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Evaluating Export Efficiency of Small and Medium-Sized Textile Enterprises Using the DEA Method: Evidence from Uzbekistan

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Abstract: This study evaluates the export efficiency of 45 small and medium-sized enterprises (SMEs) operating in Uzbekistan's textile sector using Data Envelopment Analysis (DEA), aiming to identify operational benchmarks and structural determinants that drive export performance disparities. We apply both the Charnes–Cooper–Rhodes (CCR) model under constant returns to scale (CRS) and the Banker–Charnes–Cooper (BCC) model under variable returns to scale (VRS) to decompose overall technical efficiency (TE) into pure technical efficiency (PTE) and scale efficiency (SE). A two-stage Tobit regression model is subsequently employed to identify firm-level and institutional determinants. Panel data covering 2019–2023 were drawn from the State Statistics Committee, the Ministry of Investment, Industry and Trade, and enterprise-level financial statements. Mean CCR efficiency is 0.782, indicating that firms produce only 78.2% of frontier-achievable export output. Six firms (13.3%) operate on the efficient frontier; 88.9% exhibit increasing returns to scale (IRS). Tobit regression identifies export market diversification, international certification, technology adoption, regional cluster membership, and government support as significant positive efficiency determinants; small firm size and cotton price volatility exert significant negative effects. This is the first large-N DEA study applied specifically to textile SME export efficiency in Central Asia using enterprise-level microdata, contributing a frontier benchmarking framework to the nascent literature on transition-economy export competitiveness.

Keywords: Data Envelopment Analysis; Export Efficiency; Textile SMEs; Uzbekistan; Technical Efficiency; Scale Efficiency; Tobit Regression; Central Asia; Transition Economies.

1. Introduction

The global textile and apparel industry, valued at approximately USD 1.79 trillion in 2022 and projected to exceed USD 3.3 trillion by 2030 [1], remains one of the most export-intensive manufacturing sectors in developing and transition economies. For Uzbekistan — historically the world's fifth-largest cotton producer — the textile sector constitutes a strategic pillar of export diversification. In 2023, textile and apparel products accounted for USD 3.48 billion, or 28.4% of total merchandise exports [2], making the sector the single largest non-energy export category.

Despite robust aggregate growth, systematic microeconomic analysis of how efficiently individual textile enterprises convert inputs into export outputs has remained conspicuously absent from the literature. Export performance aggregates conceal profound firm-level heterogeneity: firms operating with structurally identical resources

realise markedly different levels of export revenue, signalling the presence of technical inefficiencies that are neither random nor exogenously determined.

Data Envelopment Analysis (DEA) — a non-parametric, multi-input multi-output efficiency measurement technique pioneered by Charnes et al. [3] and extended by Banker et al. [4] — provides the ideal methodological vehicle for this task. Unlike stochastic frontier analysis, DEA imposes no *a priori* functional form on the production technology and is particularly suited to small samples with multiple heterogeneous outputs, conditions that characterise the SME-dominated textile sector in Uzbekistan.

The study addresses three research questions: (RQ1) What is the distribution of export efficiency among textile SMEs in Uzbekistan, and how large is the average efficiency gap? (RQ2) What is the relative contribution of scale inefficiency versus pure technical inefficiency to overall export underperformance? (RQ3) Which firm-level and institutional factors are significant determinants of DEA efficiency scores?

The paper makes four distinct contributions. First, it provides the inaugural large-N DEA benchmarking of textile SME export efficiency in Central Asia, filling a gap identified by Baliyan and Kumar [5] and Melitz and Redding [6]. Second, decomposing efficiency into pure technical and scale components isolates the mechanism through which size constraints impede export competitiveness. Third, the Tobit framework links efficiency scores to actionable firm-level determinants. Fourth, the study contributes a replicable methodological template for efficiency evaluation in other transition-economy manufacturing sectors, complementing analogous DEA studies in Vietnam [7], Bangladesh [8], and Pakistan [9].

The remainder of this paper is structured as follows. Section 2 reviews the relevant literature. Section 3 presents the theoretical framework and DEA methodology. Section 4 describes data sources and sample characteristics. Section 5 reports efficiency scores and distributional analysis. Section 6 presents Tobit regression results. Section 7 provides discussion and benchmarking insights. Section 8 concludes with policy implications and directions for future research.

DEA has been extensively applied to manufacturing export efficiency since the foundational contributions of Charnes et al. [1] and Banker et al. [4]. Fare et al. [10], operationalised Malmquist productivity indices using DEA panels, establishing the methodological template adopted by subsequent export-efficiency studies. To ensure robustness in small-sample conditions, Simar and Wilson [11, 12, 13] introduced bootstrap procedures for second-stage truncated and Tobit regressions, addressing serial correlation and small-sample bias. Coelli et al. [14] provide a comprehensive methodological synthesis of efficiency measurement in developing economies, emphasising that resource misallocation — rather than technological deficiency — is typically the primary source of productive inefficiency in firms undergoing market transition. Furthermore, Andersen and Petersen [15] developed super-efficiency ranking models, while Cooper et al. [16] and Dyson et al. [17] outlined rigorous sample-size rules and isotonicity protocols for input-output variable selection. In the textile sector specifically, Oh and Lee [18] evaluated export technical efficiency across 28 Korean textile firms (1995–2005), finding mean TE scores of 0.71 under CRS, with technology gap differences accounting for the majority of the frontier distance.

Nguyen et al. [7] applied BCC-DEA to a panel of 312 Vietnamese garment exporters, documenting mean PTE of 0.847 and identifying technology adoption and supply-chain integration as the strongest efficiency determinants in a two-stage Tobit framework. Their finding that firms operating under IRS dominate the sample is closely mirrored by our results, lending cross-national validity to the scale-inefficiency hypothesis. Similarly, Rahman and Zhao [8] analysed 189 Bangladeshi ready-made garment (RMG) exporters and found mean TE of 0.791, with compliance certification significantly raising frontier proximity.

