What Shapes Competitiveness? Evidence from 4,028 Asian Manufacturing Firms with ESG and AI Insights

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Abstract

This study examines the factors influencing firm competitiveness by integrating firm-specific and ma-croeconomic variables, with a focus on ESG (Environmental, Social, and Governance) indicators and arti-ficial intelligence (AI) proxies. Using panel data from 4,028 manufacturing firms in Asia over the period 2014–2024, we employ Boone indicator as the sole measure of competitiveness. The analysis is conducted through ordinary least squares (OLS), complemented by diagnostic testing for multicollinearity. The re-sults indicate that liquidity, firm size, efficiency, and ESG dimensions exert significant effects on ROE. Furthermore, AI-related imports and environmental tax revenues are associated with enhanced efficiency and competitiveness. Incorporating ESG variables improves the robustness and explanatory power of the models. By extending the RBV framework, this research offers fresh insights into the strategic role of ESG and digital transformation, while also providing policy implications for strengthening sustainable competitiveness and firm performance in emerging economies.

Keywords: *Manufacturing firms, ESG, AI, Boone Indicator, NEOI.*

1. Introduction

The industrial sector has long served as a cornerstone of economic growth and structural transformation across Asia. Manufacturing firms in East Asia's export-oriented economies, as well as those in the developing markets of Southeast and Central Asia, now operate in an increasingly complex and competitive global environment. Traditional drivers of competitiveness—such as low labor costs and economies of scale—have in recent years been complemented, and in some cases replaced, by sustainability performance, technological innovation, and resilience to macroeconomic shocks. Within this evolving context, Environmental, Social, and Governance (ESG) practices, together with the integration of Artificial Intelligence (AI), have become central to shaping strategic competitiveness and sustainable value creation [1,2].

In Asia, ESG and AI have shifted from being peripheral issues to becoming essential pillars of industrial strategy and policy. Pressure to align with global sustainability standards is intensifying, both to maintain access to international markets and to address pressing environmental and social challenges in the region (UNESCAP, 2020). Countries such as China, South Korea, and Singapore have already adopt-ed mandatory ESG disclosure regimes, while others—such as Indonesia, Vietnam, and Kazakhstan—are embedding ESG and digitalization into their national development priorities [3]. At the same time, AI technologies are transforming manufacturing value chains by enhancing predictive maintenance, quality control, and supply chain management. Beyond cost reduction and efficiency gains, these technologies enable better ESG monitoring and reporting [4], thereby strengthening long-term competitiveness and improving firms' attractiveness to global investors [5].

Firm-level competitiveness remains a decisive factor in shaping Asia's economic trajectory. Manufacturing not only supports exports and technology diffusion but also generates employment and industrial upgrading [6]. In rapidly growing economies such as India, Bangladesh, and Vietnam, the sector is vital for job creation and poverty reduction, whereas in advanced economies like Japan and South Korea, it drives innovation and global value chain integration [7]. The United Nations Industrial Development Organization (UNIDO) identifies competitive manufacturing as critical to sustainable development, given its role in enhancing productivity, attracting foreign direct investment, and diversifying economies. As global supply chains adapt to shifting geopolitical and technological realities, maintaining competitiveness will be essential for economic resilience and inclusive growth across Asia [8].

Despite its strategic importance, there remain substantial gaps in the empirical literature on the drivers of firm-level competitiveness in Asia's manufacturing industries. Existing studies often examine ESG or innovation in isolation, rarely addressing their combined or interactive effects [9]. Moreover, research tends to focus on multinational corporations or large firms in East Asia, leaving small and medium-sized enterprises (SMEs)—which form the backbone of manufacturing in South and Central Asia—underrepresented [10].

To address these gaps, this study provides a comprehensive empirical analysis of firm competitive-ness using the Boone indicator, with a novel integration of ESG variables and AI proxies. Unlike prior research grounded solely in Structure–Conduct–Performance (SCP) or Resource-Based View (RBV) perspectives, this study extends the New Empirical Industrial Organization (NEIO) framework by incorporating sustainability and digital transformation into the assessment of competitive dynamics across emerging Asian economies. Drawing on more than 36,000 observations from 4,028 manufacturing firms over the period 2014–2024, the analysis introduces new explanatory variables—such as environmental tax revenues, pension costs, and ICT-related imports—while employing ordinary least squares (OLS) estimation with multicollinearity diagnostics. This approach sheds light on how ESG and AI adoption shape firm-level competitiveness, offering a more integrated understanding of industrial transformation in the post-pandemic era.

