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Exploring the Drivers of Microregional Agricultural Labor Productivity: Empirical Insights from Portugal

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Abstract: Understanding the factors that influence agricultural productivity is critical for promoting sustainable food production, economic growth, and rural livelihoods. Despite the fact that numerous theoretical and empirical studies on agricultural productivity have been conducted in recent decades, few have focused on the local geographical level, investigating the impact of specific agroecological conditions and farming systems. The current study examines the geographical micro-level determinants of labor productivity for all farmers and agricultural holdings in Portugal by estimating the parameters of an extended Cobb–Douglas production function and using panel data techniques. In general, the findings support major findings in empirical and theoretical literature that show a positive relationship between labor productivity and farm size, mechanization, irrigation, and human capital. Labor productivity is higher in regions with a higher prevalence of Mediterranean farming systems, such as orchards, vineyards, and horticultural crops, possibly due to crop suitability and ancient specialized knowledge, implying that a shift in farming techniques and crop selection, in balance with local natural and social specificities, may increase agricultural output and income for rural communities.

Keywords: Cobb–Douglas; commune; farming systems; labor productivity; panel data; Portugal

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1. Introduction

Agricultural labor productivity varies greatly across Europe, with significant differences between the continental northern central countries and the continental peripheries, namely the Mediterranean, Eastern Europe, and Scandinavia [1]. This disparity poses a challenge to achieving balanced territorial development in rural economies and communities, which is a key priority of the European Union's rural development policies [2].

In addition to the attainment of the European Union's territorial cohesion goals, the examination and enhancement of agricultural productivity assume paramount importance in view of the prevailing global challenges confronting the agricultural sector. These challenges encompass food security, poverty reduction, adaptation and mitigation of climate change, degradation and depletion of natural resources, and global market competitiveness.

Over the past few decades, a number of empirical studies have been conducted to investigate the disparities in agricultural productivity among countries, with the aim of gaining insights into the underlying factors contributing to these variations [3–10]. Several authors have studied differences within nations, specifically in Italy, France, Czechia, and Poland [8,10–12].

To the best of the author's knowledge, there is currently no published research on agricultural labor productivity in Portugal. However, a concise analysis of available data reveals significant disparities among the NUT2 regions of Portugal (Figure 1). The mean standard output produced per annual work unit (AWU), which can be used as an approximation for agricultural labor productivity, varies from approximately EUR 10,000/AWU in the Madeira region to nearly EUR 45,000/AWU in the Alentejo region (Table 1).