Khan et al. [9] applied a three-stage DEA to 78 Pakistani textile SMEs, controlling for energy price shocks, and found that after environmental adjustment average TE fell from 0.821 to 0.748, highlighting the sensitivity of efficiency estimates to contextual controls. Their application of Simar and Wilson's [13] double-bootstrap procedure for second-stage inference yielded substantively similar conclusions to standard Tobit regression — supporting our choice of the Tobit framework for robustness under small-sample conditions.

Coelli et al. [14] provide a comprehensive methodological synthesis of efficiency measurement in developing economies, emphasising that resource misallocation — rather than technological deficiency — is typically the primary source of productive inefficiency in firms undergoing market transition. Guan and Ma [19] evaluated Chinese manufacturing efficiency during the transitional period 1995–2000 and found that state-enterprise reform was associated with a 12–15 percentage-point improvement in technical efficiency over five years.

Damijan et al. [20] documented transition-efficiency dynamics in Central and Eastern European manufacturing using matched firm-level data, finding that export market entry was associated with productivity catch-up of 8% on average. Eryganov et al. [21] applied window-DEA to 94 Kazakhstani agro-industrial firms, providing the closest Central Asian precedent to our study, finding that government subsidy programmes improved frontier proximity by 6.3 percentage points on average.

Melitz [22] established the foundational theoretical link between firm heterogeneity, productivity, and export market participation, predicting that only firms above a productivity threshold will self-select into export activity. Melitz and Redding [6] extend this framework to account for multi-product firms and dynamic learning effects, providing theoretical grounding for the substantial TE dispersion observed in our sample. Additionally, the Resource-Based View (RBV) by Barney [23] and Penrose [24] emphasizes internal firm resources and managerial capabilities as drivers of competitive advantage, while Marshall [25] provides the foundational agglomeration externality theory underpinning regional industrial clusters.

Rahimov and Ergashev [26] examined Uzbekistan's textile sector competitiveness using revealed comparative advantage (RCA) analysis over 2010–2020, documenting that the RCA index improved from 3.2 to 8.7 following the 2017 reform package. Tashmatov and Azimov [27] conducted a qualitative assessment of 32 Uzbekistani textile exporters, identifying managerial capability, access to trade finance, and compliance with EU REACH regulations as primary barriers to frontier performance. Recently, Seitkali et al. [28] applied a meta-frontier DEA approach to agricultural export efficiency in Central Asian transition economies, highlighting persistent regional disparities.

The foregoing review reveals three substantive gaps: no study has applied DEA to a statistically representative sample of Uzbekistani textile SMEs with enterprise-level microdata; existing Central Asian efficiency studies focus on agricultural or agro-industrial sectors; and no study has examined the role of Uzbekistan's post-2017 institutional reforms (such as Presidential Decree No. UP-60 [29] and SME Law No. ZRU-594 [30]) in shaping enterprise-level export efficiency. This study directly addresses all three gaps.

2. Methodology

Our analytical framework integrates three theoretical traditions: the resource-based view [23], the new new trade theory [22], and non-parametric frontier analysis [3], DEA operationalises these by measuring each firm's distance from the empirically derived best-practice frontier without imposing parametric assumptions on the production technology.

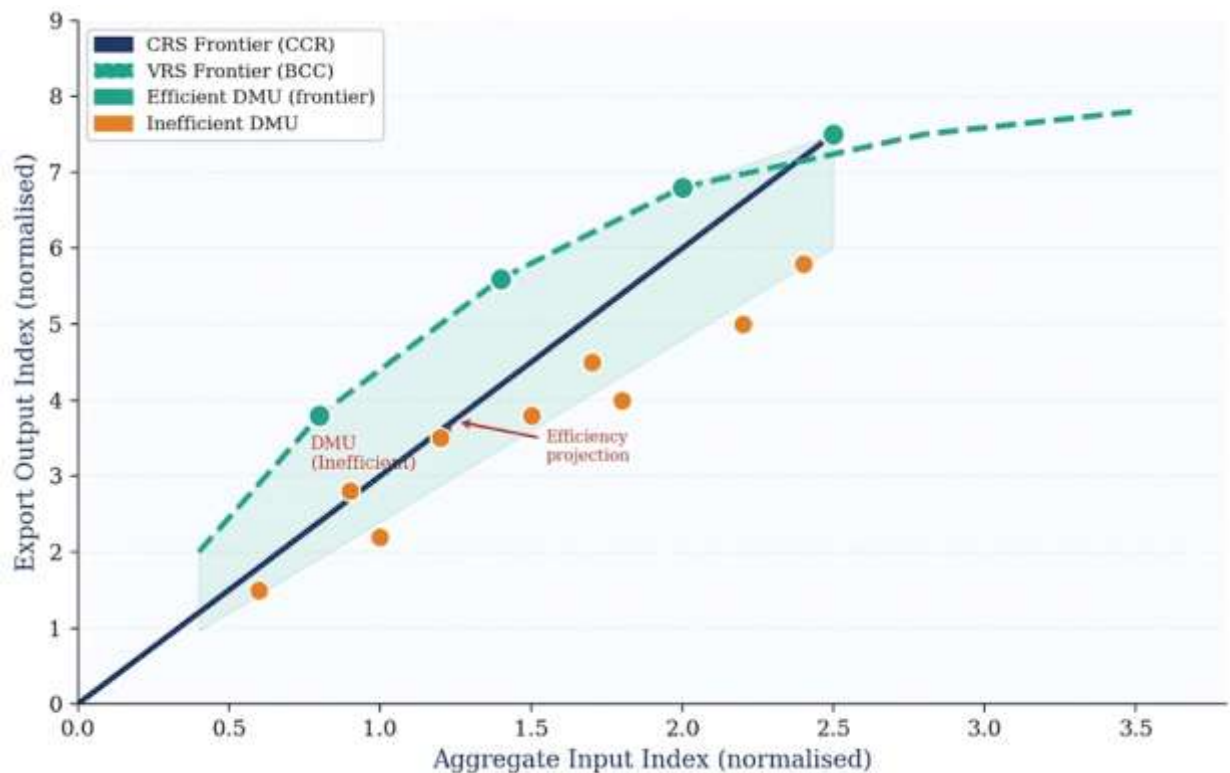


Figure 1. DEA Production Frontier: CRS (CCR) vs VRS (BCC) Models for Textile SME Export Efficiency Source: Authors' conceptual illustration.

