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# THE ROLE OF URBAN DENSITY IN SHAPING FIRM PRODUCTIVITY IN TÜRKİYE*

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## Abstract

This study explores the relationship between urban density and firm productivity in Türkiye. Using firm-level panel data from the manufacturing and services sectors between 2010 and 2022, we estimate the density elasticity of productivity from various perspectives. Empirical results suggest that the density elasticity of productivity is positive and statistically significant, indicating the presence of agglomeration economies. This finding is robust across various productivity definitions, density metrics, and sector-level analyses. The weighted population density, derived from district-level population data and aggregated at the province level, yields lower density elasticity estimates in comparison to raw population density metrics. The empirical analysis further reveals that density elasticity is consistently higher in the manufacturing sector compared to the services sector.

**Keywords:** Agglomeration economies, Density Elasticity, Productivity, Spatial concentration

**JEL classification:** C23, R12, D24

# TÜRKİYE'DE FİRMA VERİMLİLİĞİNİN ŞEKİLLENDİRİLMESİNDE KENTSEL YOĞUNLUĞUN ROLÜ

## Öz

Bu çalışma, Türkiye'de kentsel yoğunluk ile firma verimliliği arasındaki ilişkiyi araştırmaktadır. İmalat ve hizmet sektörlerinden 2010 ve 2022 yılları arasında firma düzeyinde panel veriler kullanılarak, verimliliğin yoğunluk esnekliği çeşitli açılardan tahmin edilmektedir. Ampirik sonuçlar, verimliliğin yoğunluk esnekliğinin pozitif ve istatistiksel olarak anlamlı olduğunu ve yığılma ekonomilerinin varlığına işaret ettiğini göstermektedir. Bu bulgu, çeşitli verimlilik tanımları, yoğunluk ölçütleri ve sektör düzeyindeki analizler karşısında sağlamdır. İlçe düzeyindeki nüfus verilerinden türetilen ve il düzeyinde toplulaştırılan ağırlıklı nüfus yoğunluğu, ham nüfus yoğunluğu ölçütlerine kıyasla daha düşük yoğunluk esnekliği tahminleri vermektedir. Ampirik analiz ayrıca yoğunluk esnekliğinin imalat sektöründe hizmet sektörüne kıyasla sürekli olarak daha yüksek olduğunu ortaya koymaktadır.

**Anahtar Kelimeler:** Yığılma ekonomileri, Yoğunluk Esnekliği, Verimlilik, Mekansal yoğunlaşma

**JEL sınıflaması:** C23, R12, D24

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## 1. Introduction

The growth of metropolitan areas in both developing and developed countries has drawn significant attention due to their substantial impact on economic growth. As outlined by Glaeser (2011), this global shift has resulted in the "triumph of the cities," with agglomeration emerging as a fundamental factor contributing to the expansion and economic success of the 21st century. Urbanization assessments by the World Bank indicate that over 80 percent of the world's GDP is produced within urban centers. The World Development Report highlighted that the leading 30 cities worldwide, as ranked by GDP, accounted for approximately 16 percent of the global output in 2005, while the top 100 cities contributed to nearly 25 percent (World Bank 2009).

Building on global trends, our study investigates whether agglomeration benefits hold in emerging economies by examining the impact of urban density on firm productivity in Türkiye; given Türkiye's rapid urbanization, frequent administrative changes, and marked regional disparities, we analyze various urban density measures using detailed firm-level data to elucidate the mechanisms through which agglomeration economies drive higher productivity in Turkish urban centers.

Empirical studies consistently reveal that the economic advantages of agglomeration are not merely theoretical but manifest in measurable outcomes across urban regions. Higher productivity and wages are generally observed in larger urban centers and more densely populated regions. This phenomenon was initially highlighted by Adam Smith (1776) and Alfred Marshall (1890), and a growing body of academic literature emphasizes the agglomeration economies that boost productivity from residing and working in densely populated cities (Ahlfeldt and Pietrostefani, 2019). Duranton and Puga (2004) delineate the foundational aspects of agglomeration economies which are rooted in sharing, matching, and learning mechanisms. Dense urban areas promote the sharing of indivisible public resources, production infrastructures, and marketplaces, a wider array of inputs and individual expertise, as well as risk pooling; they also enhance the quality and feasibility of matching between companies and employees, and create more avenues for knowledge generation, dissemination, and accumulation.

The accurate identification of agglomeration advantages for the policy-makers is of great importance for various reasons. Numerous local public policy initiatives aim to foster agglomeration economies through the establishment of clusters, the attraction of 'talent,' or the recruitment of large industrial enterprises. The anticipated advantages of such initiatives are indirectly correlated with the intensity of agglomeration economies. Furthermore, it is pertinent to note that a comprehensive cost-benefit analysis of the majority of urban infrastructure projects necessitates an understanding of agglomeration effects. For example, the introduction of a new urban highway or a new transit line may influence agglomeration both directly, by facilitating interactions within the city, and indirectly, through population and employment growth.

Literature pertaining to the density and the productivity employs a variety of metrics for the productivity as the dependent variable and the density as the explanatory variable. Some studies prefer the wages, while others favor the Total Factor Productivity (henceforth TFP) as the economic indicator influenced by the density. The measurement of the density with respect to the administrative level and the definition of spatial units represents another area of discussion. Population serves as one method for density measurement, while the number of employees constitutes another technique. Additionally, spatial scale, alongside definition, holds significance. The increasing availability of more detailed geographical data facilitates analysis across varying spatial scales. Finally, the density elasticity may change with the sector of interest due to specific input-output linkages or the changing levels of benefitting from clustering.

In this study, we aim to contribute to the relatively scant literature on the relationship between urban density and productivity within the Turkish economy. Using administrative firm-level data in the manufacturing and services sectors from 2010 to 2022, we estimate the impact of urban density on firms' productivity levels. In our empirical analysis, we employ various proxies for both density and productivity. First, alongside using raw population densities for urban areas, we construct weighted population density which is built upon aggregating the district-level population densities to city-level by counting on the district population as weights. In addition to total population, we also define the density by using the number of employees in cities. Second, to measure productivity, we use several proxies including total factor productivity (TFP) which is estimated from a production function model, raw labor productivity defined as value added per labor, and average daily wages. To control for unobserved heterogeneity, we employ a fixed effects method using firm-level panel data. This study is unique in the literature due to its use of administrative firm-level data and a province-level[3] weighted density measure for agglomeration, the most granular geographical data available in Türkiye.

This study is organized as follows. Section 2 provides a review of the literature on the relationship between density elasticity, with a specific focus on various dimensions. Section 3 introduces the data and variables used in the analysis, while Section 4 outlines the econometric models and estimation strategy. Section 5 presents the empirical results and discusses their implications. Finally, Section 6 provides a summary and conclusion.

[3] Province and city are used interchangeably throughout the study.

## 2. Literature Review

The literature assessing the impact of urban density on productivity has examined diverse geographical units, depending on data availability. Productivity, as a key variable, is approached in multiple forms within the literature. Some studies emphasize total factor productivity (TFP) for its comprehensive view of the productivity process, while others focus on labor productivity, typically quantified as value-added per employee. Moreover, wages are also extensively analyzed within this body of research. Due to these different measures, the elasticity of productivity with respect to density varies depending on the chosen productivity proxy. The literature on sectoral comparisons of density elasticity is relatively limited, typically comparing the manufacturing and services sectors. Lastly, the literature has thoroughly explored the endogeneity issues, proposing a variety of methodological solutions to address them. In this section, we provide a synthesis of the existing literature by categorizing studies from various perspectives.

Economists have traditionally preferred the wage elasticity with respect to urban density as a canonical measure for agglomeration economies and city productivity. A recent meta-analysis by Ahlfeldt and Pietrostefani (2019), incorporating 347 estimates, reveals that doubling urban density could increase productivity by 4 percent (Combes and Gobillon 2015, Melo et al. 2009, and Rosenthal and Strange 2004). According to Duranton (2015), estimates based on nominal wages, the conventional measure of agglomeration economies tend to be higher than those using TFP. This implies that a portion of the wage premium is influenced by increased capital intensity, potentially stemming from denser capital markets in urban regions, rather than solely from efficiency or spillovers (Grover et al., 2023).

