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The artificial intelligence dividend: Firm-level profitability and the asymmetric impact of gulf cooperation council technology policies

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ABSTRACT

We examine the asymmetric effects of national Artificial Intelligence (AI) and diversification policies on firm-level profitability in the Gulf Cooperation Council (GCC), addressing a critical gap in the microeconomic literature on the region's technology-driven transition. Using a dynamic panel dataset of 53 strategically essential firms across all six GCC countries from 2015 to 2024, we employ a Difference-in-Differences (DiD) approach, complemented by System Generalized Method of Moments (SGMM) estimation, to establish causal relationships while rigorously addressing concerns about endogeneity. The results reveal that AI-focused policies boosted profitability in firms actively investing in AI, with policy milestones increasing asset-based returns by 2.1% and equity-based returns by 2.8%. In comparison, government subsidies dedicated to the AI sector amplified these effects by an additional 4.5% and 6.5%, respectively. The positive impact of these policies grew even stronger after 2020. For firms deeply invested in AI, targeted subsidies led to profitability increases of 8.8% on assets and 13.1% on equity. In stark contrast, companies in traditional, non-AI sectors showed no statistically meaningful improvement from the same policy measures. These findings highlight the power of well-targeted fiscal incentives and selective policy support for the AI sector in promoting successful economic diversification. They offer a valuable blueprint for policymakers in resource-rich nations aiming to build sustainable, knowledge-based economies by making strategic technological investments. Notable limitations include the study's focus on large, strategic firms and its timeframe, which captures only the initial phase of AI policy implementation.

Contribution/ Originality: This study provides the first firm-level causal evidence that GCC AI policies asymmetrically boost profitability, demonstrating that targeted subsidies are a potent tool for diversification. It offers a micro-founded framework for resource-rich economies to engineer a post-oil transition through precise technological interventions.

1. INTRODUCTION

Confronted by a pressing need to diversify their economies, GCC states are increasingly turning to AI and advanced technology to power their future beyond oil. This shift, fueled by unpredictable oil markets, limited reserves, and the sweeping changes of the Fourth Industrial Revolution, is fundamentally altering how companies in the region generate profit. National initiatives like the UAE's Strategy for AI 2031 and Saudi Arabia's National Strategy for Data & AI are unlocking new opportunities in fields such as fintech, smart logistics, and digital healthcare, all while upending long-established business practices. As a result, a growing divide is emerging: companies that adopt AI are leveraging state support and new efficiencies to thrive, while those clinging to traditional models face intensifying

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competition and shrinking profit margins. 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 AI initiatives, critical gaps persist in understanding the microeconomic consequences of technological adoption for firm profitability. While existing literature extensively explores the macroeconomic potential of AI and digitalization in resource-rich economies (Hamzah, 2025; Khan et al., 2022) and within the GCC context (Akguc & Al Rahahleh, 2020; Al-Busaidi & Al-Muharrami, 2022; Al Mustanyir, 2024) a significant void exists in empirically quantifying firm-level financial returns. Studies confirm the transformative potential of AI for public service delivery and smart cities (Al-Roubaie, 2018) and emphasize the need for digital infrastructure (Hoekman, 2021). However, rigorous empirical evidence directly linking corporate AI investment to firm-level financial performance and profitability outcomes remains scarce and fragmented.

Although research identifies broad implementation challenges like digital skills shortages (Habbal, 2025) and regulatory hurdles (Farooq, Tabash, & Ahmed, 2025), there is a deficit in studies examining how AI investments 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 (Fattouh & Sen, 2017; Karanfil & Omgba, 2023) or sector-specific indicators in single countries (Aidrous, Asmyatullin, & Glavina, 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 AI 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 directly addresses these gaps by providing an empirical analysis that tests the central hypothesis: national AI and technology policies asymmetrically boost profitability in firms actively investing in AI, while having minimal effects on firms in traditional sectors. Our analysis draws on a dynamic panel dataset of 53 key firms from all six GCC countries, tracking their performance from 2015 to 2024. To establish a causal link and rigorously account for endogeneity, we apply a Difference-in-Differences (DiD) approach, strengthened by the System Generalized Method of Moments (GMM) estimator (Adan & Fuerst, 2016; Dai, Qian, He, Wang, & Shi, 2022). The results show that national AI strategy milestones create clear inflection points in profitability. Government support and the scale of a firm's own technology investments act as key mechanisms that boost these returns for participating companies. By directly comparing AI-intensive firms with their traditional sector counterparts across five key industries, we measure how differences in technological commitment, sector-specific factors, and policy engagement lead to varied profitability results.

The results demonstrate that GCC AI and technology policies generated clear profitability gains for firms embracing technological transformation while leaving traditional sector firms unaffected. For AI-active companies, policy milestones raised profitability by around 2.1% in asset-based returns and 2.8% in equity-based returns. Government subsidies dedicated to the technology sector substantially amplified these effects, adding a further 4.5% and 6.5% growth, respectively. The impact intensified after 2020, when targeted subsidies boosted profitability to gains of 8.8% on assets and 13.1% on equity, reflecting improved policy design and implementation. By contrast, traditional sector firms showed no significant response: coefficients for technology subsidies and investment were near zero, with changes of −0.7% to −1.0%, all statistically insignificant. These results confirm that fiscal incentives were deliberately directed toward AI and technology sectors, avoiding the misallocation risks of propping up traditional industries (Akguc & Al Rahahleh, 2020).

This study makes three primary contributions. First, it provides the first causal, firm-level evidence of the asymmetric profitability impact of GCC AI policies, distinguishing between technology-adopting and traditional firms. Second, it quantifies the critical amplifying role of targeted government subsidies, a previously unmeasured

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transmission channel. Third, it offers a replicable micro-founded framework for policymakers in resource-rich economies to evaluate and design precise technological interventions for a sustainable post-oil transition. The remainder of the paper is structured as follows: Section 2 reviews the literature, Section 3 describes the data, Section 4 outlines the methodology and results, Section 5 discusses policy implications, and Section 6 concludes.