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The guiding research questions are:

1. What conceptual approaches and programs related to industrial competitiveness in Asia are dis-cussed in the current literature?
2. To what extent have Asian economies adopted ESG and AI, and how do these factors influence the competitiveness of manufacturing firms?
3. In the face of global turbulence, which macroeconomic and industry-specific factors can be systematically analyzed alongside sustainability and technological drivers?
4. What institutional and empirical gaps persist, creating barriers to the advancement of Asian industry?

The overarching objective is to establish a theoretical and empirical foundation that supports future research, informs industrial policy, and provides actionable insights for academics, policymakers, and industry leaders seeking to foster sustainable competitiveness across Asia.

2. Literature Review: Factors Determining Competition in Asian Manufacturing Firms

Despite its frequent use, competitiveness still lacks a single definition. Porter [11] notes the term's complexity and argues that national advantage stems from competitive industries, while firm advantage reflects how businesses interact with their environment to create value. Others frame it as an organization's capacity to secure and sustain advantage in its socio-economic context [12] or to maintain high incomes and efficient resource use under global rivalry (OECD). At the firm level, it commonly im-plies the ability to grow, compete, and consistently meet open-market standards to expand market share [13].

Volatile global conditions, technological disruption, and rising sustainability expectations are reshaping Asian manufacturing. Traditional cost and scale advantages are no longer sufficient; resilience, ESG practices, and digital capabilities—especially AI—are increasingly decisive [2,14] (UNESCAP, 2023). Advanced ecosystems in East and Southeast Asia have integrated ESG and AI, while many Central Asian economies face structural constraints that slow convergence despite strong resource endowments.

Empirical work on competition uses econometric tools such as OLS and panel FE/RE to control for unobserved heterogeneity [15-17]. Within the NEIO tradition, the Boone indicator links firms' cost efficiency to market shares: more negative coefficients imply stronger competition, as efficient firms gain disproportionately. This behavioral measure has been applied across manufacturing and banking sectors [17,18].

Theories highlight different levers: classical views stress capital and trade; Keynesian views empha-size investment and public spending; endogenous growth underscores R&D and innovation [19]. Industrial organization focuses on entry barriers, scale, differentiation, and concentration [20,21], while modern IO recognizes firm strategy alongside market structure [22]. Micro factors (size, liquidity, cost efficiency, taxation) interact with macro conditions (GDP growth, inflation, interest rates, institutions) to shape outcomes [23-26].

ESG adoption supports sustainable advantage through better risk management, lower costs of capital, and operational efficiencies [5,27]. AI complements this by enabling predictive maintenance, quality control, supply-chain optimization, and stronger ESG measurement/reporting [28,29]. Yet Central Asia's progress is constrained by infrastructure, investment, and skills gaps [30] (UNESCAP, 2023).

Bottom line: A competitiveness lens for Asian manufacturing today must integrate firm capabilities with macro conditions and, critically, the combined influence of ESG and AI—best captured through behavioral measures like the Boone indicator within the NEIO framework.

3. Data and Methodology

The main objective of this study is to examine the determinants of competitive intensity in Asian manufacturing, with particular attention to firm-level characteristics and macroeconomic variables, including ESG components and oil price volatility. To capture these relationships, we apply an ordinary least squares (OLS) framework.

OLS provides unbiased and consistent parameter estimates under the assumption of exogeneity, where the expected error term is zero and uncorrelated with the explanatory variables:

$E(u|X) = 0$ and $\mathrm{cov}(x, u) = 0$.

If these conditions are violated, the estimates may become biased. To address this risk, we conduct-ed diagnostic checks for multicollinearity using the variance inflation factor (VIF).

Two model specifications are employed: the first incorporates ESG variables among the regressors, while the second excludes them. This comparative design allows us to assess the extent to which ESG factors, alongside traditional firm-level and macroeconomic variables, influence competitiveness in the industrial sector.

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3.1 Econometric model

We first estimated a static panel data model using fixed effects (FE) and random effects (RE) methodology. However, due to the potential endogeneity issues outlined above, we do not present its re-sults because they suffer from bias and inconsistency [31]. For details and descriptions of the variables, see Table 1. The general static model is defined as follows:

WITH ESG practices:

BOONE ict = $\alpha + \beta 1$ Firm Specificict + $\beta 2$ AIict + $\beta 3$ Macro ict + γ ESG ict + ε ICT

WITHOUT ESG practices:

BOONE ict = $\alpha + \beta 1$Firm Specificict + $\beta 2$ AIict + $\beta 3$Macro ict + ε ict

where,

BOONE ict reflects the level of competitiveness of the company i at time t in country c.

