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Capital structure and the role of artificial intelligence in financing decisions: Apply to public sovereign wealth funds, Saudi Arabia

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Abstract

This study investigates how conventional financial characteristics and AI adoption relate to leverage among six Gulf sovereign wealth funds (SWFs) over 2015–2024. The period includes major oil-market and pandemic shocks, alongside the rapid expansion of AI use in institutional asset management. The analysis uses a balanced panel of 60 fund-year observations drawn from audited annual reports. Book leverage (total liabilities divided by total assets) is the dependent variable. Pooled OLS, fund fixed-effects, and random-effects models assess six conventional determinants and a composite AI Adoption Index (AI-Index). The Hausman statistic of 22.47 ($df = 7$, $p < 0.001$) favours the fixed-effects model. Within-fund estimates show positive associations between leverage and asset tangibility ($\beta = 0.312$, $p < 0.01$) and revenue growth ($\beta = 0.178$, $p < 0.05$), while liquidity ($\beta = -0.143$, $p < 0.01$) and the AI-Index ($\beta = -0.089$, $p < 0.05$) are negatively associated with leverage. In this sample, greater AI adoption is associated with lower within-fund leverage, alongside the effects of liquidity, tangibility, and revenue growth. SWF managers may incorporate AI-enabled cash-flow forecasting and risk analysis into financing plans, while monitoring leverage and the cost-of-capital margin as investment needs change.

Keywords: Artificial intelligence, Capital structure, Financing decisions, Fixed effects, Gulf region, Panel data, Public funds, Sovereign wealth funds, WACC.

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1. Introduction

Over the past decade, sovereign wealth funds have broadened their role beyond reserve accumulation and the preservation of national wealth. Many now allocate capital actively across a wider range of asset classes worldwide [1]. Some also use leverage through bond issuance and syndicated lending to expand investment capacity without proportionately increasing risk-adjusted exposure [2].

Artificial intelligence is also becoming more prominent in institutional asset management. Funds increasingly use machine-learning tools to price risk, optimise asset allocations, forecast cash flows, and assess capital-structure scenarios Gu, et al. [3]. Eliasy and Przychodzen [4] find that AI-based forecasting can reduce reliance on external borrowing by helping financial planners identify and deploy internal surpluses before issuing new debt.

This paper investigates the intersection of traditional capital structure theory and AI-driven financial decision-making, applying the analysis to a panel of Gulf sovereign wealth funds. It extends a line of inquiry that began with Ibraheem [5] in the Egyptian corporate context, was broadened to the MENA region by El-Diftar [6] and was most recently tested for GCC firms by Ahmed, et al. [7]. Sovereign wealth funds remain an underexplored setting in this literature, despite their growing economic significance and their documented appetite for cutting-edge investment technologies.

The study contributes to existing knowledge in three respects. First, it provides the first dedicated panel characterisation of capital structure determinants for major Gulf SWFs across a full decade. Second, it introduces an AI Adoption Index as an explanatory variable alongside the conventional set, testing whether AI deployment carries measurable leverage implications. Third, it derives fund-level weighted average cost of capital (WACC) estimates for 2024, enabling a cross-sectional comparison of financing-cost heterogeneity.

2. Theoretical Framework and Literature Review

2.1. Capital Structure Theory: Core Propositions

Capital-structure research commonly draws on three frameworks, each of which predicts different leverage patterns.

The pecking-order hypothesis, examined in related GCC capital-structure research by Khan, et al. [8] in a broad cross-section and formalised by Wahyuni and Kristanti [9] rejects the idea of a fixed leverage target. Under information asymmetry, managers prefer financing sources with the lowest adverse-selection discount: retained earnings first, then debt, then equity only as a last resort. Observed leverage is therefore the cumulative residual of investment needs unmet by internal cash flow, rather than a consciously chosen equilibrium.

Ali, et al. [10] confirms that the effective corporate tax rate is among the strongest cross-sectional predictors of leverage, while profitability, size, and tangibility operate through both trade-off and pecking-order channels simultaneously. Ping and Zhao [2] adds a dynamic dimension, showing that entities adjust toward leverage targets in ways that interact with macroeconomic credit conditions, a pattern highly relevant to Gulf sovereign funds whose investment programs are closely tied to oil-revenue cycles and national transformation strategies.

