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The Significance of Economic Selection to Labor Productivity Evolution in the Turkish Manufacturing Industries

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ABSTRACT

This study examines the role of economic selection in labor productivity growth in Turkish manufacturing industries from 2011 to 2015, using firm-level data and the evolutionary Price equation. Unlike traditional shift–share methods, the Price equation enables a multi-level analysis of productivity growth, breaking it down into industry selection, firm selection, learning, entry, and exit effects. The results indicate that the primary driver of productivity growth was the learning effect—representing intra-firm improvements such as R&D and human capital development—while selection effects contributed less. In a single-level analysis, firm selection and exit effects were positive, whereas the entry effect was negative. The multi-level analysis showed a small positive industry selection effect, a negative firm selection effect, and similar patterns for entry and exit, highlighting the importance of industry-specific benchmarks. High-productivity sectors included beer, tobacco, precious metals, spacecraft machinery, pharmaceuticals, and refined petroleum. The findings suggest that productivity gains in Turkish manufacturing were modest, constrained by a non-selective incentive system and competitive pressures from trade liberalization. Policy recommendations focus on fostering innovation, increasing R&D investments, and improving the business environment to enhance sectoral competitiveness. This study offers new insights into the micro-dynamics of productivity growth within a developing country context.

Keywords: Turkish Manufacturing Industry, The Price Equation, Evolutionary Economics, Labor Productivity Growth, Structural Change, Micro Heterogeneity.

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INTRODUCTION

The micro-dynamics of overall labor productivity growth are typically broken down into intra-firm productivity, economic selection, and net entry effects. These dynamics stem from the competitive environment, which can promote productivity improvements within technologically advanced firms or sectors. Scholars generally agree that economic selection is vital for driving long-term economic growth and development (Szirmai, 2012; Lin, 2011; McMillan and Rodrik, 2011; UNIDO, 2009; Hausmann and Rodrik, 2003). The transition from primary production to manufacturing or services, and within manufacturing from labor-intensive to capital-intensive goods, has fueled the rise of new economic powers since the industrial revolution (Memedovic and Iapadre, 2009). Economic selection can encompass various aspects, including shifts in output and employment composition (Kruger, 2008). In this paper, it specifically refers to labor movement between different economic activities or industries. Patterns of economic selection may result from demand and supply forces within the economy. From a supply-side perspective, key indicators include changes in labor–augmenting technological progress, factor shares, and the elasticity of substitution between production factors across industries (Herrendorf, et al., 2015). Low per capita income restricts access to capital, raising costs for capital-intensive goods, especially when capital and labor are not easily substitutable. As income increases, structural transformation can alleviate these constraints by shifting production toward more efficient sectors, shaping the path of economic growth depending on how quickly and in what manner this shift takes place (Acemoglu and Guerrieri, 2008; ECLAC, 2012).

From a demand-side perspective, the key indicators influencing economic selection include final and intermediate demand, as well as external trade. Higher per capita income reduces food consumption and shifts demand from basic goods to manufactured products

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and then to services. Additionally, the composition of trade and the type of specialization impact economic selection, driven by natural resources and trade policies aimed at shifting the economy from primary to tertiary sectors. Whether from the supply or demand side, economic selection naturally shapes economic growth and development. Over time, the share of agriculture in GDP declines, while manufacturing and services expand. Overall, empirical studies show that the effect of economic selection positively influences labor productivity growth in Asian countries but negatively affects some Latin American and African nations (Rodrik, McMillan, and Sepulveda, 2017). The role of economic selection in the development process of developed countries is well documented, but research on developing nations is limited. Therefore, this paper aims to address this gap by analyzing how the selection effect impacts labor productivity in Turkish manufacturing firms. Since the 1980s, Turkey has undergone significant economic policy changes, shifting from an import-substituting industrialization strategy to deregulating domestic financial markets and liberalizing trade both locally and globally. As a result, Turkey's export structure has changed markedly, with the share of manufactured goods in total exports increasing to 93.7% in 2017.