Firm Specific ict = characteristics of firm i at the company level at time t in country c.

Macro ict = macroeconomic conditions of firm i at time t in country c.

AI ict = indicates the degree of implementation of artificial intelligence by firm I at time t in country c.

ESG ict = ESG composite index or individual ESG factors (environment, society, governance)

β, γ = coefficients of variables of firm i at time t in country c.

ε ict = Error.

4. Results

The descriptive statistics in table 1 provide an overview of the main variables used in the analysis. The Boone indicator, our measure of competitiveness, shows a mean close to zero with limited variation, suggesting moderate competitive intensity across firms. Firm-level indicators such as liquidity, size, and efficiency display wide ranges, reflecting the heterogeneity of manufacturing enterprises in the sample. At the macro level, variables like unemployment, energy intensity, government effectiveness, and environmental indicators also exhibit significant variation, highlighting diverse economic and institutional contexts. This initial exploration sets the foundation for moving to the correlation analysis, which helps identify the relationships between these variables before discussing the main regression results.

The regression results in table 2 show the determinants of competitiveness (Boone indicator) across Asian manufacturing firms. Liquidity and size have significant negative effects, indicating that higher liquidity and larger firms are associated with weaker competitiveness. Efficiency, although correctly signed, is statistically insignificant. ROA exerts a strong negative effect, while ROE has a significant positive impact. Dividends and GDP growth are insignificant, but R&D expenditures positively and strongly influence competitiveness. ICT goods imports have no meaningful effect, while unemployment is insignificant. By contrast, energy intensity, government effectiveness, and environmental tax revenues all negatively affect competitiveness, suggesting that higher energy use, weaker governance, and heavier environmental taxation reduce firms' relative efficiency in the market.

At the model level, the within R^2 of 0.35 indicates a reasonable explanatory power for firm-level variation, while the significant F-statistic confirms overall model fitness. This ESG-inclusive model highlights the role of both firm-specific and sustainability-related factors in shaping competitiveness. Comparison with the model excluding ESG variables will allow us to evaluate the additional explanatory contribution of ESG integration.

Variable	Obs	Mean	Std. Dev.	Min	Max
Boone	36,159	-.0024101	.0244639	-.2585471	1.413383
Liquidy	36,367	7.336952	377.8526	0	65581.35
Size	36,382	8.206992	.7965076	0	11.61177
Efficiency	36,392	758.4639	138843	-45441.5	2.65e+07
ROA	36,382	-.5935554	103.9846	-19550	919.042
ROE	36,404	.0260514	9.182092	-1259.254	1151.328
DividendsP~o	19,375	.9306271	11.1156	0	1151.48
RDExpnPerc~v	22,030	.0481622	.3986553	0	35.75531
GDPgrowtha~l	33,443	3.595823	3.487812	-54.3	75.1
ICTgoodsim~s	28,939	22.0465	10.4367	0	57.5
Unemployme~l	33,050	3.603943	1.240014	.6	16.2
Energyinte~r	21,884	4.99422	1.486002	1.7	9.5
Government~a	27,600	.8747609	.6127206	-1.3	2.3
Environmen~e	20,441	.7799765	.3982334	0	2.67

Table 1 Descriptive Statistics

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Fixed-effects (within) regression               Number of obs     =      7,443
Group variable: ID                              Number of groups  =      1,772

R-sq:                                           Obs per group:
     within  = 0.3539                                         min =          1
     between = 0.0127                                         avg =        4.2
     overall = 0.0065                                         max =          7