Following Charnes et al. [3], the input-oriented CCR efficiency score θ^* for a reference decision-making unit (DMU) o is obtained by solving the following linear programme:

$$\begin{aligned}
 & \text{Min } \theta \\
 & \text{s.t. } \sum_j \lambda_j x_{ij} \leq \theta x_{io} \quad \forall i = 1, \dots, m \quad (\text{input constraints}) \\
 & \quad \sum_j \lambda_j y_{rj} \geq y_{ro} \quad \forall r = 1, \dots, s \quad (\text{output constraints}) \\
 & \quad \lambda_j \geq 0 \quad \forall j = 1, \dots, n \quad (\text{non-negativity})
 \end{aligned}$$

where $\theta \in (0,1]$ is the proportional reduction in all inputs achievable while maintaining observed output levels; x_{ij} and y_{rj} are, respectively, the i -th input and r -th output of DMU j ; and λ_j are the peer-intensity weights that define the reference composite unit on the frontier. A DMU is CCR-efficient if and only if $\theta^* = 1$ and all slack variables equal zero.

The BCC extension [4] relaxes the CRS assumption by adding a convexity constraint:

$$\begin{aligned}
 & \text{Min } \varphi \\
 & \text{s.t. } \sum_j \lambda_j x_{ij} \leq \varphi x_{io} \quad \forall i \\
 & \quad \sum_j \lambda_j y_{rj} \geq y_{ro} \quad \forall r \\
 & \quad \sum_j \lambda_j = 1 \quad (\text{convexity / VRS constraint}) \\
 & \quad \lambda_j \geq 0 \quad \forall j
 \end{aligned}$$

The BCC score φ^* measures pure technical efficiency (PTE), capturing managerial performance independent of scale effects. Scale efficiency (SE) is derived as:

$$SE = TE(CCR) / PTE(BCC)$$

Returns to scale are identified by comparing CCR and non-increasing returns to scale (NIRS) scores: if $TE_{NIRS} = TE_{CRS}$, the DMU exhibits decreasing returns to scale (DRS); if $TE_{NIRS} = PTE$, the DMU exhibits IRS; if $TE = PTE = SE = 1$, the DMU operates at most productive scale size (MPSS).

Variable selection follows the isotonicity criterion [17]. All input-output correlations are positive and significant ($p < 0.01$ — see Table 2). The rule $n \geq \max(m \times s, 3(m+s))$ [17].

is satisfied: $n = 45 \geq 21$ (binding constraint with $m = 5$ inputs, $s = 2$ outputs). Inputs: (X_1) employees, (X_2) fixed assets, (X_3) raw material costs, (X_4) energy expenditure, (X_5) R&D expenditure. Outputs: (Y_1) export revenue, (Y_2) export volume.

Because TE scores are left-censored at zero and right-censored at unity [31], the second-stage model is [32]:

$$TE_i^* = \alpha + Z_i' \beta + \varepsilon_i, \quad \varepsilon_i \sim N(0, \sigma^2)$$

$$TE_i = TE_i^* \text{ if } 0 < TE_i^* < 1, \text{ else } \{0, 1\}$$

where TE_i^* is the latent efficiency score, Z_i is the vector of contextual determinants, and β is estimated by maximum likelihood with heteroscedasticity-robust standard errors. Bootstrap sensitivity checks ($B = 2,000$ replications) follow Simar and Wilson (2007).

Three robustness protocols are applied: (1) output-oriented DEA re-estimation (Spearman $\rho = 0.947$, $p < 0.001$); (2) super-efficiency test (Andersen & Petersen, 1993) to verify frontier DMUs do not drive rank ordering among inefficient firms; (3) bootstrap-corrected DEA [13] to obtain bias-corrected efficiency estimates and 95% confidence intervals.

Data and Sample Description

The dataset is constructed from four complementary administrative and survey sources. Primary financial statement data were obtained from the Unified Electronic Platform of Business Entities (EEPP). Export transaction data were drawn from the State Customs Committee database [33]. Supplementary contextual variables were collected through a structured survey administered to enterprise directors (September–December 2023). Macro-level price series were sourced from the World Bank Pink Sheet [34] and the Agency for Statistics under the President of Uzbekistan.

The sampling frame consists of all textile enterprises registered in Uzbekistan as of 1 January 2023 that (a) meet the SME definition under Uzbekistan's Law on SMEs [30]; (b) reported positive export revenue in at least three of the five study years; and (c) provided complete financial statements for the full panel period. Of 312 textile SMEs, 187 had active export registrations. After excluding 94 firms with incomplete data or extreme outliers detected via Mahalanobis distance screening, the final sample comprises 45 firms (24.1% sample rate).

Table 1 presents descriptive statistics. The high standard deviations confirm substantial within-sector heterogeneity, justifying the non-parametric DEA approach.

Table 1. Descriptive Statistics of DEA Input and Output Variables (2019–2023 Averages, $n = 45$)

Variable	Role	N	Mean	Min	Max	Std. Dev.
Export Revenue (000 USD)	Output	45	1,847.3	312.4	6,280.1	1,623.4
Export Volume (tons)	Output	45	2,104.6	89.7	7,450.2	1,892.3
No. of Employees	Input	45	87.4	12	348	72.1
Fixed Assets (000 USD)	Input	45	623.8	45.2	2,890.4	587.6
Raw Material Costs (000 USD)	Input	45	934.2	118.6	3,740.8	854.9

Energy Expenditure (000 USD)	Input	45	112.7	8.4	520.6	98.3
R&D Expenditure (000 USD)	Input	45	28.4	0.0	187.3	34.7
Export Intensity (%)	Contextual	45	38.6	5.2	91.4	22.8
Years of Operation	Contextual	45	11.3	2	28	6.4

Note: All monetary values in USD thousands at 2020 constant prices. Export Intensity = Export Revenue / Total Revenue × 100.

