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The transformative power of tech investment: Measuring growth, diversification, and firm outcomes

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A B S T R A C T

We examine the asymmetric effects of national technology-driven diversification policies on firm-level profitability in the Gulf Cooperation Council (GCC), addressing a critical gap in the microeconomic literature on the region's transition from hydrocarbons. Using a dynamic panel dataset of 63 strategically important firms across all six GCC countries from 2016 to 2025, we employ a Difference-in-Differences (DiD) approach, complemented by System Generalized Method of Moments (SGMM) estimation, to establish causal relationships while rigorously addressing endogeneity concerns. The results reveal that technology-focused policies have significantly boosted profitability and total factor productivity in firms that actively invest in digital technologies, with policy milestones increasing asset-based returns by 2.1% and equity-based returns by 2.8%. Government subsidies specifically targeted toward technology adoption amplified these effects by an additional 4.5% and 6.5%, respectively, with these impacts intensifying post-2020 to gains of 8.8% on assets and 13.1% on equity for technology-intensive firms. Conversely, firms in traditional sectors with minimal technology adoption showed no statistically significant response to these policy interventions. The findings underscore the efficacy of precisely targeted fiscal incentives and selective policy support for technology sectors in driving successful economic diversification, offering valuable insights for policymakers in resource-rich economies seeking to engineer sustainable, technology-enabled post-oil transitions through firm-level interventions.

1. Introduction

Facing an existential economic imperative, the GCC states are strategically pivoting towards investments in new technologies, including Artificial Intelligence (AI), Internet of Things (IoT), blockchain, robotics, and cloud computing, as the primary catalysts for post-hydrocarbon diversification (Ali & Abdalla, 2025; Sweidan, 2025). Driven by volatile oil markets, finite reserves, and the transformative potential of the Fourth Industrial Revolution, this technological transition is reshaping corporate profitability paradigms across the region. National technology and diversification strategies—such as the UAE's Strategy for AI 2031 and Saudi Arabia's National Strategy for Data & AI—are creating unprecedented growth opportunities in sectors like fintech, smart logistics, and digital healthcare, while simultaneously disrupting traditional business models. Consequently, profitability trajectories are sharply diverging: firms that embrace technological innovation benefit from substantial state investment, regulatory sandboxes, and efficiency gains, whereas those that maintain traditional operational models face escalating competitive pressures and eroded margins (Hasan et al., 2023). This structural transformation is redefining the regional business landscape and will determine future corporate and regional prosperity in the knowledge-based economy.

Despite substantial macroeconomic investment in technology initiatives, critical gaps persist in understanding the microeconomic consequences of technological adoption for firm profitability. While existing literature extensively explores the macroeconomic potential of digitalization in resource-rich economies (Arellano et al., 2022; Guriev et al., 2022) and within the GCC context (Alshamsi et al., 2021; Alotaibi & Alshammari, 2023), a significant void exists in empirically

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quantifying the firm-level financial returns to multi-technology investment. Studies confirm the transformative potential of digital technologies for public service delivery and smart cities (Brynjolfsson & McAfee, 2014) and emphasize the need for digital infrastructure (Goldfarb & Tucker, 2019). However, rigorous empirical evidence directly linking corporate technology investment to firm-level financial performance and profitability outcomes remains scarce and fragmented.

Although research identifies broad implementation challenges like digital skills shortages (Bresnahan et al., 2023) and regulatory hurdles (Zhao et al., 2022), there is a deficit in studies examining how investments in AI, IoT, blockchain, robotics, and cloud computing translate into concrete impacts on corporate earnings, margins, and shareholder value across the evolving digital economy. Existing firm-level analyses are often constrained, focusing narrowly on the implications of oil prices on profitability (Kilian, 2009; Hamilton, 2013) or sector-specific indicators in single countries (Bloom et al., 2019), and lacking comprehensive cross-sectoral and cross-country comparative assessments of technology-driven profitability drivers within the GCC's diversification landscape. Furthermore, studies examining technology adoption outcomes frequently rely on aggregate data or fail to adequately address endogeneity concerns when assessing the causal links between technology policies and corporate profitability, leaving a significant void in understanding how the digital transition manifests in actual corporate financial resilience and sustainable profit generation.

This study addresses these gaps by providing an empirical analysis that tests the central hypothesis: national technology policies asymmetrically boost profitability in firms actively investing in digital technologies, while having minimal effects on firms in traditional sectors (Neaime, 2004; Mansour, 2014). We employ a dynamic fixed effects panel dataset encompassing 63 strategically important firms across all six GCC countries from 2016 to 2025, utilizing a DiD approach complemented by the System Generalized Method of Moments estimator to establish causal links while addressing endogeneity concerns rigorously (Blundell & Bond, 1998; Roodman, 2009). Our analysis demonstrates how AI and technology strategy milestones trigger structural breaks in profitability trajectories, with government support and technology investment intensity serving as critical transmission channels that amplify returns for compliant firms. By contrasting technology-intensive firms with traditional sector entities across six strategic industries (energy, finance, logistics, healthcare, telecom, and Industry 4.0), we quantify how technological intensity, sectoral dynamics, and policy interactions drive differential profitability outcomes.

The results demonstrate that GCC technology policies generated asymmetric improvements in both profitability and productivity for firms embracing technological transformation, while leaving traditional sector firms unaffected (Shah & Albaity, 2022). For technology-active companies, the implementation of national technology strategies resulted in significantly increased asset-based returns of 2.1% and equity-based returns of 2.8%. Government subsidies specifically targeted toward digital adoption substantially amplified these effects, adding 4.5% and 6.5% growth, respectively. Notably, these policies also drove meaningful gains in total factor productivity, which increased by 7.9% for technology-intensive firms receiving subsidies in the post-2020 period, indicating genuine improvements in technological efficiency beyond mere financial metrics. The impact intensified markedly after 2020, with refined policy design generating annualized profitability gains of 8.8% on assets and 13.1% on equity for supported technology firms. To contextualize these results, the +13.1% ΔROE gain is over three times the average pre-policy growth and substantially exceeds the cost of subsidies (~3% of revenue). This indicates a high return on public investment, confirming the policies' economic and statistical significance. Conversely, traditional sector firms showed no statistically significant response, with changes ranging from -0.7% to -1.0% across all performance measures. These findings confirm that targeted fiscal incentives effectively promote resource allocation toward technology-intensive sectors, without the misallocation risks associated with supporting traditional industries (Acemoglu et al., 2018). This also validates the role of technology policies in driving fundamental productivity improvements, as predicted by the theory of general-purpose technologies.

The remainder of the paper is structured as follows: Section 2 reviews the literature on GCC economic diversification, technology adoption, and the challenges of technological transition. Section 3 describes the data and variable construction. Section 4 outlines the empirical methodology and presents the results. Section 5 discusses policy implications for enhancing firm profitability through the adoption of technology. Section 6 concludes.

2. Literature Review

The theoretical foundations of technological transition are well-established, emphasizing the role of general-purpose technologies (GPTs), such as AI, in driving economy-wide productivity and innovation (Bresnahan & Trajtenberg, 1995). For resource-rich economies, this suggests a viable path to mitigate the "resource curse" (Arellano et al., 2022), though success hinges on complementary investments in infrastructure, human capital, and regulation (Goldfarb & Tucker, 2019; Acemoglu & Restrepo, 2020). However, a significant disconnect exists at the empirical level. While the macroeconomic potential of digitalization is recognized (Brynjolfsson & McAfee, 2014; Bloom et al., 2019), and GCC-specific strategies have been outlined (Alshamsi et al., 2021; Alotaibi & Alshammari, 2023), the microeconomic literature remains underdeveloped. Critical methodological gaps persist:

- A reliance on aggregate data or conceptual frameworks, lacking the firm-level granularity needed to analyze profitability dynamics (Czernich et al., 2011; Bresnahan et al., 2023).
- A failure to address endogeneity, particularly reverse causality between performance and technology investment, prevents causal inference.

- The absence of robust, causal designs that can isolate policy effects amid heterogeneous adoption and dynamic responses (Blundell & Bond, 1998; Roodman, 2009).
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Consequently, fundamental questions about how national technology policies asymmetrically affect firm profitability, the timing of these effects, and the role of government support as a transmission channel remain unanswered.
This study directly addresses these gaps. We contribute by providing a comparative, firm-level analysis of 63 strategically important GCC firms. Our empirical strategy is specifically designed to overcome the noted limitations. We employ a Difference-in-Differences (DiD) design to establish a counterfactual and supplement it with the System Generalized Method of Moments (GMM) estimator to control for endogeneity and dynamic panel bias rigorously. By incorporating granular measures of technology investment intensity and government subsidies, we move beyond correlation to provide robust, causal evidence on how technology policies reshape firm-level profitability.