Two main strands of economic literature explore the relationship between economic selection and overall labor productivity growth. The first involves studies using traditional shift-share analysis (Fabricant, 1942; Maudos et al., 2008). This analysis breaks down changes in labor productivity into three parts: the first captures productivity gains from innovations within firms or industries (Schumpeter, 1939); the second reflects productivity shifts caused by labor moving across industries (Pasinetti, 1981); and the third shows productivity changes that result from the interaction of within-industry improvements and labor flows. The second focuses on studies employing evolutionary methods that decompose aggregate labor productivity growth while considering the roles of entering and exiting firms (Andersen & Holm, 2014; Foster et al., 1998; Baily, Hulten, and Campbell, 1992; Griliches & Regev, 1995; Disney et al., 2003; Holm, 2014). Many studies have used conventional shift-share analysis to examine the link between economic selection and labor productivity growth in Turkey. Notable examples include Akkemik (2006), Tuncer and Altiok (2011), Tuncer and Moalla (2020a), and Tuncer and Moalla (2020b). However, to our knowledge, this is the first study to apply an evolutionary approach known as the "Price Equation" to analyze the role of economic selection in the growth of labor productivity in Turkish manufacturing industries. The advantage of this approach is its capacity to analyze labor productivity changes across multiple levels, unlike traditional methods that often rely on arbitrary weighting schemes.

This paper examines two research questions: 1) How does economic selection influence overall labor productivity growth in Turkish manufacturing industries when considering firms' entry and exit? and 2) How does the length of the interval impact the results of labor productivity decomposition? The data for this study were obtained from the Turkish Statistical Institute through the Data Research Center (VAM). All work was carried out at the Regional Directorate of the Turkish Statistical Institute in Adana, Türkiye. The data, after matching the Annual Industry and Services Statistics with the Annual Business Registers Framework databases, cover the period from 2010 to 2015. A detailed analysis of industrial dynamics at both the firm and industry levels was performed to understand overall labor productivity growth. The findings align with other studies, such as those by Tuncer and Altiok (2011), Tuncer and Moalla (2020a), and Tuncer and Moalla (2020b). The empirical results suggest that the impact of economic selection on labor productivity growth during the studied period appears to be minimal. The rest of the paper is organized into five sections. The first discusses why selection matters in the productivity puzzle. The second outlines the methodology and database used to estimate labor productivity in Turkish manufacturing. The third describes the main features of Turkish manufacturing industries from 2011 to 2015. The fourth presents the findings based on the empirical evidence provided. The final section summarizes the main conclusions.

LITERATURE REVIEW: PRODUCTIVITY DECOMPOSITION AND THE SELECTION EFFECT

Since the early works of classical economists, the composition of the economic structure has been linked to economic growth and development. Economic evolution is mainly associated with economic selection (Fisher, 1939; Lewis, 1954; Kaldor, 1957; Chenery, 1960; Pasinetti, 1981; Syrquin, 2010; and Lin, 2011). The literature thoroughly documents the connection between economic selection and economic evolution. The overall growth of labor productivity is influenced by both internal and external micro-labor productivity improvements (Dosi and Nelson, 2010; Metcalfe, 1998). The structural change (i.e., selection) effect reflects the reallocation of productive resources among firms or industries and is expected to be a key factor in economic growth and productivity shifts. Much research measures how the selection effect impacts overall productivity growth through productivity decomposition techniques. These methods typically break down productivity growth into the within-industry growth effect, the static reallocation effect, and the dynamic reallocation effect. Baily et al. (1992) and Foster et al. (1998) expanded traditional decompositions to include the effects of firms entering and exiting industries. These decomposition techniques can be applied at the firm, industry, region, or country level.

Many industry- or establishment-level applications use Baily-type decompositions for the US four-digit manufacturing industries. Despite notable differences in results across various periods, data frequencies, and share specifications (labor or output), the findings can be summarized as follows: most of the total productivity improvements come from the within effect. The static reallocation effect is sometimes relatively small in absolute terms, but the dynamic reallocation effect is usually positive and significant. The overall pattern indicates that more productive new firms replace less productive ones that exit the market. In short, net entry drives overall productivity growth. In the US, new manufacturing firms typically have lower productivity than established ones. Analyses over several periods show that reallocation significantly boosts average productivity growth during recessions and reveals more substantial structural contributions when total factor productivity (TFP) is considered instead of labor productivity (Foster et al., 1998; Fagerberg, 2000; Peneder, 2003; Bartelsman and Doms, 2000). Kruger (2008) identified a notable connection between overall productivity growth and the selection effect spurred by the computer revolution, especially in high-tech and durable goods industries, when analyzing over 450 manufacturing industries from 1958 to 1996. The results also showed that economic selection, when measured by employment share, is less intense than when measured by value-added shares. From another perspective, Baily et al. (1996) interpret the positive link between rising employment and labor productivity growth as driven by idiosyncratic factors, despite significant heterogeneity across industries.