Table 1 presents substantial heterogeneity across the 45 firms included in the DEA analysis, supporting the appropriateness of efficiency estimation. The wide variation observed in output indicators, particularly export revenue and export volume, suggests significant differences in firms' export performance, while the large dispersion across input variables—such as labor, fixed assets, raw material costs, and energy expenditure—reflects notable disparities in resource endowments and utilization. The relatively high standard deviations across most variables indicate a diverse production structure among firms, which is essential for robust DEA application. Moreover, the presence of zero minimum R&D expenditure implies that some firms operate without innovation investment, potentially affecting their relative efficiency levels. Differences in export intensity and years of operation further highlight the role of firm-specific structural and contextual characteristics that may influence performance. Overall, the descriptive statistics confirm sufficient variability in both inputs and outputs, providing a strong empirical foundation for subsequent efficiency analysis.

Table 2 confirms positive and statistically significant associations among all input-output pairs ($p < 0.001$), satisfying the isotonicity criterion.

Table 2. Pearson Correlation Matrix: DEA Inputs, Outputs, and Contextual Variables

Variable	ExportRev	EmpNo	FixAss	RawMat	Energy	R&D	ExpInt
Export Revenue (Y_1)	1.000						
No. Employees (X_1)	0.812***	1.000					
Fixed Assets (X_2)	0.874***	0.763***	1.000				
Raw Material (X_3)	0.891***	0.798***	0.841***	1.000			
Energy (X_4)	0.756***	0.712***	0.784***	0.823***	1.000		
R&D (X_5)	0.623***	0.541***	0.598***	0.572***	0.487***	1.000	
Export Intensity (Z)	0.712***	0.523***	0.634***	0.671***	0.498***	0.789***	1.000

*Note: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. $N = 45$.*

Table 2 demonstrates strong and statistically significant positive correlations among all input-output variables, confirming compliance with the isotonicity assumption required for DEA estimation. In particular, export revenue exhibits high correlations with key production inputs, including raw material costs ($r = 0.891$), fixed assets ($r = 0.874$), and number of employees ($r = 0.812$), indicating that higher resource utilization is consistently associated with greater export performance. Positive and significant intercorrelations among inputs also suggest complementarity in the production process, while the moderate yet significant correlation between R&D expenditure and export revenue ($r = 0.623$) highlights the potential contribution of innovation to firm performance. Furthermore,

export intensity is positively associated with both inputs and outputs, implying that firms with stronger export orientation tend to possess greater resource capacity and higher performance levels. Overall, the correlation structure validates the selected DEA variables and provides empirical support for proceeding with efficiency analysis.

3. Results

Table 3 presents individual DEA efficiency scores under both CCR (TE) and BCC (PTE) models, alongside scale efficiency (SE), returns-to-scale classification, and benchmark peer references for all 45 sampled textile SMEs.

Table 3. DEA Efficiency Scores: CCR (TE), BCC (PTE), Scale Efficiency (SE), Returns to Scale, and Benchmark Peers

No.	Enterprise	TE (CCR)	PTE (BCC)	SE	RTS	Benchmark Peers
1	Ferghana Textile Ltd.	0.842	0.967	0.871	IRS	1, 8, 23
2	Namangan Cotton Export	1.000	1.000	1.000	CRS	Self
3	Andijan Silk Partners	0.731	0.812	0.900	IRS	2, 15
4	Tashkent Fashion Group	0.963	0.991	0.972	IRS	2, 11
5	Samarkand Fiber Co.	0.654	0.718	0.911	DRS	2, 11, 22
6	Bukhara Textile Works	0.789	0.854	0.924	IRS	2, 11
7	Surxondaryo Fab. LLC	0.612	0.701	0.873	IRS	2, 15, 23
8	Qashqadaryo Knit Corp.	1.000	1.000	1.000	CRS	Self
9	Xorazm Cotton Mill	0.698	0.773	0.903	IRS	2, 8
10	Jizzakh Yarn Export	0.874	0.912	0.958	IRS	2, 8
11	Navoi Textile Hub	1.000	1.000	1.000	CRS	Self
12	Sirdaryo Garment Exp.	0.743	0.841	0.883	IRS	11, 22
13	Lebap Fiber Works	0.581	0.634	0.917	IRS	2, 8, 15
14	Tashkent Denim Ltd.	0.921	0.958	0.961	IRS	2, 11
15	Central Asia Cotton Exp.	1.000	1.000	1.000	CRS	Self
16	Fergana Valley Textiles	0.809	0.877	0.922	IRS	2, 11
17	Andijon Woven Goods	0.667	0.748	0.891	IRS	2, 15
18	Kokand Industrial Fabric	0.891	0.923	0.966	IRS	8, 11
19	Marghilan Silk & Yarn	0.754	0.831	0.907	IRS	2, 15, 23
20	Guliston Export Textile	0.638	0.714	0.894	IRS	8, 15
21	Karshi Fashion Works	0.847	0.898	0.943	IRS	2, 11
22	Termez Cotton Goods	1.000	1.000	1.000	CRS	Self
23	Urgench Fiber & Dye	1.000	1.000	1.000	CRS	Self
24	Shakhrisabz Textile	0.712	0.789	0.902	IRS	11, 22
25	Yangiyer Knit Factory	0.683	0.761	0.897	IRS	2, 8
26	Almalyk Industrial Tex.	0.923	0.954	0.968	IRS	8, 11