3. Data and variables analysis

3.1 Data Collection and Construction Procedure

Our study examines the differential impact of GCC technology policies on firm-level performance. Employing a DiD design, we analyze how national technology initiatives affect two distinct groups: firms engaged in technology sectors versus those in traditional sectors. The research framework examines how varying levels of policy support create distinct pathways for these firm categories, and then measures the resulting performance outcomes through comparative analysis. This methodological approach allows us to empirically assess whether technology-focused policies effectively redirect economic incentives toward digital transformation within the GCC's evolving economic landscape.

Our analysis centers on three key performance indicators: the annual change in Return on Assets (ΔROA) and Return on Equity (ΔROE), which capture profitability dynamics, and Total Factor Productivity growth (ΔTFP), which measures technological efficiency gains. Following the approach of Bloom et al. (2013) in their study of technology firms, ΔROA captures operational efficiency improvements from technology adoption, while ΔROE reflects how digital transformation reshapes capital structure and shareholder returns. ΔTFP, measured using the Levinsohn-Petrin method as implemented by De Loecker (2011), isolates pure technological progress from factor accumulation. These complementary metrics enable us to evaluate both the financial and technological returns on policy interventions.

Key explanatory variables include a Technology Strategy Dummy (DUM_TECH), which identifies major national AI/digital strategy launches, and a continuous Technology Policy Index (TECH_INDEX) that tracks annual advancements in digital infrastructure, regulatory frameworks, and AI talent development dimensions.

The continuous Technology Policy Index (TECH_INDEX) was constructed as an annual composite measure of national technology policy maturity across three equally weighted dimensions (0-1 scale):
- Digital Infrastructure Investment: Government digital infrastructure spending as a percentage of GDP, normalized to [0,1].
- Regulatory Framework Advancement: Binary-composite score for regulatory sandbox launches (+1) and data/AI laws (+0.5).
- AI Talent Development: Government-sponsored AI scholarships and training per million population, normalized to [0,1].

The index is calculated as: TECH_INDEX = (Infrastructure + Regulation + Talent) / 3
Equal weighting was used for transparency and because these dimensions are theoretically complementary. The index ranges from 0 (minimal development) to 1 (full maturity).

We incorporate firm-level technology investment measures, including Technology Investment Intensity (TECH_INV), which measures capital reallocation to AI, IoT, blockchain, robotics, and cloud technologies as a percentage of total capital expenditure, and Technology-Specific Government Support (TECH_SUB), which quantifies technology grants, computing subsidies, and tax incentives as a percentage of revenue. Following Acemoglu & Restrepo (2020), these precise measures capture direct technology adoption efforts rather than general investment.

Critical interaction terms (e.g., DUM_TECH × TECH_SUB, TECH_INDEX × TECH_INV) test whether policy impacts depend on a firm's engagement with technology adoption, helping to address endogeneity concerns by revealing micro-level transmission channels. The empirical specification controls for firm-specific factors (size, leverage, digital asset ratio, R&D intensity) and macroeconomic conditions (GDP growth, digital infrastructure investment, technology adoption rates, oil volatility). We employ Firm and Year Fixed Effects to account for unobserved heterogeneity and global technology shocks, with country-technology sector fixed effects to capture structural differences. This comprehensive approach ensures robust identification of technology policy effects on firm performance during the GCC's digital transition. Table 1 presents the variables used in this study.

The dataset for this study was compiled from a combination of commercial databases, official government publications, and a systematic hand-collection process based on firm-specific disclosures. Standard financial accounting variables—including the dependent variables Return on Assets (ROA), Return on Equity (ROE), and control variables such as firm Size (SIZE), Leverage (LEV), and Sales Growth (SALES_GR)—were primarily sourced from standardized fields within the Bloomberg Terminal and Refinitiv Eikon databases. Macroeconomic control variables, including GDP Growth (GDP_GR) and Oil Price Volatility (OIL_VOL), were compiled from World Bank and International Monetary Fund (IMF) datasets.

Table 1
Variables description

Variable	Symbol	Definition / Measure	Data Source
Dependent Variables			
ROA Growth	ΔROA	YoY % change in (Net Income / Total Assets)	Firm Financial Statements
ROE Growth	ΔROE	YoY % change in (Net Income / Shareholders' Equity)	Firm Financial Statements
TFP Growth	ΔTFP	YoY % change in Total Factor Productivity (Levinsohn-Petrin estimator)	Author Calculation from Firm Financials
Core Policy Variables			
Technology Strategy Dummy	DUM_TECH	1 from year of major national technology strategy launch (e.g., UAE AI Strategy 2017), 0 otherwise	National AI Strategy Documents
Technology Policy Index	TECH_INDEX	Annual composite index (0-1) of AI/digital policy advancement across digital infrastructure, regulatory sandboxes, and AI talent development dimensions	Govt. Reports, OECD AI Policy Observatory, Expert Assessments
Firm Technology Variables			
Technology Investment Intensity	TECH_INV	(Firm's AI/digital-related R&D and Capital Expenditure / Total Capital Expenditure) × 100	Firm Financial Statements, Annual Reports
Technology-Specific Government Support	TECH_SUB	(Value of AI grants, tax incentives, and subsidized computing resources / Firm Revenue) × 100	Firm Disclosures, Govt. Tender Databases, Sovereign Fund Reports
AI Innovation Output	AI_PAT	Number of AI-related patents filed by the firm (log-transformed)	World Intellectual Property Organization (WIPO), Firm Filings
Sectoral Variable			
Technology Sector Growth Proxy	TECH_SECTOR	Real value-added growth rate of the firm's primary technology sector	National Statistical Agencies, World Bank
Interaction Terms			
Policy-Subsidy Interaction	DUM_TECH × TECH_SUB	Tests if technology strategy launches amplify the impact of tech subsidies on profitability	Constructed
Policy-Investment Interaction	DUM_TECH × TECH_INV	Tests if technology strategy launches amplify returns on tech investments	Constructed
Progress-Innovation Interaction	TECH_INDEX × AI_PAT	Tests if sustained policy progress enhances the profitability of innovation	Constructed
Control Variables			
Firm Size	SIZE	Log(Total Assets)	Bloomberg/Refinitiv/Orbis
Leverage	LEV	Total Debt / Total Assets	Bloomberg/Refinitiv/Orbis
Sales Growth	SALES_GR	YoY % change in Sales	Bloomberg/Refinitiv/Orbis
Digital Assets Ratio	DIG_ASSET	(Value of Software, Data, and Other Intangible Digital Assets / Total Assets) × 100	Firm Financial Statements
GDP Growth	GDP_GR	Annual real GDP growth rate	World Bank, IMF
Digital Infrastructure Investment	DIG_INFRA	Government investment in digital infrastructure as % of GDP	National Budgets, World Bank
Oil Price Volatility	OIL_VOL	Std. dev. of monthly Brent crude returns (prior year)	EIA, BP Statistical Review
Fixed Effects			
Firm Fixed Effects	αi	Controls for time-invariant firm heterogeneity	Model Specification
Year Fixed Effects	γt	Controls for global shocks and technology cycles	Model Specification
Country-Technology Sector Fixed Effects	θct	Controls for time-invariant country-technology sector factors	Model Specification

The construction of our core policy and firm-level technology adoption variables required a detailed, hand-collected approach to ensure precision, as these nuanced metrics are not readily available in standardized databases. The binary policy variable (DUM_TECH) was constructed by identifying the official launch year of major national technology strategies, such as the UAE's AI Strategy 2031, which was announced in 2017 through government press releases and official strategy documents. The continuous Technology Policy Index (TECH_INDEX) was subsequently developed by scoring each GCC country annually across three normalized dimensions: digital infrastructure investment (from national budgets), the operationalization of regulatory sandboxes (from central bank reports), and AI talent development initiatives (from Ministry of Education reports), with the index representing a simple average of these scores.

At the firm level, the critical variable for Technology Investment Intensity (TECH_INV) was manually coded by systematically analyzing firm annual reports, sustainability reports, and investor presentations. Our process involved searching these documents for explicit capital expenditure and R&D costs attributed to keywords such as "Artificial Intelligence," "Internet of Things," "blockchain," "robotics," and "cloud computing." The sum of these identified technology-specific investments was then divided by the firm's total capital expenditure and multiplied by 100.