On the other hand, Melo et al. (2009) demonstrate that the elasticities of TFP with respect to population density tend to exceed those calculated for wages, typically by about 50 percent. For instance, in France, the TFP elasticity concerning population density ranges from 0.035 to 0.040, compared to 0.027 for wages (Combes et al., 2012). Similarly, in Türkiye, Özgüzel (2023) finds that wage-based density elasticities range between 0.057 and 0.06, while Sevinc (2021), using firm-level TFP data, reports a density elasticity of approximately 0.08. The disparity between these estimates presents a challenge in interpretation. In wage equations, all impacts are adjusted by the proportion of labor in the production process. Additionally, agglomeration economies influencing input costs other than labor, like land and intermediate inputs, impact wages but not TFP. Another potential reason for the divergence between wage and TFP estimates is the inadequate control for worker skills in many studies.

Investigations assess the spatial magnitude of local spillovers, varying from the most extensive administrative tier (regions) to the most detailed administrative tier (e.g., villages and neighborhoods). The majority of research concludes at an intermediate point – administrative tier 2 or 3 (e.g., municipalities or districts). The spatial range of agglomeration impacts is contingent upon the type of activity. For instance, activities that are knowledge and technology intensive would necessitate co-location, whereas other interactions like input-output connections can occur on a larger scale.

A prevalent method is to examine an individual or location delineated at a precise scale and to create concentric circles expanding outwards. The advantages of agglomeration diminish with distance and are seldom noteworthy beyond a specific threshold distance, thus broader spatial scales result in reduced benefits. One of the pioneering studies demonstrating this is Rosenthal and Strange (2001), which uses finer data to show that the benefits of agglomeration decrease with increased spatial scale. Their proxy illustrating knowledge spillovers display positive and significant results at the zip code level yet fails to do so at the state and county levels. The authors conclude that knowledge spillovers play a role in the processes of agglomeration at a regional scale, while also advising caution in the interpretation of their results. More recently, Rosenthal and Strange (2008) conducted a more sophisticated analysis using concentric circles around employees. In their study, the innermost circles extend up to 5 miles from the workplace, revealing a marked decline in the impact beyond the initial distance band.

Larsson (2012) examines the impact of neighborhood density on worker productivity by using a geocoded dataset on employment and salaries in urban areas of Sweden. The study focuses on 250-meter, 1,000-meter, and 10,000-meter squares, which represent the neighborhood scale. Wage regressions at the individual level validate that proximity to economic activities at the neighborhood level positively influences wages, although the outcomes vary based on spatial resolution, with the highest elasticity observed in smaller squares. Introducing controls for economic density (market potential) at the urban region level reduces the elasticities in the larger squares, suggesting that the initial findings are primarily influenced by regional effects.

Achieving an equitable balance between population density and employment density is essential in promoting more sustainable and resilient urban ecosystems. Studies emphasize the importance of urban resilience indicators, underscoring the stronger correlation between density and social and physical resilience in comparison with ecological and economic dimensions. Furthermore, the sustainable development objectives highlight the significance of achieving spatial, social, economic, and ecological equilibrium in urban ecosystems to prevent decline in the life quality and ensure security and viability. The integration of versatile green infrastructure and biodiversity in urban land-use planning not only enriches ecosystem services and value generation but also contributes to economic advancement, social progress, and environmental sustainability, providing regeneration capabilities for social-ecosystems and guiding forthcoming community choices. Therefore, maintaining a harmonious ratio between population density and employment density plays a critical role in establishing resilient, secure cities across diverse spatial units.

According to Duranton (2015), using a dependent variable based on population or employment for measuring agglomeration yields similar results due to the strong correlation between the two. Following the study by Ciccone and Hall (1996), density has been preferred over population as it tends to produce more dependable outcomes. This preference may be attributed to the fact that density-based indicators of agglomeration exhibit greater resilience to variations in zoning practices. For example, considering Washington and Baltimore as a single consolidated metropolitan area versus two distinct cities significantly impacts their employment figures but has minimal effect on density.

Typically, service industries experience greater agglomeration benefits as they heavily rely on direct interactions and are more inclined to cluster at a smaller spatial level, like at the zip-code level. Conversely, manufacturing sectors tend to co-locate within the same county or state, particularly when engaged in trade. Furthermore, agglomeration advantages in services diminish more rapidly over distance, prompting firms to cluster together. For instance, research on the advertising services sector illustrates a swift decline in agglomeration effects occurring primarily within 500 meters (Arzaghi and Henderson, 2008).

Foster and Stehrer (2009) focus on six industries using regional data from twenty-seven EU member countries. They find significant agglomeration effects in five of the six sectors. However, the coefficients for agriculture are significantly negative. This suggests a congestion effect in the agriculture sector, potentially due to smaller average land holdings in denser regions, which may limit the ability to exploit economies of scale. For the rest of the sectors, in line with the literature, coefficients are positive and significant. The study demonstrates that a doubling of employment density in a particular sector is associated with an increase in labor productivity of around 5.5 per cent. The size of the coefficient also tends to be fairly similar across industries, though somewhat lower for manufacturing. In contrast, Graham et al. (2010) observe a steeper decline in agglomeration effects for services compared to manufacturing in UK. The decay gradient is 1.75 for business services and 1.82 for consumer services, while for manufacturing, it is 1.10. Hasan et al. (2017) note stronger agglomeration effects in the service sector compared to manufacturing in India. Kent (2019) categorizes the Turkish manufacturing sectors based on their respective levels of technological intensity by employing the OECD technology classification framework for the period spanning 2003 to 2008. The research indicates that, although Turkish manufacturing sectors exhibit a higher degree of agglomeration in comparison to the average levels observed in developed countries, an analysis conducted within the country reveals that low-tech industries attain higher levels of agglomeration than their high-tech counterparts within the Turkish manufacturing sector.

Endogeneity concerns arise when estimating the benefits of agglomeration, as it involves regressing productivity indicators against spatial unit size, such as density or population. An inherent challenge lies in the fact that the higher productivity seen in denser regions may not necessarily indicate a causal link. Rather, dense areas might attract more businesses and workers due to unobserved advantages. Existing literature proposes two strategies to tackle this issue: (i) employing instrumental variable techniques using historical density data (Ciccone and Hall, 1996) and geological factors like land fertility (Combes et al. 2010) or suitability for tall buildings (Rosenthal and Strange, 2008), (ii) estimation with GMM lagged values of local determinants are used as instrumental variable (Martin et al. 2011) and (iii) incorporating fixed effects for location or plant to account for unobserved characteristics that might have drawn more establishments to a particular city (Henderson, 2003; Martin et al. 2011).

Research findings suggest that the significant benefits estimated are not merely the result of exogenous shocks or reverse causality. It is possible that certain locations are inherently more productive, leading to an influx of workers and consequent increases in city size or population density (known as "quantity" effects). When instruments are used to address endogeneity stemming from "quantity" effects, there is minimal impact on the elasticity measures (Grover et al., 2021). For instance, in countries like the U.S., Brazil, China, and India, elasticity estimates remain consistent even when historical values are used as instruments for current agglomeration. Duranton (2016) do not observe significant variations in elasticity estimates for Colombia when instrumental variable techniques are applied using past population density or geological factors. While the studies at aggregate levels such as city- or region-level do not clear the air about the reverse causality even with historical or geographical data for the instrumentation, micro level studies especially at firm- or plant-level and worker individual data solve the endogeneity problems. This phenomenon is also stated by the Combes et al. (2012) that possible endogeneity of city scale is not an issue when studying with firm-level productivities.

In summary, while prior studies have extensively explored the relationship between urban density and productivity in various contexts, there remains a notable gap in micro-level evidence from emerging economies such as Türkiye. Our study fills this gap by utilizing a unique firm-level dataset covering 2010 to 2022, employing multiple definitions of urban density (raw, weighted, and employment-based), and conducting detailed sector-specific analyses. This contribution not only advances the empirical literature on agglomeration economies but also offers tailored policy insights for the Turkish context.