Some microeconomic studies explore the dynamics of structural change in Germany. Cantner and Krüger (2008) aim to empirically assess the impact of selection in specific German manufacturing industries. They use a nonparametric frontier function to measure total factor productivity in German manufacturing, emphasizing the important role of market entry and exit. Their findings show that more than 30% of the total productivity change from 1990 to 1998 is due to the selection effect. Additionally, they find that before German reunification, there was a strong connection between intra-firm productivity growth, above-average productive entrants, below-average productive exiters, and overall productivity change. After reunification, a significant link appeared between labor productivity growth and economic selection, driven by success-breeds-success dynamics and the widespread adoption of technological innovations across most industries.

Disney et al. (2003) examined the role of internal and external restructuring in driving overall productivity growth in UK manufacturing from 1980 to 1992. They found that external restructuring, through entry and exit, accounts for roughly 50% of labor productivity growth in the UK and up to 90% of total factor productivity growth, mainly by shutting down low-productivity facilities and establishing high-productivity ones. Furthermore, they suggest that competitive pressure on existing establishments links external restructuring and productivity growth to more behaviorally driven factors. Bottazzi et al. (2010) found a strong relationship between economic selection and labor productivity growth when using employment share for firm size, but a weak link when using sales as the weighting variable during 1989–2004 for Italian and French firms.

Holm (2014) uses Price's equation on Danish data (1992–2010) to better decompose labor productivity growth by explicitly considering structural transformation. Unlike traditional single-level methods, the multilevel approach separates entry, exit, and selection effects across industries, showing that structural shifts can significantly change measured contributions. Results indicate that industry-level selection is a key factor, with firm selection contributing up to 83% of productivity growth during some periods. The study also finds more substantial selection effects during economic downturns and shows that results are sensitive to the length of the measurement interval. It concludes that multilevel decomposition offers a more accurate view of productivity drivers and encourages policymakers to develop strategies that address industry-specific dynamics during structural change. In Asia, Timmer and Szirmai (2000) found no evidence supporting the "structural bonus" hypothesis, indicating that industry-wide factors are more influential than industry-specific ones. Fagerberg (2000) notes that structural change generally does not impact manufacturing productivity across most countries. Some data challenge the benefits of structural change; for example, Baumol (1967) emphasized that the "cost disease" occurs when labor shifts to sectors with stagnant productivity, such as services, leading to slower productivity growth.

A substantial body of research explores the link between selection and productivity growth in developed countries; however, comparability is limited due to different methodologies and timeframes constrained by data availability. There is a notable research gap regarding the relationship between economic selection and productivity growth in Turkey and other developing countries. Studies from the demand side (Celasun, 1983) and the supply side (Akkemik, 2006) both indicate that, within the Turkish economy, economic selection positively affects productivity during the inward-oriented period and negatively during the outward-oriented phase. Findings from Tuncer and Moalla (2020a, 2020b) and Moalla (2020) confirm that within-firm growth accounts for most of the labor productivity increase in the 2000s. Both Rodrik (2010) and Atiyas and Bakış (2013) find significant and positive contributions from reallocation in the 1990s and early 2000s. Tuncer and Altıok (2011) found that structural change did not impact productivity growth in Mersin Province and the Turkish manufacturing sector from 1980 to 2008. Tuncer and Moalla (2020a) similarly report small but positive effects from 2003 to 2017.

Using panel data from 1993 to 2000 for firms with over 10 employees, Taymaz and Kılıcaslan (2005) examined subcontracting in Turkey's textile and engineering sectors. They found that in engineering, subcontracting mainly occurs among similar, technologically advanced firms, whereas in textiles, it involves short-term, unequal client-subcontractor relationships. They also stressed the importance of regional clustering and networking, noting that subcontracting is more common in regions with a dense network of firms.

Taymaz and Yılmaz (2007) used Turkish manufacturing establishment-level data from 1983 to 2001 to estimate production frontiers and derive key indicators, including input elasticities, technical efficiency, and technological progress. Their results show that productivity improvements mainly stem from intra-firm productivity growth rather than structural change. They also highlight the barriers to industrial strategy caused by low technical efficiency and limited technological progress, arguing that short-term tactics like wage suppression and subcontracting could harm long-term output. Their findings emphasize the need for cohesive, long-term policies that support talent development, technology diffusion, and SME reorganization focused on productivity, while warning against continued support for consistently inefficient enterprises.