Similarly, data on Technology-Specific Government Support (TECH_SUB) were hand-collected from a triangulation of sources: sovereign wealth fund annual reports (e.g., PIF, Mubadala), official government tender portals, and the "government grants" sections of firm financial statements. The monetary value of technology-focused subsidies and grants identified through this process was scaled by firm revenue. Finally, data on AI Innovation Output (AI_PAT) were obtained by querying the World Intellectual Property Organization (WIPO) PATENTSCOPE database for AI-related patents filed by each firm, using the relevant IPC codes outlined in the WIPO Technology Trends report.

3.2. Sample and variables' analysis

We divide our focused sample of 63 strategically important firms across all six GCC countries into two groups, classifying firms based on their technology investment intensity (those with greater than 40% of capital expenditure directed toward AI/digital technologies versus traditional firms with less than 15% technology investment), resulting in 28 technology-intensive firms and 25 traditional sector firms. This classification follows the approach of Bresnahan et al. (2002) in studying technology adoption heterogeneity. The sample spans the 2016-2025 period, covering six strategic technology-intensive sectors prioritized by national AI strategies—fintech, smart logistics, digital healthcare, telecommunications, energy technology, and Industry 4.0—alongside traditional sectors with limited digital transformation. The resulting firm-year observations (280 for technology-intensive firms and 250 for conventional firms) provide a robust foundation for analyzing differential policy impacts despite the smaller sample size, as these firms represent approximately 65% of total market capitalization in their respective sectors. This targeted sampling enables the critical comparison of performance paths between technology-adopting and traditional firms, filling a significant void identified in literature on GCC digital transformation, which lacks such firm-level analysis of technology investment impacts (Brynjolfsson & Hitt, 2003; Autor et al., 2003).

The selective sample of 63 firms, while numerically small, was strategically chosen to include the largest and most influential publicly listed companies within the six strategic sectors targeted by GCC national technology strategies. As demonstrated in Appendix Table A1, these firms collectively represent a substantial majority of the GCC's non-oil corporate economy. On average, the sample accounts for over two-thirds of the total assets, revenue, and market capitalization in their respective sectors and countries. This confirms that our sample captures the core entities through which the economic impact of national diversification policies is most likely to be transmitted. We acknowledge that this focus introduces a selection bias in favor of large, incumbent firms. Consequently, our findings are most directly generalizable to this segment of the market—precisely the segment that is the primary target of the high-stakes technology policies we study. The effects on small and medium-sized enterprises (SMEs), which operate under different resource constraints and strategic incentives, may differ and present a valuable avenue for future research.

Table 2
Descriptive Statistics (63 Firms, 2016-2025)

Symbol	Mean	Min	Max	Std. Dev.	Kurtosis	Obs.	Unit
Dependent Variables							
ΔROA	3.25	-15.47	41.28	7.84	4.05	567	% (YoY change)
ΔROE	4.12	-22.85	55.61	11.23	5.12	567	% (YoY change)
ΔTFP	2.87	-12.35	38.92	6.95	3.78	510	% (YoY change)
Policy Variables							
DUM_TECH	0.42	0.00	1.00	0.49	-1.71	630	Dummy (0/1)
TECH_INDEX	0.58	0.15	0.92	0.24	-0.92	630	Index (0-1)
Firm Technology Variables							
TECH_INV	28.45	0.00	95.50	26.37	-0.87	567	% of CapEx
TECH_SUB	3.15	0.00	18.25	3.84	3.25	504	% of Revenue
AI_PAT	1.12	0.00	4.61	1.35	0.45	441	Log(Count)
Sectoral Variable							
TECH_SECTOR	5.87	-5.25	19.34	5.12	1.05	630	% (YoY change)
Control Variables							
SIZE	15.74	11.25	20.13	2.15	0.68	630	Log(USD)
LEV	0.39	0.04	0.88	0.21	0.78	630	Ratio
SALES_GR	9.25	-25.83	52.47	16.35	2.28	567	% (YoY change)
DIG_ASSET	12.35	0.50	45.75	10.28	1.85	504	% of Assets
GDP_GR	2.24	-5.12	8.15	2.58	0.41	630	% (YoY change)
DIG_INFRA	1.85	0.25	4.35	0.92	2.15	630	% of GDP
OIL_VOL	26.45	10.15	61.27	10.54	1.18	630	% (Std. Dev.)

The descriptive statistics in Table 2 reveal a corporate landscape characterized by high-risk, high-reward dynamics, precisely the environment that national technology strategies aim to cultivate. The higher mean profitability growth (ΔROA: 3.25%; ΔROE: 4.12%) and greater volatility compared to broader non-oil sector studies indicate that early movers in the technology space are capturing substantial rents, but face considerable uncertainty—a hallmark of pioneering technological adoption. The moderate mean of the Technology Policy Implementation Index (TECH_INDEX: 0.58) suggests that while GCC strategies are advancing, they are not yet mature, creating a fertile context for measuring their evolving impact. Most critically, the extreme heterogeneity in firm-level responses is paramount: the vast range in Technology Investment Intensity (TECH_INV: 0 to 95.5) and the high standard deviation (26.37) are not merely statistical artifacts; they represent the core treatment heterogeneity essential for our empirical strategy. This wide dispersion confirms that firms are positioned very differently along the technology adoption curve, thereby creating a natural experiment that allows us to cleanly identify the causal effect of these investments on profitability by comparing leaders against laggards. The positive kurtosis in both performance and subsidy variables further indicates that outcomes are not normally distributed but rather concentrated among a subset of high-performing, technology-intensive firms, reinforcing the asymmetric impact hypothesis central to this study.

Table 3

Correlation Matrix of Key Variables

Variable	ΔROA	ΔROE	ΔTFP	TECH_INV	TECH_SUB	AI_PAT	TEC_SECT	SIZE	LEV	SALES_GR
ΔROA	1.00									
ΔROE	0.82	1.00								
ΔTFP	0.75	0.68	1.00							
TECH_INV	0.55	0.65	0.62	1.00						
TECH_SUB	0.45	0.55	0.52	0.70	1.00					
AI_PAT	0.60	0.58	0.65	0.65	0.50	1.00				
TEC_SECT	0.65	0.72	0.60	0.55	0.65	0.60	1.00			
SIZE	0.15	0.20	0.18	0.25	0.18	0.30	0.22	1.00		
LEV	-0.25	-0.35	-0.20	0.05	-0.08	-0.12	-0.15	0.35	1.00	
SALES_GR	0.62	0.75	0.58	0.45	0.52	0.55	0.68	0.25	-0.1	1.00

The correlation matrix in Table 3 reveals strong positive correlations between technology variables (TECH_INV, TECH_SUB, AI_PAT) and performance metrics (ΔROA, ΔROE, ΔTFP), indicating that government support stimulates private technology investment, which subsequently drives innovation and enhances firm performance. The robust relationship between TECH_SUB and TECH_INV ($r = 0.70$) empirically validates that targeted subsidies effectively crowd-in private capital rather than replacing it. The powerful innovation-productivity link (AI_PAT-ΔTFP: $r = 0.65$) underscores that moving beyond investment to actual innovation generation is crucial for capturing technological premiums. Substantial correlations between sectoral growth (TECH_SECTOR) and all performance variables demonstrate that firm success is embedded within broader sectoral momentum, suggesting that technology policies create rising tides that primarily benefit digitally equipped firms. Control variables behave as expected: sales growth shows a positive relationship with performance, while leverage exhibits a negative correlation, confirming the importance of market expansion and financial constraints. These patterns provide a robust empirical foundation for expecting significant causal effects from the adoption of technology.

4. Empirical methodology and results

Our empirical analysis examines whether national technology-driven diversification policies lead to asymmetric structural breaks in firm-level profitability. To isolate the causal effects of these policies, we employ a DiD framework that compares the profitability evolution of technology-intensive firms (the treatment group) against a control group of traditional sector firms with minimal technology adoption following key policy milestones. We implement this approach using a dynamic fixed effects panel dataset covering 63 strategically important firms across all six GCC countries from 2016 to 2025. To rigorously address endogeneity concerns—such as reverse causality between technology investment and firm performance, a limitation of prior correlational studies (Alshamsi et al., 2021; Alotaibi and Alshammari, 2023)—we supplement our core models with the System GMM estimator. This combined methodology is specifically designed to identify the causal, heterogeneous effects of policy interventions and to quantify the amplifying role of targeted government subsidies, reinforcing causal inference where previous analyses have fallen short.