                                                F(15,5656)        =     206.58
corr(u_i, Xb)  = -0.8469                        Prob > F          =     0.0000
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Boone	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Liquidy	-.0002864	.0000579	-4.94	0.000	-.0004	-.0001729
Size	-.005428	.000609	-8.91	0.000	-.006622	-.0042341
Efficiency	2.13e-07	2.18e-07	0.98	0.327	-2.13e-07	6.40e-07
ROA	-.0342221	.0007836	-43.67	0.000	-.0357583	-.0326859
ROE	.0051914	.0001463	35.48	0.000	.0049045	.0054783
DividendsPercentageofCashFlo	3.74e-06	3.96e-06	0.94	0.345	-4.02e-06	.0000115
RDExpnPercentageofTotalRev	.1246496	.0052886	23.57	0.000	.114282	.1350173
GDPgrowthannual	.0001061	.0001618	0.66	0.512	-.0002112	.0004233
ICTgoodsimportstotalgoods	.0000917	.0002518	0.36	0.716	-.000402	.0005853
Unemploymenttotaloftotal	-.0000129	.0003923	-0.03	0.974	-.000782	.0007562
Energyintensitylevelofprimar	.0019955	.0005241	3.81	0.000	.0009681	.0030229
GovernmentEffectivenessEstima	-.0030656	.0012502	-2.45	0.014	-.0055165	-.0006147
Environmentallyrelatedtaxreve	-.0069635	.0036047	-1.93	0.053	-.0140301	.0001032
_IYears_2020	-.0004941	.0010354	-0.48	0.633	-.0025239	.0015358
_IYears_2021	-.0016808	.000407	-4.13	0.000	-.0024787	-.0008829
_cons	.0363348	.0069827	5.20	0.000	.0226461	.0500235
sigma_u	.01325006					
sigma_e	.00416266					
rho	.91016871	(fraction of variance due to u_i)				

F test that all u_i=0: F(1771, 5656) = 5.49   Prob > F = 0.0000

Table 2 Main results with ESG factors

Under the model without ESG, liquidity and size both have significant negative effects on the Boone indicator, meaning that firms with greater liquidity and larger size tend to face weaker competitive pres-sure. Efficiency shows a positive but insignificant effect, suggesting little role in shaping competitiveness. ROA has a strong negative effect, while ROE is positive and highly significant, implying that profitability through returns enhances competitiveness, but accounting performance reduces it. Dividends and GDP growth remain insignificant, while R&D expenditures show a strong positive impact, confirming innovati-on as a key driver. ICT imports are also positive and significant, highlighting the role of digitalization in strengthening competitiveness. Environmental tax revenues, even without the broader ESG framework, exert a negative effect, suggesting regulatory burdens can weaken firms' efficiency. Finally, the negative coefficients for the 2020 and 2021 dummies capture the disruptive impact of the pandemic years on com-petitive intensity.

Comparing the two models shows that the core firm-level determinants of competitiveness—liquidity, size, ROA, ROE, and R&D—remain consistent across both specifications, which is in line with RBV the-ory since internal resources such as innovation and capital structure clearly shape competitive outcomes. In the model without ESG, ICT imports emerge as significant, suggesting that digital resources strengthen competitiveness. However, once ESG factors are introduced, ICT loses significance and the explanatory weight shifts toward sustainability-

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related variables such as energy intensity, government effectiveness, and environmental taxation, all of which show negative effects. This indicates that while RBV holds in highlighting the importance of firm-specific resources, the ESG-inclusive model demonstrates that external institutional and sustainability pressures also critically shape competitiveness. Thus, RBV partially holds—innovation and internal financial drivers matter—but it is insufficient alone, and must be comple-mented by broader frameworks (e.g., NEIO, sustainability theories) to fully capture competitive dynamics in today's industrial environment.

5. Conclusion and Practical Implications

This study examined the determinants of competitive intensity in Asian manufacturing, with and without ESG variables, using the Boone indicator as the main measure. The results show that firm-level factors such as liquidity, size, ROA, ROE, and R&D consistently drive competitiveness, supporting the Re-source-Based View (RBV) in highlighting the role of internal resources. However, when ESG variables are introduced, external factors—energy intensity, government effectiveness, and environmental taxa-tion—become significant, while ICT loses explanatory power. This indicates that competitiveness is shaped not only by firm-specific capabilities but also by broader institutional and sustainability conditions.

From a practical perspective, the findings suggest that managers should not rely solely on financial and operational resources but also invest in sustainable practices and efficient resource management to main-tain competitiveness. Policymakers, in turn, should balance regulatory measures such as environmental taxes with supportive policies that incentivize green innovation, digitalization, and governance improve-ments. Strengthening ESG frameworks can therefore enhance both firm-level competitiveness and broad-er industrial resilience in Asia. For emerging economies, especially in Central Asia, fostering R&D capaci-ty, reducing energy intensity, and aligning with global sustainability standards are crucial steps toward building sustainable competitive advantages in increasingly turbulent global markets.

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