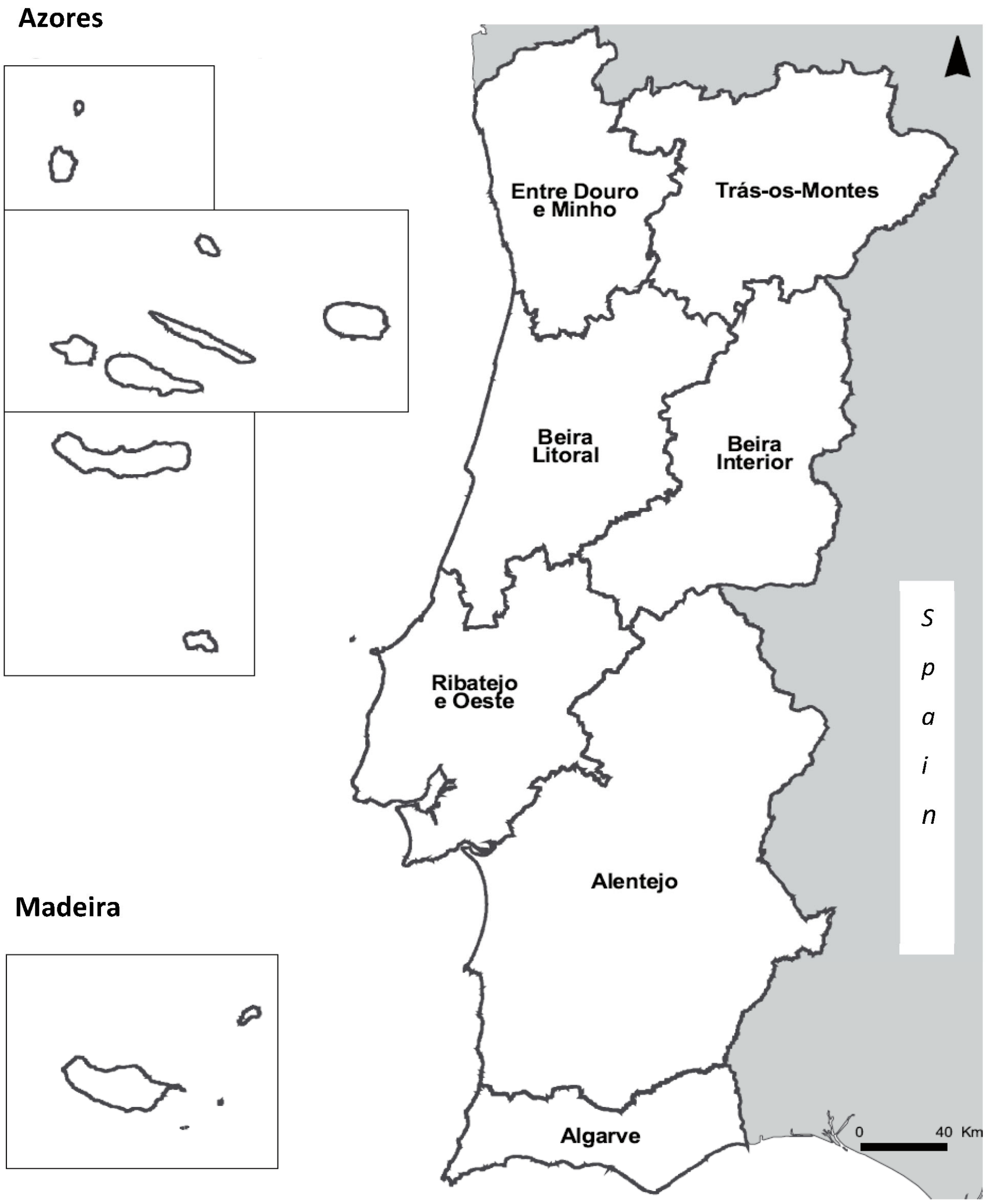

Figure 1. Portuguese agrarian regions [13].

The observed discrepancy is to be expected, considering the extensive range of farm structures, natural resource allocations, and geographical limitations such as soil composition and climate that exist within the country. According to Pelucha et al. [14], when discussing European territorial cohesion, NUT2 and NUT3 include rural areas with varying characteristics, making local or microregional analysis more appropriate. The locality's unique mix of natural resources, know-how, traditions, and culture allows for a more detailed assessment of the determinants of agricultural productivity [15]. However, there is a limited understanding of the factors that effectively influence agricultural labor productivity at a micro-level, specifically within different farming systems and production contexts. The primary focus of research on agricultural productivity has predominantly been at the national [3,16] and regional [4,9,17] scales, with a limited number of studies examining local variations, specifically at the municipal level [15]. This study specifically concentrates on the commune (*Freguesia* in Portuguese), which is the smallest administrative spatial unit in Portugal and serves as a division within a municipality.

Table 1. Portuguese average value of total standard output by annual work unit (EUR/AWU) per NUT2.

NUT2	SO (EUR/AWU)
Norte	10,989.9
Centro	18,572.8
Área Metropolitana de Lisboa	32,895.4
Alentejo	44,904.6
Algarve	27,201.3
Região Autónoma dos Açores	40,020.2
Região Autónoma da Madeira	10,033.4
Portugal	21,488.6

Source: Statistics Portugal, 2021 [17].

The objectives of this study are to produce significant findings regarding the determinants of agricultural labor productivity at a micro-regional scale and establish a basis for decision making that is grounded in empirical evidence, as well as targeted interventions that can enhance agricultural productivity and the overall welfare of people engaged in the agricultural sector. This study analyzes the trends in agricultural labor productivity over the past two decades, while also exploring the various factors that contribute to its positive or negative outcomes. The focus will be primarily on production and farming systems.

The latest proposals for the Common Agricultural Policy (CAP) for the period 2023–2027 have undergone a notable shift toward a more adaptable and contextually responsive approach [18–20]. This revised policy grants individual member states the authority to establish and implement their own national objectives and strategies by means of national strategic plans, thereby enhancing the importance of research conducted at smaller geographic levels. The examination of agricultural productivity at the micro-level will facilitate the development of suitable agricultural policies that consider the particular circumstances and unique characteristics of the local context. This approach will enhance the effectiveness of these policies in achieving higher agricultural yields and generating greater income and employment prospects in rural regions. Consequently, it will contribute to the reduction of regional disparities in terms of development. The study's emphasis on farming systems provides valuable insights for farmers and agricultural practitioners regarding resource allocation optimization and the promotion of a more efficient and sustainable agricultural sector. These insights aim to enhance the sector's resilience in the face of future challenges and disruptions.

The confirmation of previous research findings in a different context, such as Portugal, where this issue has been overlooked, can enhance the broader applicability of existing studies. This, in turn, contributes to the advancement of knowledge in the field by establishing a more consistent and robust scientific foundation. It is worth noting that agricultural productivity exhibits significant variations across different locations and time periods.

When examining the potential for generalizing empirical data from Portugal to the European Union, this research can provide insights into the factors influencing agricultural productivity in other member states, particularly those in the southern region, which face similar limitations and agricultural practices.

2. Literature Review

Differences in agricultural productivity across countries, regions, and farms can be attributed to a variety of proximate and fundamental causes. The productive factors included in any agricultural production function, namely capital, labor, and land, are the proximate causes. The fundamental causes of variations in farm efficiency can be attributed to various factors within a broader context. These factors include, but are not limited to, natural resources and environmental conditions, product and factor markets, agricultural policies, investment incentives and credit availability, human capital skills, and innovation [16,21].

The accumulation of physical capital, including machinery and infrastructure, is essential for long-term agricultural productivity growth. This is due to its ability to enhance output, ensure precision, accuracy, and consistency in production, and reduce time and labor costs [5,16,22]. The link between physical capital and technological progress has been extensively discussed in the literature. Various authors [16,22–24] have identified technological progress as the main catalyst for enhancing agricultural efficiency and productivity. Investments in research and development (R&D) play a crucial role in the advancement of improved crop varieties, innovative farming techniques, pest and disease control measures, and sustainable agricultural practices.

Nevertheless, the accumulation of human capital is essential for the successful integration of new technologies, as the proficient utilization of the most advanced innovations requires higher levels of expertise [5]. The development of human capital through education, training programs, research initiatives, and extension services plays a pivotal role in facilitating the adoption of improved practices, efficient resource management, and informed decision-making processes [25–28]. It is important to acknowledge that education is not the sole means of enhancing human capital. It is also imperative to take into account the inclusion of labor experience, learning by doing, and inherent worker skills [22].