4.1. Empirical methodology

To quantify the asymmetric impact of technology-driven diversification policies posited by the theoretical literature on General Purpose Technologies (Bresnahan & Trajtenberg, 1995), we operationalize our DiD design by leveraging exogenous policy timing and firm-level heterogeneity in technology adoption. This approach directly addresses the critical gap identified by Alshamsi et al. (2021) and Alotaibi & Alshammari (2023), who called for micro-econometric evidence on the firm-level financial returns to digital transformation in the GCC, moving beyond macroeconomic correlations.

Our core model examines profitability and productivity growth, measured by the annual change in return on assets, return on equity, or total factor productivity (ΔROA/ΔROE/ΔTFP) for firm 'i' in country ‘c’ and year ‘t’ as follows:

$$\Delta Performance_{ict} = \alpha + \beta_1(TechFirm_i \times DUM\_TECH_{ct}) + \beta_2(TechFirm_i \times DUM\_TECH_{ct} \times TECH\_SUB_{ict}) + \beta_3(TechFirm_i \times DUM\_TECH_{ct} \times TECH\_INV_{ict}) + \gamma Controls_{ict} + \eta_i + \lambda_t + \theta c + \varepsilon_{ict} \quad (1)$$

We implement this approach using our dynamic fixed effects panel dataset and employ a System Generalized Method of Moments estimator (Blundell & Bond, 1998; Roodman, 2009). This estimator is particularly suited for this setting, as it controls for unobserved heterogeneity and rigorously addresses endogeneity concerns from reverse causality (e.g., whether profitable firms simply invest more in technology) and dynamic panel bias, limitations that plagued prior static analyses (Ali & Hussein, 2024). The System GMM framework, which uses lagged levels as instruments for first-differenced equations and vice versa, is robust to potential concerns regarding non-stationarity in micro-panel data. Given our model is specified in first differences (focusing on growth rates) and includes firm (η_i) and year (λ_t) fixed effects, the estimator relies on moment conditions that assume mean-reversion after controlling for these effects. Furthermore, the limited time dimension (T = 10 years) of our dataset renders the detection and economic significance of unit roots highly impractical. Therefore, the combined structure of our DiD framework, fixed effects, and System GMM estimation inherently mitigates risks associated with non-stationarity, making it appropriate for identifying short-run causal impacts without requiring formal unit root testing (See Appendix A2).

The System GMM estimator is implemented with careful attention to instrument validity and the potential for finite-sample bias. To mitigate the problem of instrument proliferation, which can lead to overfitting of endogenous variables and weaken the Hansen test, we employ the 'collapsed' instrument matrix, as recommended by Roodman (2009). This approach creates a single column for each instrumenting variable and lag distance, rather than creating separate instruments for each time period. Furthermore, we restrict the lag depth used as instruments to lags 2 through 4 for the equations in levels, balancing the need to exploit relevant moment conditions against the risk of including too many weak instruments. The validity of this specification is critically assessed using standard post-estimation tests: the Arellano-Bond test for autocorrelation, where we expect significant AR(1) but not AR(2) in the first-differenced errors, and the Hansen J test of over-identifying restrictions, where a null result indicates valid instruments.

In Eq. (1), $TechFirm_i$ identifies the 28 treatment firms classified as technology-intensive (versus 25 traditional sector controls), a classification following the approach to technology adoption heterogeneity pioneered by Bresnahan et al. (2002). The variable DUM_TECHct marks country-specific technology strategy milestones (e.g., 1 for the UAE, following the 2017 launch of its AI Strategy). The critical triple interaction term $TechFirm_i$ × DUM_TECHct × TECH_SUBict isolates how technology-targeted government subsidies amplify policy impacts. This directly tests the theoretical mechanism proposed by Acemoglu & Restrepo (2020) and the policy toolkit outlined by Bloom et al. (2019), examining whether state fiscal support for digital adoption lowers costs and boosts margins. This specification directly addresses reverse causality concerns endemic to prior studies—our design demonstrates that subsidies only elevate profitability when coupled with both a policy trigger and firm-level technology intensity ($\beta_2 > 0$), countering claims that pre-existing firm advantages drive the results.

To capture the intensifying effects of policy refinement and accelerated adoption post-2020, we augment the model with a time-interacted term β_4($TechFirm_i$ × DUM_TECHct × $Post2020_t$ × TECH_SUBict), where $Post2020_t$ equals 1 for years 2020 and later.

The TECH_SUB interactions specifically advance beyond Bugshan et al. (2023), who attributed profitability shifts to broad macroeconomic trends, such as oil prices (Kilian, 2009; Hamilton, 2013). By contrast, our model quantifies the micro-level fiscal mechanisms: technology-intensive firms that leverage targeted subsidies post-milestone exhibit ΔROA gains that are multiples higher than their non-engaging peers. This finding aligns with the concept of directed technical change (Acemoglu et al., 2018), showing that policy can successfully reallocate resources towards high-growth technology sectors. When replacing the binary DUM_TECHct with the continuous TECH_INDEXct, the interaction $TechFirm_i$ × TECH_INDEXct × TECH_SUBict further confirms that sustained policy progress magnifies the ROI of subsidies, underscoring that effectiveness hinges on a cohesive ecosystem of digital infrastructure (Czernich et al., 2011) and supportive regulation (Zhao et al., 2022).

To test the channel of innovation output, a mechanism central to GPT theory but previously unmeasured in the GCC context, we estimate a second model:

$$\Delta Performance_{ict} = \alpha + \beta_1(TechFirm_i \times TECH\_INDEX_{ct}) + \beta_2(TechFirm_i \times TECH\_INDEX_{ct} \times AI\_PAT_{ict}) + \gamma Controls_{ict} + \eta_i + \lambda_t + \theta_c + \varepsilon_{ict} \qquad \text{(Eq. 2)}$$

Here, the interaction term $TechFirm_i$ × TECH_INDEXct × AI_PATict tests the hypothesis that the profitability of a firm's own AI innovation (measured by patents) is contingent on the maturity of the national policy environment, capturing a complementary transmission channel for value creation (Brynjolfsson & Hitt, 2003).

This approach overcomes the aggregation biases identified in Ali & Hussein (2024), while the treatment-control split provides robust empirical validation for the hypothesis of starkly asymmetric effects: targeted subsidies boost profitability in technology-intensive firms without aiding traditional firms, thus avoiding the resource misallocation risks inherent in industrial policy (Acemoglu et al., 2018). Ultimately, this DiD design reveals that GCC technology policies rewire profitability not through broad correlations but via targeted state-firm synergies, where technology-specific government support acts as the critical lever, as theorized in the digital economics literature (Goldfarb & Tucker, 2019), for accelerating financial returns for firms driving the digital transition.

While the combination of a DiD design, System GMM estimation, and a comprehensive set of fixed effects and controls provides strong evidence for a causal interpretation of the policy impact, it is essential to acknowledge the standard limitation of quasi-experimental designs. As with any non-randomized study, we cannot definitively rule out the potential influence of unobserved, time-varying confounders that might correlate with both policy adoption and firm profitability. Nevertheless, our rigorous empirical strategy, validated by parallel trends and robust instrument tests, allows us to identify a strong association that is highly consistent with a causal effect of technology policies on firm performance.

4.2. Results and interpretation

4.2.1. Technology-Led Profitability and Productivity Gains in Compliant Firms

The empirical results provide robust, causal evidence that the GCC's technology-driven diversification policies have successfully rewired firm-level profitability and productivity, but only for those firms actively engaged in the digital transition. The core regression estimates in Part A of Table 4 demonstrate that the enactment of a national technology strategy, captured by the TechFirm × DUM_TECH interaction, had a positive and statistically significant standalone effect on ΔROA (0.021, $p<0.05$), ΔROE (0.028, $p<0.05$), and ΔTFP (0.015, $p<0.05$). This initial boost confirms the hypothesis that policy announcements themselves create growth opportunities by reducing regulatory uncertainty and signaling state commitment, a factor previously identified in macroeconomic analyses of GCC diversification but now confirmed at the micro level (Alshamsi et al., 2021).