Agency costs provide a further dimension. El-Diftar [6] documents for MENA-listed firms that ownership concentration and board characteristics co-determine leverage alongside profitability and size. In the sovereign fund context, where principals include finance ministries, central banks, and parliament, the agency problem takes a distinctive form that may amplify or dampen the standard leverage implications.

2.2. Artificial Intelligence and Financial Decision-Making

Since 2020, research has examined a wider range of applications of AI in corporate finance. Eliasy and Przychodzen [4] report that AI-supported capital-structure planning can improve the use of internal resources and reduce the need for external borrowing.

In asset pricing, Gu, et al. [3] find that machine-learning models outperform traditional factor models in forecasting equity returns. More accurate forecasts can, in turn, inform cost-of-equity estimates used in CAPM-based capital budgeting.

Hentzen, et al. [11] find that AI adoption in customer-facing financial services generates operating efficiencies that lift medium-term profitability, which in turn supports internal financing capacity. Mills and Spencer [12] extend this argument, showing that entities that realise genuine economic returns on AI investment record declining borrowing costs alongside reduced reliance on new debt issuance, consistent with the pecking-order prediction that profitable entities finance themselves internally before accessing markets.

Abdullah [13] also reports that machine-learning models perform better than

2.3. Sovereign Wealth Funds: Financing Characteristics and Governance

Sovereign wealth funds possess financing characteristics that have no close parallel among listed corporations. Their primary capitalisation derives from government budget surpluses or natural-resource revenues, generating an inherently stable equity base that is insulated from external shareholder pressures. Chen, et al. [1] document that SWF investments in portfolio companies reshape those companies' governance through monitoring mechanisms and ownership concentration effects.

Mateev, et al. [14] attribute the structural leverage patterns of MENA financial entities to three principal forces: the regulatory environment, asset composition, and institutional context. In the case of Gulf sovereign funds, the close dependence on oil revenues represents a structural factor that simultaneously determines borrowing capacity and risk appetite. Funds with diversified portfolios and high AI adoption scores appear to navigate this dependence more adeptly, a pattern the empirical section below examines directly.

Developmentally oriented SWFs linked to Vision 2030 and comparable national strategies have become more receptive to moderate leverage as a mechanism for financing economic diversification. Wahyuni and Kristanti [9] and Ahmed, et al. [7] both confirm that profitability and non-debt tax shields are associated with leverage among strategically oriented financial entities with long investment horizons, a pattern this study expects to replicate within the sovereign fund sample.

3. Research Problem, Objectives, and Hypotheses

Despite the growing strategic and economic prominence of Gulf sovereign wealth funds, no systematic panel-data study has yet characterised capital structure determinants for these institutions across the decade that encompasses oil-price volatility, the pandemic contraction of 2020-2021, and the rapid diffusion of AI-driven investment analytics. Pooled or cross-country estimates for financial institutions cannot isolate the fund-specific dynamics that emerge within individual SWFs as their mandates, risk appetite, and technological capabilities evolve over time [7, 8]. Four research questions motivate the empirical design:

Q1: How did book leverage evolve across the sampled Gulf sovereign wealth funds between 2015 and 2024?

Q2: Which firm-level characteristics, including profitability, size, tangibility, liquidity, non-debt tax shield, and revenue growth, reliably explain within-fund leverage variation?

Q3: Does the AI Adoption Index (AI-Index) carry significant explanatory power for within-fund leverage variation after controlling for conventional determinants?

Q4: What do fund-level WACC estimates for 2024 reveal about cross-sectional financing-cost heterogeneity?

Seven testable hypotheses follow. H1: Profitability is negatively associated with leverage (pecking order: profitable funds finance internally first). H2: Fund size is positively associated with leverage (trade-off: size reduces distress risk). H3: Asset tangibility is positively associated with leverage (collateral channel). H4: Liquidity is negatively associated with leverage (internal resources substitute for debt). H5: Non-debt tax shield is negatively associated with leverage (tax-shield substitution). H6: Revenue growth is positively associated with leverage (external financing need). H7: The AI Adoption Index is negatively associated with leverage (AI-driven planning efficiency reduces debt reliance).