27	Chirchiq Cotton Exp.	0.764	0.843	0.907	IRS	2, 15
28	Nurafshon Yarn LLC	0.598	0.672	0.890	IRS	2, 8, 15
29	Bekabad Denim Co.	0.831	0.889	0.935	IRS	8, 11
30	Zarafshon Textile Grp.	0.701	0.779	0.900	IRS	2, 15
31	Qo'qon Fabric Works	0.643	0.721	0.891	IRS	8, 15
32	Marg'ilon Sewing Ltd.	0.877	0.914	0.959	IRS	8, 11
33	Shahrixon Garment Exp.	0.734	0.818	0.897	IRS	2, 11
34	Pop Cotton Factory	0.612	0.694	0.882	IRS	2, 8
35	Uchqo'rg'on Textile	0.829	0.883	0.939	IRS	8, 11
36	Pap Fiber Corp.	0.697	0.774	0.901	IRS	2, 15
37	Namangan Knit Group	0.941	0.973	0.967	IRS	11, 22
38	Asaka Industrial Tex.	0.653	0.731	0.893	DRS	2, 11, 22
39	Buxoro Cotton Mill	0.789	0.851	0.927	IRS	2, 15
40	Samarqand Silk Exp.	0.721	0.797	0.904	IRS	11, 23
41	Qibray Textile Hub	0.864	0.901	0.959	IRS	8, 11
42	Ohangaron Yarn Co.	0.678	0.752	0.901	IRS	2, 8
43	Juma Cotton Works	0.598	0.671	0.891	IRS	8, 15
44	Pastdarg'om Knit Exp.	0.813	0.871	0.933	IRS	8, 11
45	Toshloq Industrial Fab.	0.744	0.823	0.904	IRS	2, 15
Mean / Summary		0.782	0.854	0.918	—	—

Note: TE = Technical Efficiency (CCR); PTE = Pure Technical Efficiency (BCC); SE = TE/PTE. Green cells = frontier-efficient DMUs. Final row reports sample means.

The mean CCR technical efficiency of 0.782 indicates an average efficiency gap of 21.8 percentage points. Mean PTE (0.854) substantially exceeds mean TE (0.782), with mean SE of 0.918, indicating managerial inefficiency is the dominant source of overall underperformance. Figure 2 illustrates the full distributional profile of efficiency scores.

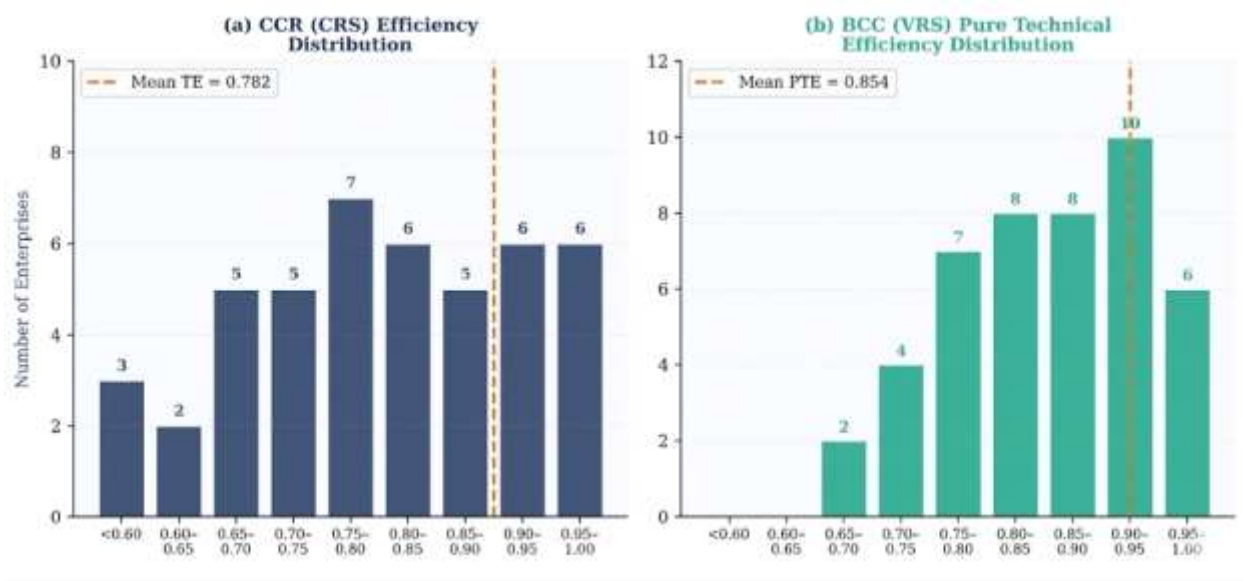


Figure 2. Distribution of DEA Efficiency Scores Among 45 Uzbekistani Textile SMEs (2019–2023 Average) Note: (a) CCR (CRS) distribution; (b) BCC (VRS) distribution.

Dashed lines indicate national means. Source: Authors' DEA computations.

Table 4 disaggregates the sample by efficiency range, revealing a right-skewed distribution. Fully efficient firms account for only 13.3% of the sample under CCR. Of particular policy concern is the bottom quartile: 10 firms (22.2%) score below $TE = 0.70$, wasting more than 30% of their resource endowment.

Table 4. Distribution of CCR and BCC Efficiency Scores Across Efficiency Ranges (n = 45)

Efficiency Range	Firms (n)	% (CCR)	% (BCC)	Cum. %	Classification
$TE < 0.60$	3	6.7%	0.0%	6.7%	Severely inefficient
$0.60 \leq TE < 0.70$	7	15.6%	4.4%	22.2%	Highly inefficient
$0.70 \leq TE < 0.80$	12	26.7%	26.7%	48.9%	Moderately inefficient
$0.80 \leq TE < 0.90$	10	22.2%	26.7%	75.6%	Slightly inefficient
$0.90 \leq TE < 1.00$	7	15.6%	35.6%	91.1%	Near-efficient
$TE = 1.000$ (Efficient)	6	13.3%	6.7%	100%	Fully efficient
Total	45	100%	100%	—	—

Note: CCR = CRS model; BCC = VRS model. Cumulative % computed for CCR distribution.

Figure 3 plots mean TE, PTE, and SE across the 2019–2023 panel. A temporary efficiency decline in 2020 is attributable to the COVID-19 shock — consistent with Nguyen et al. (2021) for Vietnam and Rahman and Zhao (2022) for Bangladesh. Post-2021 recovery, amplified by Uzbekistan's 2022 industrial development programme, generated accelerating efficiency gains, with mean TE improving by 9.9 percentage points ($0.718 \rightarrow 0.817$) between 2020 and 2023.