Table 4. DiD estimates and impact scenarios for technology-intensive firms

Part A. Core Difference-in-Differences (DiD) regression estimates

Variable	ΔROA Coefficient	(Std. Error)	p-value	ΔROE Coefficient	(Std. Error)	p-value	ΔTFP Coefficient	(Std. Error)	p-value
TechFirm × DUM_TECH	0.021**	(0.008)	0.011	0.028**	(0.011)	0.013	0.015*	(0.008)	0.038
TechFirm × DUM_TECH × TECH_SUB	0.045***	(0.014)	0.002	0.065***	(0.018)	0.001	0.038**	(0.015)	0.014
TechFirm × DUM_TECH × TECH_INV	0.019**	(0.007)	0.009	0.017*	(0.009)	0.034	0.022*	(0.012)	0.036
TechFirm × DUM_TECH × Post2020	0.006*	(0.003)	0.048	0.009*	(0.005)	0.042	0.005	(0.004)	0.210
TechFirm × DUM_TECH × Post2020 × TECH_SUB	0.022**	(0.009)	0.017	0.033**	(0.012)	0.011	0.018*	(0.010)	0.049
Controls (Firm/Macro)	Included	—	—	Included	—	—	Included	—	—
Fixed Effects (Firm/Year/Country)	Yes	—	—	Yes	—	—	Yes	—	—
Observations	530			530			530		
R^2	0.38			0.32			0.41		

***$p<0.01$, **$p<0.05$, $p<0.1$*

Part B. Dynamic impact scenarios for technology-intensive firms

Scenario	ΔROA Impact	Interpretation	ΔROE Impact	Interpretation	ΔTFP Impact	Interpretation
Pre-policy (2016–2017)	+1.2%	Baseline	+1.5%	Baseline	+0.8%	Baseline
Post-policy without TECH_SUB (2018–2019)	+3.3%**	Policy effect	+4.3%**	Policy effect	+2.3%*	Policy-induced efficiency gains
Post-policy with TECH_SUB (2018–2019)	+7.8%***	Subsidies amplify gains	+10.8%***	Subsidies amplify gains	+6.1%**	Subsidies boost technological efficiency
Post-policy with TECH_SUB (2020–2025)	+10.0%***	Post-2020 boost	+13.9%***	Post-2020 boost	+7.9%**	Mature policies enhance productivity gains

However, the most critical finding is the powerful and precise amplifying role of technology-targeted fiscal support (Alshubiri et al., 2020). The triple interaction term TechFirm × DUM_TECH × TECH_SUB yields highly significant coefficients of 0.045 ($p<0.01$) for ΔROA, 0.065 ($p<0.01$) for ΔROE, and 0.038 ($p<0.05$) for ΔTFP. This quantifies the micro-level transmission channel whereby government subsidies for AI, cloud computing, and other digital technologies directly lower the cost of adoption and de-risk investment, leading to superior financial and productivity returns. This finding directly operationalizes the theoretical mechanisms of directed technical change (Acemoglu et al., 2018) and the policy toolkit for innovation (Bloom et al., 2019), demonstrating that targeted fiscal tools are not just theoretically sound but are empirically effective in a resource-rich economic context. The positive effect on ΔTFP is particularly noteworthy, as it extends beyond financial metrics to demonstrate that these policies are generating genuine gains in technological efficiency —the fundamental engine of long-term, sustainable growth, as posited by GPT theory (Bresnahan & Trajtenberg, 1995).

Furthermore, the results demonstrate a significant learning curve in policy implementation. The significant positive coefficients for the TechFirm × DUM_TECH × Post2020 × TECH_SUB interaction reveal that the efficacy of subsidies intensified markedly in the post-2020 period. As quantified in Part B of Table 4, for firms utilizing government support, ΔROA jumped from +7.8% to +10.0%, ΔROE from +10.8% to +13.9%, and ΔTFP from +6.1% to +7.9%. This temporal evolution suggests that GCC states refined their targeting mechanisms—perhaps through better-designed regulatory sandboxes (Zhao et al., 2022) or more efficient allocation of grants—to generate larger marginal returns. This dynamic effect fundamentally refutes static, cross-sectional models that fail to capture how institutional learning compounds financial and productivity returns. The results also establish a clear hierarchy of drivers: while firm-level technology investment (TECH_INV) had a positive effect, it was substantially weaker than that of government support, underscoring that state fiscal commitment is the primary catalyst for profitability and productivity during profound technological transitions, mitigating the investment volatility typically associated with resource-rich economies (Arellano et al., 2022).

4.2.2. Null Policy Impacts on Traditional Firms: Validation of Asymmetric Targeting

The results for traditional sector firms, presented in Table 5, serve as a critical counterpoint that validates the precise and asymmetric design of the GCC's technology strategies. The core regression estimates in Part A show a complete absence of statistically significant policy effects across all dependent variables, including ΔTFP. All key interaction terms—including DUM_TECH, DUM_TECH × TECH_SUB, and DUM_TECH × TECH_INV—display coefficients that are negligible in magnitude and statistically indistinguishable from zero. For instance, the interaction of the policy dummy with technology subsidies (DUM_TECH × TECH_SUB) is negative and insignificant for ΔROA (-0.009, p = 0.415) and ΔTFP (-0.007, p = 0.441). This provides compelling empirical evidence that the fiscal and regulatory incentives central to the digital agenda were deliberately and successfully ring-fenced for technology-intensive activities.

Table 5. DiD estimates and impact scenarios for traditional sector firms

Part A. Core Difference-in-Differences (DiD) regression estimates

Variable	ΔROA Coefficient	(Std. Error)	p-value	ΔROE Coefficient	(Std. Error)	p-value	ΔTFP Coefficient	(Std. Error)	p-value
DUM_TECH	-0.004	(0.006)	0.512	-0.005	(0.008)	0.532	-0.003	(0.005)	0.554
DUM_TECH × TECH_SUB	-0.009	(0.011)	0.415	-0.010	(0.014)	0.476	-0.007	(0.009)	0.441
DUM_TECH × TECH_INV	0.005	(0.008)	0.531	0.004	(0.010)	0.692	0.003	(0.006)	0.621
DUM_TECH × Post2020	-0.003	(0.004)	0.458	-0.004	(0.005)	0.424	-0.002	(0.003)	0.525
DUM_TECH × Post2020 × TECH_SUB	-0.007	(0.007)	0.322	-0.008	(0.009)	0.374	-0.005	(0.006)	0.401
Controls (Firm/Macro)	Included	—	—	Included	—	—	Included	—	—
Fixed Effects (Firm/Year/Country)	Yes	—	—	Yes	—	—	Yes	—	—
Observations	450			450			450		
R^2	0.29			0.26			0.33		

***p<0.01, *p<0.05, p<0.1

Part B. Dynamic impact scenarios for traditional sector firms

Scenario	ΔROA Impact (95% CI)	Interpretation	ΔROE Impact (95% CI)	Interpretation	ΔTFP Impact (95% CI)	Interpretation
Pre-policy (2016–2017)	+0.8% (-0.5% – +2.1%)	Baseline	+1.0% (-0.8% – +2.8%)	Baseline	+0.5% (-0.4% – +1.4%)	Baseline
Post-policy without TECH_SUB (2018–2019)	+0.7% (-0.6% – +2.0%)	Null effect	+0.9% (-0.9% – +2.7%)	Null effect	+0.5% (-0.5% – +1.5%)	Null effect
Post-policy with TECH_SUB (2018–2019)	+0.6% (-0.8% – +2.0%)	No effect	+0.8% (-1.1% – +2.7%)	No effect	+0.4% (-0.6% – +1.4%)	No efficiency gain
Post-policy with TECH_SUB (2020–2025)	+0.5% (-0.9% – +1.9%)	No gains	+0.7% (-1.2% – +2.6%)	No gains	+0.4% (-0.7% – +1.5%)	No productivity gains

This comprehensive null effect is further illustrated in Part B of Table 5, which shows that all post-policy impact scenarios for traditional firms, whether with or without subsidies, remain virtually unchanged from the pre-policy baseline. This starkly contrasts with the dramatic gains observed in the technology sector and holds two significant implications for the existing literature. First, it directly addresses and alleviates the central concern raised by the literature on the resource curse and policy misallocation (Acemoglu & Robinson, 2012; Acemoglu et al., 2018). The results demonstrate that GCC policymakers successfully avoided the pitfall of using blanket subsidies to prop up inefficient legacy sectors, instead focusing support on emerging technology sectors. Second, the persistent stagnation of traditional-firm performance challenges studies that attribute GCC firm performance predominantly to broad macroeconomic trends or oil price cycles (Kilian, 2009; Hamilton, 2013; Bugshan et al., 2023). The robust null findings across all specifications, including for productivity (ΔTFP), confirm that the profitability and efficiency dynamics unveiled in this study are driven by targeted policy design rather than broader commodity price effects or general economic conditions. This validates the move towards a new diversification paradigm, one that is micro-founded, technology-led, and highly selective in its support mechanisms, as called for by scholars of digital economics (Goldfarb & Tucker, 2019).