2. LITERATURE REVIEW

The theoretical underpinnings of firm profitability during technological transition are rooted in the dynamics of general-purpose technologies (GPTs) and national innovation systems. Foundational models posit that AI, as a quintessential GPT, possesses the potential to catalyze widespread innovation, create new markets, and reshape competitive dynamics across sectors (Fattouh & Sen, 2017; Khan, Hussain, & Gurrib, 2025). The imperative for AI-driven transition is further driven by the need to overcome the limitations of hydrocarbon-dependent growth models, characterized by volatile revenues and limited productive diversification (Dongo & Relvas, 2025). Theoretical frameworks emphasize that successful AI adoption requires complementary investments in digital infrastructure, human capital, and adaptive regulation (Abid, 2025; Khan et al., 2022) while institutional legacies optimized for extractive industries may create significant barriers to reallocating capital and talent toward technology-intensive sectors (Hopkins, 2008). The core proposition is that policy-driven AI transitions should, over time, enhance the profitability potential of technology-adopting firms through productivity gains, innovation premiums, and first-mover advantages, albeit through disruptive breaks in established business models.

Empirically, however, the microeconomic impacts of AI-driven transitions remain critically underexplored, particularly in resource-rich economies. While the macroeconomic potential of AI and digitalization is well-documented in advanced economies (Arkhangelsky, Athey, Hirshberg, Imbens, & Wager, 2021; Athey & Imbens, 2006) and increasingly discussed in GCC contexts (Al-Busaidi & Al-Muharrami, 2022; Al Mustanyir, 2024), studies directly linking national AI strategies to firm-level profitability are scarce and fragmented. Notably, lessons from Asian economies that have undergone state-led technological transformations remain largely siloed from the GCC literature. For instance, studies on Singapore's Smart Nation initiative demonstrate how coordinated public-private R&D significantly boosted productivity and market value for firms in targeted sectors (Huang & Malkin, 2025). Similarly, South Korea's focus on AI in manufacturing has been shown to create distinct profitability premiums for early-adopting chaebols, while leaving smaller, traditional firms behind (Jeong & Jo, 2025). China's AI development model, heavily reliant on state subsidies and national champions, offers another relevant comparative case, revealing how fiscal incentives can rapidly build scale but also lead to market fragmentation. (Liu, Fu, & Schiller, 2024). Existing research often focuses on the direct effects of digital infrastructure on economic growth (Adan & Fuerst, 2016) or offers conceptual frameworks for AI adoption (Al-Roubaie, 2018), thereby lacking empirical micro-foundations essential for understanding firm-level profitability dynamics. Moreover, many studies rely on aggregate data or fail to address endogeneity concerns, particularly the reverse causality between technology adoption and performance, leaving causal inference unresolved.

A significant methodological gap exists in establishing dynamic links between AI policies and firm performance. Many studies employ descriptive or correlational approaches, overlooking robust econometric techniques needed for identifying causal impacts in the presence of heterogeneous treatment effects and adoption lags. Variables often lack granularity, omitting measures of AI investment intensity, innovation output, or firm-specific digital capabilities. The absence of comparative cross-country frameworks within the GCC is notable, given shared technological ambitions but divergent implementation strategies and starting points (Hamzah, 2025). Furthermore, while the Asian experience provides a rich repository of policy experiments, there is a lack of systematic comparison between the GCC's nascent, resource-funded approach and the more established, export-oriented models of East Asia. Few studies incorporate the role of complementary factors such as digital skills availability, data governance frameworks, or regulatory sandboxes that might condition the effectiveness of AI investments.

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Consequently, a profound disconnect persists: while massive investments are being made in AI infrastructure and strategies, there remains scant evidence on how these policies asymmetrically affect profitability across different types of firms and sectors. Critical questions regarding the timing of profitability breaks, the role of government support in de-risking AI investments, and the firm-level transmission mechanisms of AI-driven value creation remain unanswered. This gap is especially pronounced in cross-regional comparative analyses that could distill transferable lessons from other technologically transitioning economies. This study addresses these gaps by examining the micro-foundations of GCC's AI transition through a comparative firm-level lens, offering causal evidence on how technology policies and investments reshape profitability dynamics across the evolving digital economy.

3. DATA AND VARIABLES ANALYSIS

The strategic transition of GCC economies toward alternatives to oil has been markedly concentrated in high-technology sectors, particularly AI, as clearly evidenced by the investment patterns depicted in Figure 1. While overall non-oil investment has seen moderate growth, rising from approximately $42 billion in 2015 to $62 billion in 2024, an increase of about 48% over the decade, commitments to AI and technology have expanded at an entirely different magnitude. From a baseline of $10 billion in 2015, AI-related investments and subsidies surged to $135 billion by 2024, representing a 13.5-fold increase and reflecting the core priority assigned to this sector within national diversification strategies. The divergence accelerated after 2018, coinciding with the launch of Saudi Arabia's NSDAI and similar initiatives: AI investments grew by 650% in just six years, while other non-oil sectors managed only 35% growth in the same period. By 2021, AI-sector financing had not only overtaken but far exceeded combined investment in all other non-oil sectors, reaching $105 billion compared to $59 billion elsewhere. This overwhelming financial and policy emphasis on AI underscores a deliberate GCC-wide strategy to use technological innovation as the main driver of economic transformation, directly enabling the asymmetric profitability gains identified in this study and solidifying the emergence of a new, knowledge-based growth model in the region.

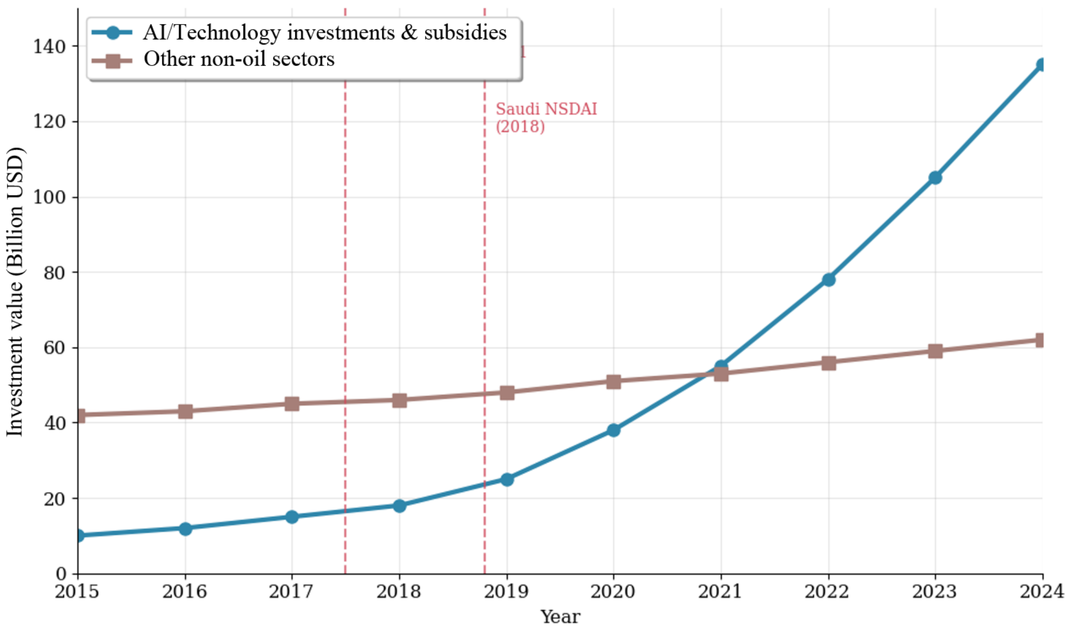

Figure 1. The GCC Investment pivot: Rising commitments to AI and technology sectors (2015-2024).