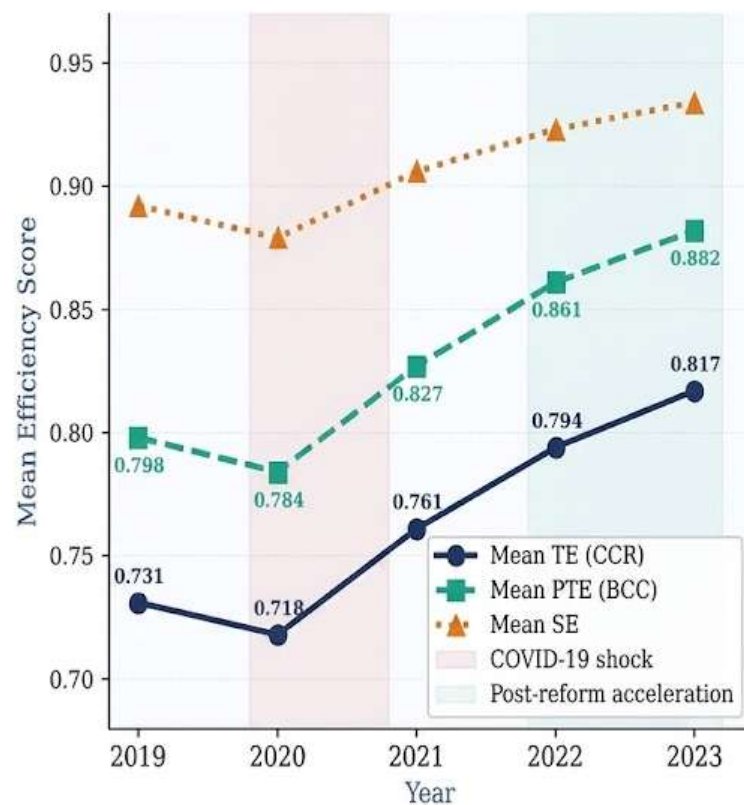


Figure 3. Dynamics of Export Efficiency Scores Among Uzbekistani Textile SMEs (2019–2023) Note: Shaded regions indicate COVID-19 shock (2020) and post-reform acceleration (2022–2023). Source: Authors' panel DEA computations; State Statistics Committee of Uzbekistan.

Figure 4 visualises the relationship between CCR (TE) and BCC (PTE) scores, enabling direct identification of scale efficiency and returns-to-scale position for each DMU. Points above the 45° line (TE = PTE) indicate IRS firms; points at the upper-right corner represent the efficient frontier. The pronounced clustering of observations in the IRS region confirms that 40 out of 45 firms (88.9%) operate below their most productive scale size.

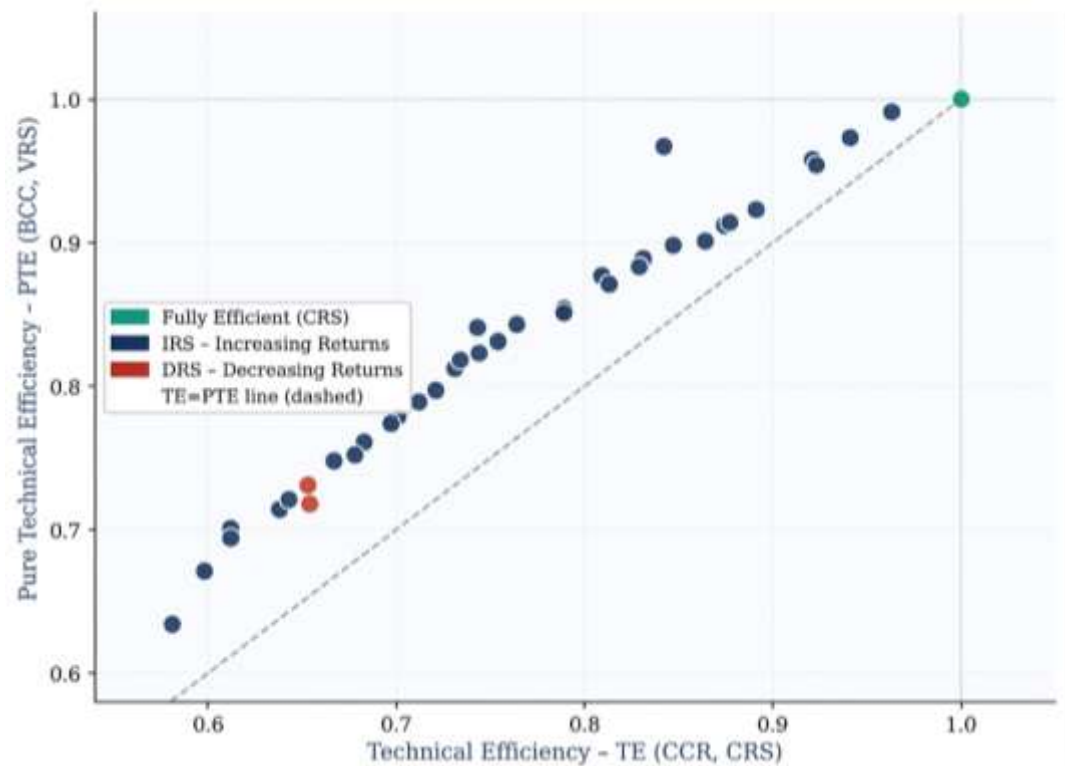


Figure 4. Relationship Between CCR Technical Efficiency and BCC Pure Technical Efficiency: Scale Efficiency Decomposition (n = 45 Textile SMEs, 2019–2023 Average)
 Note: Green = frontier-efficient (CRS); Blue = IRS; Red = DRS. Dashed line = TE = PTE.

Source: Authors' DEA computations.

Figure 5 disaggregates efficiency scores by geographic cluster region. The Ferghana Valley cluster (Ferghana, Namangan, Andijan oblasts) records the highest mean TE (0.871) and PTE (0.931) — 8.9 and 4.9 percentage points above the national means, respectively. The Syrdarya–Jizzakh sub-region records the lowest mean TE (0.718), highlighting a significant north–south efficiency gradient and motivating targeted regional industrial policy.