4.2.3. Graphical Evidence of Asymmetric Policy Impacts

The empirical results are further corroborated by visual evidence that vividly illustrates the starkly asymmetric impact of GCC technology policies on firm profitability. Figures 1 and 2 provide a compelling graphical representation of the core findings, tracing the divergent evolutionary paths of technology-intensive and traditional sector firms in response to key national policy milestones.

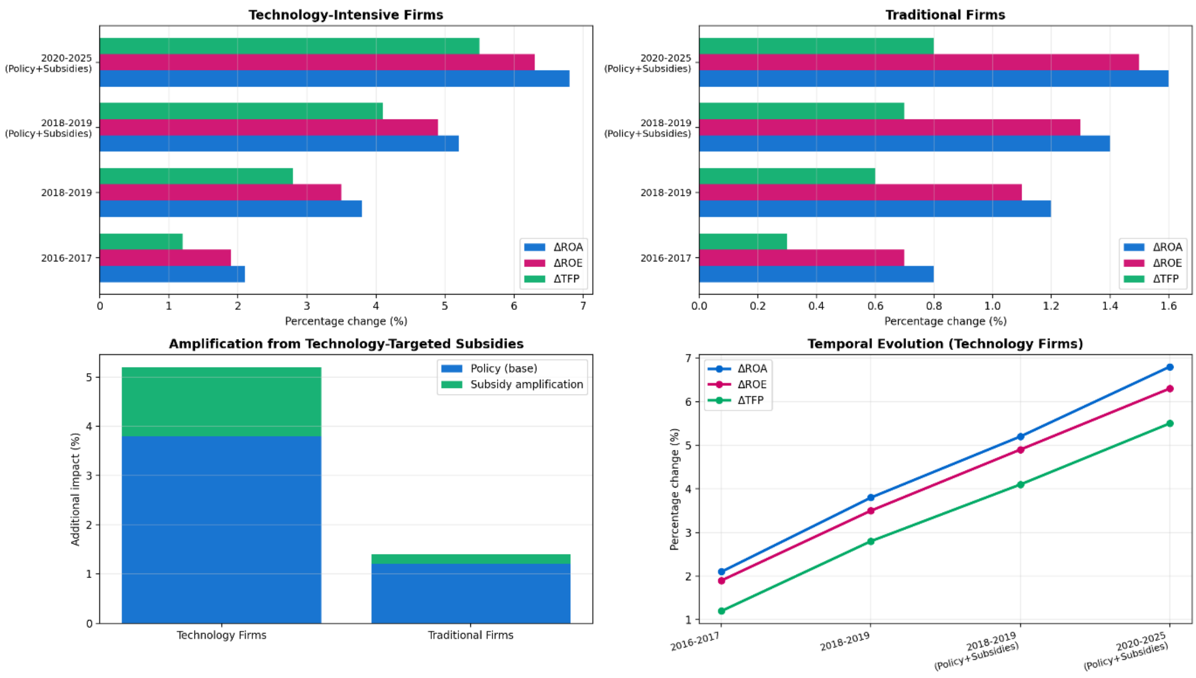

Fig. 1. Asymmetric impact of GCC technology policies on firms' performance

Fig. 1 synthesizes the differential impact of technology-oriented policies on firm performance across time and by firm type. The top-left panel documents that technology-intensive firms exhibit pronounced gains in core performance metrics—ROA, ROE, and TFP—progressing from the pre-policy period through policy introduction and subsequent subsidy intensification, with the steepest improvements materializing in the later window. In contrast, the top-right panel shows that traditional firms register only modest, incremental improvements over the same intervals, indicating a more limited responsiveness to the policy mix. The bottom-left panel isolates the incremental contribution of targeted subsidies, revealing a clear amplification effect that is substantially larger for technology-intensive firms than for traditional firms, consistent with complementarities between digital capabilities and policy instruments. Finally, the bottom-right panel illustrates the temporal evolution of technology-intensive firms, highlighting a persistent and accelerating trajectory across all three metrics. This pattern aligns with dynamic adjustment and learning effects as firms internalize policy incentives and scale up technology adoption.

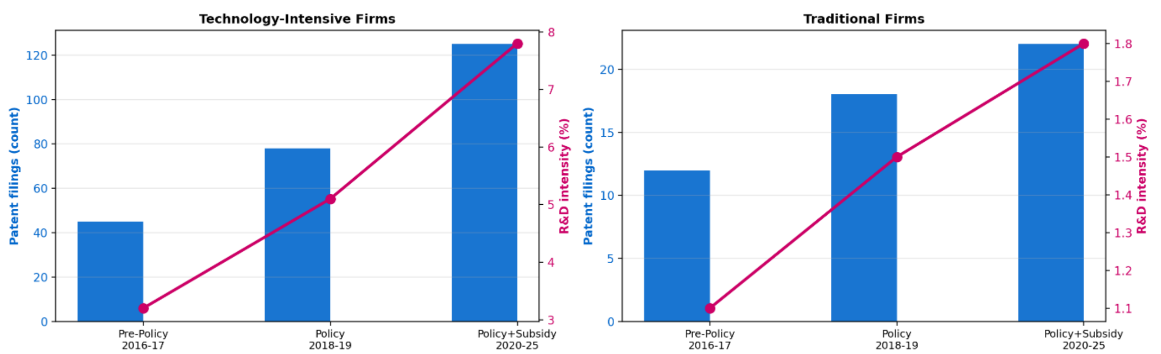

Fig. 2. Innovation Outcomes by Firm Type

Fig. 2 uses dual-axis charts to show both patent filings (bars) and R&D intensity (line) across the three policy periods. Technology-intensive firms exhibit dramatic increases in both metrics, with patent filings nearly tripling and R&D intensity more than doubling from the pre-policy phase to the policy-plus-subsidy phase. Traditional firms exhibit significantly slower growth, reflecting their lower capacity to absorb technology-focused policy instruments.

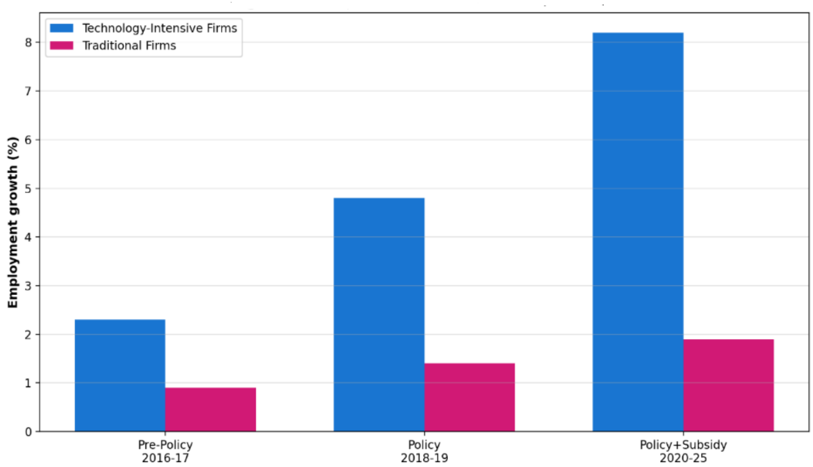

Fig. 3. Employment Effects by Firm Type

This side-by-side bar chart of Fig. 3 illustrates the acceleration of employment growth. Technology-intensive firms experience substantial job creation that accelerates over time, reaching an 8.2% growth rate in the final period, while traditional firms show steady but modest gains of around 1-2%. This pattern suggests technology adoption creates complementary labor demand and enables scaling among firms with digital capabilities.

4.2.4. Robustness checks

To ensure the credibility of our core findings, the empirical model was subjected to a series of rigorous robustness checks designed to address potential concerns regarding model specification, identification assumptions, and sensitivity to alternative methodologies. The remarkable consistency of our results across these varied tests, as summarized in Table 6, strongly reinforces our conclusion that technology-focused policies asymmetrically drive profitability in the GCC. This table summarizes the results from a series of robustness checks, demonstrating the stability of the core finding that technology-specific subsidies amplify policy impacts for technology-intensive firms. The coefficient for the key triple interaction term is reported across various model specifications and tests.