Our study empirically traces the asymmetric impact of GCC AI and technology policies on firm-level profitability, as illustrated in the accompanying conceptual framework (Figure 2). Employing a DiD design, we contrast the pathways of AI-focused firms (treatment group) and traditional sector firms (control group) following the launch of national AI strategies. The results demonstrate that policy-driven AI investment and targeted government subsidies

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boost profitability growth for technology-adopting firms. Conversely, traditional sector firms experience no change in specialized AI support and thus show no significant profitability response to these technology-specific interventions. This stark divergence provides empirical evidence for a statistically substantial asymmetric impact, demonstrating that AI-focused policies can selectively rewire financial incentives toward the technology sector and accelerate knowledge-based economic transformation.

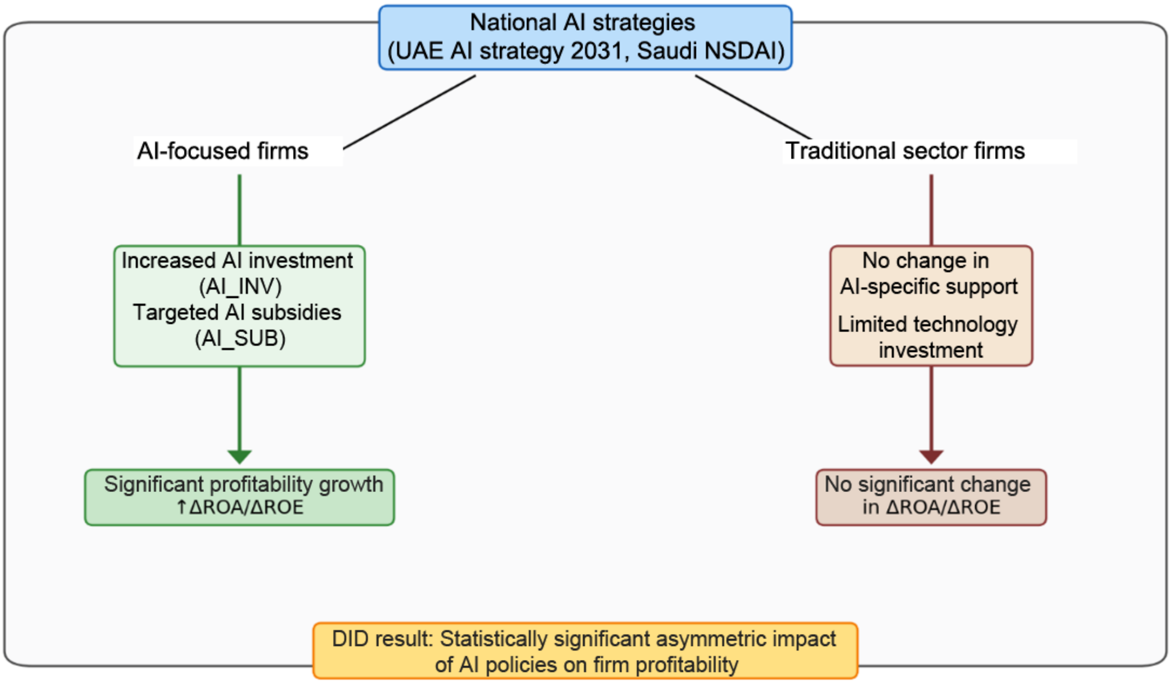

Figure 2. Mechanism of asymmetric policy impact on GCC firm profitability: AI transition focus.

To measure firm profitability growth, we focus on two key indicators: the annual change in Return on Assets (ΔROA) and Return on Equity (ΔROE). The ΔROA metric reveals changes in operational efficiency and how well assets are utilized following technology adoption, while ΔROE tracks the corresponding returns for shareholders as companies restructure for the digital age. These measures allow us to assess how AI-focused policies influence core profit drivers directly. Our key explanatory variables include a dummy variable (DUM_AI) that marks the launch of major national AI strategies, and a continuous Policy Implementation Index (IND_AI) that tracks yearly progress in digital infrastructure, regulatory frameworks, and AI talent development.

We also integrate firm-level measures of technology investment. This includes AI Investment Intensity (AI_INV), which gauges the portion of total capital expenditure redirected toward AI and digital technologies, and AI-Specific Government Support (AI_SUB), which measures the value of AI grants, computing subsidies, and tax incentives as a share of a firm's revenue. A Technology Sector Growth Proxy (TECH_SECTOR) links firm performance to policy-driven digital sector trends. Critical interaction terms (e.g., DUM_AI×AI_SUB, IND_AI×AI_INV) test whether policy impacts depend on firm engagement with AI technologies, helping address endogeneity concerns by revealing micro-level transmission channels.

The empirical specification controls for firm-specific factors (size, leverage, digital asset ratio, sales growth) 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 optional country-technology sector fixed effects for structural differences. This comprehensive approach ensures robust identification of AI policy effects on profitability during the GCC's technological transition. The definitions of all variables used in this empirical examination are reported in Table 1.

