_INV	POS_SHARE	ROA	ROE	ROIC	EPS	SIZE	SAIBOR
TECH_INV	1.000	0.229	0.146	0.268	0.188	0.024	0.037	−0.041
POS_SHARE		1.000	**0.564**	**0.609**	**0.612**	**0.626**	**0.753**	−0.283
ROA			1.000	**0.907**	0.750	0.526	0.445	0.112
ROE				1.000	**0.749**	0.592	0.466	0.098
ROIC					1.000	0.341	0.288	0.155
EPS						1.000	**0.749**	−0.076
SIZE							1.000	−0.194
SAIBOR								1.000

Note. Pearson correlation coefficients. POS_SHARE and SIZE show high correlation ($r = 0.753$), but VIF analysis confirms no multicollinearity concerns (all VIF < 2.3). All DT variables use one-quarter lag ($t-1$). $N = 600$ bank-quarter observations.

5.2. Diagnostic Tests

Hausman test ($\chi^2 = 340.808$, $p < 0.001$) confirms fixed effects. Breusch–Pagan ($BP = 28.051$, $p < 0.001$) confirms heteroskedasticity. Breusch–Godfrey ($LM = 407.008$, $p < 0.001$) confirms serial correlation. Pesaran (2004) CD test ($CD = 7.080$, $p < 0.001$) indicates cross-sectional dependence. Maximum VIF = 2.202.

5.3. Baseline Results

Table 3. Impact of Digital Transformation on Financial Performance

	Panel A: POS_SHARE (Customer-Facing)				Panel B: TECH_INV (Back-Office)		
	(1) ROA	(2) ROE	(3) ROIC	(4) EPS	(5) ROA	(6) ROE	(7) ROIC
L1_POS_SHARE	2.711*	46.315***	20.812	0.622			
SE	(1.398)	(12.804)	(16.246)	(0.428)			

L1_TECH_INV					0.985	14.607***	8.106***
SE					(0.759)	(5.600)	(2.596)
R^2 (within)	0.075	0.156	0.156	0.404	0.095	0.207	0.219
N	590	590	590	590	590	590	590

Note. ***p* < 0.01,** p* < 0.05, *p* < 0.10. Bank-clustered standard errors in parentheses. All models include bank fixed effects. Controls: SIZE, GDP_Growth, Inflation, Oil_Price, SAIBOR.

Table 3 presents the baseline fixed effects results. The coefficient for POS_SHARE on ROE (β = 46.315, p < 0.001) should be interpreted within the observed sample range rather than as a marginal effect at mean values. Given that POS_SHARE ranges from 0 to 35.8 percent in the sample, a 10-percentage-point increase in digital penetration (approximately one standard deviation) corresponds to a 4.6 percentage point increase in ROE—representing approximately 38 percent of the sample mean. An interquartile shift from the 25th percentile (2.8 percent) to the 75th percentile (14.4 percent) corresponds to a 5.4 percentage point ROE increase. While substantial, these effects are consistent with DeYoung et al. (2007) finding of 1.5–2.0 percentage point ROA advantages for internet-active banks, scaled by the sample leverage multiplier of 7.12. TECH_INV significantly improves ROE (β = 14.607, p = 0.009) and ROIC (β = 8.106, p = 0.002). Non-significant effects of POS_SHARE on ROIC and EPS, and of TECH_INV on ROA and EPS, reflect denominator composition and leverage mechanics: ROIC's invested capital base is less leverage-sensitive; EPS is influenced by share issuance; and back-office efficiency gains are economically meaningful relative to equity but small relative to total assets.