Regarding land, there is a growing recognition that farm size influences technical efficiency and overall farm performance. However, it is worth noting that there is no consensus on the specific direction of this relationship. Some authors have reported that larger farm sizes are associated with higher levels of efficiency [4,22]. However, other researchers have demonstrated that the association between these variables does not always exhibit a linear pattern [8]. Indeed, it has been observed that once a specific size threshold is surpassed, there is a potential decline in efficiency [26,29]. The positive relationship can be explained by the fact that larger farms may experience advantages in terms of enhanced labor division, improved accessibility to raw materials, increased capital resources, and the adoption of innovative technologies and practices that can augment productivity [1,12]. In addition, small farms frequently engage in income diversification as a means of addressing the difficulties associated with achieving economies of scale. This strategy involves allocating relatively less effort towards agricultural activities [30–32]. An inverse relationship between farm size and productivity was discovered mainly in developing economies, and it was observed primarily for land productivity rather than labor productivity [15].

The availability and quality of natural resources such as land, water, and climate conditions are fundamental determinants of agricultural productivity. Suitable soil fertility, favorable topography, sufficient water resources, and appropriate climatic conditions are essential factors for achieving successful agricultural production [16]. One crucial factor in explaining productivity is the extent of irrigated land, which plays a significant role in mitigating adverse climatic conditions in specific semi-arid European areas [16], including the majority of the Portuguese territory.

Policies and institutional support play a significant role in directly influencing and contributing to the efficiency and productivity of agricultural systems. Agricultural subsidies have the potential to impede or delay the departure of labor from the agricultural sector by maintaining or augmenting farmers' income, thereby exerting a detrimental influence on productivity. In contrast, agricultural policies play a significant role in enhancing productivity by offering farmers more consistent prospects and encouraging capital investment in agricultural operations. The Common Agricultural Policy (CAP) has consistently prioritized the increase in agricultural output, as demonstrated by its continuous commitment to providing assistance for farm restructuring and modernization [9]. Many studies [3,8,9,33] have consistently revealed a favorable influence of structural funds on these economic indicators. On the contrary, direct payments seem to have the opposite effect. Garrone et al. [34] found that, on average, CAP subsidies have a positive impact on the growth of agricultural labor productivity. However, this aggregate effect conceals significant heterogeneity in the effects of different types of subsidies. Pillar I decoupled payments, and some Pillar II payments, have a positive effect on productivity, while coupled Pillar I subsidies have the opposite effect, slowing productivity growth.

Agricultural productivity is influenced by various social and institutional factors, such as land tenure systems, property rights, governance structures, and social support systems. According to Liu et al. [6], the productivity growth rate in both the short and long term is significantly influenced by the availability of healthcare services in rural areas, as well as the spillover effects of research from other regions and non-agricultural sectors. External factors, particularly the capacity of non-agricultural sectors to attract workers from the agricultural sector, play a crucial role in explaining labor productivity [16]. The enhancement of productivity may occur if there is migration from the agricultural sector and rural areas, in cases where the agricultural labor force is deemed inefficient [22,35].

Economic factors, including market access, pricing mechanisms, trade policies, and infrastructure, exert a significant influence on agricultural productivity. Farmers are encouraged to invest in modern and productivity-enhancing practices, provided they possess good access to markets, fair pricing mechanisms, and a favorable economic environment. To account for overall economic development, several authors have used gross domestic product (GDP) as a metric for evaluating disparities in agricultural productivity [4,16,36,37]. The rationale is that agricultural labor in advanced economies is expected to exhibit higher productivity levels as a result of enhanced infrastructure and improved market accessibility [16].

Finally, location is another major driver of productivity growth. As stated by Ženka et al. [15], farms located in metropolitan areas face the challenge of high rental costs, which requires the enhancement of their technical efficiency or a shift towards the production of commodities with higher value-added and increased yields. Farmers can derive advantages from different forms of urbanization economies, including the advantageous proximity to a sizable market for their agricultural products and the ability to sell directly to final customers, public canteens, and restaurants, thereby avoiding burdensome transaction costs associated with intermediaries.

The topic of agricultural productivity has received significant attention in academic literature, particularly at the national and regional scales [3,4,9,16,17]. Many studies have investigated the factors that contribute to the observed patterns of "convergence" or "divergence" in agricultural productivity among different nations and regions [3,11,16,38]. Limited research has been conducted on local-level agricultural labor productivity, with the study conducted by Ženka et al. [15] being a notable exception. Furthermore, there is a scarcity of studies that specifically examine labor productivity in various farming systems across different regions. Two studies, conducted by Veysset et al. [12] and Błazejczyk-Majka et al. [39], examined the labor productivity trends in different agricultural systems. Veysset et al. [12] focused on the trajectory of labor productivity in suckler cattle production systems in France, while Błazejczyk-Majka et al. [39] investigated the labor productivity of field crop farms and mixed farms in both new and old EU member states. Nevertheless, there is a significant lack of comprehensive understanding regarding the interregional distribution of labor productivity within various agricultural systems. Therefore, it is interesting to investigate the extent to which farming systems have contributed to the progressive enhancement of agricultural value per unit of labor across various regions. Due to the diverse nature of the agricultural industry, which encompasses various crops, animals, and production methods, and the significant influence of seasonal variations and weather conditions on agricultural output, it is important to note that short-term fluctuations may not accurately represent long-term patterns. Nevertheless, researchers often face the challenge of the limited availability of coherent time series data at the national or regional levels, which consequently restricts the scope of their studies to shorter time periods [4,8]. Furthermore, most studies rely on databases that are designed for specific purposes, such as the Farm Accountancy Data Network (FADN) [10,12,39], and do not include all farms, thus potentially limiting their ability to capture the complete spectrum of farming system variability.