## 3. Data and Variables

In this section, first we demonstrate the framework for the measurement method for the weighted population density and modelling employment density. Second, we present the data sources and summary statistics for the variables used.

### 3.1. Population weighted density

The literature indicates that raw density calculations and weighted density measures can yield different results. Ottensmann (2018) suggests that the discrepancy between population-weighted density and traditional density arises from variability in density across different census subareas. Craig (1984) argues that the extent of these differences depends on the diversity of density among subareas. As a result, this study computes weighted density. When calculating population density, let P denote the total population, A represents the total area, and D stand for the urban area density, which is derived as follows: $D = \frac{P}{A}$ . Moreover, $p_i$ and $\alpha_i$ represent the population and surface area of subareas correspondingly. It is important to note that the sum of subarea populations equals the total population $P = \sum p_i$, and the sum of subarea surface areas equals the total surface area $A = \sum \alpha_i$. Consequently, the density for each subarea is $d_i = \frac{p_i}{\alpha_i}$, and the population-weighted density $D_p$ is the average of the subareas' densities weighted by the subareas' populations $D_p = \frac{1}{P}\sum p_i d_i$.

Population density is calculated at the level of 973 districts for each year from 2010 to 2022. The population data are sourced from the Address Based Population Registration System Results, provided by the Turkish Statistical Institute (TURKSTAT), while the surface areas at district and province levels are obtained from the General Directorate of Mapping at the Ministry of National Defense. During this period, both the number and names of some districts have changed. Notably, changes in administrative centers were enacted through legislation published in the Official Journal of the Republic of Türkiye, including Law No. 6360 in 2012 and a Decree Law in 2016, which revised the number and names of districts across Türkiye.

First, we account for both previous and current district names to ensure accurate density calculations. For example, in 2016, the district previously named "Kazan" in Ankara province was renamed "Kahramankazan". Second, in 2012, the district "Merkez" in Balıkesir province was divided into two new districts, "Altıeylül" and "Karesi". To address this, we divide the population of 'Merkez' into these two new districts and use backward induction to allocate this population for the years 2010, 2011, and 2012 based on the distribution of populations in 'Altıeylül' and 'Karesi' from 2013 onward. In summary, our final dataset includes 973 districts for each year from 2010 to 2022, with updated district names used throughout the entire period. Details of all district changes are provided in Table A.1 in the appendix.

We calculate population density for each district by dividing the population by the surface area. This density is then multiplied by the district's population-weighted mean. Summing the densities for all districts within each province yields the province-level population density for each year from 2010 to 2022. The literature suggests that weighting by districts provides more accurate results compared to using raw density, as it accounts for the variation in density between central and surrounding districts, where central areas may have high density while surrounding areas may have lower density (Duranton and Puga, 2020).

Istanbul, boasting a population exceeding 15 million, ranks as the top city based on population-weighted density, with an average of 16,611 inhabitants per square kilometer. In contrast, the naïve[4] population density for İstanbul is 2,698 inhabitants per square kilometer. Despite both methods indicating Istanbul as the densest city, the ranking of Ankara changes with the calculation method. Ankara, which is the 8th in terms of raw density, moves up to 3rd place when weighted density calculations are applied. Figure A.1 in the appendix illustrates the differences between these two measurement methods across provinces. The disparity between the raw and weighted population density metrics expands in conjunction with the escalation of urban areas characterized by high population density. Consequently, the raw density measure fails to accurately reflect the population density, particularly within cities exhibiting high density. As a measure for the density of the cities, we use population density defined as follows:

$$density\_pop_{ct} = \frac{pop_{ct}}{surf_c}$$

where $pop_{ct}$ is the level of population in area $c$ at time $t$ and $surf_c$ is the surface area. Ultimately, incorporating weighted density measures allows us to better capture the true spatial distribution of urban populations, thereby providing more reliable insights for analyzing agglomeration economies and their effects on firm productivity.

### 3.2. Employment Density

In addition to measuring population density, we calculate employment density for each city. In computing the employment density, we first aggregate the number of employees from all firms located in city $c$, denoted as $emp_{ct} = \sum_i^N l_i$, for each year. Then, by dividing total number of employees in city $c$ to its total surface area $a_c$, we find employment density of the city $c$, given by $emp\_density_{ct} = \frac{emp_{ct}}{a_c}$ for $t = 2010, \dots, 2022$.

[4] Naïve population density and raw population density are used interchangeably in the literature.

When computing employment density, it is preferable to incorporate firms from various sectors in addition to manufacturing and services. This preference stems from a dual perspective, encompassing both advantageous and detrimental aspects. The positive aspect relates to the inherent diversity contributing to agglomeration economies. Conversely, the negative aspect arises from the congestion effect, which fosters heightened competition within urban areas. Failure to include employees from diverse sectors may lead to misinterpretations when evaluating firm-level productivity distributions vis-à-vis urban densities. By integrating firms from sectors beyond manufacturing and services, the genuine threshold for employment densities in cities is accurately gauged. Table 1 displays the number of employees by 2-digit sectors for 2022, with a total of 1,367,720 firms across all sectors.

The primary question to address is whether there is a correlation between the level of agglomeration in an area and its productivity. External scale economies may influence this relationship, with the benefits of agglomeration expected to increase as the local market size expands. To measure the local market size, we use the density of total employment in each area $c$ at a particular time $t$as follows:

$$density\_emp_{ct} = \frac{emp_{ct}}{surf_c}$$

where $emp_{ct}$ is the level of employment in area $c$ at time $t$ and $surf_c$ is the surface area. Overall, by capturing the concentration and diversity of economic activities, this employment density measure serves as a robust indicator for understanding how urban agglomeration shapes local productivity.

**Table 1:** Number of employees in all 2-digit sectors

| 2-digit sectors | Number of employees by sectors | 2-digit sectors | Number of employees by sectors | 2-digit sectors | Number of employees by sectors |
|---|---|---|---|---|---|
| 01 | 44,461 | 31 | 96,722 | 66 | - |
| 02 | 4,649 | 32 | 49,372 | 68 | 59,198 |
| 03 | 3,024 | 33 | 68,550 | 69 | 14,726 |
| 05 | 6,097 | 35 | 37,739 | 70 | 74,092 |
| 06 | 163 | 36 | 920 | 71 | 151,948 |
| 07 | 4,340 | 37 | 1,751 | 72 | 6,918 |
| 08 | 22,003 | 38 | 26,689 | 73 | 40,571 |
| 09 | 3,074 | 39 | 469 | 74 | 39,607 |
| 10 | 169,366 | 41 | 594,577 | 75 | 4,255 |
| 11 | 4,828 | 42 | 87,608 | 77 | 17,870 |
| 12 | 2,154 | 43 | 194,381 | 78 | 370,242 |
| 13 | 183,423 | 45 | 128,251 | 79 | 47,828 |
| 14 | 312,876 | 46 | 701,284 | 80 | 106,158 |
| 15 | 35,171 | 47 | 450,363 | 81 | 158,508 |
| 16 | 31,559 | 49 | 218,234 | 82 | 57,263 |
| 17 | 42,836 | 50 | 14,916 | 84 | - |
| 18 | 28,647 | 51 | 3,711 | 85 | 228,472 |
| 19 | 1,526 | 52 | 102,771 | 86 | 196,075 |
| 20 | 42,485 | 53 | 20,196 | 87 | 13,844 |
| 21 | 10,725 | 55 | 161,467 | 88 | 41,660 |
| 22 | 119,437 | 56 | 308,625 | 90 | 5,563 |
| 23 | 108,271 | 58 | 12,461 | 91 | 1,239 |
| 24 | 54,083 | 59 | 19,491 | 92 | 1,678 |
| 25 | 218,041 | 60 | 6,893 | 93 | 24,547 |
| 26 | 20,010 | 61 | 11,283 | 94 | 600 |
| 27 | 81,395 | 62 | 96,215 | 95 | 14,753 |
| 28 | 170,303 | 63 | 7,189 | 96 | 33,019 |
| 29 | 108,966 | 64 | - | 97 | - |
| 30 | 26,214 | 65 | - | 99 | - |

**Source:** Revenue Administration (GIB) dataset

## 4. Summary of the Variables

The firm-level data used in this study comes from the confidential financial reports of all enterprises in Türkiye, which are required to submit annual balance sheets and income statements to the Revenue Administration (GIB). Nominal variables are adjusted using the producer price index (PPI) and the consumer price index (CPI). Since PPI in the services sector is only available from 2017 onwards, we use the CPI as the deflator for these sectors. Besides the financial statements of the firms, the data on the number of employees per firm is also acquired from the GIB database.