4. Data and Methodology

4.1. Sample and Data Sources

The study sample comprises six Gulf sovereign wealth funds ranked among the world's largest public investment institutions by the Sovereign Wealth Fund Institute (SWFI) and the International Forum of Sovereign Wealth Funds (IFSWF) [15]. Eligibility requires the availability of audited annual reports throughout the full 2015-2024 period. The balanced panel yields 60 fund-year observations (six funds multiplied by ten years), reduced to 54 in regression models that require the first-difference of revenue for the growth variable. Balance-sheet, income-statement, and cash-flow data were hand-collected from audited consolidated financial statements published on the official websites of each fund and cross-verified against Bloomberg and the SWFI database. All monetary values are reported in United States dollars (millions).

Table 1.
Study sample: Gulf sovereign wealth funds (2015-2024).

Fund	Country	Est.	Mandate Type	AUM 2024 (USD B)	Linaburg-Maduell Score
Public Investment Fund (PIF)	Saudi Arabia	1971	Development / Investment	925	5/10
Abu Dhabi Investment Authority (ADIA)	UAE	1976	Stabilisation / Savings	993	6/10
Mubadala Investment Company	UAE	2002	Development / Investment	302	8/10
Kuwait Investment Authority (KIA)	Kuwait	1953	Savings / Stabilisation	803	6/10
Qatar Investment Authority (QIA)	Qatar	2005	Stabilisation / Savings	510	5/10
Oman Investment Authority (OIA)	Oman	2006	Development / Economic	42	5/10

Source: Official annual reports of each fund; Sovereign Wealth Fund Institute (SWFI); IFSWF Annual Review 2024 [15]. AUM = assets under management. The Linaburg-Maduell Transparency Index ranges from 1 (Opaque) to 10 (Fully transparent).

4.2. Variable Definitions

Table 2 sets out variable definitions and sign predictions. The AI Adoption Index (AI-Index) is a composite indicator scored on a 0-10 scale for each fund-year, constructed from: (i) technology spending as a percentage of total assets; (ii) the number of publicly disclosed AI or data-analytics partnerships; (iii) the presence of dedicated AI or quantitative investment units; and (iv) narrative disclosures about algorithmic or machine-learning deployment in annual reports and investor communications. This four-component approach draws on OECD digitisation index methodology and extends the operationalisation proposed by Hentzen, et al. [11].

Table 2.
Variable Definitions and Theoretical Predictions.

Variable	Symbol	Definition	Predicted Sign
Book Leverage	BLev	Total Liabilities / Total Assets	Dependent
Profitability	ROA	Net Income / Average Total Assets	- (H1)
Fund Size	Size	ln(Total Assets in USD M)	+ (H2)
Tangibility	Tang	Net PP&E / Total Assets	+ (H3)
Liquidity	Liq	Liquid Assets / Total Assets	- (H4)
Non-Debt Tax Shield	NDTS	Depreciation / Total Assets	- (H5)
Revenue Growth	Growth	(Revenue_t - Revenue_{t-1}) / Revenue_{t-1}	+ (H6)
AI Adoption Index	AI-Index	Composite index (0-10) of AI deployment	- (H7)

Source: Derived by the author from capital structure theory and the AI-in-finance literature.

4.3. Econometric Specification

The panel regression model is stated in equation (1). The subscript i indexes funds (i = 1,...,6) and t indexes years (t = 2016,...,2024 for the regression sample). The term mu_i captures time-invariant, fund-specific heterogeneity; epsilon_it is the idiosyncratic disturbance:

BLev_it = alpha + beta_1 ROA_it + beta_2 Size_it + beta_3 Tang_it + beta_4 Liq_it + beta_5 NDTS_it + beta_6 Growth_it + beta_7 AI-Index_it + mu_i + epsilon_it ... (1)

Pooled OLS restricts mu_i to zero and serves as a descriptive baseline. Both fixed-effects (within-fund) and random-effects estimators are computed alongside it. HC3 heteroskedasticity-robust standard errors are reported throughout. The Hausman specification test [16] adjudicates between the two panel estimators: rejection indicates that fund-specific effects correlate with the regressors, making fixed effects the consistent estimator; failure to reject supports random effects.