5.4. Combined Model (H3)

Table 4. Combined Model: Both DT Dimensions

Variable	**(1) ROA**	**(2) ROE**	**(3) ROIC**	**(4) EPS**
Panel A: Customer-Facing Digitalization (POS_SHARE)				
L1_POS_SHARE	1.869	34.214***	13.791	0.512
SE	(1.421)	(13.002)	(15.829)	(0.461)
Panel B: Back-Office Technology Investment (TECH_INV)				
L1_TECH_INV	0.871	12.523***	7.266***	0.114
SE	(0.713)	(4.404)	(1.783)	(0.123)
R^2 (within)	0.104	0.253	0.238	0.408
Wald test (δ_1=δ_2)	Z = 0.579	Z = 1.612	Z = 0.422	Z = 0.768
p-value	0.562	0.107	0.673	0.443
N	590	590	590	590

Note. **$p < 0.01$,** p* < 0.05, $p < 0.10$. Both DT proxies included simultaneously. Wald tests H_0: δ_POS = δ_TECH.
Both coefficients retain significance for ROE (POS: $\beta = 34.214$, $p = 0.009$; TECH: $\beta = 12.523$, $p = 0.005$), suggesting independent effects. The POS point estimate is 2.7 times larger than the TECH estimate, supporting H3 directionally. The Wald test ($Z = 1.612$, $p = 0.107$) does not reject coefficient equality at conventional levels, though with only ten clusters this test has limited statistical power. The magnitude difference is economically meaningful even if statistical significance is not achieved.

5.5. Vision 2030 Interactions

TECH_INV interactions are positive and significant for ROA ($\beta = 2.340$, $p = 0.001$), ROE ($\beta = 12.020$, $p = 0.034$), and EPS ($\beta = 0.410$, $p = 0.035$), supporting H4a. POS_SHARE interactions are negative and significant for ROE ($\beta = -13.362$, $p = 0.021$) and ROIC ($\beta = -22.226$, $p = 0.002$), supporting H4b. POST_VISION captures the aggregate institutional regime shift including Vision 2030, fintech licensing, SAMA reforms, and COVID-19.

5.6. Robustness

Drop-one-bank jackknife: POS → ROE ranges 33.5–55.9, all significant at 5 percent. Winsorisation: $\beta = 46.280$ ($p < 0.001$). COVID control in combined model: POS → ROE ($\beta = 29.941$, $p = 0.012$), TECH → ROE ($\beta = 9.391$, $p = 0.001$), COVID ($\beta = -4.253$, $p < 0.001$). TECH effects persist at four-quarter lags ($\beta = 13.451$, $p = 0.006$), supporting Brynjolfsson and Hitt (2003).

6. Discussion

6.1. Customer-Facing Digitalization

The finding that POS_SHARE predicts ROE ($\beta = 46.315$, $p < 0.001$) aligns with both transaction cost economics and disruptive innovation theory. Interpreted within the observed data range, banks at the 75th percentile of digital penetration exhibit ROE approximately 5.4 percentage points higher than banks at the 25th percentile. Digital channels replace expensive branches (Williamson, 1985) and capture transaction revenues under network effects (Katz & Shapiro, 1985; Boot et al., 2021). This finding extends prior literature by demonstrating substantial returns in an emerging market context where aggregate IT productivity measures have typically produced null or weak results (Beccalli, 2007; Philippon, 2016). The divergence from European banking studies may reflect Saudi Arabia's state-coordinated digitalization, which accelerated adoption faster than market-driven contexts and created stronger institutional complementarities (Hertog, 2010; Frame & White, 2004).

The magnitude of the coefficient is corroborated by drop-one-bank stability (range: 33.5–55.9) and winsorisation ($\beta = 46.280$). In cross-study calibration, DeYoung et al. (2007) discovered 1.5–2.0 percentage point ROA benefits of internet banking; multiplied by the leverage multiplier of the sample (7.12), this produces an ROE effect of 10.7–14.2 percentage points per unit of adoption given the broader scope of POS_SHARE, which encompasses the entire payment ecosystem rather than a single channel. Scott et al. (2017) reported long-run profitability improvement through SWIFT of 8.6 percent which, when multiplied by bank leverage, yields a comparable impact. The combined model coefficient ($\beta = 34.214$) is more conservative, reflecting shared explanatory power with TECH_INV. POS_SHARE functions both as a technology input and as an outcome of customer adoption; it captures revenue growth from merchant fees, transaction processing income, and digital cross-selling, thereby producing effects that substantially exceed those attributable to cost reduction alone (Thakor, 2020; Boot et al., 2021).

