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Modeling Potential Productivity Gains from SME Growth: A Monte Carlo Simulation for Turkish Manufacturing Firms

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ABSTRACT

Purpose: The paper estimates the labor-productivity gains that Turkish manufacturing small- and medium-sized enterprises (SMEs) can expect when they scale up from micro to small and from small to medium size classes.

Methodology: Using value-added-per-employee data from TurkStat, we run Monte Carlo simulations that keep the technological tier constant while varying firm size. Log-normal and gamma shock processes are combined with three coefficients of variation (0.5, 1.0, 2.0) to represent alternative degrees of within-class heterogeneity.

Findings: High-technology SMEs realize the highest average gains—around TL 260–370 thousand—especially in the small-to-medium transition. Low-technology firms show modest mean improvements and a rising probability of negative outcomes as heterogeneity increases. Log-normal shocks generate fatter upper tails and more extreme winners, whereas gamma shocks deliver narrower central ranges but still sizable outliers at high dispersion.

Originality: This is among the first studies to quantify potential productivity pay-offs from SME scaling in Turkey within a fully stochastic framework. By modeling technology-conditioned heterogeneity with aggregate data, it offers fresh evidence for designing conditional subsidies and other targeted industrial-policy tools.

Keywords: SMEs, Labor Productivity, Economies of Scale, Monte Carlo Simulation, Technology Intensity, Manufacturing Industry.

JEL Codes: C63, L25, L60, O14, O33.

KOBİ Büyümesinden Kaynaklanan Potansiyel Verimlilik Kazançlarının Modellenmesi: Türk İmalat Sanayii İçin Bir Monte Carlo Simülasyonu

ÖZET

Amaç: Bu çalışma, Türkiye imalat sanayiinde faaliyet gösteren küçük ve orta büyüklükteki işletmelerin (KOBİ), mikro ölçekten küçük ölçeğe ve küçük ölçekten orta ölçeğe geçiş yapmaları halinde elde edebilecekleri işgücü verimliliği kazanımlarını tahmin etmeyi amaçlamaktadır.

Yöntem: TÜİK'in çalışan başına katma değer verileri kullanılarak, teknolojik düzey sabit tutulurken firma ölçeğinin değiştiği Monte Carlo simülasyonları gerçekleştirilmiştir. Sınıf içi heterojenliği temsil etmek üzere log-normal ve gamma şok süreçleri; 0,5, 1,0 ve 2,0 olmak üzere üç farklı değişim katsayısıyla birleştirilmiştir.

Bulgular: Yüksek teknoloji düzeyindeki KOBİ'ler, özellikle küçükten orta ölçeğe geçişte, ortalama 260–370 bin TL arasında değişen en yüksek verimlilik artışlarını sağlamaktadır. Düşük teknoloji firmaları ise daha sınırlı ortalama artışlar göstermekte; heterojenlik düzeyi arttıkça olumsuz sonuçlarla karşılaşma olasılığı da yükselmektedir. Log-normal şoklar daha kalın üst kuyruklara ve aşırı yüksek performans gösteren firmalara yol açarken, gamma şokları daha dar merkezi dağılımlar üretmekte; ancak yüksek saçılma düzeylerinde yine de dikkate değer aykırı değerlere rastlanmaktadır.

Özgünlük: Bu çalışma, Türkiye'de KOBİ'lerin ölçek büyütmesinden doğabilecek potansiyel verimlilik kazanımlarını tamamen stokastik bir çerçevede niceliksel olarak ortaya koyan ilk çalışmalardan biridir. Teknolojiye bağlı heterojenliği toplulaştırılmış veriyle modelleyerek, koşullu teşvikler ve hedefe yönelik sanayi politikaları için yeni ve özgün bir kanıta dayalı yaklaşım sunmaktadır.

Anahtar Kelimeler: KOBİ'ler, İşgücü Verimliliği, Ölçek Ekonomileri, Monte Carlo Simülasyonu, Teknoloji Yoğunluğu, İmalat Sanayi.

JEL Kodları: C63, L25, L60, O14, O33.

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1. INTRODUCTION

Over the past several decades, the relationship between firm size and productivity has attracted sustained scrutiny from scholars and policymakers alike. At its core, the debate asks how businesses balance the cost savings afforded by economies of scale against the rising coordination costs that accompany organizational expansion. The theoretical foundations trace back to Coase's (1937) seminal insight that firms internalize transactions only until the marginal cost of managing them equals the cost of using the market. Subsequent research has refined this logic by demonstrating that elements of the external environment, such as competitive intensity, agglomeration forces, and institutional quality, critically shape the scope for firms to grow or contract (OECD, 2019: 147-150).

Yet the size-productivity nexus is neither static nor uniformly positive. Empirical studies frequently identify contexts in which smaller enterprises outperform larger rivals, especially in industries that reward flexibility, rapid decision-making, and niche specialization (Covin and Slevin, 1989; Hodgson et al., 2017). Episodic demand surges, such as those triggered by a public-health emergency, can also yield abrupt, if sometimes transitory, expansions that lift the productivity of otherwise modestly sized producers (OECD, 2021: 81). Consequently, researchers generally reject the notion of a single "optimal" scale; instead, firm size emerges from the interactions among technology, market structure, institutions, and managerial strategy (Hallberg, 2000: 4).

Small and medium-sized enterprises (SMEs) occupy a pivotal position in this discourse. They possess outsized potential for rapid growth (O'Regan et al., 2006; Cravo et al., 2012; Mason and Brown, 2013; Gherghina et al., 2020) and innovation (Klewitz and Hansen, 2014; Saunila, 2020), yet they often struggle to match the efficiency of larger corporations (Taymaz, 2005; Díaz and Sánchez, 2007; Yang and Chen, 2009; Arbelo et al., 2022). Constraining factors include scarce internal resources (Lee et al., 1999), limited access to external finance (Beck and Demirguc-Kunt, 2006), skills deficits (Lehner and Sundby, 2018), technological hurdles (Elhusseiny and Crispim, 2022), and intense pressure from scale-advantaged incumbents (Özbuğday, 2024). SMEs are also more exposed to sunk-cost losses and institutional rigidities, such as onerous regulation and inadequate infrastructure, that exacerbate scaling costs (Kumar et al., 1999; OECD, 2019: 151). Nevertheless, evidence shows that once SMEs attain the scale needed to absorb fixed costs and embed advanced technologies, their productivity can converge with, or even exceed, that of larger competitors (Lundvall and Battese, 2000; Medrano-Adan et al., 2018).

Although a universally "optimal" size remains elusive, many governments center their industrial strategies on raising SME productivity through growth-oriented policies (Smallbone et al., 1998; Surya et al., 2021). The priority is acute in Turkey, where SMEs exhibit persistently lower productivity than large enterprises (Akcigit et al., 2020). Successive five-year development plans therefore stress SME upgrading. The Seventh Plan (State Planning Organization, 1995) framed competitiveness around high value-added production, advanced technology, and skilled labor, but acknowledged financing, marketing, and productivity bottlenecks. The Eighth Plan (State Planning Organization, 2001) extended tax concessions and investment deductions while urging greater credit access and R&D participation. The Ninth Plan (State Planning Organization, 2006) introduced venture-capital and credit-guarantee schemes and championed digital transformation. The Tenth Plan (State Planning Organization, 2014) promoted SME–large-firm collaboration and integration into global value chains. The Eleventh Plan (Presidency of Strategy and Budget, 2020) reinforced financial literacy, digitalization, and clustering initiatives, whereas the Twelfth Plan (Presidency of Strategy and Budget, 2023) placed green and digital transitions at center stage. Despite these efforts, SMEs still account for only a modest share of national value-added.