According to empirical research, reallocating resources to high-productivity firms or industries can boost productivity and economic growth. However, this process is not automatic. Its effect depends on the context, the direction of resource reallocation, key factors such as technological innovation, market competition, institutional frameworks, and the methods used for evaluation. Unlike previous studies, the main contribution of this research is to analyze labor productivity patterns using firm-level data, explicitly considering entry and exit effects in the Turkish manufacturing industry.

METHODOLOGY and DATA

The methodology established by Foster et al. (1998) is the most frequently used technique for productivity decomposition analysis in the literature. The results are often not comparable due to different timeframes and various methods used to derive overall results from sub-populations. A slight generalization of this widely used method in biology is known as Price's equation, with the primary reference being Price (1970). This study employs the "Price Equation" to assess the significance of the selection effect in overall labor productivity growth. Price's equation is an evolutionary tool inspired by theoretical evolutionary biology and applied in economics (Metcalfe, 1994; Andersen, 2004). It provides a consistent way to break down the sources of aggregated labor productivity growth at a more detailed level. Unlike traditional decomposition methods, the Price equation has been used to analyze productivity at more disaggregated levels to better understand productivity patterns. Holm (2014), Rice (2004), and Morris and Lundberg (2011) suggest that examining evolution at a more detailed level can lead to improved estimates of the dynamics. The general decomposition of evolution developed by Price includes both the selection and innovation effects (Frank, 1995). The productivity decomposition equation can be written as follows:

$$\Delta Z = \frac{\mathrm{Cov}\,(w_i, z_i)}{W} + \frac{E(w_i \Delta z_i)}{W}$$

Where ($\Delta Z = Z' - Z$) shows the change in labor productivity from the base year to the final year, with Z representing the average labor productivity in the base year and Z′ in the final year. The first term on the right side of Price's equation indicates the economic selection effect, or the reallocation effect among firms. It is defined as the covariance between changes in weights (w_i) and productivity (z_i). The second term on the right reflects the learning effect, also called the intra-firm or innovation effect. This part of productivity growth comes from internal firm processes, such as R&D activities. Labor productivity (z_i), which shows competitive advantage, is measured as the firm's real value added per worker. Firm size (s_i) is measured by the firm's share of total employment. By including the effects of firms entering and leaving the market, we arrive at the single-level decomposition form of Price's equation.

$$\Delta Z = \sum_{i \in C} \Delta s_i (z_i - Z) \quad \text{(Selection effect)}$$

$$+ \sum_{i \in C} s_i' \Delta z_i \quad \text{(Learning effect)}$$

$$+ \sum_{i \in N} s_i' (z_i' - Z) \quad \text{(Entry effect)}$$

$$- \sum_{i \in X} s_i (z_i - Z) \quad \text{(Exit effect)}$$

Where the superscript (') refers to the final year. To reach the multilevel decomposition technique of Price's equation, we replace the subscript i for firms with the subscript j for industries[1], such that:

$$\Delta Z = \sum_j \Delta s_j \left(z_j - Z\right) \quad \text{(Industry selection effect)}$$

$$+ \sum_j s_j' \sum_{i \in C_j} \Delta s_{ij} \left(z_{ij} - z_j\right) \quad \text{(Firm selection effect)}$$

$$+ \sum_j s_j' \sum_{i \in C_j} s_{ij}' \Delta z_{ij} \quad \text{(Learning effect)}$$

$$+ \sum_j s_j' \sum_{i \in N_j} s_{ij}' \left(z_{ij}' - z_j\right) \quad \text{(Entry effect)}$$

$$- \sum_j s_j' \sum_{i \in X_j} s_{ij} \left(z_{ij} - z_j\right) \quad \text{(Exit effect)}$$

The first component of this decomposition equation is the industry selection effect. It captures how industry choice influences overall productivity growth, especially when sectors with above-average productivity expand at the expense of less productive sectors. The second component relates to the firm selection effect, also known as the inter-firm, intra-industry effect, similar to the single-level decomposition that considers selection among firms. The third component is the learning or intra-firm effect, which measures gains from processes within individual firms. The fourth and fifth components represent the entry and exit effects, respectively. These effects are assessed relative to the overall average productivity. Like other decomposition methods, this equation is an identity. The multilevel decomposition assumes that selection among firms occurs only within sectors, eliminating the need to perform separate decompositions for each sector and then combine the results arbitrarily. We believe that the multilevel Price equation provides clearer insights when analyzing key patterns in the growth of overall labor productivity (Holm, 2014).