3. Materials and Methods

3.1. Data

This study made use of data from the Portuguese Agricultural Census (AC) at the commune level, which is the smallest administrative division unit in Portugal. There are 3091 communes in Portugal, of which 2882 are on the mainland, 155 are in the autonomous region of the Azores, and 54 are in the autonomous region of Madeira. Due to missing values and the removal of urban communes with less than 10 farms, only 2878 communes were used for this study.

The AC covers the entire national territory. It is a comprehensive statistical survey that includes data from all farms in the country, generating results at highly detailed geographical levels. The data-collection process involves face-to-face interviews conducted by duly authorized interviewers and is designed to meet both national and international statistical requirements [40]. These data provide valuable insights into the agricultural populations and their respective production methods [41]. Key areas covered by the AC include the structure of farms, agricultural production systems, production methods, agricultural labor, sources of income, gainful activities not directly related to agricultural holdings, and farm succession. In Portugal, the AC was carried out every ten years from 1979 to 2019. However, to ensure conceptual consistency and coherence in the analysis, the present study focuses solely on data from the years 1999, 2009, and 2019.

AC data provide a valuable tool for researchers in a variety of fields, from agronomy to social sciences and economics, and they offer numerous benefits [42,43]: (1) the data cover all farmers, households, and holdings in the country; (2) the data provide a comprehensive view of the territory by including information on a wide range of production, economic, demographic, social, and geographic characteristics; (3) the data are collected every ten years, allowing researchers to examine changes over time; (4) the data are collected using standardized methods and are subject to rigorous quality-control measures, ensuring the data's reliability and accuracy; (5) the data are presented at various geographic levels, which can be useful for researchers interested in studying the characteristics of specific regions or comparing different regions; (6) the data are open to the public and easily accessible, through various online databases, to researchers from various disciplines and locations.

Furthermore, using data from a single source reduces the issue of measurement errors caused by different collection methods, instruments, or human intervention.

3.2. Model

In light of various labor productivity studies [9,44–46], a Cobb–Douglas production function was assumed to describe the production technology. The Cobb–Douglas production function is widely popular, due to its straightforward functional form, evident economic relevance, and ease of estimation. Although standard Cobb–Douglas production functions only consider factors like capital, labor, and technology, they can be expanded to consider additional factors that affect output, such as farming system, education, training, and age, taking the following form [44,47–49]:

$$Y_{it} = A_{it} K_{it}^{\alpha} L_{it}^{\beta} T_{it}^{\gamma} \exp(\varphi' P_{it}) \tag{1}$$

where Y_{it} denotes the output of subject i in the period t, A_{it} is a constant known as total factor productivity or total factor efficiency, K_{it} is physical capital input, L_{it} is labor input, T_{it} is land input, and P_{it} is the vector of the fundamental variables.

By taking the natural logarithms of both sides of Equation (1), we can obtain the following expression:

$$lnY_{it} = lnA_{it} + \alpha lnK_{it} + \beta lnL_{it} + \gamma lnT_{it} + \varphi' P_{it} + \varepsilon_{it} \tag{2}$$

Here, ε_{it} represents the error term, assumed to be independent and identically distributed.

To measure labor productivity, we can use the logarithm of output per worker, as expressed by:

$$ln\left(\frac{Y_{it}}{L_{it}}\right) = lnA_{it} + \alpha lnK_{it} + (\beta - 1)lnL_{it} + \gamma lnT_{it} + \varphi' P_{it} + \varepsilon_{it} \quad (3)$$

3.3. Variables

Agricultural labor productivity is typically calculated as the ratio of gross added value per worker, or AWU [22,24,37,50]. However, gross added value is not available in the Portuguese statistics at the commune level; consequently, standard output (SO) per AWU was used as a proxy for labor productivity, as suggested by Giannakis and Bruggeman [17], and was included in the model as the dependent variable in its logarithmic format. (The standard output of an agricultural product (crop or livestock) is the average monetary value of the agricultural output at farm-gate price, in euros per hectare or per head of livestock, taking into account regional (NUT 2) productivity. The regional SO coefficient for each product is an average value over a reference period (usually 5 years). The sum of all the SOs multiplied per hectare of crop and per head of livestock in a farm is a measure of its overall economic size, expressed in euros [51].) Due to the fact that this analysis spanned three years (1999, 2009, and 2019), the values were deflated using the Producer Price Index.

Based on the typology of agricultural productivity drivers identified in Section 2, the model's explanatory variables are divided into four broad categories: proximate causes (capital, labor, and land) and three groups of fundamental causes. Fundamental causes include farm characteristics (crops, livestock, irrigation, and land tenure), farmer characteristics (training and education, age, gender, and time spent on agricultural activities), and contextual factors. Table 2 provides a concise description of each of the model's variables.

Higher capital endowments in terms of machinery are expected to have a positive effect on the level of labor productivity because the importance of machinery, together with fertilizers, has significantly increased in the productive process and agricultural development [15]. Following Martín-Retortillo and Pinilla [16], the number of tractors was used as a proxy for capital intensification. The variable capital (*lnK*) is expressed as the natural logarithm of the average number of tractors per farm. The labor input is expressed as the natural logarithm of the average AWU per farm (*lnL*), while the land input is given by the natural logarithm of the average UAA in hectares (*lnT*).