Against this backdrop, we ask: *How much would Turkish manufacturing SMEs gain in productivity if they grew?* Addressing this question illuminates the scale–productivity trade-off and informs the design of support mechanisms. Conceptual precision is essential: whereas *growth* denotes any increase in size, *scaling* implies a more-than-proportional rise in performance relative to inputs (Palmié et al., 2023; Coviello et al., 2024). A firm may grow without scaling, but cannot scale without growing. Clarifying this distinction prevents conflation of mere expansion with efficiency-enhancing scale-ups.

To quantify potential gains, we conduct Monte Carlo simulations in which firms migrate from the micro to the small and from the small to the medium class while holding their technology tier constant. The underlying productivity metric—value-added per employee—derives from the Turkish Statistical Institute's SME Statistics. Because productivity is non-negative and right-skewed, we model shocks with both log-normal and gamma distributions and vary the coefficient of variation (CV) to represent differing degrees of heterogeneity.

The simulations reveal three key patterns. First, high-technology SMEs reap the largest and most robust gains, particularly in the Small → Medium transition, whereas low-technology firms exhibit modest averages and pronounced downside risk as heterogeneity intensifies. Second, increasing CV widens the distribution of outcomes, lowers medians, and pushes the left tail into negative territory even for technologically advanced firms; the effect is more acute under log-normal shocks, which possess fatter upper tails. Third, although mean gains remain positive for most scenarios, extreme values become sizable at CV = 2, which indicates that indiscriminate support could finance unproductive expansions.

In sum, the study contributes to the literature by demonstrating how heterogeneity in technology adoption conditions the expected returns to scale. Practically, it underlines the need for evidence-based, segment-specific industrial policies if Turkey is to close its SME productivity gap and enhance its global competitiveness.

The remainder of the paper is organized as follows. Section 2 describes the data sources and outlines the Monte-Carlo methodology. Section 3 presents the simulation results. Section 4 interprets these findings in light of the Turkish manufacturing context and derives policy implications. Section 5 concludes by summarizing the principal insights, acknowledging limitations, and suggesting avenues for future research.

2. DATA and METHODOLOGY

2.1. Data

The dataset used in this study is derived from the SME Statistics published by the Turkish Statistical Institute (TurkStat, 2024). This dataset represents the most comprehensive and recent information on SMEs in Turkey and is compiled using multiple data sources. These sources include the Annual Industry and Service Statistics, foreign trade statistics, research and development (R&D) activities data, entrepreneurship and business demography statistics, and patent application and registration data obtained from the Turkish Patent and Trademark Office. Some of these data sources are administrative sources that include records from various government institutions, while others include survey-based data collected through structured questionnaires and statistical inquiries.

The dataset includes a variety of variables that provide a comprehensive view of SME performance in the Turkish manufacturing sector. These variables include the number of enterprises, turnover, production value, value added at factor costs, total purchases of goods and services, personnel costs, the number of employees, and value-added per employee. The number of enterprises reflects the distribution of firms across size and technology categories, while turnover captures the total sales of goods and services during the reference period. Production value measures the total monetary value of production activities, including sales, stock changes, and resale activities. The value added at factor costs represents the gross income from operating activities, adjusted for subsidies and indirect taxes. Total purchases of goods and services account for inputs consumed in production, excluding capital goods, and personnel costs reflect total expenditures on wages and social security contributions. The number of employees encompasses paid employees, owners, unpaid family members, and apprentices, while value added per employee serves as a key measure of labor productivity, calculated as the ratio of value added at factor costs to the number of employees.

The dataset classifies enterprises based on the definitions provided by the Ministry of Science, Industry, and Technology, using the number of employees and financial thresholds. At the time when the data was compiled, micro enterprises were defined as those with fewer than 10 employees and annual net sales revenue or financial balance sheets not exceeding 10 million Turkish Lira. Small enterprises employ fewer than 50 people and have annual net sales or financial balance sheets not exceeding 100 million Turkish Lira, while medium enterprises employ fewer than 250 people and have annual net sales or financial balance sheets not exceeding 500 million Turkish Lira.

In addition to firm size, the dataset incorporates a classification of technology intensity based on the Eurostat NACE Rev.2 framework, adapted to the ISIC Rev.4 classification system. These classifications include high-technology, medium-high-technology, medium-low-technology, and low-technology industries. For example, high-technology industries include pharmaceuticals, electronics, optical products, and aerospace manufacturing, while medium-high-technology sectors encompass chemicals, electrical equipment, motor vehicles, and medical devices. Medium-low-technology industries include rubber and plastic products, basic metals, and shipbuilding, while low-technology industries consist of traditional sectors such as food and beverages, textiles, furniture, and wood products.

2.2. Descriptive Statistics

Table 1 presents a detailed overview of the Turkish manufacturing industry's key performance indicators, categorized by firm size (micro, small, and medium-sized enterprises) and their respective technology levels (high, medium-high, medium-low, and low technology). These indicators include the number of enterprises, turnover, production value, value-added at factor costs, total purchases of goods and services, changes in stocks of goods and services, personnel costs, the number of employees, and value-added per employee.

Micro-enterprises dominate numerically, with 385,672 firms employing 573,969 people, yet they contribute relatively little in economic terms. Their turnover (TL 631.20 billion) and value-added (TL 110.13 billion) yield labor productivity of only TL 124,813 per employee. Within this group, high-technology micro-enterprises stand out, achieving TL 232,112 in value-added per employee, while low-technology firms, which make up the largest subset, lag at TL 103,067.

Small enterprises, totaling 57,960, show substantially higher economic contributions. Their turnover (TL 1,887.25 billion) and value-added (TL 329.19 billion) produce a labor productivity of TL 348,574 for 931,510 employees. High-technology small firms are the most productive at TL 567,261 per employee, whereas the much larger segment of low-technology firms records a lower figure, TL 274,371.

Although medium-sized enterprises number only 14,238, they generate the greatest economic output, with TL 2,855.11 billion in turnover and TL 627.20 billion in value-added. Employing 1,213,662 people, this category achieves the highest productivity—TL 516,501 per employee. Especially notable are high-technology medium enterprises, which reach TL 927,959 per employee.

Building on the data presented in Table 1 and Table 2 illustrates the relative contributions of different firm sizes and technology levels as a proportion of the sector's total. The ratios emphasize the stark disparities between the numerical dominance of micro-enterprises and their limited economic contributions. Micro-enterprises make up 84.23% of all firms but account for only 10.33% of value-added at factor costs. Their productivity is the lowest overall, especially among low-technology enterprises, which represent nearly half of all micro-enterprises yet provide just 4.96% of value-added. High-technology and medium-high-technology micro-enterprises perform relatively better, though they constitute only a small fraction of the category.

Small enterprises, comprising 12.66% of all firms, contribute a higher 30.87% of value-added at factor costs. Within this group, high-technology small firms, although only 0.14% of all enterprises, reach the highest productivity. Medium-high-technology small firms also perform well, whereas low-technology small firms, which are more numerous, show lower productivity levels. Medium-sized enterprises, though just 3.11% of firms, produce 58.81% of value-added at factor costs, which reflects greater scale and efficiency. High-technology medium firms, at only 0.05% of all enterprises, display particularly high productivity. Medium-high-technology firms likewise excel, while those in low-technology sectors, despite their sizeable share of value-added, trail in productivity.

These descriptive statistics point to the role of technology in shaping productivity and economic contributions in the Turkish manufacturing sector. High-technology firms, though a small fraction of the total (less than 1%), consistently achieve the highest value-added per employee. Conversely, low-technology firms, which dominate numerically, particularly among micro and small enterprises, exhibit significantly lower productivity. As firms scale from micro to small and medium-sized enterprises, their economic contributions and labor productivity improve markedly, which reflects economies of scale and enhanced operational efficiency. Medium-sized enterprises, despite being the smallest group numerically, contribute the most to the sector's overall performance.