6.2. Back-Office Technology

TECH_INV enhances ROE ($\beta = 14.607$, $p < 0.01$) and ROIC ($\beta = 8.106$, $p < 0.01$) through the efficiency channel predicted by transaction cost economics. The coefficient is approximately one-third that of POS_SHARE, consistent with TECH_INV capturing cost reduction alone whereas POS_SHARE captures both cost reduction and market expansion. TECH_INV four-quarter-lag persistence ($\beta = 13.451$, $p = 0.006$) validates the delayed productivity hypothesis proposed by Brynjolfsson and Hitt (2003)—a temporal pattern distinguishing back-office from front-office digitalization with direct capital-budgeting implications.

6.3. Competitive Convergence and Institutional Complementarity

These interaction outcomes are consistent with the amplification of back-office returns by Vision 2030 (H4a), and are expected to be in line with institutional complementarity (Brynjolfsson & Hitt, 2003; North, 1990): regulatory infrastructure, development of digital payment ecosystems, fintech licensing, and policy-induced demand for digital services provided the complementary conditions needed to activate returns on prior technology investments. This finding extends the institutional framework of North (1990) by demonstrating that complementarity operates at the level of specific technology types: back-office investments, which depend on the broadest range of institutional conditions, benefit most from reform. Decreasing returns to POS_SHARE (H4b) demonstrate competitive convergence (Lieberman & Montgomery, 1988; Ethiraj & Zhu, 2008): as all banks increased digital channels, differentiation was decreased, which is consistent with the predictions of Barney (1991) that benefits decline as resources are widely used and lose their uniqueness. For emerging economies pursuing digital transformation, these results imply that first-mover advantages in customer-facing digitalization are time-limited and erode as the industry digitises; sustained differentiation must therefore shift toward service quality, user experience, and analytical capabilities.

It should be acknowledged that the interpretation of Vision 2030 effects as institutional complementarity rests on timing correlations rather than causal identification. The post-2016 period coincided with global fintech growth, regulatory changes beyond Vision 2030, and eventually COVID-19 disruption. While bank fixed effects absorb time-invariant heterogeneity and the lag structure mitigates simultaneity, confounding factors cannot be fully ruled out. The structural break analysis should therefore be interpreted as descriptive evidence consistent with institutional theory (North, 1990; Brynjolfsson & Hitt, 2003) rather than definitive proof of policy effects.

6.4. Practical Implications

The coefficient ratio of 2.7:1 indicates that marginal customer-facing investment yields higher equity returns; however, the diminishing returns observed after Vision 2030 suggest that this gap is narrowing, with early movers gaining disproportionately and late movers better served by investing in back-office efficiency. The results also inform capital budgeting decisions: customer-facing investments should be evaluated over shorter horizons (one-quarter effects), whereas back-office investments warrant longer evaluation windows (four-quarter effects). For equity analysts, digital transformation is best measured in terms of ROE/ROIC and not ROA, as aggregate IT expenditure masks heterogeneity in value-creation mechanisms.

Such results help in addressing the IT productivity paradox (Brynjolfsson, 1993): disaggregation reveals that the paradox may stem from aggregating heterogeneous technology types (Kohli & Devaraj, 2003; Tambe & Hitt, 2012), realisation delays are concentrated in back-office investments, and the moderating influence of the institutional environment is asymmetric across technology types.

7. Conclusions

This study demonstrates that disaggregating digital transformation in Saudi banking uncovers mechanism-specific, institution-contingent correlations with financial performance that are amplified by banking leverage. Customer-facing digitalization exhibits larger associations with equity returns than back-office investment, combining transaction cost reduction (Williamson, 1985) and market capture (Christensen, 1997) effects. A combined model confirms that these associations are independent, and the modest correlation between proxies ($r = 0.229$) supports the disaggregation approach. The post-2016 period—coinciding with Vision 2030 implementation—correlates with increased back-office returns and reduced customer-facing advantages, patterns consistent with institutional complementarity and competitive convergence theories (North, 1990; Barney, 1991; Lieberman & Montgomery, 1988), though confounding factors cannot be fully ruled out.