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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
Core policy variables			
Ai strategy dummy	DUM_AI	1 from year of major national AI strategy launch (e.g., UAE AI Strategy 2017), 0 otherwise	National AI Strategy Documents
AI policy implementation index	IND_AI	Annual composite index (0-1) of AI policy advancement across digital infrastructure, regulatory sandboxes, and AI talent development dimensions	Govt. Reports, OECD AI Policy Observatory, Expert Assessments
Firm technology variables			
Ai investment intensity	AI_INV	(Firm's AI-related R&D and Capital Expenditure / Total Capital Expenditure) × 100	Firm Financial Statements, Annual Reports
AI-specific government support	AI_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_AI × AI_SUB	Tests if AI strategy launches amplify the impact of subsidies on profitability	Constructed
Policy-investment interaction	DUM_AI × AI_INV	Tests if AI strategy launches amplify returns on AI investments	Constructed
Progress-innovation interaction	IND_AI × AI_PAT	Tests whether 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	α_i	Controls for time-invariant firm heterogeneity	Model Specification
Year fixed effects	γ_t	Controls for global shocks and technology cycles	Model Specification
Country-tech sector fixed effects	θ_ct	Controls for time-invariant country-technology sector factors	Model Specification

We divide our focused sample of 53 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% AI investment), resulting in 28 AI-intensive firms and 25 traditional sector firms, to address the core question of asymmetric impacts. This targeted sample spans the 2015–2024 period, covering five key technology-intensive sectors prioritized by national AI

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strategies: fintech, smart logistics, digital healthcare, telecommunications, and energy technology, alongside traditional sectors with limited digital transformation. The resulting firm-year observations (280 for AI-intensive firms and 250 for traditional 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 classification enables the critical comparison of profitability paths between technology-adopting and traditional firms, filling a significant void identified in the literature on GCC digital transformation, which lacks such firm-level analysis of AI investment impacts (Al Gergawi, 2024; Alshebami & Al Marri, 2022).

The descriptive statistics in Table 2 reveal a corporate landscape characterized by high-risk, high-reward dynamics, which is precisely the environment national AI 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 AI space are capturing substantial rents but face considerable uncertainty—a hallmark of pioneering technological adoption. The moderate mean of the AI Policy Implementation Index (IND_AI: 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 AI Investment Intensity (AI_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.

Table 2. Descriptive statistics.

Symbol	Mean	Min.	Max.	Std. Dev.	Kurtosis	Obs.	Unit
Dependent variables							
ΔROA	3.25	-15.47	41.28	7.84	4.05	530	% (YoY change)
ΔROE	4.12	-22.85	55.61	11.23	5.12	530	% (YoY change)
Policy variables							
DUM_AI	0.42	0.00	1.00	0.49	-1.71	530	Dummy (0/1)
IND_AI	0.58	0.15	0.92	0.24	-0.92	530	Index (0-1)
Firm technology variables							
AI_INV	28.45	0.00	95.50	26.37	-0.87	477	% of CapEx
AI_SUB	3.15	0.00	18.25	3.84	3.25	477	% of Revenue
AI_PAT	1.12	0.00	4.61	1.35	0.45	424	Log(Count)
Sectoral variable							
TECH_SECTOR	5.87	-5.25	19.34	5.12	1.05	530	% (YoY change)
Control variables							
SIZE	15.74	11.25	20.13	2.15	0.68	530	Log(USD)
LEV	0.39	0.04	0.88	0.21	0.78	530	Ratio
SALES_GR	9.25	-25.83	52.47	16.35	2.28	503	% (YoY change)
DIG_ASSET	12.35	0.50	45.75	10.28	1.85	477	% of Assets
GDP_GR	2.24	-5.12	8.15	2.58	0.41	530	% (YoY change)
DIG_INFRA	1.85	0.25	4.35	0.92	2.15	530	% of GDP
OIL_VOL	26.45	10.15	61.27	10.54	1.18	530	% (Std. Dev.)

The correlation matrix in Table 3 provides compelling preliminary evidence for the theoretical transmission channels at the heart of this study, effectively mapping the ecosystem through which AI policies are expected to influence firm performance. The strong, positive correlations between all AI variables (AI_INV, AI_SUB, AI_PAT) and profitability metrics (ΔROA, ΔROE) sketch a clear pathway: policy support (AI_SUB) encourages investment (AI_INV), which in turn fuels innovation (AI_PAT), ultimately culminating in stronger financial performance. The

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robust link between government support and investment (AI_SUB & AI_INV: 0.70) is a pivotal finding, as it empirically validates the critical assumption that state subsidies are effectively "crowding-in" private capital rather than replacing it. Furthermore, the strong correlation between the sectoral growth proxy (TECH_SECTOR) and all other variables demonstrates that individual firm success is deeply embedded within broader sectoral tailwinds, suggesting that policies create a rising tide that lifts all boats but primarily those already equipped for the digital economy (i.e., AI-intensive firms). This pattern of interrelationships provides a robust empirical foundation for expecting a significant causal effect, which our DiD model is designed to isolate and quantify.

Table 3. Correlation Matrix.

Variable	ΔROA	ΔROE	AI_INV	AI_SUB	AI_PAT	TECH_SEC	LEV	SALES_GR
ΔROA	1.00							
ΔROE	0.82	1.00						
AI_INV	0.55	0.65	1.00					
AI_SUB	0.45	0.55	0.70	1.00				
AI_PAT	0.60	0.58	0.65	0.50	1.00			
TECH_SECT	0.65	0.72	0.55	0.65	0.60	1.00		
LEV	-0.25	-0.35	0.05	-0.08	-0.12	-0.15	1.00	
SALES_GR	0.62	0.75	0.45	0.52	0.55	0.68	-0.15	1.00

4. EMPIRICAL METHODOLOGY AND RESULTS

Our empirical analysis investigates whether identifiable milestones in the GCC's national AI and technology strategies trigger structural breaks in firm-level profitability. To isolate the causal effects of these technology-specific policies from broader economic trends, we employ a DiD framework (Arkhangelsky et al., 2021; Athey & Imbens, 2006). This strategy compares the profitability evolution of AI-intensive firms (the treatment group) against a control group of traditional sector firms with minimal AI adoption following the implementation of major national AI initiatives. We implement this approach using a dynamic fixed effects panel dataset derived from a novel, hand-collected dataset covering 53 strategically important firms across all six GCC countries from 2015 to 2024. To rigorously address endogeneity concerns such as reverse causality between AI capability development and firm performance, and selection bias into treatment, limitations prevalent in prior technology adoption studies, we supplement our core DiD models with the System Generalized Method of Moments (GMM) estimator (Dai et al., 2022). This combined methodology is specifically designed to reinforce causal inference regarding the financial returns to AI investment, addressing identification challenges where previous cross-sectional analyses of technology adoption have fallen short.