The permission to use the firm-level data for this study was granted through a protocol signed between the Turkish Statistical Institute and Mersin University/ Department of Economics. This protocol allows access to TÜİK microdata via the Data Research Center (VAM) located in Adana, Türkiye. Under this agreement, the available micro datasets include the Research and Development Survey for Industry and Service Enterprises (2003–2018), the Environmental Employment, Revenue, and Expenditure Statistics in Enterprises (2007–2016), the Annual Industry and Service Statistics (2009–2017), the Annual Industrial Products (PRODCOM) Statistics (1990–2017), the Innovation Survey (2002–2016) and the Annual Business Registers Framework (2005–2017).

The available data covers the period from 2010 to 2015 and is classified according to NACE Rev.2 at the four-digit level. This paper examines the evolution of labor productivity from 2011 to 2015. We include all firms of different sizes during this period and categorize them into three groups: (1) firms present in both pre- and post-evolution populations (C), meaning continuing firms; (2) firms present only in the pre-evolution population (X), meaning firms that exit the industry; and (3) firms present only in the post-evolution population (N), meaning entrants. The total number of firms during this period is 65,719. Of these, 18,528 firms exist in both 2011 and 2015 (C), 21,451 only in 2011 (X), and 25,740 only in 2015 (N). Three variables from the database are used: the total value added by the firms (VA), total full-time equivalent employment over the years, and industry classification. Additionally, we adjust for inflation using the Producer Price Index (PPI) (2003=100), obtained from the Data Research Center (VAM). All analyses were performed at the Regional Directorate of the Turkish Statistical Institute in Adana, Turkey. To the best of our knowledge, this is the first study to employ an evolutionary approach (the Price equation) at the firm-level data to decompose labor productivity in Turkish manufacturing industries.

[1] For a more detailed derivation of the Price Equation see Holm (2014) and for the proof of this type of decomposition see Appendix to Andersen (2004).

Table 1. Entry and Exit Rates for All Firms (2010-2015)

Period	Entrants	Continuing Firms	Exiters	Entry Rates	Exit Rates
2010-2015	26326	17942	14946	44%	25%
2010-2011	18301	21678	11210	36%	22%
2010-2012	22470	19481	13407	41%	24%
2011-2015	25740	18528	21451	39%	33%
2012-2013	19161	26399	15552	31%	25%
2014-2015	15948	28318	15508	27%	26%
2013-2015	19511	24758	20805	30%	32%

Source: Authors calculation based on TurkStat Annual Industry and Services Statistics and Annual Business Registers micro databases.

Economic Selection and Labor Productivity Evolution in the Turkish Manufacturing Industries

The shared database provides data on both value added and the number of workers at the firm level, which is used here to analyze the evolution of labor productivity in Turkish manufacturing industries from 2010 to 2015. In 2010, manufacturing industries accounted for 30% of total value added, but this decreased to 19% by 2015. Regarding employment (the number of employed workers), a pattern of economic selection is also evident. The share of employed workers declined from 41% in 2010 to 32% in 2015. To better understand the relationship between the selection process and changes in labor productivity, we distinguish among three groups of firms: entrants present in the final year, exiters present only in the base year, and continuing firms present in both the base and final years within the studied period. This paper reports results for the period from 2010 to 2015. Table 1 displays the number of new entrants, continuing firms, and exiting firms, along with the entry and exit rates for this interval.

Between 2011 and 2015, we observed a high entry rate in 2011 and a high exit rate in 2015 compared to other periods. The data show that about 90.82% of the firms that exited had labor productivity below the average labor productivity of the pre-evolution population (Z2011 = 31498.04). The results are mixed; in other words, some exiters had labor productivity above the average in the pre-evolution population. This may occur because firms shifted between industries rather than fully exiting. There is a negative relationship between labor productivity and the employment shares of the exiters (Pearson coefficient = -0.07). Conversely, about 89.1% of the entrants have labor productivity below the average of the pre-evolution population (Z2011 = 31498.04) and below that of the post-evolution population (Z2015 = 35978.60). Only 10.9% of the entrants have labor productivity above the average of both populations. The entry impact likely results from firms switching industries rather than entrepreneurial entry, which could be the main reason for this outcome. There is a negative relationship between labor productivity and the employment shares of the entrants (Pearson coefficient = -0.11).

Table 2. Continuing firms' employment share and labor productivity during the period of (2011-2015)

Firms	Employment share		Labor productivity		
	2011	2015	2011	2015	
			$>Z_{2011}$(%)	$>Z_{2011}$(%)	$>Z_{2015}$(%)
Successful Upsizers+	36	40	59	77	65
Successful Downsizers++	50	46	66	80	74
Unsuccessful Downsizer+++	8	7	86	79	71
Unsuccessful Upsizers++++	6	7	91	82	73

+ These firms managed to boost their labor productivity while also raising their employment shares.