This study has limitations that bound its conclusions and qualify generalisations. First, with only ten banks, statistical power is limited—effects must be economically large to achieve significance, and modest but meaningful relationships may be missed. The Wald test for coefficient equality (H3) illustrates this constraint: the 2.7:1 ratio suggests meaningful economic differences even when statistical significance is not achieved. Second, Vision 2030 coincided with global fintech growth, regulatory changes, and COVID-19, complicating clean attribution; the 2016 break is treated as a descriptive structural shift rather than a causal instrument. Third, POS_SHARE and TECH_INV are coarse proxies that miss technological heterogeneity (e.g., mobile wallets, AI, cloud infrastructure) and may partly capture unobserved bank quality or management capability. Fourth, the observational design cannot eliminate endogeneity despite multiple robustness checks; the associations documented should inform future research and policy design rather than guide definitive causal inference. Finally, the single-country focus limits external validity—the findings reflect Saudi Arabia's state-coordinated institutional context and may not generalise to market-driven economies or different regulatory environments. Future research should develop composite digital indices encompassing multiple channel types, employ multi-country GCC or MENA panels to test the generalisability of institutional complementarity and competitive convergence, leverage natural experiments or regulatory variation for stronger causal identification, and investigate emerging first-mover advantages associated with mobile-wallet and platform-based banking technologies.

List of Abbreviations

Abbreviation	Definition
DT	Digital Transformation
EPS	Earnings Per Share
FE	Fixed Effects
GCC	Gulf Cooperation Council
ICC	Intraclass Correlation Coefficient
IT	Information Technology
IV-2SLS	Instrumental Variable Two-Stage Least Squares
POS	Point of Sale
ROA	Return on Assets
ROE	Return on Equity
ROIC	Return on Invested Capital
SAIBOR	Saudi Arabian Interbank Offered Rate
SAMA	Saudi Central Bank
SD	Standard Deviation
SE	Standard Error
TCE	Transaction Cost Economics
VIF	Variance Inflation Factor

Declarations

Ethics Approval and Consent to Participate
Not applicable. This study uses publicly available secondary data from listed banks and does not involve human participants, human data, or human tissue.

Consent for Publication
Not applicable.

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Salah Alsaad: Supervision, Validation, Writing—review & editing.
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All three authors read and approved the final manuscript.

Availability of Data and Materials
The datasets analyzed during this study are not publicly available due to commercial licensing restrictions from Refinitiv (LSEG) Eikon and Bloomberg Terminal. Derived data supporting the findings of this study are available from the corresponding author upon reasonable request, subject to a data use agreement. The statistical code used for analysis is available in the supplementary materials.

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Not applicable.

References

Alqahtani, F., & Mayes, D. G. (2018). Financial stability of Islamic banking and the global financial crisis: Evidence from the Gulf Cooperation Council. *Economic Systems*, *42*(2), 346–360. https://doi.org/10.1016/j.ecosys.2017.08.003

Angrist, J. D., & Pischke, J. S. (2009). *Mostly harmless econometrics: An empiricist's companion*. Princeton University Press.

Arellano, M., & Bond, S. (1991). Some tests of specification for panel data. *Review of Economic Studies*, *58*(2), 277–297. https://doi.org/10.2307/2297968

Athanasoglou, P. P., Brissimis, S. N., & Delis, M. D. (2008). Bank-specific, industry-specific and macroeconomic determinants of bank profitability. *Journal of International Financial Markets, Institutions and Money*, *18*(2), 121–136. https://doi.org/10.1016/j.intfin.2006.07.001

Babina, T., Fedyk, A., He, A., & Hodson, J. (2022). Fintech, regulatory arbitrage, and the rise of shadow banks. *Journal of Financial Economics*, *146*(3), 801–826. https://doi.org/10.1016/j.jfineco.2022.06.004

Banker, R. D., Bardhan, I. R., Chang, H., & Lin, S. (2006). Plant information systems, manufacturing capabilities, and plant performance. *MIS Quarterly*, *30*(2), 315–337. https://doi.org/10.2307/25148729

Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, *17*(1), 99–120. https://doi.org/10.1177/014920639101700108

Beccalli, E. (2007). Does IT investment improve bank performance? Evidence from Europe. *Journal of Banking & Finance*, *31*(7), 2205–2230. https://doi.org/10.1016/j.jbankfin.2006.10.011

Berger, A. N. (2003). The economic effects of technological progress: Evidence from the banking industry. *Journal of Money, Credit and Banking*, *35*(2), 141–176.