Table 1. Basic indicators in the Turkish manufacturing industry by size class and technology level

Size Class	*Technology Level*	*Number of Enterprises*	*Turnover (in billion TL)*	*Production Value (in billion TL)*	*Value Added at Factor Costs (in billion TL)*	*Total Purchases of Goods and Services (in billion TL)*	*Change in Stocks of Goods and Services (in billion TL)*	*Personnel Costs (in billion TL)*	*Number of Employees*	*Value Added at Factor Cost per Employee (in TL)*
Micro	Total	385,672	631.20	573.80	110.13	600.21	76.26	85.07	573,969	124,813
	High	2,620	5.89	5.38	1.23	5.45	0.71	0.83	4,069	232,112
	Medium-high	41,550	101.00	92.25	17.10	95.69	11.30	11.36	70,131	179,033
	Medium-low	122,884	221.21	199.79	38.94	209.33	26.23	25.55	170,642	144,923
	Low	218,618	303.10	276.38	52.86	289.74	38.02	47.33	329,127	103,067
Small	Total	57,960	1,887.25	1,681.27	329.19	1,735.66	173.38	185.83	931,510	348,574
	High	638	21.65	19.16	6.09	18.19	2.52	3.31	10,708	567,261
	Medium-high	10,224	391.35	353.15	76.48	352.92	37.44	38.96	161,565	470,325
	Medium-low	17,928	617.89	547.37	112.94	557.58	51.80	59.08	280,731	397,929
	Low	29,170	856.35	761.58	133.68	806.98	81.62	84.48	478,506	274,371
Medium	Total	14,238	2,855.11	2,639.59	627.20	2,498.91	264.74	306.51	1,213,662	516,501
	High	217	54.08	47.84	18.06	42.82	6.21	7.84	19,456	927,959
	Medium-high	2,714	622.20	589.71	159.91	526.11	61.81	71.42	221,207	722,740
	Medium-low	4,248	946.10	875.80	210.95	812.72	78.81	93.36	342,257	616,095
	Low	7,059	1,232.72	1,126.24	238.29	1,117.27	117.91	133.89	630,742	377,503
SMEs	Total	457,870	5,373.55	4,894.65	1,066.52	4,834.78	514.38	577.41	2,719,141	350,703

Table 2. Basic ratios in the Turkish manufacturing industry by size class and technology level

Size Class	*Technology Level*	*Number of Enterprises*	*Turnover*	*Production Value*	*Value Added at Factor Costs*	*Total Purchases of Goods and Services*	*Change in Stocks of Goods and Services*	*Personnel Costs*	*Number of Employees*
Micro	Total	84.23%	11.75%	11.72%	10.33%	12.41%	14.83%	14.73%	21.11%
	High	0.57%	0.11%	0.11%	0.12%	0.11%	0.14%	0.14%	0.15%
	Medium-high	9.07%	1.88%	1.88%	1.60%	1.98%	2.20%	1.97%	2.58%
	Medium-low	26.84%	4.12%	4.08%	3.65%	4.33%	5.10%	4.43%	6.28%
	Low	47.75%	5.64%	5.65%	4.96%	5.99%	7.39%	8.20%	12.10%
Small	Total	12.66%	35.12%	34.35%	30.87%	35.90%	33.71%	32.18%	34.26%
	High	0.14%	0.40%	0.39%	0.57%	0.38%	0.49%	0.57%	0.39%
	Medium-high	2.23%	7.28%	7.22%	7.17%	7.30%	7.28%	6.75%	5.94%
	Medium-low	3.92%	11.50%	11.18%	10.59%	11.53%	10.07%	10.23%	10.32%
	Low	6.37%	15.94%	15.56%	12.53%	16.69%	15.87%	14.63%	17.60%
Medium	Total	3.11%	53.13%	53.93%	58.81%	51.69%	51.47%	53.08%	44.63%
	High	0.05%	1.01%	0.98%	1.69%	0.89%	1.21%	1.36%	0.72%
	Medium-high	0.59%	11.58%	12.05%	14.99%	10.88%	12.02%	12.37%	8.14%
	Medium-low	0.93%	17.61%	17.89%	19.78%	16.81%	15.32%	16.17%	12.59%
	Low	1.54%	22.94%	23.01%	22.34%	23.11%	22.92%	23.19%	23.20%
SMEs	Total	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%

2.3. Methodology

In this study, we examine the transitions of firms across different size classes—specifically, from micro to small and from small to medium—while holding the technological category constant. This is achieved using a Monte Carlo approach, which estimates the distribution of these changes based on input parameters, including firm-level heterogeneity and assumed statistical distributions. The goal is to provide a probabilistic understanding of the gains or losses associated with firm transitions.

Our primary data are averages of *value-added per employee* for each size and technology group. These aggregated means serve as the basis for modeling the distribution of individual firm productivity values, given that microdata on individual firms is unavailable. Since we only have aggregate information, we must make assumptions about the underlying distribution of productivity values across firms within each size and technology category.

A common starting point for modeling firm-level productivity gains is to use distributions that capture the inherent skew and non-negativity of productivity changes. Both the log-normal and gamma distributions can be appropriate choices, given that many of the underlying drivers of firm growth (e.g., capital investments, learning-by-doing, network effects) tend to generate right-skewed outcomes (see Krüger (2006) for a discussion of the manufacturing productivity distribution). A log-normal distribution is often favored in economic contexts where the observed variable (in this case, productivity gains) arises from multiplicative processes. If each incremental improvement compounds the last, through factors such as technology adoption, managerial skill, or agglomeration economies, then taking logs and assuming normality in that transformed space can provide a realistic fit. Empirically, firm size and productivity levels are frequently found to be log-normally distributed (Cortés et al., 2021; Ishikawa et al., 2022; Musa et al., 2024), which reflects how multiple random factors multiply together to yield overall performance outcomes. By contrast, the gamma distribution is also suitable for modeling continuous, non-negative, skewed variables (e.g., Cabral and Mata, 2003; Okubo and Tomiura, 2014). It is especially intuitive where the “accumulation” of incremental gains may be viewed in an additive framework over time or across different sources of improvements. For example, if a firm grows by adopting several discrete process innovations—each contributing a certain portion of efficiency gains—then the sum of these additive innovations could follow a gamma process.

Under a log-normal model, we assume that the natural logarithm of the firm-level *value-added per employee* X is normally distributed, as expressed in Equation 1:

$$ln(X) \sim N(\mu, \sigma^2) \tag{1}$$

Given the log-normal specification in Equation 1, the expected value of X is given by Equation 2:

$$\mathbb{E}[X] = e^{\mu+\frac{\sigma^2}{2}} \tag{2}$$

Similarly, based on the log-normal assumption in Equation 1, the variance of X can be derived as shown in Equation 3:

$$Var(X) = \left(e^{\sigma^2} - 1\right)e^{2\mu+\sigma^2} \tag{3}$$

Using the expressions for the mean and variance from Equations 2 and 3, the coefficient of variation (CV) is defined as shown in Equation 4:

$$CV = \frac{\sqrt{Var(X)}}{\mathbb{E}[X]} \tag{4}$$

Substituting the expressions for $\mathbb{E}[X]$ and $Var(X)$ from Equations 2 and 3 into the definition of CV in Equation 4, we obtain the following relationship for the log-normal distribution in Equation 5:

$$e^{\sigma^2} = 1 + CV^2 \rightarrow \sigma^2 = log(1 + CV^2) \tag{5}$$

Given the *observed* mean $M = \mathbb{E}[X]$ and using the identity from Equation 2 along with the expression for σ^2 from Equation 5, we can solve for μ as shown in Equation 6:

$$M = e^{\mu+\frac{\sigma^2}{2}} \rightarrow \mu = log(M) - \frac{\sigma^2}{2} \tag{6}$$

Thus, once *we* choose a CV, we can determine μ and σ entirely from M.