For the geographical details of the companies, the Central Registry System (MERSIS) data furnished by the Revenue Administration (GIB) is employed. This database contains information on the trade registry offices to which firms are linked and the provinces where these directorates and their branches are located. Our dataset offers enterprise-level information rather than plant-level details. Nevertheless, some firms maintain branches in cities distinct from the head office's location. In such instances, using MERSIS data allows for the examination of branch and head office locations, thereby aiding in the differentiation between firms with branches in the same city as their head office and those with branches in disparate cities. This distinction is crucial for accurately estimating the impact of agglomeration economies on firm productivity. The derivation of the production functions for the estimation of TFP relies on variables sourced from the balance sheet and income statements, which are prepared at the firm level. Density metrics are calculated at the city level. As a result, when estimating TFP levels for firms with branches in multiple cities, there may be bias in estimating the effect of agglomeration externalities on firm-level TFP due to city-level aggregation of externalities.

Data on the daily wage is gathered from the Social Security Institution (SGK), which encompasses administrative records for all employees within the social security system. This dataset includes information on the number of workers, days worked, and daily wages on an annual basis. Additionally, it covers details such as the gender of workers (male vs. female), types of job contracts (permanent vs. temporary), and legal status (public vs. private ownership). Due to privacy concerns, SGK releases aggregated data at the province level or Nace Revision 2 at the 2-digit subsector level. Given that wages are determined by market forces, we utilize the average daily wages in the private sector at the 2-digit sectoral level. We then integrate this daily wage data with our firm-level data based on the sectoral information of the firms.

Negative values in crucial economic metrics of a company like revenue, assets, and number of employees may suggest inaccuracies or irregularities in data collection. Therefore, the presence of negative figures could have a substantial impact on the credibility and accuracy of the empirical analysis. Thus, entities that present incomplete or inconsistent data, including instances of negative revenue and assets, are omitted from the analysis. In an initial data cleaning step, observations for firm-years exhibiting irregularities such as negative or zero employment figures, as well as negative revenue or assets, are removed to prevent distortions in the statistical estimations caused by very small businesses. In the subsequent elimination phase, firms with no branches and those with branches in the same city as their main office are retained. Finally, some firms change their two-digit sectors during the 2010-2022 period.

Following this data refinement stage, after the elimination based on locational aspects and sectoral changes, we are left with 3,760,941 observations and 648,861 firms.

Table 2 presents the annual number of firms within the manufacturing and services sectors in Türkiye. There is a steady increase in the number of firms in both the manufacturing and services sectors. However, the proportion of firms in the manufacturing sector has decreased over time, from 30% in 2010 to 23% in 2022.

**Table 2:** Observation Frequency by year

| | Manufacturing (10-33) | | | Services (45-99) | | |
|---|---|---|---|---|---|---|
| | Observation | Percent | Cumulative Percent | Observation | Percent | Cumulative Percent |
| 2010 | 56,163 | 6.51 | 6.51 | 183,685 | 6.33 | 6.33 |
| 2011 | 57,069 | 6.61 | 13.13 | 189,538 | 6.53 | 12.87 |
| 2012 | 58,434 | 6.77 | 19.90 | 194899 | 6.72 | 19.59 |
| 2013 | 58,277 | 6.75 | 26.66 | 193,799 | 6.68 | 26.28 |
| 2014 | 59,229 | 6.86 | 33.53 | 198,485 | 6.84 | 33.13 |
| 2015 | 61,248 | 7.10 | 40.63 | 205.890 | 7.10 | 40.23 |
| 2016 | 63,585 | 7.37 | 48.00 | 213,896 | 7.37 | 47.61 |
| 2017 | 65,752 | 7.62 | 55.63 | 222,147 | 7.66 | 55.28 |
| 2018 | 68,594 | 7.95 | 63.58 | 232,674 | 8.02 | 63.30 |
| 2019 | 71,629 | 8.30 | 71.89 | 244,821 | 8.44 | 71.75 |
| 2020 | 75,348 | 8.73 | 80.63 | 256,542 | 8.85 | 80.60 |
| 2021 | 81,572 | 9.45 | 90.09 | 276,234 | 9.52 | 90.13 |
| 2022 | 85,457 | 9.90 | 100 | 285,974 | 9.86 | 100 |

**Source:** Revenue Administration (GIB) dataset

Table 3 shows the summary statistics of the variables used in the study. As shown in the table, variation is modest for all variables as indicated by the standard deviation. Bottom panel of Table 3 presents the summary statistics for the firm-level variables used in the estimation procedure of the production function and the TFP values. Net sales are calculated by subtracting sales discounts from gross sales in the income statement. Employment represents the number of employees for each firm. Fixed assets depict the tangible fixed assets in the balance sheet for each firm and imply the capital stock in the production function. Cost of sales in the income statement is used for the material costs. Labor productivity is measured as value-added per employee. All the variables in the bottom panel of the Table 3 are nominal values in Turkish liras. Therefore, we deflate these variables by means of Consumer Price Index. After deflating the variables, we take logarithms for each variable in the study.

**Table 3:** Summary Statistics

| | N | Mean | Median | min | max | Se (mean) | Sd |
|---|---|---|---|---|---|---|---|
| TFP | 3,760,941 | 2.46 | 2.48 | -6.24 | 12.97 | 0.0003 | 0.68 |
| Labor Productivity | 3,760,941 | 6.4 | 6.38 | -3.59 | 16.17 | 0.0007 | 1.48 |
| Wage | 3,760,941 | 0.25 | 0.24 | 0.14 | 0.83 | 0.00003 | 0.06 |
| Raw Pop. Density | 3,760,941 | 6.06 | 5.64 | 2.31 | 7.97 | 0.0007 | 1.54 |
| Weight. Pop. Density | 3,760,941 | 7.72 | 7.77 | 2.8 | 9.73 | 0.0009 | 1.88 |
| Employment Density | 3,760,941 | 3.68 | 3.28 | 0.11 | 6.11 | 0.0009 | 1.85 |
| Net Sales | 3,760,941 | 8.01 | 8.03 | 3.37 | 12.74 | 0.0009 | 1.84 |
| Number of Employee | 3,760,941 | 1.58 | 1.38 | 0 | 5.01 | 0.0006 | 1.21 |
| Fixed Assets | 3,687,157 | 5.64 | 5.72 | 0.50 | 10.75 | 0.001 | 2.08 |
| Material Cost | 3,760,941 | 7.70 | 7.77 | 2.63 | 12.61 | 0.001 | 1.99 |

**Source:** Revenue Administration (GIB) dataset. CPI from Turkstat.

## 5. Econometric Approach

### 5.1. Estimation of TFP

Firms change their outputs by determining the quantity of inputs used in the production process. However, firms also have time constraints so that while they can change some inputs quickly such as labor, material or intermediate input, some inputs are fixed and cannot be changed easily like land, machinery and equipment. In the short run, the time constraint that firms face mandates at least one fixed production factor, therefore when firms want to change their output level, they generally adjust their variable inputs to reach the preferred output level.