Berger, A. N., & Bouwman, C. H. (2013). How does capital affect bank performance during financial crises? *Journal of Financial Economics*, *109*(1), 146–176. https://doi.org/10.1016/j.jfineco.2013.02.008

Bharadwaj, A. S. (2000). A resource-based perspective on information technology capability and firm performance. *MIS Quarterly*, *24*(1), 169–196. https://doi.org/10.2307/3250983

Boot, A. W. A., Hoffmann, P., Laeven, L., & Ratnovski, L. (2021). Fintech: What's old, what's new? *Journal of Financial Stability*, *53*, 100836. https://doi.org/10.1016/j.jfs.2021.100836

Brynjolfsson, E. (1993). The productivity paradox of information technology. *Communications of the ACM*, *36*(12), 66–77. https://doi.org/10.1145/163298.163309

Brynjolfsson, E., & Hitt, L. M. (2003). Computing productivity: Firm-level evidence. *Review of Economics and Statistics*, *85*(4), 793–808. https://doi.org/10.1162/003465303772815736

Cameron, A. C., Gelbach, J. B., & Miller, D. L. (2008). Bootstrap-based improvements for inference with clustered errors. *Review of Economics and Statistics*, *90*(3), 414–427. https://doi.org/10.1162/rest.90.3.414

Christensen, C. M. (1997). *The innovator's dilemma*. Harvard Business School Press.

Coase, R. H. (1937). The nature of the firm. *Economica*, *4*(16), 386–405.

Damodaran, A. (2012). *Investment valuation* (3rd ed.). Wiley.

DeYoung, R., Lang, W. W., & Nolle, D. L. (2007). How the internet affects output and performance at community banks. *Journal of Banking & Finance*, *31*(4), 1033–1060. https://doi.org/10.1016/j.jbankfin.2005.11.002

Dietrich, A., & Wanzenried, G. (2011). Determinants of bank profitability before and during the crisis. *Journal of International Financial Markets, Institutions and Money*, *21*(3), 307–327. https://doi.org/10.1016/j.intfin.2010.11.002

Driscoll, J. C., & Kraay, A. C. (1998). Consistent covariance matrix estimation with spatially dependent panel data. *Review of Economics and Statistics*, *80*(4), 549–560. https://doi.org/10.1162/003465398557825

Ethiraj, S. K., & Zhu, D. H. (2008). Performance effects of imitative entry. *Strategic Management Journal*, *29*(8), 797–817. https://doi.org/10.1002/smj.699

Fuster, A., Plosser, M., Schnabl, P., & Vickery, J. (2019). The role of technology in mortgage lending. *Review of Financial Studies*, *32*(5), 1854–1899. https://doi.org/10.1093/rfs/hhz018

Frame, W. S., & White, L. J. (2004). Empirical studies of financial innovation: Lots of talk, little action? *Journal of Economic Literature*, *42*(1), 116–144. https://doi.org/10.1257/002205104773558065

Frame, W. S., & White, L. J. (2014). Technological change, financial innovation, and diffusion in banking. In A. N. Berger, P. Molyneux, & J. O. S. Wilson (Eds.), *The Oxford handbook of banking* (2nd ed., pp. 486–507). Oxford University Press.

Gomber, P., Kauffman, R. J., Parker, C., & Weber, B. W. (2018). On the fintech revolution. *Journal of Management Information Systems*, *35*(1), 220–265.

Gujarati, D. N., & Porter, D. C. (2009). *Basic econometrics* (5th ed.). McGraw-Hill.

Hausman, J. A. (1978). Specification tests in econometrics. *Econometrica*, *46*(6), 1251–1271. https://doi.org/10.2307/1913827

Hertog, S. (2010). *Princes, brokers, and bureaucrats: Oil and the state in Saudi Arabia*. Cornell University Press.