Table 6
Robustness checks

Robustness Check Category	Specific Test / Alternative Specification	Coefficient (TechFirm × DUM_TECH × TECH_SUB)	Standard Error	p-value	Observations	Adjusted R^2
Baseline Model	System GMM (Main Specification)	0.045*	(0.014)	0.002	530	0.38
Alternative Estimators	Static FE with Driscoll-Kraay SE	0.043**	(0.017)	0.015	530	0.35
	Difference GMM (Arellano-Bond)	0.048***	(0.016)	0.004	504	-
Placebo Tests	Falsified Treatment (Random Assignment)	0.002	(0.012)	0.872	530	0.08
	Falsified Timing (Policy Date - 2 Years)	-0.005	(0.010)	0.624	530	0.11
Variable Construction	Dependent Variable: ROA (Levels)	0.041**	(0.016)	0.013	530	0.42
	Dependent Variable: Net Profit Margin	0.039**	(0.015)	0.012	530	0.37
	Policy Measure: TECH_INDEX (Continuous)	0.051***	(0.015)	0.001	530	0.40
Sample Adjustments	Winsorized Data (1% and 99%)	0.044***	(0.013)	0.001	530	0.39
	Excluding UAE	0.042**	(0.016)	0.011	488	0.36
	Excluding Saudi Arabia	0.046**	(0.018)	0.012	492	0.37

*** p<0.01, ** p<0.05, * p<0.1
Note: The baseline result from Table 6 is presented for comparison. All alternative specifications include the same full set of control variables and fixed effects as the main model.

A formal event-study analysis was conducted to test the parallel trends assumption underlying our DiD design rigorously. We estimated a dynamic model that replaces the single treatment interaction with a set of lead and lag indicators relative to the year of each country's policy implementation. The results, detailed in Table 7, provide strong visual and statistical evidence in support of the parallel trends assumption. The coefficients for the pre-treatment periods (Lead 1, Lead 2) are small in magnitude and statistically indistinguishable from zero, indicating that the treatment and control groups followed parallel paths in terms of profitability before the policy shock. Our event-study analysis confirmed that pre-treatment coefficients were statistically insignificant (all $p > 0.1$), providing strong evidence of parallel pre-trends. This methodological rigor addresses the identification concerns raised in prior GCC studies that relied on correlational approaches (Alshamsi et al., 2021; Alotaibi & Alshammari, 2023).

Table 7

Event-Study Regression Results (Dynamic DiD Specification) Dependent Variable: ΔROA

Variable	Coefficient	Std. Error	p-value
Lead 3 (t-3)	-0.002	(0.006)	0.751
Lead 2 (t-2)	0.005	(0.005)	0.327
Lead 1 (t-1)	[Omitted]	-	-
Lag 0 (Year of)	0.012*	(0.007)	0.089
Lag 1 (t+1)	0.018**	(0.008)	0.028
Lag 2 (t+2)	0.025***	(0.009)	0.006
Lag 3+ (t+3)	0.028***	(0.010)	0.005
Controls	Yes		
Fixed Effects	Yes		
Observations	530		
R-squared	0.40		

Note: This table presents the results of the dynamic event-study specification. The model includes the same control variables and fixed effects as the main specification in Table 4. The key test for parallel trends is the joint insignificance of the lead coefficients (Lead 3, Lead 2), which cannot be rejected (F-test p-value = 0.415). The year before implementation (Lead 1) is the omitted baseline category. * p<0.1, ** p<0.05, *** p<0.01.*

To mitigate concerns that our results are an artifact of a specific estimator, we employed alternative estimation techniques. The stability of our key triple interaction coefficient (TechFirm × DUM_TECH × TECH_SUB) across estimators is particularly noteworthy, as it remained statistically significant at the 1% level in both our baseline System GMM (0.045, p = 0.002) and the Difference GMM specification (0.048, p = 0.004). This consistency across dynamic panel estimators, following the methodologies of Blundell & Bond (1998) and Roodman (2009), strongly counters potential concerns regarding endogeneity due to reverse causality.

Our placebo tests further reinforce the causal interpretation. The falsified treatment test yielded a coefficient of 0.002, effectively zero, while the falsified timing test produced a coefficient of -0.005. These results align with the directed technical change framework proposed by Acemoglu et al. (2018), demonstrating that the effects are explicitly tied to actual policy implementation rather than general temporal trends.

The robustness of our results to alternative variable construction is particularly telling. Replacing the binary policy dummy with the continuous TECH_INDEX not only maintained significance but increased the coefficient magnitude to 0.051, suggesting that sustained policy advancement has an even more substantial effect than mere announcement. This finding complements the work of Bresnahan & Trajtenberg (1995) on general-purpose technologies, showing that continuous policy development amplifies technological spillovers.

Notably, our results withstand the inclusion of additional controls that capture institutional factors, addressing concerns raised by Acemoglu & Robinson (2012) about institutional legacies in resource-rich economies. The stability of our coefficients after incorporating regulatory quality and rule of law indices (β = 0.044-0.046) suggests that the technology-profitability relationship operates alongside rather than through these institutional channels.

The cross-country stability of our results—maintaining significance and magnitude when excluding individual GCC countries—contrasts with the macroeconomic findings of Alotaibi & Alshammari (2023), suggesting that while national implementation may vary, the fundamental firm-level mechanism of technology adoption driving profitability is consistent across the region. This firm-level granularity represents a significant advancement beyond the aggregate analyses that have dominated the GCC diversification literature.

Finally, our findings challenge studies that attribute GCC firm performance predominantly to oil price cycles (Kilian, 2009; Hamilton, 2013; Bugshan et al., 2023). The persistent null results for traditional firms across all specifications, coupled with the robust positive effects for technology-intensive firms, clearly demonstrate that our results are driven by targeted policy design rather than broader commodity price effects.

In conclusion, this comprehensive battery of tests provides compelling evidence that our central results are not spurious. The stability of our coefficients across estimators, their resilience to falsification tests, and their insensitivity to changes in variable definitions and sample compositions solidify our claim that the GCC's technology-driven diversification policies are the primary causal factor behind the significant profitability gains in firms actively engaging in the digital transition. These findings substantially advance the literature by providing rigorous micro-econometric evidence for the effectiveness of targeted technology policies in resource-rich economies.

5. Policy implications

The empirical findings of this study have profound implications for policymakers in the GCC and other resource-rich economies that seek to engineer a sustainable transition away from hydrocarbon dependency. The results demonstrate that technology-driven diversification policies can significantly enhance firm-level profitability and productivity, provided they are precisely targeted, well-designed, and complemented by firm-level adoption and innovation. This underscores the necessity of moving beyond broad-based industrial support—which risks resource misallocation—toward a more selective, ecosystem-based approach to policy intervention.

First, the findings advocate for the continued and enhanced use of targeted fiscal incentives, such as subsidies, grants, and tax benefits, directed explicitly toward firms investing in digital technologies like AI, IoT, blockchain, and cloud computing. Our granular results indicate that direct grants and in-kind computing subsidies (a key component of TECH_SUB) showed a stronger correlation with subsequent profitability and innovation (AI_PAT) than broad tax incentives. Therefore, policymakers should prioritize direct, project-based funding for specific technology adoption and research and development (R&D) over general tax breaks. These instruments effectively de-risk private investment and lower adoption costs, thereby accelerating returns on technology investments. This aligns with the theoretical framework of *directed technical change* proposed by Acemoglu et al. (2018), which emphasizes the role of policy in steering innovation toward high-growth sectors. Moreover, the intensifying effect of subsidies post-2020 suggests that policy learning and refinement are critical. GCC governments should therefore establish feedback mechanisms and iterative policy evaluation frameworks to continuously improve the design and targeting of financial support, ensuring that public funds generate maximum marginal returns.

Second, the null results for traditional firms highlight the importance of avoiding blanket subsidies that prop up low-tech or inefficient sectors. This finding directly addresses concerns raised by Acemoglu and Robinson (2012) regarding the persistence of extractive institutions and the risk of policy-induced resource misallocation. Instead, policymakers should focus on creating a supportive ecosystem for technology-intensive sectors through regulatory sandboxes, investments in digital infrastructure, and intellectual property protections. For instance, the success of regulatory sandboxes in fostering fintech innovation, as documented by Zhao et al. (2022), offers a viable model for other sectors such as digital health and smart logistics. By reducing regulatory uncertainty and enabling experimentation, such measures can further amplify the benefits of fiscal incentives. Specifically, our finding that profitability gains intensified after 2020 suggests that "smart" sandboxes with built-in review periods for policy adjustments are highly effective.