Alternatively, instead of the log-normal specification in Equation 1, we may assume that the firm-level variable X follows a gamma distribution with shape α and scale θ, as defined in Equation 7:

$$X \sim \Gamma(\alpha, \theta) \tag{7}$$

Under the gamma distribution specified in Equation 7, the expected value and variance of X are given by Equations 8 and 9, respectively:

$$\mathbb{E}[X] = \alpha\theta \tag{8}$$

$$Var(X) = \alpha\theta^2 \tag{9}$$

Using the expressions for the mean and variance from Equations 8 and 9, the squared coefficient of variation for the gamma distribution is given by Equation 10:

$$CV^2 = \frac{Var(X)}{(\mathbb{E}[X])^2} = \frac{\alpha\sigma^2}{(\alpha\sigma)^2} = \frac{1}{\alpha} \tag{10}$$

Rearranging Equation 10, we directly solve for the shape parameter α, as shown in Equation 11:

$$\alpha = \frac{1}{CV^2} \tag{11}$$

Substituting the expression for α from Equation 11 into the definition of the mean in Equation 8, and using the observed mean $M = \mathbb{E}[X]$, we solve for the scale parameter θ as shown in Equation 12:

$$M = \alpha\theta \rightarrow \theta = M.CV^2 \tag{12}$$

Thus, given M and CV, we find $\alpha = 1/CV^2$ and $\theta = M \cdot CV^2$.

In the absence of microdata, the CV represents an analyst's assumption about firm-level heterogeneity. A low CV (e.g., 0.5) implies that firms are more homogeneous and clustered tightly around the mean production value. A high CV (e.g., 2.0) suggests extreme heterogeneity, with a wide dispersion of firm-level production values. We vary the CV across several scenarios to understand how increasing heterogeneity affects the range of possible outcomes.

Our primary interest lies in estimating the incremental gain in productivity if a firm transitions from one size class to another (e.g., from micro to small). Conceptually, we compare a random draw X_{from} from the "From" size-class distribution (parameterized by μ, σ, or α, θ) to a random draw X_{to} from the "To" size-class distribution. The increment is defined in Equation 13:

$$\Delta = X_{to} - X_{from} \tag{13}$$

Because we do not have pairwise firm-level data, we approximate this process via a Monte Carlo simulation:

1. For each simulation run $i = 1, \ldots, N_{sim}$:
   - Draw $X_{from,i}$ from the distribution defined by M_{from} and the chosen CV.
   - Draw $X_{to,i}$ from the distribution defined by M_{to} and the same CV.
   - Compute the increment $\Delta_i = X_{to,i} - X_{from,i}$.
2. After N_{sim} simulations, we have a large sample $\{\Delta_1, \Delta_2, \ldots, \Delta_{N_{sim}}\}$. This empirical distribution of Δ allows us to estimate the expected incremental gain (mean $\bar{\Delta} = \frac{1}{N_{sim}} \sum_{i=1}^{N_{sim}} \Delta_i$), the median incremental gain, which is the 50th percentile of Δ_i, and various percentiles, such as the 5th, 25th, 75th, and 95th percentiles, to assess the distribution's spread and the range of plausible outcomes.

Thus, the simulation function calculates the incremental productivity (Δ) between two size classes by first deriving the mean productivity per enterprise in each size class. These means are used to parameterize the chosen statistical distribution based on the specified CV. For log-normal distributions, the parameters are the logarithmic mean and standard deviation, adjusted for variability. For gamma distributions, the shape and scale parameters are derived from the mean and CV. Using these parameters, large random samples of *value-added per employee* are generated for each size class, which simulates the possible range of outcomes. The difference between the simulated production values for the "to" and "from" size classes is then calculated for each simulation, which yields a distribution of Δ values.

The simulation is applied iteratively across different CV levels, size transitions, and technology categories. The mean gain reflects the average incremental benefit across many simulations and can be interpreted as the expected outcome if a large number of firms were to move up a size class under these conditions. The median gain represents a "typical" or "central" scenario, which is less sensitive to extreme outliers than the mean. The percentiles (5th, 25th, 75th, 95th) illustrate the probability distribution of possible outcomes. For instance, a positive 5th percentile implies that even the relatively pessimistic cases are still profitable transitions, while a negative 5th percentile suggests that a nontrivial portion of firms might experience no net gain, or even a loss, under the chosen assumptions.

To ensure exact reproducibility, we initialize the random-number generator with a fixed seed before running any simulations, so that every rerun produces the identical sequence of Monte Carlo draws—and hence the same density curves, boxplots, and summary statistics. We then vary the coefficient of variation (CV) across three levels (0.5, 1.0, and 2.0) to represent increasing heterogeneity in value-added per employee: a larger CV produces fatter tails around the $\Delta = 0$ peak, which reflects more dispersed firm-level productivity. Finally, we ran 100,000 replications for every CV level. This simulation length exceeds the thresholds suggested in Monte-Carlo error studies: Koehler et al. (2009) show that achieving a Monte-Carlo standard error ≤ 0.05 for the 97.5th percentile of a bootstrap distribution can require "just under 100,000" draws. Because tail percentiles converge far more slowly than central moments, using the same order of magnitude here ensures that the Monte-Carlo standard errors attached to our reported means, medians, and 5th–95th percentiles of Δ are comfortably below 1 % of the point estimates, which provides the stability and precision demanded by policy evaluation.

3. RESULTS

The results presented in Table 3 and Table 4 offer a detailed analysis of the incremental gains in value-added per employee during transitions between firm sizes (Micro → Small, Small → Medium) across different technology levels and coefficients of variation. These tables model the assumed distribution of gains using both the log-normal and gamma distributions. Table 3 reveals a pronounced technology gradient in incremental value-added when the simulated shocks follow a log-normal distribution. Under low heterogeneity (CV = 0.5), the average gain for high-technology firms reaches TL 266,395 in the Micro → Small transition and TL 360,537 in the Small → Medium step, whereas their low-technology counterparts realize only TL 118,626 and TL 98,988, respectively. Increasing the coefficient of variation to 2.0 barely changes the average gains recorded by high-technology firms. For the Micro → Small transition, the mean stands at TL 266,395 when CV = 0.5, rises marginally to TL 269,956 at CV = 1.0, and then settles at TL 258,946 at CV = 2.0. A similar stability appears for the Small → Medium step, where the corresponding means are TL 360,537, TL 362,237, and TL 368,982. This near-constancy implies that the thicker right tail of the log-normal distribution largely offsets the growing frequency of adverse shocks as heterogeneity increases.

Measures of central tendency, however, are markedly less resilient. For high-technology firms, the median Micro → Small gain contracts from TL 227,353 at CV = 0.5 to TL 164,592 at CV = 1.0 and plunges to TL 86,443 at CV = 2.0; the median for Small → Medium falls in parallel from TL 307,147 to TL 221,749 and finally to TL 118,692. The widening gap between means and medians, therefore, signals a rising likelihood of zero or negative outcomes as dispersion intensifies. Consistent with this interpretation, the interquartile range for Micro → Small broadens from [TL 62,489; TL 429,237] to [–TL 88,079; TL 403,818], while the 5th percentile deteriorates from –TL 174,771 to –TL 779,205 and the 95th percentile extends from TL 835,185 to TL 1,794,614. Low-technology firms display the same qualitative pattern from a markedly lower base. Their median Micro → Small gain declines from TL 104,908 to TL 66,680 and TL 3,522 as CV rises, and the lower-tail risk deepens (5th percentile from –TL 120,708 to –TL 645,258) even though the mean hovers near TL 118,000. These results indicate that while expected gains are largely insensitive to additional heterogeneity, both the modal outcome and the distribution's tails become considerably more volatile, an effect that is especially pronounced among firms operating with low technological intensity.