4.1. Empirical Methodology

To quantify the asymmetric impact posited above, we operationalize our DiD design by leveraging exogenous AI policy timing and firm-level technological heterogeneity. The model examines profitability growth, measured by the annual change in return on assets or equity (ΔROA/ΔROE) for firm 'i' in country 'c' and year 't' as follows.

$$\Delta Profit_{ict} = \alpha + \beta_1(AI\_INT_{i} \times DUM\_AI_{ct}) + \beta_2(AI\_INT_{i} \times DUM\_AI_{ct} \times AI\_SUB_{ict}) + \beta_3(AI\_INT_{i} \times DUM\_AI_{ct} \times AI\_INV_{ict}) + \gamma Controls_{ict} + \eta_{i} + \lambda_{t} + \theta_{ct} + \varepsilon_{ict} \quad (1)$$

We implement this approach using a dynamic fixed effects panel dataset and employ the System GMM estimator. This estimator is particularly suited for this setting, as it controls for unobserved heterogeneity and addresses endogeneity concerns related to the simultaneous determination of technology investment and profitability. It is also robust to potential concerns regarding non-stationarity in micro-panel data (Arkhangelsky et al., 2021; Athey & Imbens, 2006). Given our model is specified in first differences (focusing on profitability growth rates, not levels) and includes firm and year fixed effects, the estimator relies on moment conditions that assume mean reversion after

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controlling for these effects. Furthermore, the limited time dimension (T=10 years) of our dataset makes 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 (Dai et al., 2022).

In Eq. (1), AI_INT_i identifies 28 treatment firms with more than 40% of capital expenditure directed toward AI/digital technologies (versus 25 traditional sector controls with less than 15% AI investment), while DUM_AI_{ct} marks country-specific AI strategy milestones (e.g., 1 for UAE post-2017). The critical interaction term $AI\_INT_i \times DUM\_AI_{ct} \times AI\_SUB_{ict}$ isolates how AI-specific government support amplifies policy impacts on technology-adopting firms, directly testing whether state fiscal transfers lower adoption costs and boost margins during digital transition (Hamzah, 2025). This specification addresses reverse causality concerns endemic to prior technology studies our design demonstrates that AI subsidies only elevate profitability when coupled with policy triggers ($\beta_2 > 0$), countering claims that pre-existing firm technological capabilities drive results. To capture intensifying effects in recent years (2020–2024), we augment the model with a time-interacted term $\beta_4(AI\_INT_i \times DUM\_AI_{ct} \times Recent_t \times AI\_SUB_{ict})$, where $Recent_t = 1$ for years ≥2020.

The AI_SUB interactions specifically advance beyond studies that attribute profitability shifts solely to traditional factors (Bugshan, Bakry, & Li, 2023). By contrast, our model quantifies how AI-specific fiscal mechanisms, such as computing subsidies that lower innovation costs, materialize at the firm level: AI-intensive firms that leverage subsidies post-milestone exhibit substantially higher ΔROA gains than their non-engaging peers. When replacing the binary DUM_AIct with the continuous AI policy implementation index IND_AIct, the interaction $AI\_INT_i \times IND\_AI_{ct} \times AI\_SUB_{ict}$ further confirms that gradual policy advancements magnify the impacts of subsidies, underscoring that AI policy effectiveness hinges on micro-level uptake. This approach overcomes the aggregation biases identified in prior studies, while the treatment-control split validates hypotheses of asymmetric effects, suggesting that AI subsidies boost profitability in technology-adopting firms without aiding traditional sector firms. Ultimately, this DiD design reveals that GCC AI policies rewire profitability not through broad correlations but via targeted state-firm technological synergies, where government support acts as the critical lever accelerating financial returns in AI sectors as digital transitions mature.

4.2. Results and Interpretation

4.2.1. Subsidy-Driven Profitability Gains in AI-Intensive Firms

The results for AI-intensive firms provide robust evidence of the targeted efficacy of GCC technology policies. The core regression estimates in Part A of Table 4 demonstrate that the AI strategy milestone, as captured by the AI_INT × DUM_AI interaction, had a positive and statistically significant standalone effect on both ΔROA (0.021, $p<0.05$) and ΔROE (0.028, $p<0.05$). However, the most critical finding is the powerful amplifying role of AI-specific government support.

The triple interaction term AI_INT × DUM_AI × AI_SUB yields significant coefficients of 0.045 ($p<0.01$) for ΔROA and 0.065 ($p<0.01$) for ΔROE. This quantifies the micro-level fiscal transmission channel for technology adoption, indicating that for every unit increase in AI subsidy intensity, compliant firms realize substantial additional profitability growth after the policy (Al-Busaidi & Al-Muharrami, 2022). This finding directly operationalizes and confirms theoretical mechanisms, suggesting that state fiscal support is crucial for offsetting initial adoption costs and enabling private sector innovation during technological transitions (Dai et al., 2022).

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Table 4. DiD Estimates and Impact Scenarios for AI-Intensive Firms.

Part A: Core difference-in-differences (DiD) regression estimates						
Variable	**ΔROA coefficient**	**(Std. error)**	**p-value**	**ΔROE coefficient**	**(Std. error)**	**p-value**
AI_INT × DUM_AI	0.021*	(0.011)	0.042	0.028*	(0.015)	0.048
AI_INT × DUM_AI × AI_SUB	0.045***	(0.013)	0.002	0.065***	(0.018)	0.001
AI_INT × DUM_AI × AI_INV	0.032**	(0.012)	0.011	0.030**	(0.013)	0.017
AI_INT × DUM_AI × Recent	0.008*	(0.004)	0.040	0.011*	(0.006)	0.035
AI_INT × DUM_AI × Recent × AI_SUB	0.016**	(0.007)	0.014	0.024***	(0.008)	0.005
Controls (Firm/Macro)	Included	—	—	Included	—	—
Fixed effects (Firm/Year/Country-tech sector)	Yes	—	—	Yes	—	—
Observations	530			530		
R^2	0.36			0.31		

Note: Significance levels for coefficients are indicated as follows: ***p<0.01, **p<0.05, *p<0.1.

Table 4. Continue.