In order to examine the effect of agricultural systems on labor productivity, two categories of variables were considered: crops and livestock. Regarding crops, the intention was to include the country's major crops according to the classification of Commission Regulation (EC) No. 1242 of 2008. With the exception of animal fodder, cereals (5.9%) and horticulture (1.3%) are the primary temporary crops in Portugal in terms of utilized-agricultural-area (UAA) composition. Permanent crops, such as fruit plantations, olive groves, and vineyards, hold significant importance, accounting for 2.0%, 9.5%, and 4.4% of the UAA, respectively. It is noteworthy that the UAA comprises over 60% of grasslands and fodder [52]. Because grazing livestock (i.e., cattle, sheep, and goats) were included as variables, the model did not account for the area devoted to animal feed. The variables related to livestock are expressed in the number of animals per ha of UAA. Crop variables can offer valuable insights into agroecological conditions, albeit in an indirect manner. The growth of different crops is reliant upon crucial variables, including temperature, precipitation, soil type, and sunlight. Farmers strategically choose crops that are well suited to the unique environmental conditions of their particular location, with the aim of optimizing productivity. This deliberate selection process leads to the cultivation of a diverse range of crops, thereby creating an agricultural landscape that harmonizes with the natural environment of the region.

Table 2. Variables description.

Variable	Description
Dependent variable	
ln(Y/L)	Natural logarithm of the average value of total SO per AWU
Explanatory variables	
Production factors	
lnK	Natural logarithm of the average number of tractors per holding
lnL	Natural logarithm of the average number of AWU per holding
lnT	Natural logarithm of the average UAA (ha) per holding
Farm characteristics	
Crops	
fruit	Proportion of fruit area (%) in UAA
olives	Proportion of olive grove area (%) in UAA
vineyard	Proportion of vineyard area (%) in UAA
cereals	Proportion of cereal area (%) in UAA
horticulture	Proportion of horticulture area (%) in UAA
Livestock	
cattle	Number of cows per ha of UAA
sheep	Number of sheep per ha of UAA
goat	Number of goats per ha of UAA
irrigation	Proportion of irrigable area (%) in UAA
tenure	Proportion of owned land (%) in UAA
Farmer characteristics	
no training	Proportion of farmers (%) with no agricultural formal training
education	Proportion of farmers (%) with a secondary/higher level of education
age	Average age of sole holders measured in years
gender	Proportion of women (%) among farmers
part time	Proportion of farmers (%) working part time at the farm
Contextual factors	
population	Familiar agricultural population density (Number/km^2)
Time	
time0	=1 if 1999 and =0 otherwise
time1	=1 if 2009 and =0 otherwise
time2	=1 if 2019 and =0 otherwise

In regions that experience significant drought conditions, such as the central and southern regions of Portugal, the utilization of irrigation systems can play a crucial role in enhancing agricultural productivity. The implementation of irrigation systems has been found to have a beneficial impact on the level of technical efficiency, due to its ability to enhance average crop yield and mitigate variability in situations where natural precipitation is insufficient [1]. It is also recognized as a response by producers to adapt to climate change [53,54]. The variable *irrigation*, which measures the proportion of irrigable area in UAA, was incorporated into the model in order to capture this effect.

The share of owned land (*tenure*) was used to assess the impact of landownership on labor productivity. It is usually claimed that farmers who possess land ownership tend to exhibit higher levels of productivity, which can be attributed to their implementation of superior resource management strategies and increased investment in fixed assets [15,55,56].

The two first farmer characteristics, namely training and education, encompass two facets of human capital. The variable *no training* denotes the percentage of farmers who lack formal agricultural training and primarily rely on their practical agricultural experience. Farmer's *education* is expressed as the share of sole holders (thus designated as farmers) who attained a secondary or higher level of education, with or without agricultural training. According to Giannakis and Bruggeman [17], farmers who possess a greater degree of training and education exhibit a greater propensity to embrace technological advancements and external knowledge, thereby enabling them to effectively navigate and adjust to global shifts. Age is often regarded as a component of human capital, as it is commonly associated with the managerial skills of farmers and their propensity to innovate, embrace contemporary agricultural practices and technologies, and access funding opportunities [4,17,57,58]. The age of farmers is expressed by the average age of farmers within the commune.

In relation to gender, it is worth noting that, while not universally agreed upon, a significant number of studies suggest that businesses owned by women tend to demonstrate comparatively slower rates of growth, smaller scales, and lower levels of profitability and productivity. There are several factors that may contribute to the underperformance of businesses owned by women, such as domestic responsibilities, limited experience in management, and gender-based disparities in accessing capital. Hoang et al. [59] presented the main arguments on this topic, despite the fact that their research was not explicitly devoted to agriculture. In the current framework, the gender variable is operationalized as the ratio of female farmers.

The variable *part time*, which refers to farmers' involvement in non-farm activities for income, has the potential to influence agricultural labor productivity in either a positive or negative manner. It can have a positive impact by facilitating innovation through improved access to credit and investment [60–62]. Conversely, it may also have a negative effect by diverting farmers' attention and effort away from their agricultural activities, resulting in a negative correlation between pluriactivity and labor productivity [17].

In order to incorporate the influence of external factors, the variable "population" was introduced as a means to quantify the effect of farm population on labor productivity. This variable is a measure of agricultural population density, expressed as the familiar agricultural population per square kilometer. Several studies have provided evidence indicating that increased population density has a direct adverse influence on the productivity of agricultural labor [9,17], while also exerting an indirect negative effect by impeding the process of structural change [4].