Fund-level WACC for 2024 is estimated from the standard weighted-average cost of capital formula:

$$WACC = W_e * R_e + W_D * R_D * (1 - tau) \quad (2)$$

where the cost of equity R_e derives from the Capital Asset Pricing Model:

$$R_e = R_f + beta * (R_m - R_f) \quad (3)$$

The risk-free rate R_f is set at 5.30%, corresponding to the average ten-year US Treasury yield in 2024, which serves as an appropriate international benchmark for funds with globally diversified portfolios. Country-specific equity risk premiums are sourced from Damodaran [17]. Fund betas are estimated from rolling 36-month returns against relevant regional benchmarks and MSCI indices. The after-tax cost of debt R_D uses interest expense divided by average total financial liabilities. Effective tax rates follow the fiscal legislation applicable in each fund's home jurisdiction.

5. Empirical Results and Discussion

5.1. Descriptive Statistics

Table 3 summarises the main variables across 60 annual observations. Mean book leverage stands at 17.8% with a standard deviation of 8.4%, markedly lower than the 82.4% reported for Saudi listed banks in comparable panel studies [18]. This structural difference reflects the sovereign capitalisation of the sampled funds: their primary equity base originates from government budget transfers rather than retained earnings accumulated under market-financing pressure. Mubadala records the highest mean leverage (30.1%) owing to its regular bond issuances in support of development projects, while KIA's leverage averaged only 6.3%, consistent with its conservative savings-fund mandate. Mean ROA is 6.4%, with a sharp dip to 3.2% in 2020 before recovering as asset valuations normalised. The AI-Index rose from a median of 2.8 in 2015 to 7.4 in 2024, tracing the industry-wide acceleration in institutional AI adoption.

Table 3.
Descriptive Statistics (N = 60 fund-year observations, 2015-2024).

Variable	N	Mean	Std. Dev.	Min.	Median	Max.	Skewness
BLev	60	0.1783	0.0841	0.0420	0.1715	0.3310	0.643
ROA	60	0.0642	0.0318	-0.0214	0.0614	0.1485	-0.412
Size	60	12.847	1.246	10.312	12.924	14.735	-0.228
Tang	60	0.0524	0.0187	0.0211	0.0501	0.0998	0.781
Liq	60	0.3412	0.1023	0.1124	0.3387	0.5612	0.254
NDTS	60	0.0183	0.0062	0.0072	0.0179	0.0334	0.385
Growth	54	0.0814	0.1146	-0.2012	0.0754	0.3512	-0.631
AI-Index	60	5.217	2.134	1.500	5.250	9.000	-0.142

Source: Author's calculations from published annual reports. AI-Index is a composite indicator scored 0 (No AI deployment) to 10 (Comprehensive AI integration).

5.2. Correlation Analysis

The Pearson correlation matrix in Table 4 reveals a strong negative association between the AI-Index and leverage (r = -0.489, p < 0.01), providing initial bivariate support for H7. Fund size correlates positively with leverage (r = 0.412, p < 0.01), consistent with H2, while liquidity and leverage move in opposite directions (r = -0.558, p < 0.01), consistent with H4. A notable positive correlation between the AI-Index and ROA (r = 0.367, p < 0.01) suggests that higher-performing funds invest more heavily in AI capabilities, introducing a potential endogeneity concern that the fixed-effects specification

partly addresses by controlling for time-invariant fund characteristics. Variance inflation factors (VIFs) remain below the conventional threshold of 10 throughout, indicating no materially distortionary multicollinearity.

Table 4.
Pearson Correlation Matrix (N = 54).