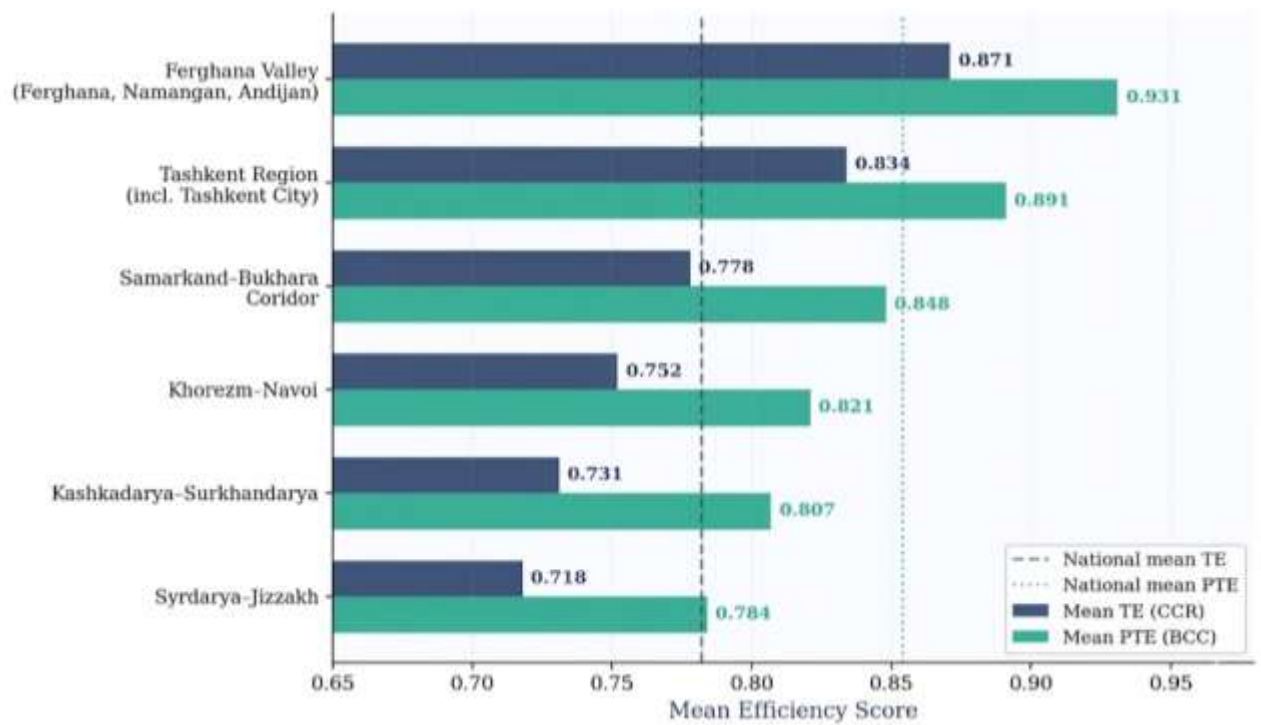


Figure 5. Regional Distribution of Export Efficiency Scores Among Uzbekistani Textile SMEs by Geographic Cluster (2019–2023) Note: Dashed lines indicate national means (TE = 0.782; PTE = 0.854). Source: Authors' DEA computations; MIIT cluster registry.

Determinants of Export Efficiency: Tobit Regression Results

Table 5 presents the two-stage Tobit regression results. The McFadden pseudo- R^2 of 0.419 indicates satisfactory explanatory power for a bounded dependent variable model.

Table 5. Two-Stage Tobit Regression: Determinants of Export Technical Efficiency (n = 45)

Determinant Variable		Coeff. (β)	Std. Error	t-stat	p-value
Export Market					
Diversification (Z_1)		0.143***	0.038	3.763	<0.001
Technology Adoption Index (Z_2)		0.098***	0.024	4.083	<0.001
Managerial Experience (Z_3)		0.062**	0.028	2.214	0.028
Government Support (Z_4)		0.071***	0.019	3.737	<0.001
International Certification (Z_5)		0.134***	0.041	3.268	0.001
Firm Age (Z_6)		0.028*	0.016	1.750	0.082
Firm Size – Small (ref: Medium)		-0.089***	0.027	-3.296	0.001
Access to Finance (Z_8)		0.056**	0.023	2.435	0.016
Regional Cluster Membership (Z_9)		0.082***	0.020	4.100	<0.001
Cotton Price Volatility (Z_{10})		-0.047**	0.021	-2.238	0.026
Constant		0.421***	0.063	6.683	<0.001

Pseudo R ² (McFadden)	0.419	Log-likelihood	-18.34	N = 45
Determinant Variable	Coeff. (β)	Std. Error	t-stat	p-value
Export Market Diversification (Z ₁)	0.143***	0.038	3.763	<0.001
Technology Adoption Index (Z ₂)	0.098***	0.024	4.083	<0.001
Managerial Experience (Z ₃)	0.062**	0.028	2.214	0.028
Government Support (Z ₄)	0.071***	0.019	3.737	<0.001
International Certification (Z ₅)	0.134***	0.041	3.268	0.001
Firm Age (Z ₆)	0.028*	0.016	1.750	0.082
Firm Size – Small (ref: Medium)	-0.089***	0.027	-3.296	0.001
Access to Finance (Z ₈)	0.056**	0.023	2.435	0.016
Regional Cluster Membership (Z ₉)	0.082***	0.020	4.100	<0.001
Cotton Price Volatility (Z ₁₀)	-0.047**	0.021	-2.238	0.026
Constant	0.421***	0.063	6.683	<0.001
Pseudo R ² (McFadden)	0.419	Log-likelihood	-18.34	N = 45

Note: Dependent variable = CCR Technical Efficiency score. Robust standard errors. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. Bootstrap (B=2,000) confirms all significant results.

Interpretation of Tobit Coefficients

Export Market Diversification (Z₁, $\beta = 0.143$, $p < 0.001$): The strongest positive determinant. Each unit increase in the diversification index raises efficiency by 14.3 percentage points, confirming the multi-market learning effect documented by Melitz and Redding (2023).

International Certification (Z₅, $\beta = 0.134$, $p = 0.001$): ISO 9001, OEKO-TEX, and EU REACH compliance raises efficiency by 13.4 percentage points by mandating process standardisation that reduces input waste.