Katz, M. L., & Shapiro, C. (1985). Network externalities, competition, and compatibility. *American Economic Review*, *75*(3), 424–440. https://doi.org/10.2307/1813707

Kohli, R., & Devaraj, S. (2003). Measuring information technology payoff: A meta-analysis. *Information Systems Research*, *14*(2), 127–145. https://doi.org/10.1287/isre.14.2.127.16018
Lieberman, M. B., & Montgomery, D. B. (1988). First-mover advantages. *Strategic Management Journal*, *9*(S1), 41–58. https://doi.org/10.1002/smj.4250090106
Martins, C., Oliveira, T., & Popovič, A. (2014). Understanding the internet banking adoption. *International Journal of Information Management*, *34*(1), 1–13.
Mata, F. J., Fuerst, W. L., & Barney, J. B. (1995). Information technology and sustained competitive advantage. *MIS Quarterly*, *19*(4), 487–505. https://doi.org/10.2307/249630
Mithas, S., Tafti, A., Bardhan, I., & Goh, J. M. (2012). Information technology and firm profitability: Mechanisms and empirical evidence. *MIS Quarterly*, *36*(1), 205–224. https://doi.org/10.2307/41410392
North, D. C. (1990). *Institutions, institutional change and economic performance*. Cambridge University Press.
Penman, S. H. (2013). *Financial statement analysis and security valuation* (5th ed.). McGraw-Hill.
Pesaran, M. H. (2004). General diagnostic tests for cross section dependence in panels (CESifo Working Paper No. 1229).
Petersen, M. A. (2009). Estimating standard errors in finance panel data sets. *Review of Financial Studies*, *22*(1), 435–480. https://doi.org/10.1093/rfs/hhn053
Pierri, N., & Timmer, Y. (2022). Tech intensity and the fragility of the US banking system. *American Economic Review*, *112*(7), 2334–2372. https://doi.org/10.1257/aer.20210113

Philippon, T. (2016). The fintech opportunity (NBER Working Paper No. 22476).
Roodman, D. (2009). How to do xtabond2. *Stata Journal*, *9*(1), 86–136.
SAMA. (2023). *Annual report 2023*. Saudi Central Bank. https://www.sama.gov.sa
Saudi Vision 2030. (2016). *Saudi Arabia's Vision 2030*. https://www.vision2030.gov.sa
Scott, S. V., Van Reenen, J., & Zachariadis, M. (2017). The long-term effect of digital innovation on bank performance. *Research Policy*, *46*(5), 984–1004. https://doi.org/10.1016/j.respol.2017.01.012
Sealey, C. W., & Lindley, J. T. (1977). Inputs, outputs, and a theory of production and cost at depository financial institutions. *Journal of Finance*, *32*(4), 1251–1266.
Solow, R. M. (1987, July 12). We'd better watch out. *New York Times Book Review*, p. 36.
Stock, J. H., & Yogo, M. (2005). Testing for weak instruments in linear IV regression. In D. W. K. Andrews & J. H. Stock (Eds.), *Identification and inference for econometric models* (pp. 80–108). Cambridge University Press.
Tambe, P., & Hitt, L. M. (2012). The productivity of information technology investments. *Information Systems Research*, *23*(3), 599–617. https://doi.org/10.1287/isre.1120.0428
Teece, D. J. (2007). Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal*, *28*(13), 1319–1350. https://doi.org/10.1002/smj.640

Thakor, A. V. (2020). Fintech and banking: What do we know? *Journal of Financial Intermediation*, *41*, 100833. https://doi.org/10.1016/j.jfi.2019.100833
Verhoef, P. C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Dong, J. Q., Fabian, N., & Haenlein, M. (2021). Digital transformation: A multidisciplinary reflection and research agenda. *Journal of Business Research*, *122*, 889–901. https://doi.org/10.1016/j.jbusres.2019.09.022
Vial, G. (2019). Understanding digital transformation: A review and a research agenda. *Journal of Strategic Information Systems*, *28*(2), 118–144. https://doi.org/10.1016/j.jsis.2019.01.003
Webb, M. D. (2014). Reworking wild bootstrap-based inference for clustered errors (Queen's Working Paper No. 1315).
Wernerfelt, B. (1984). A resource-based view of the firm. *Strategic Management Journal*, *5*(2), 171–180. https://doi.org/10.1002/smj.4250050207

Williamson, O. E. (1985). *The economic institutions of capitalism*. Free Press.
Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data* (2nd ed.). MIT Press.