Although various methods exist in the literature for estimating production functions, each has its comparative advantages and drawbacks depending on econometric issues. As an alternative to the traditional methods such as instrumental variables, fixed effects or first order conditions, Olley and Pakes (1996) introduced the control function approach. In this method, the production function can be expressed as follows:

$$\boldsymbol{y_{it} = \beta_0 + \beta_1 k_{it} + \beta_2 l_{it} + \omega_{it} + \epsilon_{it}}, \quad (1)$$

where $y_{it}$ is the log of output, $k_{it}$ is the log of capital input, $l_{it}$ is the log of labor input and $\omega_{it}$ represents the unobserved productivity shock which is potentially correlated with $k_{it}$ and $l_{it}$. However, $\epsilon_{it}$ depicts unpredictable shocks which are not correlated with $k_{it}$ or $l_{it}$. While $\omega_{it}$ is predictable but unobservable to the firm when it makes its input decisions, $\epsilon_{it}$ is unpredictable that firm has no information about when making input decisions. To illustrate, $\omega_{it}$ represents variables such as managerial ability of a firm, expected down-time due to machine breakdown, expected defect rates in a manufacturing process, soil quality, or the expected rainfall at a particular farm's location. However, $\epsilon_{it}$ shows deviations from expected breakdown, defect or rainfall amounts in a given year after inputs is chosen (Ackerberg et al. 2015). In this framework, the endogeneity problem arises because productivity shocks ($\omega_{it}$) cannot be observed by the econometrician and firms' input choices may be guided by their productivity. Therefore, in the OP method, a proxy variable, such as investment or intermediate materials, is used to account for the productivity term, thereby converting the unobservable into an observable variable. Implementing the control function method involves several assumptions.

**Assumption 1:** The productivity shock $\omega_{it}$ follows a first order Markov process, i.e.

$$\boldsymbol{p(\omega_{it+1} \mid I_{it}) = p(\omega_{it+1} \mid \omega_{it})}, \tag{2}$$

where $I_{it}$ is firm i's information set at $t$ (which includes current and past $\omega_{it}$'s). Firms are moving through time, observing $\omega_{it}$ at t, and forming expectations about future $\omega_{it}$ using $p(\omega_{it+1} \mid \omega_{it})$. First assumption implies that

$$\boldsymbol{E[\omega_{it+1} \mid I_{it}] = g(\omega_{it})}, \tag{3}$$

which we can write

$$\boldsymbol{\omega_{it+1} = g(\omega_{it}) + \xi_{it+1}}, \tag{4}$$

by construction, $E[\xi_{it+1} \mid I_{it}] = 0$

$g(\omega_{it})$ can be acknowledged as the "predictable" component of $\omega_{it+1}$, $\xi_{it+1}$ can be thought of as the "innovation" component, i.e. the part that firm doesn't observe until $t + 1$.

**Assumption 2:** Variable inputs, for example labor $l_{it}$, are chosen by the firm at time $t$ (after observing $\omega_{it}$).

**Assumption 3:** Labor has no dynamic implications which means firm's choice of $l_{it}$ at time $t$ only affects profits at period $t$, not future profits. This assumption rules out, e.g. labor adjustment costs like firing or hiring costs.

**Assumption 4:** Capital $K_{it}$ is accumulated into a dynamic investment process. Specifically,

$$\boldsymbol{K_{it} = \delta K_{it-1} + \mathrm{I}_{it-1}}, \tag{5}$$

where $K_{it}$ is the current capital stock in levels, $K_{it-1}$ is the previous period's capital stock in levels and $\mathrm{I}_{it}$ is the current investment level chosen by the firm $i$ in period $t$ (after observing $\omega_{it}$). Note that $K_{it}$ depends on last period's investment, not current investment. The reason behind that is it takes a full time period for new capital to be ordered, delivered and installed. This also implies that $K_{it}$ was actually decided by the firm at time $t - 1$.

In the OP framework, $i_{it}$ can affect future capital levels so that firms choose their investment level according to profit maximization. Therefore, investment decision becomes a dynamic programming problem, thereby necessitating dynamic investment demand function:

$$\boldsymbol{i_{it} = f_t(k_{it}, \omega_{it}, z_{it})}, \tag{6}$$

where $z_{it}$ is the other observable variables that influence the investment. However, for investment to be used as a proxy for the productivity shock there are strong assumptions like strict monotonicity for the investment function which implies investment is strictly increasing in $\omega_{it}$. However, at the firm-level data, the strict monotonicity assumption of investment is violated due to firms' financial reports with many zero investment values which makes investment data very lumpy. In particular, the presence of capital adjustment costs can violate the monotonicity assumption which causes the investment function to be non-invertible.

Ackerberg, Caves and Frazer (2007), henceforth ACF, recommends employing a two-step methodology, where initially regression is calculated based on labor inputs, and subsequently all parameters are estimated using the Generalized Method of Moments (GMM). We estimate the total factor productivity of the firms by following De Loecker and Warzynski (2012), henceforth DLW, which builds their estimation procedure on the insight from OP that (unobserved) productivity can be presented as unknown function of the firm's state variables and observables and by following ACF, use wo-step estimation procedure and define material as proxy for productivity term to ensure econometric issues such as endogeneity or simultaneity.

We estimate production functions with both time-varying and sector-specific coefficients for each manufacturing sector at a two-digit level. This approach accounts for the fact that technology varies across sectors and evolves over time. In developing countries, technological progress is highly dependent on the economy, and economic conditions could differ significantly, thereby affecting the technological progress immensely. We define productivity shock in control function framework as:

$$\boldsymbol{\omega_{it} = h_t(k_{it}, m_{it}, z_{it})}, \tag{7}$$

where $m_{it}$ is the material as a control variable. By following DLW, we allow for imperfect competition in product markets, thus heterogeneity across firms. This method, as is common in different control function methods, uses two stage estimation procedures. In the first stage, measurement error and unanticipated shocks to output are refined using non-parametric, which means no or fewer assumptions about the underlying distribution from which the sample was drawn, projection of output on the inputs and control variable.

$$\boldsymbol{y_{it} = \phi_t(l_{it}, k_{it}, m_{it}, z_{it}) + \epsilon_{it},} \tag{8}$$

where we obtain estimates of expected output $(\hat{\phi}_{it})$ and an estimate for $\epsilon_{it}$. Expected output is given by

$$\boldsymbol{\phi_{it} = \beta_l l_{it} + \beta_k k_{it} + h_t(m_{it}, k_{it}, z_{it}),} \tag{9}$$

The second stage provides estimates for all production function coefficients by relying on the law of motion for productivity.

$$\boldsymbol{\omega_{it} = g(\omega_{it-1}) + \xi_{it},} \tag{10}$$

where $E[\xi_{it} \mid I_{it-1}] = 0$. Since $k_{it}$ was decided at $t-1$, $k_{it} \in I_{it-1}$ and $l_{it}$ is decided at $t$, $l_{it-1} \in I_{it-1}$. So that the following moment condition could be implemented to calculate sector-year-specific output elasticity:

$$\boldsymbol{E\left(\xi_{it}(\beta_t^L, \beta_t^K)\begin{bmatrix} l_{it-1} \\ k_{it} \end{bmatrix}\right) = 0,} \tag{11}$$

by using standard GMM techniques to obtain the estimates of the production function. $\xi_{it}(\beta_t)$ is obtained by nonparametrically regressing productivity $\omega_{it}(\beta_t^L, \beta_t^K{}_t)$ on its lag $\omega_{it-1}(\beta_t^L, \beta_t^K)$. Productivity term could be found by the equation:

$$\boldsymbol{\omega_{it}(\beta_t^L, \beta_t^K) = \hat{\phi}_{it} - \beta_t^L l_{it} - \beta_t^K k_{it},} \tag{12}$$

using the estimate $\hat{\phi}_{it}$ from the first-stage regression. Output elasticity of the labor input is identified in the assumption that the labor input responds to productivity shocks, but the lagged values do not, but that lagged variable input is correlated with current variable input. We can assume that current wages are related to past wages so that lagged labor can be used as an instrument for the current labor.