++ These firms improved their labor productivity alongside a decrease in their employment shares.

+++ These firms saw a drop in both their labor productivity and employment shares.

++++Those firms experienced a decline in labor productivity while their employment shares increased.

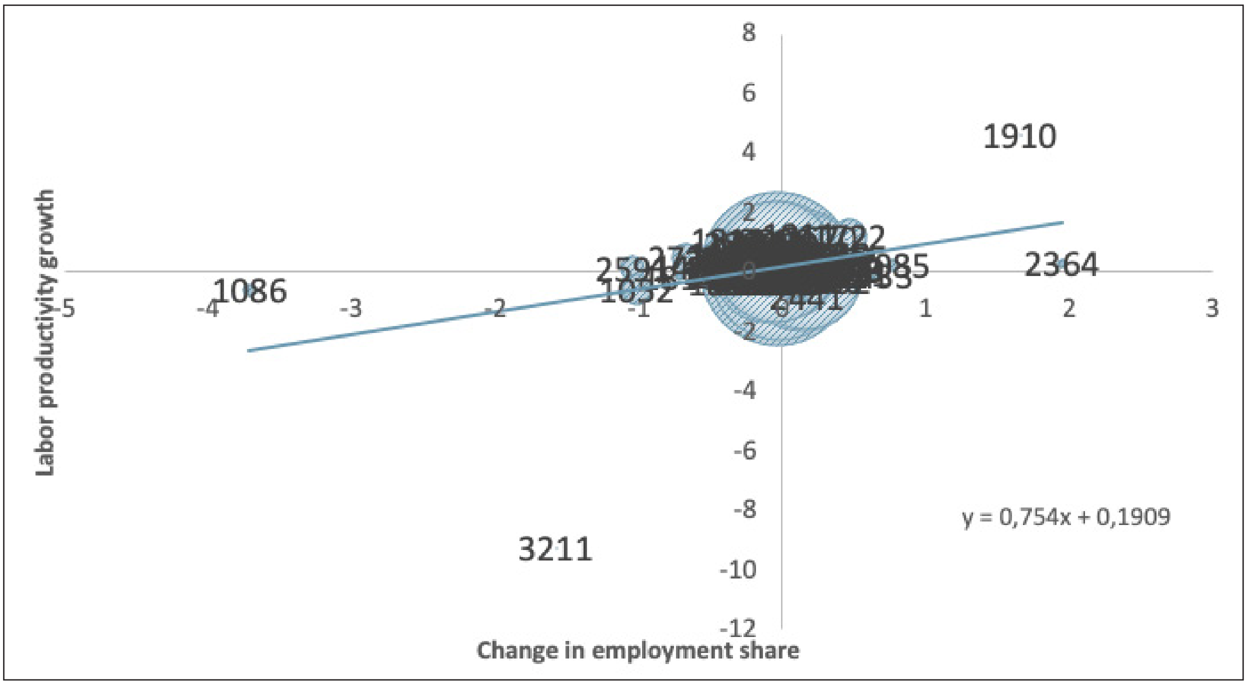

Figure 1. Correlation between the change in employment share and the labor productivity growth at the C firm level during 2011-2015. Note: The size of the circles represents employment shares in the initial year (2011). The line represents fitted values of a linear regression of changes in firms' productivity to total productivity by changes in employment shares.

Based on the Kernel density estimator, the overall picture of the manufacturing industries' structure shows that many firms have low labor productivity, and this productivity decreases as employment shares increase. Table 2 displays the employment shares and labor productivity of continuing firms from 2011 to 2015. The continuing firms are divided into four groups: successful upsizers, successful downsizers, unsuccessful downsizers, and unsuccessful upsizers.

Based on Table 2, we found that, contrary to traditional beliefs, productivity growth in Turkish manufacturing industries during the studied period was not caused by downsizing. The data show that approximately 78% of the continuing firms experienced improvements in labor productivity. Additionally, there was a positive relationship between changes in employment share and labor productivity growth during this period (Figure 1).