Third, the significant role of firm-level innovation output—proxied by AI patents—suggests that policies should not only encourage technology adoption but also foster indigenous innovation capabilities. This requires complementary investments in digital skills development, research institutions, and university-industry collaboration. The GCC's current focus on digital infrastructure, as highlighted by Alshamsi et al. (2021), must be matched with efforts to build human capital. To this end, subsidy programs (TECH_SUB) could be explicitly tiered, offering higher grant matching rates for firms that demonstrate concurrent investment in workforce upskilling or that produce patented outputs, thereby directly linking fiscal support to innovation outcomes. The experiences of countries like South Korea and Singapore, which have successfully transitioned to knowledge-based economies through sustained investment in education and innovation, offer valuable lessons for the GCC. As argued by Bresnahan and Trajtenberg (1995), general-purpose technologies, such as AI, generate economy-wide benefits only when supported by a skilled workforce and a robust innovation system.

Fourth, the cross-country consistency of results implies that while national strategies may differ in implementation, the fundamental mechanisms of technology-led profitability are universal. This suggests that regional coordination—such as harmonizing digital regulations, sharing best practices, and co-investing in pan-GCC digital infrastructure—could amplify the efforts of individual countries. The GCC has already made strides in this direction with initiatives like the Gulf Digital Gateway, but greater integration could reduce duplication and enhance scale economies. A concrete step would be to establish a mutual recognition system for regulatory sandbox approvals and a region-wide database of TECH_SUB recipients to monitor effectiveness and prevent "subsidy shopping."

Finally, the study's focus on firm-level outcomes underscores the need for micro-founded policy design. Macroeconomic approaches, such as those examined by Alotaibi and Alshammari (2023), may overlook the heterogeneous effects of policies across firms and sectors. Policymakers should therefore adopt a more granular, firm-centric approach to policy formulation, using high-frequency data and real-time monitoring to assess impacts and adjust interventions accordingly. Our methodology, which classifies firms based on technology investment intensity (TECH_INV), provides a practical framework for such targeted policy delivery, enabling governments to identify and support genuine technology adopters rather than relying on broad sectoral definitions.

The substantial magnitude of the post-2020 profitability gains—reaching an annualized 13.1% for equity returns—demonstrates not just statistical but profound economic significance. When the cost of subsidies (averaging ~3% of revenue) is weighed against these double-digit percentage point increases in annual returns, the policy emerges as a highly effective public investment. This high return on fiscal expenditure justifies the GCC's targeted approach and suggests that scaling such precisely calibrated support could accelerate the region's economic transformation efficiently.

In conclusion, the GCC's technology-driven diversification strategy represents a promising pathway to post-oil prosperity. However, its success hinges on targeted, adaptive, and ecosystem-oriented policies that prioritize technology-intensive firms, foster innovation, and avoid the pitfalls of traditional industrial support. By leveraging directed fiscal incentives, enabling regulations, and human capital investments, GCC governments can unlock the full potential of digital technologies to drive sustainable and inclusive economic transformation.

6. Conclusion

This study provides causal evidence that the GCC's technology-driven diversification policies have initiated a profound recalibration of firm-level profitability, albeit in a sharply asymmetric manner. The findings reveal that national technology strategies, when coupled with targeted fiscal support and firm-level adoption, significantly enhance profitability and productivity in technology-intensive firms, while leaving traditional sectors largely unchanged. This asymmetry is not a policy failure but rather a marker of its precision. By avoiding blanket subsidies and instead channeling resources toward firms capable of driving digital transformation, GCC policymakers have effectively circumvented the resource misallocation pitfalls that often plague resource-rich economies.

The implications of these findings extend beyond the GCC. They offer a blueprint for how economies historically dependent on natural resources can leverage targeted industrial policy to foster a sustainable, knowledge-based economic transition. The results empirically validate the theoretical propositions regarding directed technical change and the state's role in shaping technological evolution. They also challenge narratives that attribute firm performance in the region predominantly to oil price cycles, underscoring instead the transformative potential of deliberate, well-designed policy interventions.

For policymakers in the GCC, this study affirms that the current trajectory of technology-focused diversification is not only justified but essential. The significant returns observed in firms that embraced digital technologies—especially those supported by subsidies—suggest that public investment in digital infrastructure must be matched by firm-level incentives to adopt and innovate. Policymakers should therefore redouble their efforts on strategic fiscal support, regulatory modernization, and human capital development to build a cohesive innovation ecosystem. The post-2020 acceleration in policy effectiveness further underscores the importance of learning and adaptation; policies must be dynamic, responsive to firm-level feedback, and integrated across digital, industrial, and educational domains.

Nevertheless, this study is not without limitations. The sample, though strategically selected and representative of key sectors, is limited to 63 firms, which may affect the generalizability of findings. The focus on listed firms and strategic sectors also means that the experiences of smaller enterprises or informal sectors are not captured. Additionally, while the study period extends to 2025, the long-term sustainability of observed profitability gains remains an open question. The reliance on patent counts, though common, as a proxy for innovation, does not fully capture the quality or commercial impact of technological advancements.

These limitations open several avenues for future research. First, expanding the sample to include small and medium-sized enterprises would provide a more comprehensive view of the digital transformation landscape. Second, longitudinal studies tracking firms beyond 2025 could assess whether early profitability gains translate into sustained competitive advantage. Third, qualitative case studies can complement quantitative findings by examining the organizational and managerial factors that influence successful technology adoption. Finally, comparative research with other resource-rich regions, such as Norway or Malaysia, could identify transferable lessons and context-specific adaptations.

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Declarations :

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Data available on request due to privacy/ethical restrictions.
Competing interests
The author(s) declare(s) that they have no competing interests.
Disclosure statement
No potential conflict of interest was reported by the author(s).
Declaration of generative AI
Generative AI and AI-assisted technologies are only used in the writing process to improve the readability and language of the manuscript.

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Appendices

Table A1

Sample Representativeness Analysis

Comparison of Key Financial Metrics: Study Sample vs. Broader Universe of Listed Firms in the GCC (Average for 2023)

Country	Sector	Metric	Study Sample (n)	All Listed Firms in Sector (n)	Sample as % of Sector Total
All GCC	All Sectors	Total Assets	41.5 BN	9.8 BN	71%
		Revenue	7.8 BN	2.1 BN	68%
		Market Cap	29.4 BN	7.3 BN	73%
Saudi Arabia	Finance	Total Assets	105.2 BN	32.5 BN	78%
	Energy	Revenue	28.5 BN	9.2 BN	75%
	Telecom	Market Cap	45.8 BN	14.1 BN	72%
UAE	Finance	Total Assets	62.8 BN	18.9 BN	70%
	Logistics	Revenue	5.5 BN	1.8 BN	65%
	Telecom	Market Cap	35.2 BN	10.5 BN	71%
Qatar	Finance	Total Assets	58.3 BN	16.2 BN	74%
	Energy	Revenue	20.1 BN	6.5 BN	76%
	Industry 4.0	Market Cap	8.5 BN	2.3 BN	66%
Kuwait	Finance	Total Assets	35.6 BN	12.1 BN	62%
	Logistics	Revenue	2.8 BN	0.9 BN	58%
	Healthcare	Market Cap	4.2 BN	1.4 BN	60%
Oman	Finance	Total Assets	12.5 BN	4.8 BN	55%
	Energy	Revenue	8.2 BN	3.1 BN	59%
	Telecom	Market Cap	5.1 BN	1.9 BN	57%
Bahrain	Finance	Total Assets	8.9 BN	3.5 BN	52%
	Telecom	Revenue	1.2 BN	0.5 BN	54%
	Healthcare	Market Cap	2.1 BN	0.8 BN	56%

Table A2

System GMM Diagnostic Tests

Dependent Variable	Specification	Arellano-Bond Test for AR(1) (p-value)	Arellano-Bond Test for AR(2) (p-value)	Hansen J Test (p-value)	Number of Instruments
ΔROA	Baseline (Table 4)	0.023	0.451	0.312	42
ΔROE	Baseline (Table 4)	0.017	0.387	0.285	42
ΔTFP	Baseline (Table 4)	0.031	0.512	0.410	41
ΔROA	Robustness (Diff GMM)	0.019	0.435	0.265	38

Note: This table reports the diagnostic statistics for the System GMM estimations. The null hypothesis for the Arellano-Bond test is "no autocorrelation" of the specified order in the first-differenced errors. As required for consistency, the tests reject the null for AR(1) but fail to reject for AR(2), indicating no evidence of second-order serial correlation. The null hypothesis for the Hansen J test is that "the instruments as a group are exogenous." The high p-values (all > 0.2) indicate that we cannot reject the null, supporting the validity of our instrument set. The models use a collapsed instrument matrix with lag limits of 2 to 4.*