The model does not take into consideration other external factors, such as natural resource endowment and environmental constraints, that explain labor productivity, because of a lack of information at the commune level. In relation to agricultural policies, investment incentives and product, factor, and credit markets, as well as the broader macroeconomic context, the conditions are uniform throughout the country, thus precluding their utilization as explanatory factors for variations observed at the commune level. However, in order to account for potential variations in those factors over time, three dummy time variables were incorporated into the estimation process. These variables serve to control for omitted variables that are shared by all communes but exhibit temporal variability. The inclusion of time-fixed effects permits the control of time-related effects that would otherwise be overlooked, thereby mitigating bias arising from unobserved variables that exhibit temporal variation. Dummy variables are frequently employed in econometric models to incorporate time-specific effects or shocks that may not be adequately captured by other variables in the model [32,63–66]. The dummy variables *time0*, *time1*, and *time2* are assigned a value of 1 if the observation corresponds to the years 1999, 2009, or 2019, respectively, and a value of 0 otherwise.

3.4. Descriptive Statistics

Table 3 presents the main descriptive statistics for the variables examined in the study. It is important to acknowledge that the values presented do not accurately represent the overall means and proportions of the country. The data represent the mean of the average values of the variables across the communes in the year 2019.

Table 3. Descriptive statistics.

Variables	Mean	S.D.	Min.	Max.
Y/L	18,751.7	20,479.0	1120.1	236,110.5
K	0.7	0.35	0.0	3.4
L	1.1	0.6	0.2	16.2
T	13.0	28.5	0.1	402.5
fruit	5.5	11.7	0.0	100
olives	10.2	16.1	0.0	88.0
vineyard	11.8	18.0	0.0	97.2
cereals	7.7	10.3	0.0	91.4
horticulture	3.1	7.7	0.0	87.2
cattle	0.76	1.25	0.00	9.29
sheep	0.79	1.04	0.00	32.15
goat	0.31	0.52	0.00	5.61
irrigation	34.0	30.6	0.0	99.9
tenure	81.0	18.7	6.7	100
no training	51.3	18.2	0.0	100
education	19.3	10.0	0.0	0.0
age	63.7	3.9	39.0	76.0
gender *	32.7	12.5	3.4	100
part time	84.3	17.0	11.0	100
population	13.2	13.1	0.3	285.9

* For binary variables the mean corresponds to relative frequency; standard deviations are omitted.

The average value of total SO per AWU is EUR 18,752, spanning from EUR 1120 to EUR 236,110. This variability reflects the diverse nature of farming systems observed throughout the country. Furthermore, the data indicate that small-scale farming prevails in the majority of the communes, with an average employment of 1.1 AWU and an average UAA of 13.0 hectares per farm. Once more, the range of values for both variables emphasizes the inherent variability present in the Portuguese agricultural sector. Permanent crops hold significant importance in various contexts. On average, a significant proportion exceeding 25% of the UAA is allocated to the cultivation of fruits, olive groves, and vineyards. The role of irrigation is significant, as irrigated areas account for an average of 34.0% of the UAA. However, in certain communes, the proportion of irrigated land approaches 100%. In terms of land ownership, farmers possess over 80% of the UAA. Farmers are characterized by limited training and education, as well as by advanced age. On average, around one-third are women and more than 80% work part time in agriculture.

3.5. Estimation Procedures

Among the various analytical tools available, panel data models have emerged as powerful and appropriate tools to study agricultural productivity, due to their unique abilities to harness longitudinal data over time and across multiple entities [11,16,28]. The benefits of using panel models, as well as details on panel data models and methods, are discussed in several textbooks [67,68]. The following benefits are emphasized: (i) panel data have the capability to identify and quantify effects that are not discernible in either cross-sectional or time series data alone; (ii) panel data account for individual heterogeneity; (iii) additionally, panel data provide a greater amount of information and variability, reduced collinearity among variables, increased degrees of freedom, and enhanced efficiency. In order to assess the presence of multicollinearity, a correlation matrix was built, and the variance inflation factor (VIF) was calculated, as shown in Appendix A (Tables A1 and A2). The findings did not provide evidence for the existence of collinearity.

Fixed effects have been used in the estimation of regression, for two primary reasons. First, the Hausmann test, comparing fixed-effect (FE) and random-effect (RE) estimations, soundly rejected the null hypothesis that the RE estimator is consistent (X^2 = 516.26; Prob > X^2 = 0.0000). Second, FE estimation addresses the presence of spatial heterogeneity, which encompasses variations in soil quality and climate that were not adequately captured by the regressors. This approach helps to mitigate concerns about potential endogeneity and spatial dependencies that may arise from the omission of relevant variables.

We may still have a problem with biased parameter estimates if there remain any significant unobserved time-varying differences across communes. In addition, some variables may exhibit reverse causality. For example, when farmers become more productive and increase their incomes, they may be able to afford to introduce new machinery or buy extra land. Two commonly employed approaches for addressing the issue of reverse causality in empirical research are dynamic panel models (DPMs) and instrumental variables (IVs). In addition to the fact that these approaches face some criticism [69], it is not feasible to estimate a DPM in the current scenario, due to the ten-year duration of our observations. It is implausible to assume that the value of the dependent variable is influenced by a value observed a decade prior. On the other hand, it is extremely difficult to identify reliable instruments that exhibit correlation with machinery or land acquisitions while also maintaining orthogonality with productivity. Given that fixed-effects models primarily utilize changes within entities over time, they are less prone to concerns regarding reverse causality. Consequently, I anticipate that potential issues of endogeneity did not impact the outcomes of this study.