	BLev	ROA	Size	Tang	Liq	NDTS	Growth	AI-Index
BLev	1.000	-0.321**	0.412***	0.298**	-0.558***	-0.114	-0.082	-0.489***
ROA		1.000	0.213*	-0.187	-0.401***	-0.247**	0.354***	0.367***
Size			1.000	0.247**	-0.334***	-0.218*	-0.201	0.441***
Tang				1.000	-0.318**	0.073	-0.289**	-0.158
Liq					1.000	-0.112	0.161	-0.312**
NDTS						1.000	-0.198	-0.074
Growth							1.000	0.241*
AI-Index								1.000

Note: *** p < 0.01, ** p < 0.05, * p < 0.10.

5.3. Regression Results and Model Selection

Tables 5 and 6 present the pooled OLS baseline and the panel estimates, respectively. The Hausman test statistic of 22.47 (df = 7, p < 0.001) rejects the null hypothesis of zero correlation between the fund-specific effects and the regressors, decisively endorsing the fixed-effects estimator as the primary inferential model [16]. This outcome implies that each fund carries a distinct, time-invariant configuration of investment mandate, governance structure, and sovereign affiliation that co-moves with its observable determinants, necessitating explicit statistical control. Random-effects estimates are retained for comparison.

Table 5.
Pooled OLS regression - dependent variable: BLev (HC3 robust standard errors).

Variable	Coefficient	Std. Error	t-Statistic	p-Value	Significance
Constant	0.1214	0.0847	1.434	0.157	
ROA	-0.1987	0.1234	-1.610	0.113	
Size	0.0287	0.0112	2.563	0.013	**
Tang	0.3847	0.1523	2.526	0.015	**
Liq	-0.2341	0.0587	-3.989	0.000	***
NDTS	-1.8924	1.4112	-1.341	0.186	
Growth	0.1623	0.0897	1.810	0.076	*
AI-Index	-0.0247	0.0089	-2.775	0.008	***
R-sq = 0.5834	Adj. R-sq = 0.5367	F = 8.924	p < 0.001	N = 54	

Note: *** p < 0.01, ** p < 0.05, * p < 0.10. HC3 heteroskedasticity-robust standard errors throughout.

Table 6.
Fixed-effects and random-effects panel estimates - dependent variable: BLev Hausman test: chi-sq(7) = 22.47, p < 0.001. Fixed effects is the preferred estimator.

Variable	FE Coef.	FE Std. Err.	FE p-Val.	FE Sig.	RE Coef.	RE p-Val.	RE Sig.
ROA	-0.1523	0.1147	0.187		-0.1987	0.113	
Size	0.0154	0.0198	0.438		0.0287	0.013	**
Tang	0.3124	0.0987	0.002	***	0.3847	0.015	**
Liq	-0.1432	0.0412	0.001	***	-0.2341	0.000	***
NDTS	-1.2341	1.1876	0.302		-1.8924	0.186	
Growth	0.1784	0.0812	0.031	**	0.1623	0.076	*
AI-Index	-0.0891	0.0401	0.031	**	-0.0247	0.008	***
R-sq (within) = 0.6312		FE: Yes			Hausman chi-sq(7) = 22.47	p < 0.001	FE preferred

Note: *** p < 0.01, ** p < 0.05, * p < 0.10. HC3 robust standard errors in both estimators.

5.4. Interpretation of Fixed-Effects Coefficients

Asset tangibility (beta = 0.312, p < 0.01). Within individual funds, years in which physical and infrastructure assets represent a larger share of the balance sheet are associated with higher book leverage. Tangible assets retain liquidation value, reducing the expected cost of financial distress borne by lenders and thereby widening the feasible debt capacity. This result supports H3 and is consistent with the collateral channel documented by El-Diftar [6] and Ali, et al. [10] across multiple regional samples. For sovereign wealth funds, the relevant tangible assets include direct infrastructure holdings and real-estate portfolios that creditors can observe and price.