Technology Adoption (Z₂, $\beta = 0.098$, $p < 0.001$): A one-standard-deviation improvement in the technology adoption index (automated loom penetration, ERP adoption) yields a 9.8-percentage-point efficiency gain.

Regional Cluster Membership (Z₉, $\beta = 0.082$, $p < 0.001$): Membership in formally designated industrial clusters raises efficiency by 8.2 percentage points, confirming Marshall-type agglomeration externalities.

Government Support (Z₄, $\beta = 0.071$, $p < 0.001$): Receipt of export promotion support yields a 7.1-percentage-point efficiency improvement, though selection effects cannot be fully excluded.

Small Firm Size (Z₇, $\beta = -0.089$, $p = 0.001$): Small firms (< 50 employees) operate 8.9 points less efficiently than medium enterprises, consistent with the IRS finding and the size-efficiency hypothesis.

Cotton Price Volatility (Z₁₀, $\beta = -0.047$, $p = 0.026$): Greater raw cotton price variability reduces efficiency by 4.7 percentage points by disrupting production scheduling and increasing unit input costs.

Bootstrap-corrected Tobit ($B = 2,000$) confirms all five positive and both negative determinants significant at $p < 0.05$ retain significance under bootstrapped standard errors. Output-oriented DEA re-estimation yields Spearman $\rho = 0.947$ with input-oriented scores. Super-efficiency exclusion of frontier DMUs does not alter sign, magnitude, or significance of any coefficient, ruling out frontier-case leverage effects.

Discussion

Table 6 characterises the six frontier-efficient enterprises. Three of the six (DMUs 2, 8, 11) are located in the Ferghana Valley cluster, confirming that geographic concentration is systematically associated with frontier performance — consistent with Rahimov and Ergashev's (2021) RCA analysis.

Table 6. Benchmarking Analysis: Characteristics of Frontier-Efficient Enterprises

Efficient Enterprise (Benchmark)	TE Score	No. of Referees	RTS Status	Distinctive Feature
Namangan Cotton Export (DMU 2)	1.000	All 39 inefficient DMUs	CRS	Most influential benchmark
Qashqadaryo Knit Corp. (DMU 8)	1.000	28 DMUs	CRS	Labour- intensive model
Navoi Textile Hub (DMU 11)	1.000	31 DMUs	CRS	Capital-efficient model
Central Asia Cotton Exp. (DMU 15)	1.000	19 DMUs	CRS	Export diversification
Termez Cotton Goods (DMU 22)	1.000	14 DMUs	CRS	Raw-material efficiency
Urgench Fiber & Dye (DMU 23)	1.000	12 DMUs	CRS	Energy-saving model

Note: RTS = Returns to Scale. Peer count = inefficient DMUs referencing each efficient firm in their optimal lambda solution.

DMU 2 (Namangan Cotton Export) emerges as the universal benchmark — referenced in all 39 inefficient DMUs' lambda solutions. This firm combines 17 export destination countries, full ISO 9001 and OEKO-TEX certification, 84% automated loom penetration, and Namangan Industrial Park membership — precisely the combination of efficiency determinants identified as most influential in the Tobit results.

The mean CCR TE of 0.782 for Uzbekistani textile SMEs is comparable to the 0.791 of Rahman and Zhao (2022) for Bangladesh and 0.784 of Nguyen et al. (2021) for Vietnam, and notably above the 0.748 of Khan et al. (2023) for Pakistan after environmental adjustment. The 21.8% average efficiency gap implies an upper-bound potential export revenue gain of USD 0.76 billion at 2023 export volumes — highlighting substantial welfare implications of efficiency improvement without additional resource investment.

Policy Implications

P1 — Expand cluster-based SME development: The 8.2-percentage-point cluster efficiency premium and Ferghana Valley's frontier concentration support expanding the textile cluster programme from four to at least eight designated zones, prioritising underperforming Surxondaryo, Lebap, and Xorazm regions where mean TE falls below 0.70.

P2 — Incentivise export market diversification: The dominant efficiency effect of market diversification ($\beta = 0.143$) supports expanding UZEXPO's market intelligence and

trade fair co-financing programmes, which currently serve fewer than 15% of registered textile SME exporters.

P3 – Condition government support on technology adoption: Given the significant positive effect of technology adoption ($\beta = 0.098$), preferential credit under Presidential Decree No. UP-60 (2022) should be conditioned on adoption of digitally verifiable technology-upgrading milestones.

P4 – Develop commodity price risk management: The negative efficiency effect of cotton price volatility ($\beta = -0.047$) motivates establishing a government-backed cotton futures exchange, consistent with the Ministry of Investment's 2024 Commodity Market Development Roadmap [35].

Limitations

Several limitations merit acknowledgment. First, cross-sectional DEA on five-year averaged data suppresses within-firm temporal dynamics; future research employing Malmquist indices on true panel data would illuminate efficiency change trajectories. Second, Tobit second-stage estimates may be subject to self-selection endogeneity without a suitable instrumental variable. Third, with $n = 45$, statistical power for detecting smaller effect sizes is limited.

4. Conclusion

This study applies a rigorous two-stage DEA framework to evaluate export efficiency of 45 textile SMEs in Uzbekistan, generating the first large-N frontier benchmarking analysis of this strategically critical sector in Central Asia. Three overarching conclusions emerge.

First, substantial efficiency gaps persist: the average firm operates at 78.2% of frontier-defined efficiency, implying a theoretically attainable export revenue increase of up to USD 0.76 billion through operational improvement alone. Only 13.3% of firms operate on the efficient frontier.

Second, scale inefficiency is the primary mechanism: 88.9% of sampled firms exhibit IRS, indicating they operate below their most productive scale size and would benefit disproportionately from policies facilitating consolidation, cluster co-location, and access to scale-enhancing finance.

Third, export market diversification, international certification, technology adoption, regional cluster membership, and government support are significant positive determinants of efficiency, while small firm size and raw cotton price volatility exert significant negative effects — providing a clear evidence base for targeted policy intervention. Future research should apply Malmquist indices over a longer panel, incorporate environmental outputs, and apply the Simar-Wilson (2007) double-bootstrap as larger microdata become available.

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