Given the potential for panel data to be significantly compromised by atypical observations, such as outliers, resulting from a non-robust centering procedure [70], a robust estimation was employed to address the issue of heteroskedasticity. The econometric procedures were conducted using the STATA/IC 16.1 (StataCorp, College Station, TX, USA) software.

4. Results and Discussion

The estimation results are displayed in Table 4, showing that most explanatory variables in the econometric model present statistical significance, with p-values under 1%. The results also indicate a rise in local labor productivity from 1999 (the base year) to 2019, although the differences between 1999 and 2009 were not statistically significant.

As anticipated, the econometric model demonstrates that the level of utilization of productive factors plays a crucial role in elucidating variations in labor productivity at the micro-level across different geographical regions. The importance of the number of workers and land area per farm is emphasized by statistically significant coefficients and the anticipated signs. A 1% rise in the average AWU per farm results in a decrease in labor productivity of 0.69%, while a 1% increase in the average UAA per farm leads to an increase in labor productivity of 0.51%. The land market in Portugal exhibits inflexibility and a consistent prevalence of small farms, due to a combination of institutional, social, and market factors [71]. The escalation of agricultural land prices, driven in part by the incorporation of CAP payments [66,72,73], does not encourage farmland expansion. In recent decades, there has been a growing emphasis on implementing policies aimed at augmenting the size of farms, such as land consolidation schemes or the establishment of land banks. Nevertheless, due to the emotional attachment that owners frequently associate with their plots, the level of engagement in these initiatives was notably minimal [67]. At present, public support for modernization investments does not include land acquisition, which may be a significant barrier to the establishment of new farmers and the growth of existing farmers. Policies aimed at facilitating land acquisition, specifically targeting young farmers, as well as enhancing access to credit and financial services, have the potential to influence the size of farms. Although larger farms have the potential to be more productive, it is important to acknowledge that the concentration of agriculture on these larger farms can result in adverse effects on both the environment and rural communities [74,75]. Therefore, it is imperative for policymakers to consider the implementation of regulations and incentives to promote productivity on smaller farms. This could involve encouraging the consolidation or formation of cooperatives, facilitating access to affordable credit, and prioritizing research agendas that focus on technologies and practices that are both accessible and applicable to small- and medium-sized farms.

Table 4. Fixed-effects estimation results.

Variables	Coef. (Robust)	t	p > |t|
lnL	−0.6913 **	−25.48	0.000
lnK	0.0739 **	2.88	0.004
lnT	0.5110 **	21.69	0.000
fruit	0.0196 **	9.06	0.000
olives	−0.0021	−1.58	0.114
vineyard	0.0036 **	3.51	0.000
cereals	−0.0010	−1.01	0.311
horticulture	0.0133 **	5.83	0.000
cattle	0.1905 **	13.16	0.000
sheep	0.0216	1.51	0.131
goat	0.0603 **	3.80	0.000
irrigation	0.0030 **	6.89	0.000
tenure	−0.0015	−3.29	0.001
no training	−0.0001	−0.09	0.926
education	0.0038 **	3.07	0.002
age	−0.0058 *	−2.06	0.040
gender	−0.0035 **	−4.33	0.000
part time	0.0013 **	4.58	0.000
population	−0.0028 **	−4.00	0.000
time1	0.0220	0.46	0.647
time2	0.1746 **	3.97	0.000
constant	8.3556 **	43.15	0.000
R^2: within = 0.5144 between = 0.6603 overall = 0.6476		F (21, 2877) = 245.45 Prob > F = 0.0000	

** *p*-value < 0.01; * *p*-value < 0.05.

The significance of capital intensity, as indicated by the number of tractors per farm, is noteworthy, although its impact on productivity is relatively minor. When there is a 1% increase in the average number of tractors per farm, there is an approximate 0.07% increase in average labor productivity. Mechanization allows farms to scale up their operations more easily and allows for more timely and precise operations, such as planting and harvesting at optimal times, resulting in higher crop quality and yields per worker. In communes where the majority of individual farmers may face financial constraints in acquiring their own machinery, the implementation of custom hiring services can serve as an incentive mechanism. This arrangement enables multiple farmers to collectively bear the expenses associated with mechanized equipment, thereby facilitating cost-sharing among them.

In relation to farming systems, with the exception of olives and cereals, which exhibit a statistically insignificant negative influence on local labor productivity, all other crops demonstrate a positive impact. The impact is particularly notable in communities where there is a higher prevalence of fruit trees. An increase of one percentage point in the proportion of fruit in UAA is associated with an approximately 2 percent rise in local labor productivity. The obtained outcome is somewhat surprising, considering the labor-intensive nature of orchard management, which involves activities such as pruning, pest control, and harvesting. However, the heightened demand for labor has the potential to result in a more optimal distribution of labor and enhanced labor productivity. Furthermore, orchards require skilled labor for a variety of tasks, which can encourage the hiring of better-qualified agricultural workers. Similar outcomes are noted in communes characterized by a greater presence of horticulture and vineyards, wherein a rise in labor productivity of 1.33 percent and 0.36 percent is observed for every one-percentage-point increase in their share of UAA, respectively. Cattle production and goat production yield significant positive effects as well. The introduction of an additional cow or goat per hectare of UAA results in approximate increases of 19% and 6% in local labor productivity, respectively. Animal husbandry, apart from its role in the production of goods, exerts an influence on productivity in the form of fixed capital [16]. The finding that Mediterranean farming systems in Portugal exhibit higher agricultural labor productivity underscores the need to capitalize on the local climate and know-how advantages, while also addressing environmental challenges. Encouraging crop diversification within Mediterranean farming systems can lead to increased productivity and reduced risk. In addition, it can enhance food security by increasing the availability of locally grown fruits, vegetables, and other crops, thus reducing the dependency on imported goods. However, climate change poses challenges to Mediterranean farming, including increased temperatures and changing precipitation patterns [76–78]. Drought-resistant crop varieties and improved water management should be prioritized in national agricultural policy and research agendas to ensure long-term productivity.