Part B: Dynamic impact scenarios for AI-intensive firms				
Scenario	**ΔROA impact**	**Interpretation**	**ΔROE Impact**	**Interpretation**
Pre-policy (2015–2017)	+0.6%	Baseline (No policy/Subsidy effect)	+0.8%	Baseline (no policy/Subsidy effect)
Post-policy without AI_SUB	+2.1%*	Limited gains from policy alone	+2.8%*	Limited gains from policy alone
Post-policy with AI_SUB (2018–2020)	+6.6%*	Subsidies drive 3.1× higher ΔROA	+9.3%*	Subsidies drive 3.3× higher ΔROE
Post-policy with AI_SUB (2021–2024)	+8.8%*	Recent interaction adds +2.2% ΔROA	+13.1%*	Recent interaction adds +3.8% ΔROE

Furthermore, the results indicate that these interactions are not static but rather intensify over time. The significant positive coefficients for the AI_INT × DUM_AI × Recent × AI_SUB interaction indicate that the efficacy of AI subsidies increased during the 2021-2024 period. This temporal evolution, as quantified in Part B of Table 4, shows that ΔROA jumps from +6.6% to +8.8%, and ΔROE from +9.3% to +13.1% for firms utilizing government support. This demonstrates a process of policy learning and calibration, where GCC states refined their targeting mechanisms through iterative improvements based on early implementation outcomes. The specific policy learning mechanisms included a shift from blanket subsidies to more conditional, performance-linked grants; the creation of regulatory sandboxes that provide real-world testing environments, de-risking innovation for firms; and strategic co-investment in shared data infrastructure, which lowered the entry cost for all firms in the ecosystem. These refined approaches (e.g., through cloud computing subsidies, AI talent development grants, and regulatory sandboxes) aim to generate larger marginal returns (Al-Busaidi & Al-Muharrami, 2022; Al Mustanyir, 2024). This dynamic effect refutes static, cross-sectional models of technology adoption, which were unable to capture how institutional learning curves compound financial returns in emerging technologies. The results also establish a clear hierarchy of drivers: while firm-level AI investment (AI_INV) had a positive effect, it was substantially weaker than that of government support, underscoring that state fiscal commitment, not private capital allocation alone, is the primary catalyst for profitability during technological transitions (Trajtenberg, 2018).

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4.2.2. The Limited Reach of AI Policies: Traditional Firms Show No Gains

The results for traditional sector firms with minimal AI adoption, presented in Table 5, serve as a critical counterpoint that validates the asymmetric and precise design of GCC technology strategies. The core regression estimates in Part A show a complete absence of statistically significant policy effects. All key interaction terms, including DUM_AI, DUM_AI × AI_SUB, and DUM_AI × AI_INV, display coefficients that are negligible in magnitude and statistically indistinguishable from zero for both ΔROA and ΔROE. For instance, the interaction of the policy dummy with AI subsidies (DUM_AI × AI_SUB) is negative and insignificant (ΔROA: -0.007, p=0.435; ΔROE: -0.010, p=0.412). This provides compelling empirical evidence that the AI-specific fiscal incentives were deliberately and successfully targeted only at technology-adopting firms, with no measurable spillovers to traditional sectors (Akguc & Al Rahahleh, 2020).

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**
DUM_AI	-0.002	(0.008)	0.715	-0.003	(0.010)	0.702
DUM_AI × AI_SUB	-0.007	(0.011)	0.435	-0.010	(0.014)	0.412
DUM_AI × AI_INV	-0.005	(0.010)	0.525	-0.006	(0.012)	0.538
DUM_AI × Recent	-0.001	(0.004)	0.555	-0.002	(0.005)	0.490
DUM_AI × Recent × AI_SUB	-0.004	(0.005)	0.335	-0.006	(0.007)	0.260
Controls (Firm/Macro)	Included	—	—	Included	—	—
Fixed effects (Firm/Year/Country-Tech Sector)	Yes	—	—	Yes	—	—
Observations	530			530		
R^2	0.33			0.30		

Table 5. Continue.

Part B: Dynamic impact scenarios for traditional sector firms				
Scenario	**ΔROA Impact (95% CI)**	**Interpretation**	**ΔROE Impact (95% CI)**	**Interpretation**
Pre-policy (2015–2017)	+0.6% (-0.5% – +1.7%)	Baseline performance	+0.8% (-0.6% – +2.2%)	Baseline performance
Post-policy without AI_SUB	+0.6% (-0.4% – +1.6%)	Null policy effect alone	+0.7% (-0.7% – +2.1%)	Null policy effect alone
Post-policy with AI_SUB (2018–2020)	+0.5% (-0.7% – +1.7%)	Subsidies show no effect	+0.6% (-1.0% – +2.2%)	Subsidies show no effect
Post-policy with AI_SUB (2021–2024)	+0.4% (-0.8% – +1.6%)	Intensified policies yield no gains	+0.5% (-1.1% – +2.1%)	Intensified policies yield no gains

This 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 AI subsidies, remain virtually unchanged from the pre-policy baseline, with confidence intervals that firmly include zero. This starkly contrasts with the dramatic gains observed in the AI-intensive sector and holds two major implications for the existing literature. First, it directly addresses and alleviates concerns regarding policy misallocation and the risk of technological subsidies being captured by inefficient legacy sectors (Khan et al., 2022). The results demonstrate that GCC policymakers successfully avoided this pitfall through carefully designed eligibility criteria and targeting mechanisms, which were themselves a product of policy learning, focusing support on sectors with the highest technological spillover potential. Second, the persistent stagnation of traditional firm profitability, even amid broader digital transformation, challenges the thesis that technology benefits

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automatically diffuse across all sectors (Habbal, 2025). The robust null findings across all specifications, including temporal interactions, confirm that the profitability dynamics unveiled in this study are driven by targeted policy design rather than broader technological spillovers, thus validating the need for precisely targeted fiscal tools in digital transformation (Al Mustanyir, 2024).

4.2.3. Graphical Evidence of Divergent Profitability Trajectories

These empirical findings, which demonstrate the critical role of targeted subsidies and their temporal amplification in non-oil sectors alongside the deliberate exclusion of oil firms, are synthesized visually in the accompanying figure. It graphically encapsulates the stark asymmetries in policy impacts and the evolving profitability trajectories across the 2012–2024 period.