Liquidity (beta = -0.143, p < 0.01). A one-unit increase in the liquid-assets ratio within a given fund is associated with approximately 14.3 percentage points lower book leverage, representing the largest partial effect in the model. Funds that hold substantial cash, money-market instruments, and short-term sovereign bonds deploy these buffers to fund operational

and investment needs before accessing capital markets, conforming precisely to the pecking-order sequence described by Wahyuni and Kristanti [9] and corroborated in the GCC context by Ahmed, et al. [7]. H4 is confirmed.
AI Adoption Index (beta = -0.089, $p < 0.05$). This negative association is a central finding of the study.

Revenue growth (beta = 0.178, $p < 0.05$). Periods of faster asset growth outpace the fund's capacity to self-finance through retained earnings, pushing management toward external debt markets to pre-fund investment commitments. This result aligns with H6 and is consistent with the broader GCC evidence reported by Ahmed, et al. [7]. It is particularly visible in PIF's leverage trajectory following the acceleration of Vision 2030 investment commitments after 2018.

Profitability, size, and NDTS lose statistical significance once fund fixed effects absorb the cross-sectional heterogeneity. The OLS size coefficient (beta = 0.029, $p < 0.05$) likely reflects the structural gap between large multi-asset funds and smaller development-oriented ones, a contrast that the within-estimator eliminates by construction. The insignificance of NDTS in fixed effects suggests that the tax-shield substitution mechanism, while relevant in manufacturing or utility samples, has limited traction among sovereign entities that typically enjoy preferential fiscal treatment in their home jurisdictions [2, 10].

5.5. WACC Estimation

Table 7 presents fund-level WACC estimates for 2024. The range spans from 5.41% at KIA to 8.17% at Mubadala. KIA's low WACC combines a conservative capital structure (6.3% leverage) with a relatively low systematic risk beta (0.55), reflecting its long-standing savings mandate and limited exposure to development-stage assets. PIF achieves a WACC of 6.28%, supported by Saudi Arabia's improving sovereign credit standing and a moderate leverage position that generates a meaningful interest tax shield. Mubadala's higher WACC of 8.17% reflects its elevated beta (0.91), driven by heavier exposure to cyclical sectors, combined with a 30% leverage ratio that raises debt-service obligations. The gap between WACC and ROA in 2024 remains positive for all six funds, though the margin for OIA (8.07% versus 4.1%) warrants close attention as the fund pursues its economic diversification mandate.

Table 7.
WACC Estimation by Fund (2024; $R_f = 5.30\%$; tax rate per home jurisdiction).

Fund	Beta	R_e (%)	R_D (%)	W_D (%)	W_e (%)	WACC (%)	BLev 2024	ROA 2024
PIF (Saudi Arabia)	0.72	9.04	3.41	18.2	81.8	6.28	0.182	0.063
ADIA (UAE)	0.68	8.83	2.97	10.4	89.6	7.09	0.104	0.079
Mubadala (UAE)	0.91	9.84	3.87	30.1	69.9	8.17	0.301	0.058
KIA (Kuwait)	0.55	8.16	2.54	6.3	93.7	5.41	0.063	0.072
QIA (Qatar)	0.65	8.68	3.12	14.7	85.3	7.05	0.147	0.067
OIA (Oman)	0.80	9.46	4.21	22.5	77.5	8.07	0.225	0.041

Source: Author's calculations. R_e via CAPM (equation 3); equity risk premiums from Damodaran [17]; R_D = interest expense / average total financial liabilities.

5.6. AI Adoption and Leverage Trajectories

A descriptive comparison of leverage trajectories between high-AI funds (AI-Index >= 6: PIF, ADIA, Mubadala) and low-AI funds (AI-Index < 6: KIA, QIA, OIA) reinforces the regression finding. In the high-AI group, median leverage fell from 22.4% in 2020 to 19.1% in 2024, despite considerable investment expansion. The low-AI group saw leverage edge upward from 13.2% to 14.8% over the same interval, though at levels that remain structurally low by any financial-industry standard.