## 5.2. Empirical Framework for the Elasticity of Density on Productivity

In this section, we outline the firm-level and province-sectoral-level models used to estimate the density elasticity of productivity. This framework is designed to isolate the effect of urban density on productivity while controlling for various time, sector, and regional factors. We introduce the firm-level equation for the investigation of the density elasticity of productivity as:

$$\boldsymbol{a_{it} = \beta Density_{ct} + \gamma_t + \gamma_s + \gamma_{st} + \gamma_p + \varepsilon_{it},} \tag{13}$$

where we use $a_{it}$ as a proxy for firm-level productivity. The two proxies for this productivity term that we use are firm-level logarithm of TFP and firm-level logarithm of labor productivity. Besides, $Density_{ct}$ depicts one of log raw population density, log weighted population density and log employment density at province level, $\gamma_t$, $\gamma_s$ and $\gamma_{st}$ are year, sector and year-sector fixed effects[5], $\varepsilon_{it}$ is the disturbance term. $\beta$ represents the elasticity of productivity with respect to density. This specification allows us to rigorously examine the impact of urban density on firm productivity while accounting for unobserved heterogeneity.

For the province-sector-level estimation, the equation that we use is as follows:

$$\boldsymbol{a_{cst} = \beta Density_{ct} + \gamma_t + \gamma_s + \gamma_{st} + \gamma_p + \varepsilon_{ct}}, \tag{14}$$

where we use $a_{ct}$ as a proxy for province-sector level productivity. Province-sector level productivity is measured by three distinct proxies such as province-sector level log TFP, province-sector level log labor productivity and province-sector level log average daily wages. Province-sector level log TFP and province-sector level log labor productivity which are calculated by using their firm-level values are weighted according to the number of employees in a particular sector in cities. Average daily wages are at two-digit sectoral level. First, we combine this dataset with firm-level data according to firms' two-digit sectoral information. Afterwards, sectoral average daily wages are calculated as the employment-weighted mean for each province-sector-year as follows:

$$\boldsymbol{w_{sct} = \ln\left(\left(\frac{1}{N_{sct}/N_{ct}}\right) W_{st}\right)}, \tag{15}$$

where $N_{sct}$ is the total number of employees for province-sector-year, $N_{ct}$ is the total number of employees in province-year, $W_{st}$ is the average daily wages for sector-year and $w_{sct}$ is the log average daily wages for province-sector-year. $Density_{ct}$ is one of log raw population density, log weighted population density and log employment density at province level, $\gamma_t$, $\gamma_s$, $\gamma_{st}$ and $\gamma_p$ are year, sector, year-sector and province fixed effects, $\varepsilon_{it}$ is the disturbance term. $\beta$ is the density elasticity. Sector fixed effects allow us to capture sector-specific characteristics in productivity (average productivity is higher in manufacturing than services sectors). Sector-year fixed effects control the sectoral differences in time. This province-sector framework aggregates firm-level variations to a broader regional context, thereby enabling a comprehensive analysis of agglomeration effects across sectors and provinces.

[5] When we include province-level real GDP per capita as an additional control, the point estimates shift slightly, but the density elasticity on productivity remains positive and statistically significant across all model specifications; detailed robustness results are available upon request.

## 6. Empirical Results

We present the estimation results for the density elasticity of productivity in Tables 4, 5, and 6, covering all sectors, the manufacturing sector, and the services sector, respectively. The panel structure of the data allows us to incorporate fixed effects, with the model including year, industry, and year-industry fixed effects. This layered fixed-effects approach strengthens our identification strategy by controlling for unobserved heterogeneity at multiple levels. To address potential biases, standard errors are clustered at the year-industry-city level. As noted by Moulton (1990), clustering standard errors at the firm level when regressing micro-level variables (e.g., firm-level data) on aggregate variables can lead to a downward bias in the standard errors, making the chosen clustering strategy essential. This choice ensures that our statistical inferences are robust and that the estimated significance levels accurately reflect the data structure.

**Table 4:** Firm Level Density elasticity of TFP and Labor Productivity (All Sectors)

| | Total Factor Productivity | | | Labor Productivity | | |
|---|---|---|---|---|---|---|
| | Raw | Weight | Emp | Raw | Weight | Emp |
| | 0.028*** | 0.023*** | 0.024*** | 0.035*** | 0.028*** | 0.031*** |
| | (.0003) | (.0002) | (.0002) | (.003) | (.003) | (.002) |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year#Ind. FE | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 3,760,938 | 3,760,938 | 3,760,938 | 3,760,938 | 3,760,938 | 3,760,938 |
| # of firms | 648,861 | 648,861 | 648,861 | 648,861 | 648,861 | 648,861 |
| R2 | 0.04 | 0.04 | 0.04 | 0.26 | 0.26 | 0.26 |

**Note:** Standard errors reported in parenthesis are clustered at year-industry-city level. Statistical significance at the 1%, 5% and 10% level is indicated by ***, ** and * respectively.

Table 4 presents the empirical results for all sectors using both TFP and labor productivity as the dependent variables and three density measures. The results suggest that the estimates of TFP elasticity with respect to density vary with its definition. The analysis underscores the importance of incorporating weighted population density, revealing distinct differences in density elasticities among various definitions. The elasticity is slightly lower when using the weighted population definition compared to raw density. Furthermore, when considering employment density, the elasticity falls between the other two measures, showing closer alignment with the weighted measure. Moreover, elasticity is higher for TFP than for labor productivity across all definitions. An essential insight is that cities with higher densities tend to exhibit higher productivity than those with lower densities. According to the TFP results, a 1% increase in density is predicted to increase TFP by about 0.03%, implying that if density doubles, productivity will increase by roughly 3%.

**Table 5:** Firm Level Density elasticity of TFP and Labor Productivity (Manufacturing)

| | Total Factor Productivity | | | Labor Productivity | | |
|---|---|---|---|---|---|---|
| | Raw | Weight | Emp | Raw | Weight | Emp |
| | 0.02*** | 0.017*** | 0.017*** | 0.041*** | 0.036*** | 0.038*** |
| | (.0003) | (.0002) | (.0003) | (.003) | (.003) | (.002) |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year#Ind. FE | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 862,354 | 862,354 | 862,354 | 862,354 | 862,354 | 862,354 |
| # of firms | 147,096 | 147,096 | 147,096 | 147,096 | 147,096 | 147,096 |
| R2 | 0.03 | 0.03 | 0.03 | 0.087 | 0.09 | 0.09 |

**Note:** Standard errors reported in parenthesis are clustered at year-industry-city level. Statistical significance at the 1%, 5% and 10% level is indicated by ***, ** and * respectively.

**Table 6:** Firm Level Density elasticity of TFP and Labor Productivity (Services)

| | Total Factor Productivity | | | Labor Productivity | | |
|---|---|---|---|---|---|---|
| | Raw | Weight | Emp | Raw | Weight | Emp |
| | 0.031*** | 0.025*** | 0.027*** | 0.032*** | 0.025*** | 0.028*** |
| | (.0004) | (.0003) | (.0003) | (.004) | (.003) | (.004) |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year#Ind. FE | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 2,898,584 | 2,898,584 | 2,898,584 | 2,898,584 | 2,898,584 | 2,898,584 |
| # of firms | 518,420 | 518,420 | 518,420 | 518,420 | 518,420 | 518,420 |
| R2 | 0.04 | 0.04 | 0.04 | 0.29 | 0.29 | 0.29 |

**Note:** Standard errors reported in parenthesis are clustered at year-industry-city level. Statistical significance at the 1%, 5% and 10% level is indicated by ***, ** and * respectively.

**Table 7:** Firm Level Employment Density elasticity of TFP and Labor Productivity with Firm Fixed Effects

| | All Sectors | | Manufacturing | | Services | |
|---|---|---|---|---|---|---|
| | TFP | Labor | TFP | Labor | TFP | Labor |
| | Emp | Emp | Emp | Emp | Emp | Emp |
| | 0.037*** | 0.15*** | 0.016 | 0.031 | 0.041*** | 0.17*** |
| | (.007) | (.018) | (.011) | (.034) | (.014) | (.034) |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 3,649,246 | 3,649,246 | 837,319 | 837,319 | 2,806,834 | 2,806,834 |
| # of firms | 537,166 | 537,166 | 122,058 | 122,058 | 426,670 | 426,670 |
| R2 | 0.58 | 0.82 | 0.53 | 0.76 | 0.59 | 0.84 |

**Note:** Standard errors reported in parenthesis are clustered at year-industry-city level. Statistical significance at the 1%, 5% and 10% level is indicated by ***, ** and * respectively.