Figure 1 presents kernel-density estimates of the simulated incremental gain (Δ, expressed in million TL) for each technology–size transition under successive coefficients of variation. When heterogeneity is low (CV = 0.5), the distributions are sharply peaked around zero and decay rapidly, which signals limited dispersion in value-added improvements. As CV rises to 1.0 and, especially, to 2.0, the curves flatten and widen, which indicates that a much larger share of probability mass migrates to the distributional tails. The expansion is asymmetric: the right tail thickens more than the left, most visibly for high- and medium-high-technology firms, thereby generating the positive skew that drives the mean upward even as the median falls (cf. Table 3). The box-and-jitter plots in Figure 2 reinforce this pattern. For every technology tier, the inter-quartile range broadens monotonically with the coefficient of variation, while whiskers lengthen and the incidence of extreme points escalates when CV = 2. The Small → Medium transition among high-technology firms is illustrative: its inter-quartile span at CV = 2 is an order of magnitude larger than at CV = 0.5, and individual simulations exceed TL 150 million on the upside. Although the magnitude of these effects diminishes with technological intensity, even low-technology panels display a pronounced widening of their central and tail regions. Taken together, the two figures visually corroborate the tabulated results: increasing variability amplifies distributional spread, accentuates positive skewness, and elevates the probability of both large gains and sizable losses, with the phenomenon most acute in technologically advanced segments.

In the gamma specification (Table 4), the pattern of average incremental value-added broadly mirrors that obtained under the log-normal assumption: high-technology establishments still post the largest expected gains. At CV = 0.5, for example, the mean Δ for the Micro → Small transition equals TL 265,360, compared with TL 173,756 for medium-low- and TL 118,626 for low-technology producers. At this low level of heterogeneity, the gamma model places slightly more mass near the center of the distribution: the median gain for high-technology Micro → Small is TL 234,410, which exceeds the log-normal counterpart of TL 227,353. The advantage diminishes quickly as dispersion rises. When the CV is lifted from 0.5 to 1.0, the median Micro → Small gain for high-technology firms drops from TL 234,410 to TL 152,228; a further increase to CV = 2.0 pushes the median down to just TL 10,311. Under the log-normal benchmark, the decline, although sharp, is less severe, with medians falling from TL 227,353 to TL 164,592 and then to TL 86,443. Dispersion also enlarges the spread of outcomes. The inter-quartile range broadens from TL 47,551–452,928 at CV = 0.5 to –TL 127,081–416,200 at CV = 2.0. Tail behavior shifts in parallel: the 5th percentile slips from –TL 203,656 to –TL 1,203,648, while the 95th percentile climbs from TL 844,001 to TL 2,489,411. These movements show that higher heterogeneity simultaneously increases the likelihood of very large gains and of substantial losses, with the gamma distribution producing particularly pronounced tail risk.

Low-technology firms exhibit the same qualitative dynamics from a markedly lower base. Their median Micro → Small gain diminishes from TL 104,908 at CV = 0.5 to TL 66,680 at CV = 1.0 and collapses to TL 3,522 at CV = 2.0, while the lower 5th percentile deteriorates to –TL 645,258, even though mean gains remain close to TL 118,000. Collectively, these results show that while the gamma and log-normal specifications yield comparable expectations across technology classes, they differ materially in their distributional implications: the gamma model produces a slightly more conservative center when variability is modest, yet it generates fatter tails as dispersion rises, which accentuates both downside and upside risk under high-heterogeneity regimes.

Figure 3 depicts kernel-density estimates for the gamma simulations. When the coefficient of variation is small (CV = 0.5), the density functions are sharply peaked and narrowly concentrated around Δ ≈ 0 million TL, which indicates limited dispersion in incremental value-added. As heterogeneity increases to CV = 1 and CV = 2, the distributions flatten and widen, with mass shifting into both positive and negative tails; nevertheless, the right tail remains modestly thicker, especially for high- and medium-high-technology firms, which echoes the larger means reported in Table 4. Compared with their log-normal counterparts, the gamma curves are visibly tighter at low CV and broaden more gradually. The box-and-jitter plots in Figure 4 corroborate these patterns. At CV = 0.5, virtually all technology groups exhibit narrow inter-quartile ranges and only a handful of outliers. Raising the CV to 1 enlarges the IQRs and introduces a moderate number of extremes, while CV = 2 produces a pronounced spread and a sizeable cluster of outliers, most conspicuously for the Small → Medium transition among high-technology firms and for both transitions in the medium-high tier. Even so, the vertical range of these outliers is markedly smaller than in the log-normal case. Low-technology panels illustrate the same progression but from a considerably narrower base: at CV = 2, their IQRs remain modest, and extreme positive realizations rarely exceed 10 million TL, again consistent with the milder tail behavior documented in Table 4.

Taken together, the two figures visually reinforce the tabulated evidence. The gamma specification yields tightly clustered outcomes when firm-level heterogeneity is modest, and although variability rises substantially with CV, the resulting distributions remain more compact than under log-normal shocks. Consequently, the gamma model portrays a less extreme but still widening risk–return profile as production heterogeneity intensifies, particularly in technologically advanced segments.

Table 3. The incremental gains in value-added per employee for transitions between firm sizes across different technologies and coefficients of variation (in Turkish Lira, assumed distribution of gains: Log-normal distribution)

Technology	*Transition*	*Coefficient of Variation*	*Mean*	*Median*	*Q5*	*Q25*	*Q75*	*Q95*
High	Micro → Small	0.5	266,395.29	227,352.63	-174,771.31	62,488.52	429,236.95	835,185.41
High	Small → Medium	0.5	360,536.95	307,147.47	-413,715.77	25,074.37	641,752.68	1,312,269.56
Medium-high	Micro → Small	0.5	229,949.80	197,726.70	-134,600.61	60,687.64	363,317.62	704,061.52
Medium-high	Small → Medium	0.5	249,588.65	213,315.02	-374,574.06	-14,367.52	473,647.12	995,650.99
Medium-low	Micro → Small	0.5	174,104.75	148,261.31	-146,804.70	30,810.45	290,363.26	579,802.94
Medium-low	Small → Medium	0.5	213,793.24	181,088.91	-316,516.93	-11,837.72	405,129.35	854,150.78
Low	Micro → Small	0.5	117,398.44	100,415.53	-108,028.89	17,931.19	199,851.17	400,239.39
Low	Small → Medium	0.5	98,624.60	83,671.78	-252,139.48	-41,399.23	223,669.59	498,138.65
High	Micro → Small	1	269,956.49	164,592.32	-475,722.25	-39,926.34	468,051.19	1,344,411.02
High	Small → Medium	1	362,236.71	221,748.53	-960,531.45	-133,694.27	715,021.27	2,135,689.84
Medium-high	Micro → Small	1	231,219.07	144,128.16	-380,102.09	-24,799.14	395,403.42	1,113,206.98
Medium-high	Small → Medium	1	254,318.12	152,758.51	-827,204.31	-135,978.94	541,310.72	1,662,164.65
Medium-low	Micro → Small	1	174,314.30	105,147.66	-370,778.70	-42,416.31	321,042.76	934,071.96
Medium-low	Small → Medium	1	212,559.34	131,509.47	-710,460.78	-115,344.68	458,944.25	1,375,810.89
Low	Micro → Small	1	119,651.29	74,117.82	-261,460.70	-30,982.56	223,040.29	644,582.16
Low	Small → Medium	1	95,101.53	56,777.95	-526,542.80	-107,476.99	256,818.52	834,024.09
High	Micro → Small	2	258,945.66	86,443.01	-779,204.53	-88,078.53	403,818.17	1,794,613.64
High	Small → Medium	2	368,981.74	118,691.74	-1,515,295.61	-192,800.14	640,123.41	2,952,756.34
Medium-high	Micro → Small	2	230,519.62	77,350.38	-615,878.13	-65,785.03	349,027.36	1,538,347.22
Medium-high	Small → Medium	2	244,727.27	79,117.18	-1,305,769.66	-179,736.94	485,939.94	2,255,536.30
Medium-low	Micro → Small	2	173,138.66	56,828.11	-594,129.52	-71,572.16	280,867.59	1,270,003.17
Medium-low	Small → Medium	2	214,100.22	66,961.59	-1,087,815.69	-150,626.66	406,437.45	1,938,510.05
Low	Micro → Small	2	117,308.56	38,654.34	-427,949.59	-50,654.98	194,422.87	899,718.49
Low	Small → Medium	2	96,395.21	30,237.75	-783,732.67	-121,254.13	238,879.52	1,162,572.34