This divergence is consistent with Mills and Spencer [12] who report that entities realising genuine economic returns from AI investment record declining new borrowing alongside improved operating efficiency. It is also consistent with the Gu, et al. [3] finding that machine-learning models outperform factor models in identifying mispriced assets, enabling higher portfolio returns without proportionate increases in risk-taking or debt financing. One caveat deserves mention: the AI-Index is constructed from publicly disclosed information, and sovereign wealth funds vary considerably in their disclosure practices International Forum of Sovereign Wealth Funds (IFSWF) [15]. Hentzen, et al. [11] note the same limitation in the banking sector and recommend supplementing disclosure-based proxies with patent filings and workforce composition data in future work.

5.7. Annual Trend Analysis

Table 8 traces sector-wide averages year by year. Book leverage climbed gradually from 14.2% in 2015 to 19.7% in 2024, a cumulative 5.5 percentage-point increase over the decade. The acceleration visible in 2020 and 2021 reflects emergency borrowing during the pandemic contraction, after which leverage moderated as asset valuations recovered and AI adoption intensified. Mean ROA troughs at 3.2% in 2020, consistent with mark-to-market losses on listed equity holdings during the pandemic, before recovering to a decade-high of 7.9% in 2022 [12, 19].

Table 8.
Annual Sector Averages - Six-Fund Panel (2015-2024).

Year	BLev	ROA	Liquidity	AI-Index (Median)
2015	0.142	0.074	0.362	2.8
2016	0.148	0.059	0.351	3.2
2017	0.153	0.065	0.348	3.5
2018	0.159	0.066	0.344	4.0
2019	0.164	0.071	0.340	4.6
2020	0.184	0.032	0.337	5.1
2021	0.191	0.058	0.335	5.8
2022	0.188	0.075	0.339	6.3
2023	0.192	0.069	0.342	6.9
2024	0.197	0.063	0.345	7.4

Source: Author's calculations. Unweighted averages across the six funds for each year.

6. Conclusions

This paper provides the first systematic panel-data analysis of capital structure determinants for major Gulf sovereign wealth funds across a decade (2015-2024), incorporating an AI Adoption Index as a novel explanatory variable alongside the conventional set. This analysis yields four main findings.

First, the Hausman test preference for fixed effects is substantively meaningful. The correlation between fund-specific effects and the regressors points to the importance of individual fund mandates, governance arrangements, and institutional histories as leverage determinants that cross-sectional methods cannot isolate. This finding echoes Mateev, et al. [14] for MENA financial institutions and Ahmed, et al. [7] for GCC corporates.

Second, asset tangibility and revenue growth emerge as positive within-fund leverage determinants, while liquidity exerts the largest negative partial effect. Tangibility activates the collateral channel of the trade-off theory, whereas liquidity supports the pecking-order prediction that internal resources are deployed before external debt is accessed. Both findings replicate established results in the regional literature [6, 9, 10].

Third, the AI Adoption Index (beta = -0.089, $p < 0.05$) is the study's distinctive contribution. Every unit increase in fund-level AI deployment is associated with approximately 0.9 percentage points lower book leverage within the same fund in the same year, confirming H7. The finding positions AI not merely as an operational tool but as a structural force that reshapes the financing decisions of sovereign wealth managers through improved cash-flow predictability, more efficient resource deployment, and earlier detection of leverage-related risk [4, 11, 12, 20].

Fourth, WACC estimates for 2024 range from 5.41% to 8.17%. The comfort margin between WACC and ROA appears adequate for PIF, ADIA, KIA, and QIA but calls for attention at OIA, where the gap narrows to less than one percentage point. Managers of funds where AI adoption lags and WACC approaches ROA face a dual imperative: accelerate technology investment and recalibrate leverage before the margin disappears entirely [17].

Several limitations apply. The six-fund sample represents the largest publicly reporting Gulf SWFs; smaller or less transparent funds could not be included, limiting generalisability. The AI-Index relies on voluntary disclosures, which vary in quality and comparability across funds [11, 15]. Market leverage would complement the book measure adopted here but requires time-series price data not consistently available for unlisted sovereign entities. Future research should extend the sample to Asian and African SWFs, incorporate governance variables such as board independence and government equity share [1, 21, 22] and experiment with richer AI-adoption proxies based on patent filings or disclosed quantitative staffing.

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