The highest rates of labor productivity growth were achieved by continuous firms in the manufacture of coke oven products (1910), meat processing and preservation (1011), and sanitary and toilet requisites (1722). To provide more details, the productivity of these ongoing firms was higher than the pre-evolution average, increasing from 72% in 2011 to 79% in 2015. Nearly 71% of the continuing firms in 2015 had labor productivity above the post-evolution average. In 2011, the highest labor productivity within group C was observed in firms manufacturing beer (1105), tobacco products (1200), and precious metals (2441). In 2015, firms in spacecraft and related machinery (3030), pharmaceutical preparations (2120), and refined petroleum products (1920) showed high labor productivity. The Pearson coefficient indicates a negative correlation between labor productivity growth and changes in employment shares in 2011 (-0.11) and 2015 (-0.09). These variations among sub-industries and firms during this period are seen as key factors driving the process of economic selection.

RESULTS

Labor productivity increased by 0.14 over the period from 2011 to 2015. The results indicated that the primary driver of overall labor productivity growth, according to both the single- and multi-level Price equations, was the learning effect. However, the single-level Price equation underestimates the learning effect compared to the results derived from the multi-level Price equation (Table 3).

Based on the single-level Price equation, the firm selection effect (0.02) is positive, indicating that firms existing in both pre- and post-evolution populations increase their labor productivity more than the manufacturing industry's average as their employment shares grow. The contribution of the learning effect (0.11)

Table 3. One- versus multi-level decomposition

Eq.	industry selection	Firm selection	learning	entry	exit	Total
	2011-2015, ΔZ/Z=0.14 (Z_{2015}= 35978.60, Z_{2011}= 31498.04)					
multilevel	0.0007	-0.003	0.14	-0.05	0.05	0.14
%	(0.50)	(-2.30)	(98.11)	(-31.65)	(35.34)	(100.0)
single level	-	0.02	0.11	-0.08	0.09	0.14
%	-	(14.28)	(78.57)	(-57.14)	(64.29)	(100.0)

Source: Decomposition of manufacturing labor productivity growth (ΔZ/Z) using the single-level Price's equation and its multi-level version. Values represent percentage point contributions to overall manufacturing growth. Values in parentheses indicate the share of each contribution in percentages.

is also positive. The positive exit effect (0.09) suggests that the labor productivity of those exiting is below the overall labor productivity in the base year. The negative value of the entry effect (-0.08) indicates that entrants' productivity was lower than the overall manufacturing labor productivity during the studied period.

Based on the multilevel Price equation, the positive contribution of the industry selection effect (0.0007) indicates that industries tend to increase (decrease) their labor productivity while simultaneously raising (reducing) their labor shares, often at the expense of other industries. The industry selection effect is very small, which can be explained by the generally low labor productivity across industries during the studied period. The negative firm selection effect (-0.003) suggests that incumbent firms were unable to significantly boost their labor productivity relative to the average productivity of their industries despite changes in their employment shares over the interval. A positive contribution from the learning effect (0.14) was derived from the multilevel Price equation. The positive exit effect (0.05) indicates that exiting firms had productivity levels below the mean labor productivity of the subpopulation before evolution. Conversely, the negative entry effect (-0.05) means that new entrants' productivity was below that of the subpopulation at the base year.

When comparing the single and the multilevel equation:

1. The single-level Price equation indicated a positive firm selection effect, while the multilevel Price equation showed a negative firm selection effect along with positive entry and industry selection effects. This difference arises from the distinct reference points for productivity—sub-industry averages in the multilevel approach versus the overall manufacturing average in the single-level approach—highlighting the importance of industry-specific comparisons for policy development. Although these firms perform below their industry average, their productivity remains above the overall manufacturing average, a pattern confirmed through Kernel density estimation as well. Between 2011 and 2015, the entry creation rate was 39%, but only 10.9% of entrants exceeded the average productivity of the combined pre- and post-entry populations, suggesting that much of the observed entry effect results from firms shifting between sub-industries rather than from genuine new firm creation or market exit.
2. The empirical results revealed a positive exit effect in both single- and multilevel decompositions, indicating that the productivity of firms exiting after the study period was lower than that of their respective industries or the overall manufacturing. Between 2011 and 2015, the exit rate reached 33%, with approximately 90.8% of these firms exhibiting below-average labor productivity prior to their departure. Notably, some discrepancies emerged between the single- and multilevel approaches. For example, in industries such as fertilizers and nitrogen compounds (2016), primary plastic forms (2030), paints, varnishes, and related coatings (2059), other chemical products n.e.c. (2120), pharmaceutical preparations (2313), hollow glass (2313), and cement (2351), as well as in several manufacturing activities including cold forming or folding (2640), consumer electronics (2680), magnetic and optical media (3011), shipbuilding (3012), pleasure and sporting boat construction (3040), military fighting vehicle production (3040), and motorcycle manufacturing (3091), firm exits had mixed effects—reducing aggregate labor productivity according to the single-level Price Equation but increasing it under the multilevel Price Equation. This divergence underscores the analytical value of the multilevel Price Equation in capturing the complexity of

selection effects. It offers a more refined basis for formulating micro-level policies to strengthen targeted economic sectors.