Table 4. The incremental gains in value-added per employee for transitions between firm sizes across different technologies and coefficients of variation (in Turkish Lira, Assumed distribution of gains: Gamma distribution)

Technology	*Transition*	*Coefficient of Variation*	*Mean*	*Median*	*Q5*	*Q25*	*Q75*	*Q95*
High	Micro → Small	0.5	265,359.91	234,410.28	-203,656.46	47,551.15	452,928.24	844,000.56
High	Small → Medium	0.5	360,076.10	315,338.35	-455,203.15	-2,748.07	678,442.93	1,322,653.33
Medium-high	Micro → Small	0.5	231,583.90	205,521.79	-155,666.07	49,335.51	386,064.86	708,560.51
Medium-high	Small → Medium	0.5	249,809.17	219,113.79	-401,872.43	-33,533.75	504,238.72	1,001,871.82
Medium-low	Micro → Small	0.5	173,755.61	153,736.64	-167,273.29	19,425.13	308,076.57	581,889.05
Medium-low	Small → Medium	0.5	213,274.35	189,091.60	-346,590.49	-26,767.56	431,265.55	849,046.12
Low	Micro → Small	0.5	118,626.28	104,907.68	-120,708.08	10,061.57	213,109.40	403,756.92
Low	Small → Medium	0.5	98,988.38	87,866.52	-264,218.41	-52,661.48	239,184.53	500,560.02
High	Micro → Small	1	266,879.21	152,227.57	-588,757.41	-97,453.78	548,039.71	1,462,321.96
High	Small → Medium	1	358,063.04	196,879.44	-1,151,292.85	-237,880.74	836,371.24	2,334,172.48
Medium-high	Micro → Small	1	230,375.52	131,891.74	-465,076.30	-75,108.23	460,789.42	1,224,601.23
Medium-high	Small → Medium	1	249,708.18	136,942.30	-982,056.32	-217,527.86	640,454.53	1,805,153.92
Medium-low	Micro → Small	1	176,684.53	100,057.99	-446,592.07	-81,953.46	377,230.08	1,031,990.56
Medium-low	Small → Medium	1	215,882.04	117,447.20	-828,785.54	-180,498.36	543,672.02	1,538,786.35
Low	Micro → Small	1	119,102.43	66,679.97	-318,884.55	-61,346.56	260,925.50	708,740.06
Low	Small → Medium	1	98,590.49	52,094.75	-596,568.81	-149,390.94	313,721.29	928,346.96
High	Micro → Small	2	263,013.46	10,311.45	-1,203,648.22	-127,081.33	416,199.92	2,489,410.60
High	Small → Medium	2	354,362.82	10,685.04	-2,294,753.62	-260,506.33	638,744.61	4,069,641.14
Medium-high	Micro → Small	2	233,707.01	9,435.65	-968,612.82	-97,939.14	351,901.92	2,128,514.01
Medium-high	Small → Medium	2	247,750.01	6,195.72	-1,940,926.55	-227,684.02	494,445.77	3,261,353.96
Medium-low	Micro → Small	2	174,765.04	5,712.54	-906,261.08	-100,639.48	288,789.56	1,778,496.30
Medium-low	Small → Medium	2	202,457.35	4,641.81	-1,651,304.43	-198,223.22	413,229.45	2,626,203.18
Low	Micro → Small	2	113,856.33	3,522.03	-645,257.52	-71,781.68	193,162.48	1,222,810.62
Low	Small → Medium	2	93,339.36	1,724.19	-1,155,426.13	-144,767.86	246,103.26	1,627,323.17

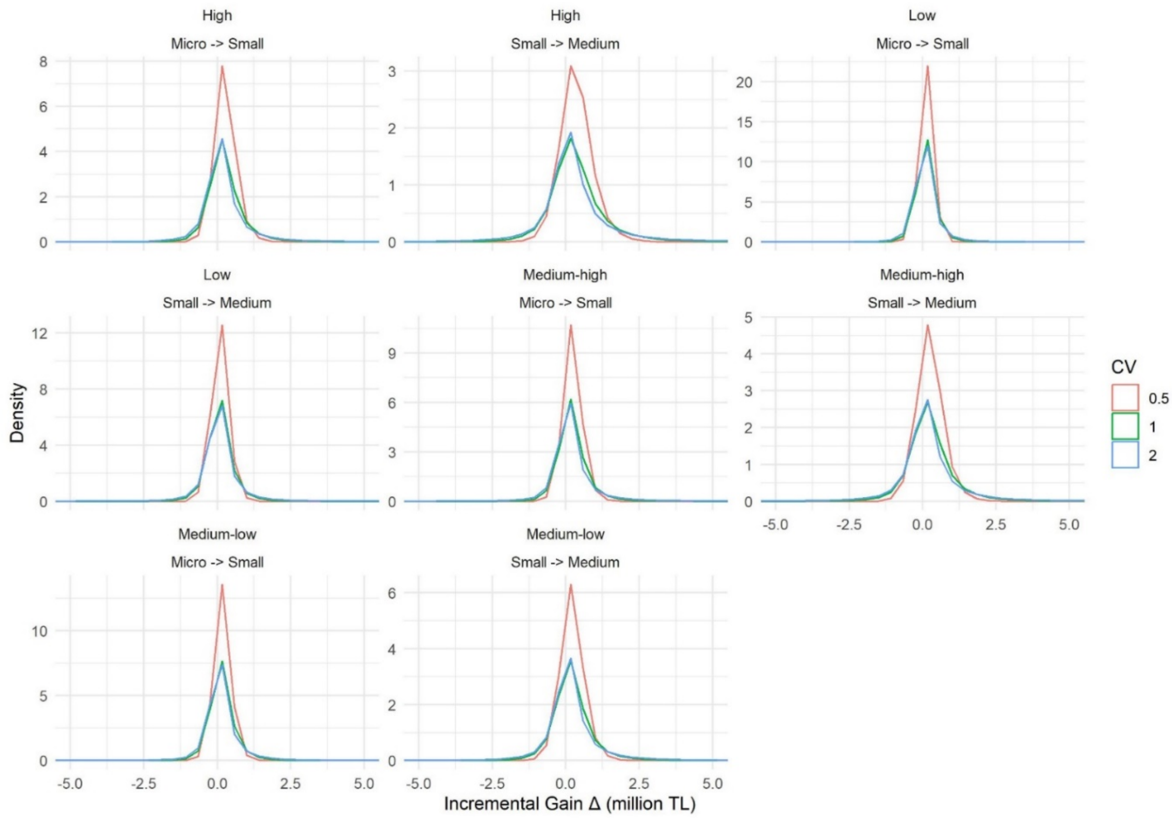

Figure 1. Density plot of incremental gains in value-added per employee from transitions between firm sizes across different technologies and coefficients of variation (Assumed distribution of gains: Log-normal)