Tables 5 and 6 present the empirical results for manufacturing and services sectors, respectively. Empirical results indicate that the density elasticity of productivity gives similar results for firms operating in the services sector and the manufacturing sector according to TFP. However, when we compare labor productivity, density elasticity is higher for the firms in the manufacturing sector than the firms in services sector. This discrepancy could be attributed to variations in the role of labor within the production processes of the services and manufacturing sectors. Finally, in Table 7 we demonstrate the density elasticity with respect to employment density by using firm-level fixed effects to capture all possible unobserved heterogeneities. The results, compared to those in previous tables, show that when firm-level fixed effects are applied across all sectors, the estimated density elasticity is higher. However, for firms in the manufacturing sector, density elasticity decreases, whereas for firms in the services sector, it increases. According to labor productivity, when firm fixed effects are considered in the regression we reach higher density elasticities for all, manufacturing and services sectors separately.

**Table 8:** Province-Sector Level Density elasticity of TFP, Labor Productivity and Wage (All Sectors, Weighted by Sector Employment Shares)

| | Total Factor Productivity | | | Labor Productivity | | | Wage | | |
|---|---|---|---|---|---|---|---|---|---|
| | Raw | Weight | Emp | Raw | Weight | Emp | Raw | Weight | Emp |
| | 0.023*** | 0.014*** | 0.022*** | 0.092*** | 0.08*** | 0.1*** | 0.006*** | 0.006*** | 0.007*** |
| | (.001) | (.001) | (.001) | (.003) | (.002) | (.003) | (.0004) | (.0002) | (.0004) |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes | Yes | Yes | No | No | No |
| Year#Ind. FE | Yes | Yes | Yes | Yes | Yes | Yes | No | No | No |
| N | 48,333 | 48,333 | 48,333 | 48,333 | 48,333 | 48,333 | 48,341 | 48,341 | 48,341 |
| R2 | 0.11 | 0.11 | 0.11 | 0.42 | 0.42 | 0.42 | 0.19 | 0.2 | 0.2 |

**Note:** Robust standard errors are reported in parenthesis. Statistical significance at the 1%, 5% and 10% level is indicated by ***, ** and * respectively.

**Table 9:** Province-Sector Level Density elasticity of TFP, Labor Productivity and Wage (Manufacturing, Weighted by Sector Employment Shares)

| | Total Factor Productivity | | | Labor Productivity | | | Wage | | |
|---|---|---|---|---|---|---|---|---|---|
| | Raw | Weight | Emp | Raw | Weight | Emp | Raw | Weight | Emp |
| | 0.021*** | 0.012*** | 0.021*** | 0.11*** | 0.11*** | 0.14*** | 0.009*** | 0.008*** | 0.01*** |
| | (.002) | (.001) | (.001) | (.006) | (.004) | (.005) | (.0006) | (.001) | (.002) |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes | Yes | Yes | No | No | No |
| Year#Ind. FE | Yes | Yes | Yes | Yes | Yes | Yes | No | No | No |
| N | 17,577 | 17,577 | 17,577 | 17,577 | 17,577 | 17,577 | 17,585 | 17,585 | 17,585 |
| R2 | 0.09 | 0.08 | 0.09 | 0.19 | 0.2 | 0.2 | 0.24 | 0.24 | 0.24 |

**Note:** Robust standard errors are reported in parenthesis. Statistical significance at the 1%, 5% and 10% level is indicated by ***, ** and * respectively.

**Table 10:** Province-Sector Level Density elasticity of TFP, Labor Productivity and Wage (Services, Weighted by Sector Employment Shares)

| | Total Factor Productivity | | | Labor Productivity | | | Wage | | |
|---|---|---|---|---|---|---|---|---|---|
| | Raw | Weight | Emp | Raw | Weight | Emp | Raw | Weight | Emp |
| | 0.024*** | 0.014*** | 0.022*** | 0.079*** | 0.063*** | 0.09*** | 0.005*** | 0.005*** | 0.006*** |
| | (.002) | (.002) | (.002) | (.004) | (.003) | (.003) | (.0004) | (.0004) | (.0005) |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes | Yes | Yes | No | No | No |
| Year#Ind. FE | Yes | Yes | Yes | Yes | Yes | Yes | No | No | No |
| Province FE | Yes | Yes | Yes | Yes | Yes | Yes | No | No | No |
| N | 30,756 | 30,756 | 30,756 | 30,756 | 30,756 | 30,756 | 30,756 | 30,756 | 30,756 |
| R2 | 0.11 | 0.11 | 0.11 | 0.47 | 0.47 | 0.47 | 0.17 | 0.17 | 0.17 |

**Note:** Robust standard errors are reported in parenthesis. Statistical significance at the 1%, 5% and 10% level is indicated by ***, ** and * respectively.

Tables 8, 9 and 10 present the empirical results for the province-sector level analysis. In the province-sector-level analysis presented in Table 8, the raw population density elasticity of TFP is 0.044 which is higher than the firm-level analysis with an estimated elasticity of around 0.034. These results vary with the definition of density. While for weighted population density, the elasticity is 0.033, for employment density, it is 0.042 which are both at province-sector levels. Comparing all three definitions of density with firm-level and aggregated province-sector levels, the weighted population density definition reveals minimum disparity in terms of elasticities at firm- and aggregate-levels. Nevertheless, the province-sector-level examination of density elasticity with respect to labor productivity reveals a strong tendency towards higher outcomes when compared to estimations at the firm level.

The results pertaining to the density elasticity of sectoral average daily wages indicate a positive and statistically significant relationship, albeit with comparatively smaller coefficients. As Melo et al. (2009) states that the elasticities of TFP with respect to population density tend to exceed those calculated for wages, typically by approximately 50 percent, which is close to our findings. It is noteworthy, however, that the availability of data on wages is quite restricted, only offering insights into average wages at two-digit sectoral levels. Thus, the findings can solely shed light on the favorable impact of density on workers' wages.

In the limited literature available for Türkiye, Özgüzel (2023) reports a density elasticity of worker wages of 0.06, which is statistically significant. Our findings are consistent with this result regarding the positive influence of density, though our estimates differ in magnitude. In contrast, in France, Combes et al. (2012) find that the TFP elasticity concerning population density ranges from 0.035 to 0.040, compared to 0.027 for wages which are close to our results. The consistency observed between the results from province-sector and firm-level analyses supports the assertion made by Combes et al. (2012) that the potential endogeneity of city scale may not be a significant issue in studies of firm-level productivity, particularly in the context of TFP analysis, even when instrumental variables for density measures are not employed. Lastly, a comparison across sectors reveals consistent outcomes when compared to estimations at the firm level. Specifically, in both the province-sector-level analysis and in firm-level analysis, the density elasticity of TFP, wages and labor productivity are all found to be higher for the manufacturing sector compared to the services sector which is more obvious especially for labor productivity. This aligns with the literature suggesting that manufacturing benefits more from density effects compared to services. However, it is important to consider that conducting this analysis at a finer geographical scale, such as the zip-code level, could potentially reveal stronger agglomeration effects for the services sector due to its reliance on face-to-face interactions.

## 7. Conclusion

The rise of the urban population over the past two centuries has rendered the notion of density as a pivotal aspect among the other factors influencing economy. Türkiye, as a developing economy that underwent urbanization relatively recently, provides a compelling context for examining the relationship between population density and economic indicators. This study aimed at contributing to the limited literature on the relationship between density and productivity in Turkish economy, particularly at the micro level.