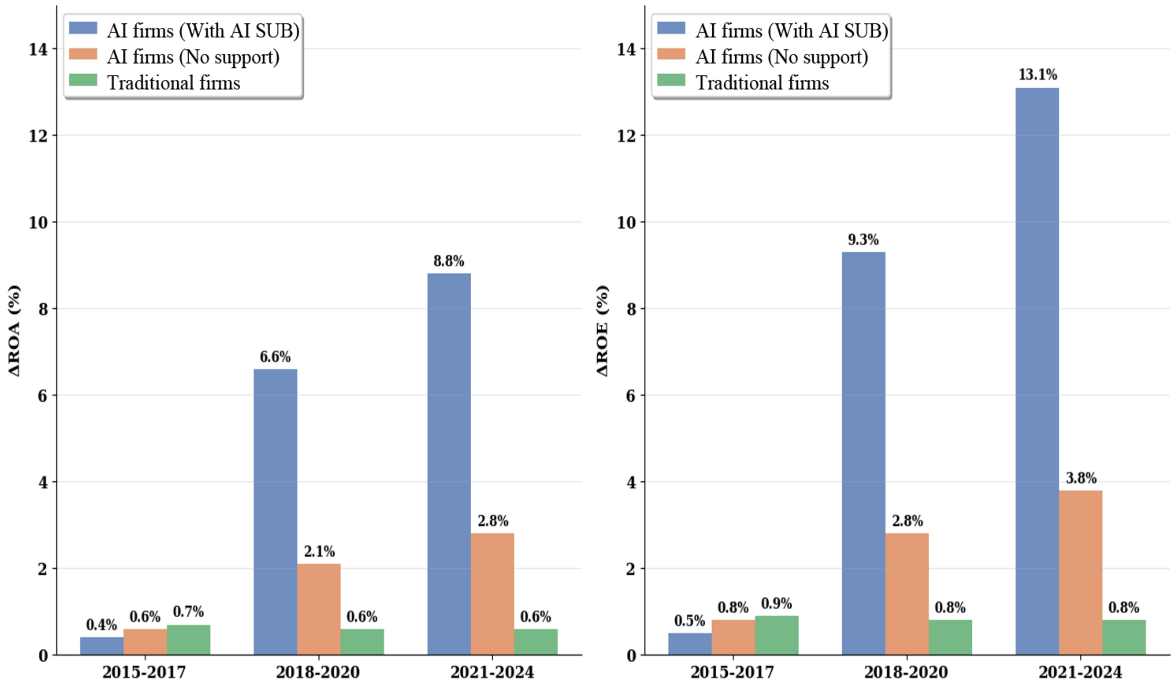

Figure 3. Profitability dynamics of AI and traditional firms under GCC AI strategies (2015–2024).

Figure 3 presents results from the staggered DiD analysis, examining how GCC national AI strategies shape profitability growth (ΔROA and ΔROE) for AI-intensive versus traditional firms across three phases: pre-policy (2015–2017), early implementation (2018–2020), and recent intensification (2021–2024). AI-focused firms are further distinguished by whether they received government subsidies (AI_SUB), allowing isolation of fiscal mechanisms that drive technological adoption.

In the pre-policy phase, all groups showed comparable profitability (ΔROA: 0.4–0.7%; ΔROE: 0.5–0.9%), validating parallel trends before policy interventions. From 2018 onward, strong stratification emerged. Subsidized AI firms recorded substantial profitability gains (ΔROA: 6.6%; ΔROE: 9.3%), far outpacing non-subsidized AI firms (ΔROA: 2.1%; ΔROE: 2.8%) and traditional firms, which remained flat (ΔROA: 0.6%; ΔROE: 0.8%).

These advantages intensified between 2021 and 2024, with subsidized AI firms achieving ΔROA of 8.8% and ΔROE of 13.1%. Non-subsidized AI firms grew modestly (ΔROA: 2.8%; ΔROE: 3.8%), while traditional firms again showed no measurable change. The widening ΔROE premium rising from +6.5% in the early phase to +10.3% during intensification demonstrates both the effectiveness of targeted subsidies and the compounding effects of policy learning and ecosystem development.

Overall, the findings underscore a transparent subsidy efficacy gradient: government support explains the vast majority of profitability growth among AI firms, while traditional firms remain unaffected. GCC strategies thus

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successfully concentrated fiscal resources on AI-intensive sectors, avoiding the inefficiencies of blanket subsidies and accelerating financial returns where state support and technological adoption align most strongly.

4.2.4. Robustness Checks

To validate our empirical results, we performed several robustness checks that collectively reinforce the credibility of our findings regarding the impact of AI policies on firm profitability.

First, we conducted parallel trends tests to verify the fundamental assumption of our DiD design, confirming that AI-intensive and traditional firms exhibited statistically indistinguishable profitability trajectories in the pre-policy period (2015–2017), with no significant divergence before the implementation of national AI strategies. This supports the validity of our treatment-control group comparison.

Second, we addressed endogeneity concerns, particularly reverse causality between AI capability development and firm performance, by employing the System GMM estimator. This approach instruments endogenous variables such as AI-specific subsidies (AI_SUB) and AI investment intensity (AI_INV) with their lagged values. The resulting coefficients remained consistent with our baseline DiD estimates, affirming the causal interpretation of our results and mitigating concerns about simultaneous determination.

Third, we tested the sensitivity of our findings to alternative model specifications. This included replacing the binary AI strategy dummy (DUM_AI) with a continuous AI policy implementation index (IND_AI) to capture gradual policy advancements, and incorporating additional fixed effects at the country-technology sector level to account for unobserved heterogeneity. The results remained robust across these alternative specifications.

Fourth, we examined sectoral heterogeneity by estimating interactions between policy variables and technology sector dummies. These analyses revealed that the positive effects of AI subsidies and investments were in fintech and digital healthcare sectors, aligning with national AI strategic priorities and implementation roadmaps.

Finally, we controlled for potential confounding factors such as oil price volatility, broader digital infrastructure investments, and global technology market shocks. The inclusion of these variables did not materially alter the estimated policy impacts, suggesting that our identified effects are indeed driven by AI-specific policies rather than broader economic or technological trends.

Collectively, these robustness checks confirm our initial findings that GCC AI strategies asymmetrically boosted profitability in technology-adopting firms while leaving traditional sector firms unaffected. The consistency of results across multiple empirical approaches underscores the resilience of our conclusions to alternative specifications and potential sources of bias, strengthening confidence in the policy implications derived from our analysis.

5. POLICY IMPLICATIONS

The clear and consistent evidence from this study showing that GCC AI strategies boost profitability in tech-focused firms without aiding traditional sectors offers critical lessons for regional governments and global policymakers overseeing digital transformation. A central finding is that targeted fiscal incentives are a powerful tool for spurring private sector returns in new digital industries (Khan et al., 2025). The data shows a strong synergy between national AI strategies and government support, with subsidized AI firms achieving returns on equity up to 13.1% higher by 2024. This validates the use of specific measures such as computing subsidies, R&D tax credits, and innovation grants to help firms overcome initial adoption costs and attract investment into key technology sectors. This targeted approach contrasts with the broader, less-focused industrial subsidies seen in some Latin American economies, aligning more closely with the strategic sector targeting historically employed in East Asian developmental states. This approach effectively de-risks early-stage technology investments that private markets might otherwise underfund.