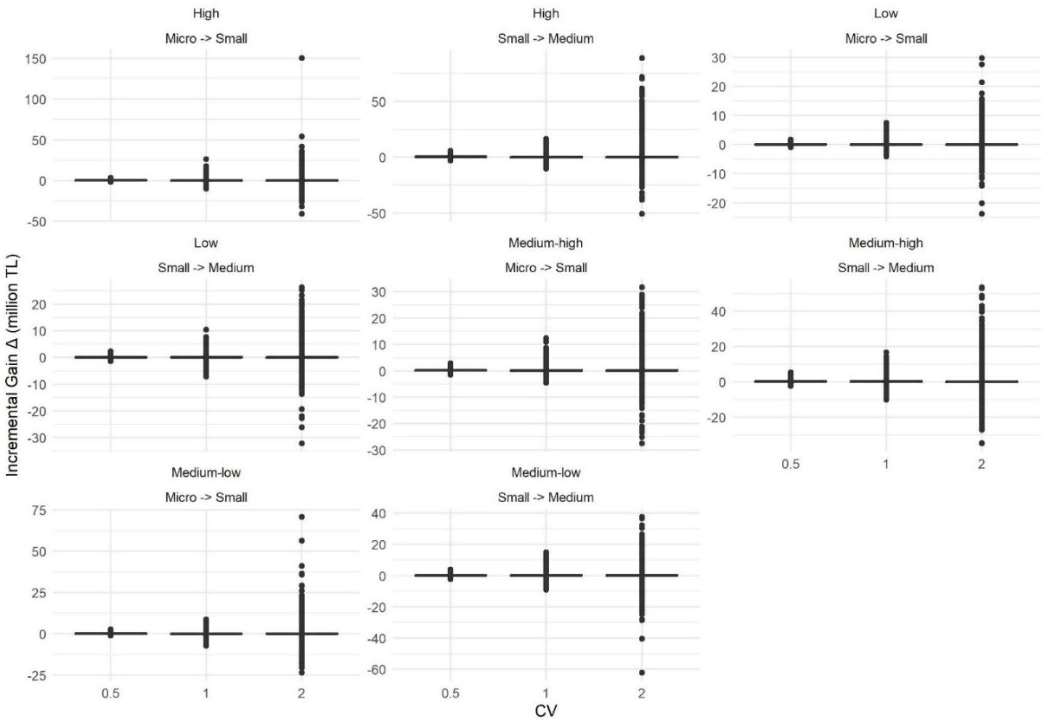

Figure 2. Boxplot of incremental gains in value-added per employee from transitions between firm sizes across different technologies and coefficients of variation (Assumed distribution of gains: Log-normal)

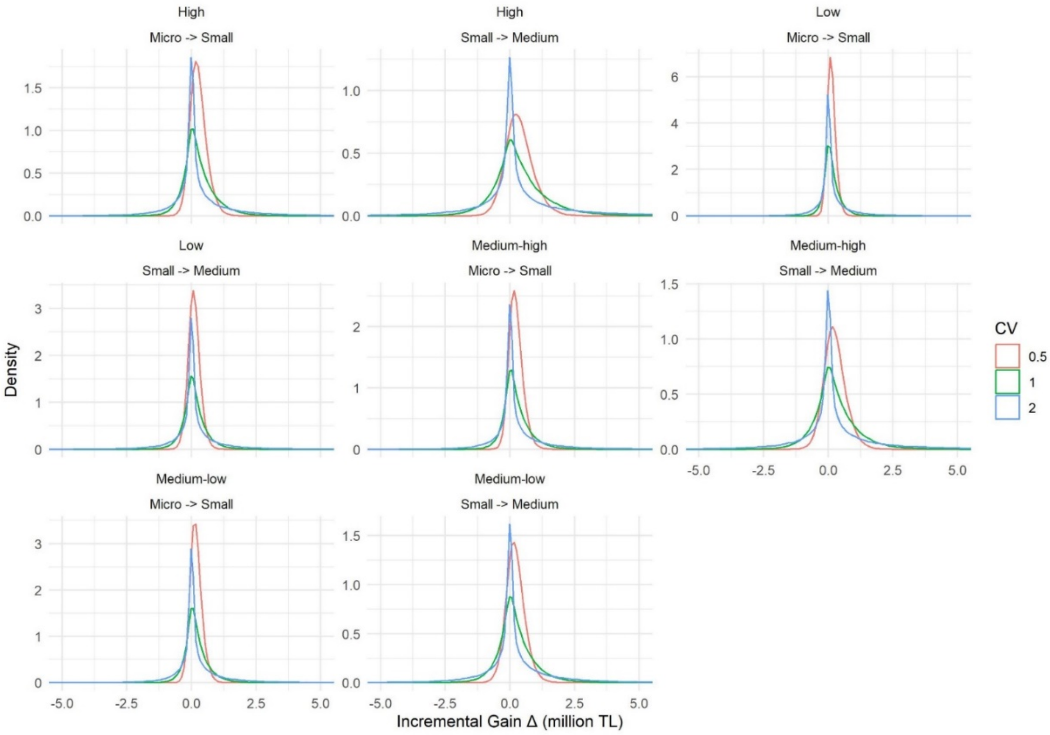

Figure 3. Density plot of incremental gains in value-added per employee from transitions between firm sizes across different technologies and coefficients of variation (Assumed distribution of gains: Gamma)

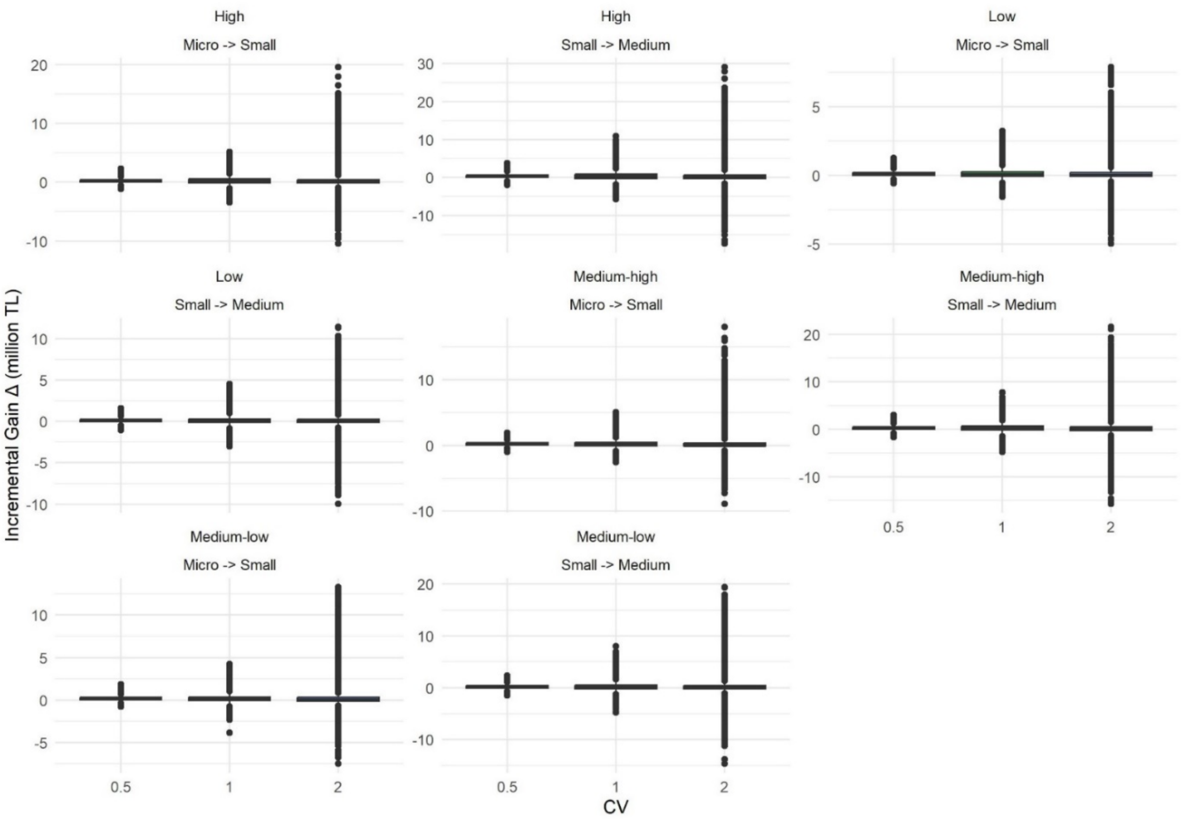

Figure 4. Boxplot of incremental gains in value-added per employee from transitions between firm sizes across different technologies and coefficients of variation (Assumed distribution of gains: Gamma)