3. The empirical results indicate that the primary factor driving productivity growth for both single-level and multilevel techniques is the learning effect. This underscores the importance of accumulating physical and human capital, as well as investing in R&D activities to enhance overall manufacturing labor productivity.

Firms entering the market exhibit varying productivity levels; however, the entry effect captures only those that survive until the end of the final year of observation. Consequently, more extended study periods introduce a survivor bias, as firms that exit before the final year are excluded from the decomposition analysis. To mitigate this bias, we assessed the impact of labor reallocation on overall productivity change using multiple sub-periods: 2010–2011, 2010–2012, 2011–2015, 2012–2013, 2013–2015, 2014–2015, and 2010–2015. This design allows for comparisons between analyzing a single six-year period (2010–2015) and aggregating three consecutive two-year periods (2010–2011, 2012–2013, 2014–2015), as well as between the six years and the sum of two three-year periods (2010–2012, 2013–2015). Table 4 presents the results of this segmentation, which decomposes productivity growth over an extended horizon into shorter periods to examine their effects separately.

Table 4. Splitting up the data and summing over periods

# Period (s) of # year(s)	industry selection	Firm selection	learning	entry	exit
2010-2015, ΔZ/Z=0.20					
1 of 6	-0.06	-0.01	0.27	-0.04	0.04
%	-26.97	-5.85	130.76	-17.24	19.30
2 of 3	-0.06	0.01	0.06	-0.06	0.07
3 of 2	-0.02	0.03	0.36	-0.08	0.06

Source: Decomposition of manufacturing labor productivity growth (ΔZ/Z) using the multilevel Price's equation. Values show percentage point contributions to changes in manufacturing labor productivity. The data are divided into several shorter periods, which are decomposed separately.

The results indicated that the entry effect is smaller when viewed as the sum of sub-periods. Additionally, as the period shortens, the exit effect becomes more noticeable. The industry and firm selection effects over a single decomposition period are smaller than when they are summed across shorter periods (3 of 2). The firm selection effect turns positive as the interval decreases, showing that firms' productivity is not evenly distributed around the industry average. In other words, firms differ in labor productivity. We believe these findings could be valuable to stakeholders from various backgrounds, such as company managers, investors, researchers, and policymakers. In other words, these results encourage further investigation into the factors that boost labor productivity in some years and those that reduce it in others.

IN CONCLUSION

Labor productivity growth can stem from internal drivers—such as R&D, human capital accumulation, and skill development—or external shifts in labor allocation from low to high value-added economic activities. The selection effect, whereby more productive firms replace less efficient ones, can either enhance or hinder growth, depending on market dynamics and competitive pressures. The impact of selection on overall productivity growth can be positive, as seen in many Asian countries, or negative, as observed in some Latin American and African countries. The productivity decomposition is well studied in developed economies, while evidence from developing countries remains scarce.

Using Price's Equation, this study examined the selection effect with firm-level data in Turkish manufacturing (2011–2015). Single-level analysis identified learning, firm selection, and exit effects as key contributors to labor productivity growth, while multilevel analysis highlighted learning and positive exit effects. We also identified high-productivity sectors—such as beer (1105), tobacco (1200), precious metals (2441), spacecraft machinery (3030), pharmaceuticals (2120), and refined petroleum (1920)—whose employment shares increased alongside productivity growth. Additionally, high labor productivity growth was observed in firms producing coke oven products (1910), meat processing and preservation (1011), household and sanitary goods (1722), and optical instruments and photographic equipment (2670), which also saw above-average gains in employment share. Conversely, several industries experienced high productivity growth despite a decline in their employment shares.

The labor productivity growth in Turkish manufacturing industries during the period was modest, partly due to a non-selective incentive system and competitive pressures from trade liberalization that forced less productive firms to adapt or exit. Strengthening the business environment through regulatory reforms and enhanced innovation policies, particularly increased R&D investment, is essential. Future research should explore total factor productivity as a more comprehensive measure for analyzing the interplay between selection and productivity growth.

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