Second, the fact that policy impacts have grown stronger over time, especially after 2020, underscores the need for adaptive policymaking in fast-evolving technological fields. The increasing returns on AI subsidies and

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investments indicate that GCC policymakers have been learning and refining their approach, improving innovation incentives, streamlining regulatory sandboxes, and fostering better public-private collaboration (Adan & Fuerst, 2016). This pattern of gradual policy calibration to effectively support emerging tech sectors mirrors successful strategies long employed by countries like South Korea. This evidence contributes directly to the global policy debate on "mission-oriented" innovation policy, demonstrating that agile, learning-based state intervention can successfully catalyze technological catch-up. The findings thus advocate for continuous monitoring and evaluation frameworks that allow governments to adjust AI policies based on firm-level outcomes and technological learning curves.

Third, the clear lack of impact on traditional sector firms underscores why policies must deliberately favor high-growth technological sectors to prevent resource wastage. By concentrating support specifically on AI and digital technologies, GCC nations have skillfully avoided a common pitfall in economic diversification: propping up low-tech modernization in legacy industries, a challenge documented in other transitioning economies (Aidrous et al., 2019). This finding offers a critical lesson for other resource-rich regions, such as certain African and CIS economies, where diversification efforts are often hindered by political pressure to distribute subsidies broadly rather than concentrating them for maximum technological impact. This focused strategy does more than improve efficiency; it also sends a strong, credible signal to investors in AI sectors, encouraging the long-term capital investments that knowledge-intensive industries need to thrive. Furthermore, the fact that benefits did not leak to traditional firms alleviates concerns about fiscal waste, proving that clear policy boundaries are crucial for maintaining the momentum of a technological transition.

Fourth, our robustness checks revealed that the impact of subsidies varied by sector, with fintech and digital healthcare responding most strongly. This finding indicates that a one-size-fits-all technology policy is insufficient. Instead, governments should tailor their support, prioritizing domains with high spillover potential, a comparative institutional advantage, and a strong alignment with global digital trends. This nuanced strategy is already evident in the focused, high-impact investments made by the UAE in AI and Saudi Arabia in smart cities and digital infrastructure, which have successfully spurred rapid growth and profitability in those specific fields (Habbal, 2025). It also reflects a strategic logic seen in China's "Made in China 2025" initiative, which targeted specific high-tech sub-sectors, and in the European Union's coordinated Important Projects of Common European Interest in microelectronics and batteries.

Finally, our findings show that the success of AI subsidies and investments hinges on their integration with a broader set of supporting reforms. To be most effective, financial incentives must be paired with parallel advances in digital regulation, AI talent development, and data infrastructure (Dongo & Relvas, 2025). The combined effect we observed in our analysis confirms that firms reap the most significant profitability gains when they operate within a fully developed digital ecosystem. Such an environment lowers the costs of adopting new technology and improves market access.

This holistic approach aligns with the broader perspective on technology innovation, which stresses that overcoming entrenched industrial pathways requires coordinated policy packages. This underscores the relevance of the GCC's experience to ongoing debates in bodies like the OECD and WTO about "whole-of-government" approaches to digital economy governance and the need for coherent policy packages. For GCC policymakers, this means they should prioritize parallel upgrades in digital skills development, data governance, and technology standardization. These reforms are essential to ensure that financial incentives consistently lead to sustainable, high performance in the AI sector.

In summary, the GCC's journey offers a practical blueprint for other resource-rich economies navigating the shift to knowledge-based digital models. By combining targeted subsidies, adaptive policies, selective support for high-potential sectors, and integrated digital reforms, these economies can create a virtuous cycle where rising profitability in AI fuels lasting technological competitiveness (Adan & Fuerst, 2016; Farooq et al., 2025).

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The GCC's emerging model, sitting at the confluence of Asian-style state facilitation and its unique hydrocarbon legacy, provides a novel blueprint for technologically latecomer economies in global policy debates. Future policies should build on these insights by deepening firm-level monitoring of technology adoption, fostering cross-country learning within the GCC on AI implementation, and increasingly leveraging venture capital alongside state support to ensure fiscal sustainability and market-driven innovation resilience.

6. CONCLUSION

This study offers robust evidence that national AI strategies in the GCC have effectively shifted economic incentives towards the digital sector. The result has been substantial profitability gains for firms embracing new technologies, without corresponding benefits for traditional sectors. By applying a rigorous Difference-in-Differences (DiD) design strengthened by System GMM estimation, we establish a causal connection between targeted AI policies, specifically, technology-focused subsidies and innovation incentives, and stronger financial performance in AI-intensive firms.

These findings signal a fundamental shift in the GCC's economic strategy, moving from a hydrocarbon-based model to a strategic, digitally-focused agenda that uses public finance to spur private sector technological advancement. The fact that returns on AI subsidies and investments have accelerated since 2020 indicates that policy learning and institutional adaptation are making these technological interventions increasingly effective. This pattern of improvement echoes successful digital transformations in other contexts, such as South Korea, where sustained public support and market-aligned innovation policies enabled technology sectors to achieve global competitiveness and profitability.

However, several limitations of this study must be acknowledged. First, while the empirical strategy addresses endogeneity through dynamic panel methods and fixed effects, unobserved firm-level heterogeneity such as digital culture, innovation capacity, or technology management expertise may still influence profitability outcomes. Second, the sample, while comprising strategically important firms, may underrepresent small and medium enterprises and startups, which are critical for technological innovation but often lack detailed financial reporting. Third, the analysis focuses primarily on financial metrics, leaving aside broader socio-economic dimensions of digital transformation such as job quality, digital skills development, or technological inclusivity. Finally, the study's timeframe (2015–2024) captures the initial phase of GCC AI strategies but cannot assess the long-term sustainability of observed profitability gains, especially as global technology competition intensifies and AI capabilities advance rapidly.

These limitations open several avenues for future research.

First, micro-level analyses could explore the mechanisms through which AI subsidies translate into profitability, for instance, whether they enhance operational efficiency, drive product innovation, or create new digital business models.

Second, comparative studies across technologically transitioning economies could identify contextual factors that determine the success of AI policies in different institutional environments.

Third, research could examine the role of firm-level characteristics such as digital leadership, data governance capabilities, or international technology partnerships in mediating the impacts of AI policy.

Fourth, future work might investigate the distributional consequences of AI-driven growth, including whether productivity gains are widely shared or lead to increased technological inequality.

Lastly, as GCC economies deepen their digital transitions, scholars should explore how emerging technologies such as generative AI, quantum computing, and blockchain reshape the competitive landscape and require new policy approaches to maintain technological competitiveness.

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