Our study reveals a positive and statistically significant density elasticity of productivity in Türkiye, indicating the presence of agglomeration economies. This finding is robust across various productivity definitions, density metrics, and sectoral analyses, all of which consistently point towards a positive and highly significant density elasticity. Further analysis indicates that the weighted population density, derived from district-level population data and aggregated at the province level, yields lower density elasticity levels in comparison to raw population density metrics. Moreover, using TFP offers a more comprehensive understanding of the firm's production processes, showing more reliable outcomes. Both firm-level and province-sector level analyses demonstrate that density elasticity is notably higher in the manufacturing sector compared to the services sector. Despite the prevalent literature advocating for the use of instrumental variables in exploring the density-productivity relationship, our study, while not employing this method, aligns with existing research, particularly when TFP is considered as the dependent variable.

Understanding the determinants of agglomeration economies has significant policy implications for enhancing national productivity, reducing regional inequalities, and improving individual well-being. While agglomeration generally leads to greater efficiency, the past few decades have seen increasingly uneven regional development in Türkiye. This has led to substantial income and employment disparities across regions, triggering migration, a concentration of population in metropolitan and coastal areas, and the deterioration and isolation of inland regions.

Additionally, according to TURKSTAT Population Projections 2023-2100, Türkiye' s total fertility rate has declined from 2.38 in 2001 to 1.51 in 2023, following a relatively stable renewal level of 2.1 between 2003 and 2014. Under the low scenario, assuming this downward trend continues, the population is expected to peak at nearly 90 million in 2044 before falling below 55 million by 2100. Therefore, urban planning must consider how total population size and distribution affect overall economic productivity and sectoral performance. Since the density elasticity of productivity is higher in the manufacturing sector than in services, policymakers should tailor their strategies to enhance productivity based on sectoral needs. To boost sectoral productivity, policymakers should focus on identifying and addressing the evolving needs of the knowledge-intensive services sector and the technology-intensive manufacturing sector. For example, manufacturing may benefit more from policies that promote clustering and industrial parks, while services might require improvements in digital connectivity and urban infrastructure.

Building on this study, future research may focus on addressing potential econometric concerns and refining the models and the data sets used. In addition to employing historical or geographical data as a proxy for population density to mitigate endogeneity challenges, exploring alternative econometric approaches could be valuable. Another promising avenue for future research involves incorporating additional sector-specific, provincial, and worker-specific characteristics as control variables in the models. Furthermore, literature about the density-productivity nexus from the perspectives of selection and sorting assert that exclusively highly productive firms are able to survive in densely populated urban areas, suggesting that the elevated productivity levels witnessed in such regions may stem from this phenomenon. These aspects will be considered in our future research efforts.

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## Appendix

**Figure A.1:** weighted vs raw population density measure (log)

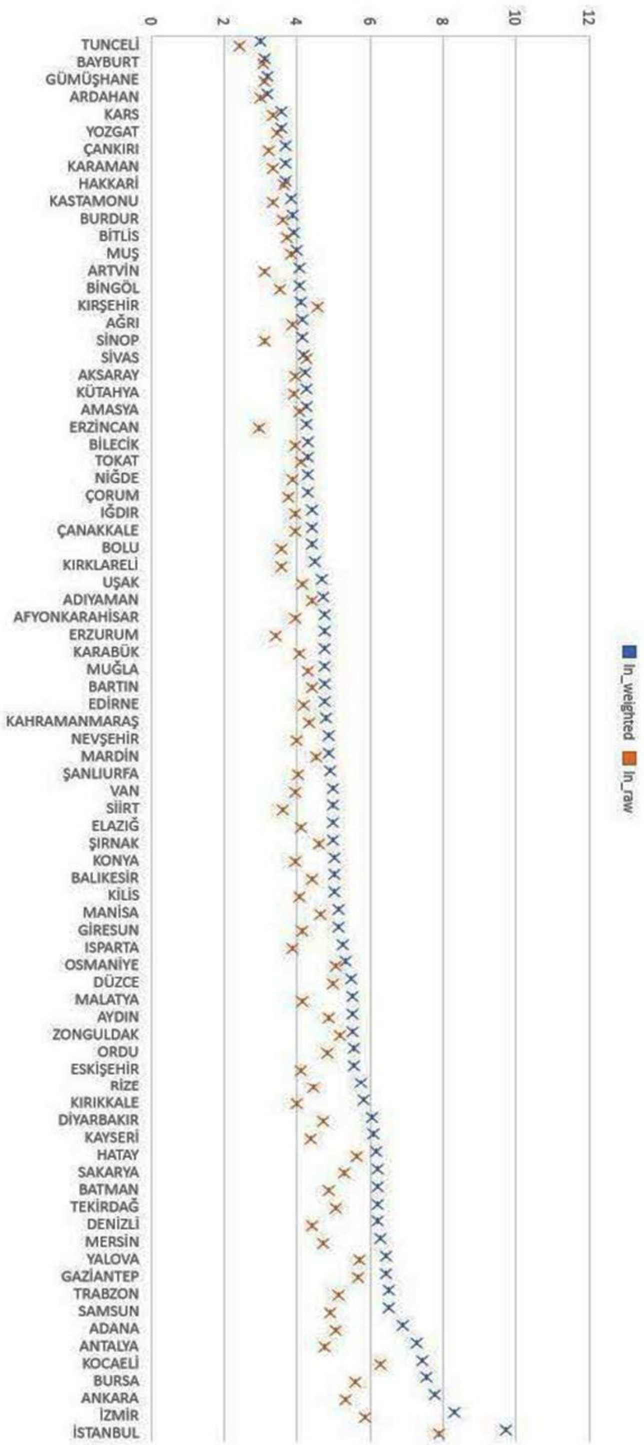

**Table A.1:** Changes in District status in years

| Province | District | Date of status change |
|---|---|---|
| Aksaray | Sultanhanı | 2017 Decree-law; previously affiliated town of Central district |
| Ankara | Kahramankazan | 2016 Decree-law; previous name is Kazan |
| Artvin | Kemalpaşa | 2017 Decree-law; previously affiliated town of Hopa |
| Aydın | Efeler | 2012 Law no 6360; replacing the name of Central district as Efeler |
| Balıkesir | Altıeylül<br>Karesi | 2012 Law no 6360; Central district is divided into two |
| Hakkari | Derecik | 2018; previously affiliated town of Şemdinli |
| Hatay | Antakya<br>Defne | 2012 Law no 6360; Central district is divided into two |
| Hatay | Arsuz | 2012 Law no 6360; previously affiliated town of İskenderun |
| Hatay | Payas | 2012 Law no 6360; previously affiliated town of Dörtyol |
| İstanbul | Eyüpsultan | 2017 Law no 7039; previous name is Eyüp |
| Kahramanmaraş | Dulkadiroğlu<br>Onikişubat | 2012 Law no 6360; Central district is divided into two |
| Malatya | Battalgazi<br>Yeşilyurt | 2012 Law no 6360; Central district is divided into two |
| Manisa | Şehzadeler<br>Yunusemre | 2012 Law no 6360; Central district is divided into two |
| Mardin | Artuklu | 2012 Law no 6360; replacing the name of Central district as Artuklu |
| Muğla | Menteşe | 2012 Law no 6360; replacing the name of Central district as Menteşe |
| Muğla | Seydikemer | 2012 Law no 6360; previously affiliated town of Fethiye |
| Ordu | Altınordu | 2012 Law no 6360; replacing the name of Central district as Altınordu |
| Şanlıurfa | Eyyübiye<br>Haliliye<br>Karaköprü | 2012 Law no 6360; Central district is divided into three |
| Tekirdağ | Ergene | 2012 Law no 6360; previously affiliated town of Çorlu |
| Tekirdağ | Kapaklı | 2012 Law no 6360; previously affiliated town of Çerkezköy |
| Tekirdağ | Süleymanpaşa | 2012 Law no 6360; replacing the name of Central district as Süleymanpaşa |
| Trabzon | Ortahisar | 2012 Law no 6360; replacing the name of Central district as Ortahisar |
| Van | İpekyolu<br>Tuşba | 2012 Law no 6360; Central district is divided into two |
| Zonguldak | Kilimli<br>Kozlu | 2012 Law no 6360; Central district is divided into three as Kilimli Kozlu and Center |