4. DISCUSSION and POLICY IMPLICATIONS

The simulation evidence confirms that productivity gains from growth are strongly stratified by technological intensity. Under modest heterogeneity (CV = 0.5), high-technology firms realize mean incremental value-added on the order of TL 260–360 thousand when moving from Micro → Small or Small → Medium, whereas low-technology firms capture barely TL 100 thousand. These gaps reflect the broader pattern that high-knowledge SMEs systematically outperform low-tech peers once scale expands (Raes, 2021). Median gains follow the same ranking but fall much more steeply as dispersion rises: at CV = 2, the typical increase for a high-technology Micro → Small transition collapses to roughly TL 10 thousand, and the lower quintile turns decisively negative. Low-technology enterprises experience an even sharper erosion, with fifth-percentile outcomes approaching –TL 650 thousand. These results indicate a central dilemma: although average returns to scaling remain positive, the probability of adverse outcomes escalates rapidly with heterogeneity, particularly in technologically less-advanced segments.

When heterogeneity is limited, broad-based or blanket incentives can be justified. For example, at CV = 0.5, the entire inter-quartile range for high-technology Micro → Small upgrades lies above zero; a modest, untargeted subsidy is therefore unlikely to fund outright failures. By contrast, once CV reaches unity, the left tail of several transitions—most notably Small → Medium among medium-high technology firms—extends deeply into negative territory. Recent OECD guidance stresses that such contexts call for conditional, milestone-based instruments rather than flat-rate grants (OECD, 2025: 8-12). In such settings, policy should shift from uniform to conditional instruments: performance-contingent grants tied to R&D or workforce-development milestones, credit guarantees that phase out if pre-specified productivity thresholds are missed, or tiered co-financing that increases with demonstrated learning effects.

For low-technology enterprises, the simulations suggest that scaling alone delivers limited and volatile pay-offs. International evidence now shows that digital capability, lean-process adoption, and knowledge-network participation must precede scaling if growth incentives are to be cost-effective (Sagala and Őri, 2024). The ECB's 2024 survey on digitalization and productivity similarly finds that productivity gains materialize only after complementary organizational changes, with laggard SMEs showing no uplift until digital skills are embedded firm-wide (ECB, 2024). The policy priority for this cohort should therefore be capability enhancement, such as adoption of digital tools, lean-production methods, or participation in cluster-based knowledge networks, before subsidizing physical expansion. Such sequencing raises the median gain and compresses the downside risk, which makes subsequent growth incentives more cost-effective. This strategy is consistent with recent findings that technology adoption disproportionately disadvantages low-skill workers, which indicates the critical role of upskilling and reskilling initiatives to bolster the productivity of less-advanced firms (Hötte et al., 2023).

The results for CV = 2 reveal how sensitive risk assessments are to the statistical model chosen for the shocks. When incremental gains are drawn from a log-normal distribution, the simulated density has a very "fat" right tail. This statistical shape means that, although most firms achieve moderate outcomes, a non-trivial fraction realizes exceptionally large productivity gains. In policy terms, a support scheme evaluated under log-normal shocks will appear to create many "big winners." By contrast, using a gamma distribution produces a narrower central hump and thinner tails. Extreme gains or losses still occur, but they are both less frequent and less extreme, while most firms remain clustered near the median outcome. Thus, simply switching distributional assumptions can change the apparent balance between upside potential and downside risk.

Because program performance looks better or worse depending on these assumptions, policymakers should stress-test any proposed scheme with multiple stochastic specifications rather than rely on a single "best-guess" distribution. Evaluation reports should present not only expected net benefits but also percentile-based risk metrics, such as the 5^{th}, 25^{th}, 75^{th}, and 95^{th} percentiles, to show how many firms may fail to benefit or may achieve outsized gains under each scenario. After a policy is launched, its real-world outcomes should be continuously monitored and broken down by technology tier, size transition, and the distribution originally assumed. Such disaggregated tracking allows officials to detect whether observed volatility exceeds the tolerance built into the design and to adjust subsidy rates, eligibility rules, or complementary capability-building measures before fiscal exposure grows too large.

The findings reinforce the OECD's call for "tailored" entrepreneurship and SME policies that recognize the diversity of firm trajectories. Blanket subsidies risk misallocation (Shane, 2009; Schoar, 2010), whereas segmentation by technological intensity and growth path, consistent with recent typologies proposed by Raes (2021), enables a more efficient match between instruments and needs. High-tech, high-growth ventures may warrant milestone-linked R&D support, while smaller, process-oriented firms may benefit more from workforce-upskilling vouchers or advisory services. Contemporary evidence on R&D persistence underscores why financially healthier SMEs sustain innovation longer; firms with robust balance sheets exhibit significantly higher R&D survival rates, which validates the need for finance-contingent instruments (Chirita et al., 2025).

In sum, the simulations recommend a graduated support architecture. Where lower-tail outcomes remain negative even under conservative shock assumptions, subsidies should be paired with—if not preceded by—capability-building interventions. Conversely, transitions whose entire inter-quartile range remains positive (e.g., high-technology Micro → Small at CV ≤ 1) lend themselves to modest, broad-based incentives. By conditioning assistance on both the technology level and heterogeneity, policymakers can maximize aggregate productivity gains while containing fiscal and economic risk.

5. CONCLUSION

The present simulations indicate the centrality of technological intensity and size upgrading in determining the value-added gains realized by Turkish manufacturing SMEs. Across all stochastic scenarios, high-technology firms display the greatest scope for productivity improvements, whereas low-technology enterprises generate smaller and markedly more volatile returns, especially when heterogeneity rises. Scale effects are likewise salient: transitions from Small → Medium systematically yield larger expected gains—and wider risk envelopes—than moves from Micro → Small, which confirms that the productivity benefits of expansion accelerate with firm size. These patterns call for differentiated policy instruments that match firms' technological capabilities and risk profiles, which range from performance-contingent subsidies for high-tech upgraders to capability-building or cluster-based programs for low-tech producers whose downside risk remains pronounced.

Several caveats temper these conclusions. First, the analysis relies on aggregated size-class data; the attendant averaging may conceal important micro-level heterogeneity in managerial quality, market power, or supply-chain embeddedness. Second, although the juxtaposition of log-normal and gamma shocks provides a useful robustness check, both distributions are stylized proxies; richer firm-level panels would permit estimation of empirical shock processes and, by extension, more finely tuned policy stress tests.

Even so, the findings speak to practical debates. They strengthen the case for evidence-based industrial policies that segment the SME population by technology tier and growth trajectory rather than adopting one-size-fits-all interventions.

Conflict of Interest
No potential conflict of interest was declared by the author(s).

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Compliance with Ethical Standards
It was declared by the author(s) that the tools and methods used in the study do not require the permission of the Ethics Committee.

Ethical Statement
It was declared by the author(s) that scientific and ethical principles have been followed in this study and all the sources used have been properly cited.

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