An explanation of the variations in agricultural labor productivity also includes irrigation. When there is a one-percentage-point increase in the proportion of irrigated land, there is a corresponding 0.3% increase in local labor productivity. This finding supports the existing evidence of the positive impact of irrigation on agricultural output at a global scale [16,29,79,80]. In the context of Portugal, a country characterized by a Mediterranean climate, the practice of irrigation has a notable impact on crop yields [81,82] and, as a result, on the overall productivity of labor. This assertion holds true for other nations in southern Europe as well. In Spain, which is recognized as one of the driest countries in Europe, the practice of irrigated farming encompasses a proportion of agricultural land that is less than one-third. However, it significantly contributes to crop production, accounting for over two-thirds (79%) of the total output [83]. Infrastructure development should be prioritized by the government and agricultural organizations in order to increase farmers' access to irrigation, while avoiding over-extraction and negative environmental impacts. Sustainable irrigation practices and regulations should be implemented to improve efficiency, reduce water waste, and protect water resources and ecosystems [78].

Tenure, despite having a small coefficient, is statistically significant, demonstrating that in communes where farmers own a greater proportion of UAA, labor productivity is lower. When the percentage of UAA owned by farmers increases by one percentage point, local labor productivity decreases by 0.15 percent. This is a surprising result because, as stated previously, most literature shows that tenants are typically less productive than farmland owners [15,55,56]. However, the opposite relationship has also been documented in research. For instance, Karagiannis and Sarris [1] discovered that an increase in the proportion of rented land increased technical efficiency and output for Greek tobacco producers. Possibly, tenants are more market-oriented and make greater use of the institutions and modern inputs associated with greater levels of efficiency [29].

Regarding human capital, *training* appears to have no effect on productivity, as the coefficient is extremely small and statistically insignificant. Education, on the contrary, has a positive impact [16,17,22]. While training can improve specific agricultural skills and tasks, education is crucial in providing a broader knowledge base, problem-solving abilities, adaptability, and the ability to innovate—all of which are important for long-term agricultural productivity and sustainability. The potential disparity in the influence of training on productivity in relation to the significance of education could potentially be attributed to the intricate and dynamic characteristics of the agricultural sector, wherein profound comprehension and flexibility are imperative for achieving favorable outcomes.

An increase of one percentage point in the proportion of farmers possessing a secondary or higher-education level is associated with an approximate 0.38 percent rise in local labor productivity. This finding aligns with multiple studies that have demonstrated a positive correlation between higher levels of education and significant improvements in agricultural productivity.

As expected, age has a negative impact on local labor productivity. For each year of increase in the average age of farmers in the commune, productivity decreases by 0.58 percent. One of the main goals of the 2014–2022 CAP period was to address the issues confronting young farmers and encourage them to continue working in their parents' businesses [75]. In addition to the start-up aid provided to young farmers as part of Pillar II, the Young Farmers Scheme was created to encourage farmers under the age of 40 to pursue farming. This scheme is still in use in current European national development programs, and it is expected to have an impact on farmer rejuvenation and agricultural productivity [84].

A greater proportion of women farmers has the same effect as age. The local labor productivity declines by 0.35 percent for every percentage point increase in the proportion of female farmers in a commune. Since more than 60% of Portuguese farms are small, employing less than 1 AWU [52], the majority of the work is performed by the farmer himself or herself. In such a context, it is plausible that female farmers are less productive than male farmers, either due to sociocultural constraints or to innate physical differences [85].

The presence of part-time farmers has a positive impact on local labor productivity. When the percentage of part-time farmers rises by one percentage point, productivity rises by 0.13 percent. In Portugal, part-time farms typically employ family members and cultivate a limited area, allowing farmers to focus their attention and resources on specific crops or livestock and to adopt more intensive practices, thereby enhancing the control of technology and the efficiency of input use [39]. The findings appear to contradict the prevalent notion in Portuguese political discourse that professional farmers, with specialized knowledge and a large economic dimension, are more efficient and competitive in food production [86].

Finally, as expected and in line with the literature [9,17], agricultural population density has a negative effect on productivity. The phenomenon of population decline leads to a decrease in competition for vital resources such as land and water, thereby enabling farmers to relinquish the utilization of less fertile soils and augment the scale of their agricultural operations. Between the years 1999 and 2019, there was a notable decline of 46% in the agricultural population of Portugal. Simultaneously, the average UAA witnessed an increase from 9.6 hectares to 13.6 hectares [87].

5. Conclusions

This study offered a thorough examination of the localized geographical factors that influence labor productivity in the agricultural sector. The results align with existing empirical and theoretical literature, providing further support for the widely accepted understanding of the key variables influencing labor productivity. The findings of this study demonstrate a noteworthy connection between several important variables and labor productivity.

To begin with, the size of a farm appears to be a crucial factor, as larger farms exhibit higher levels of productivity. This finding offers empirical evidence in favor of the hypothesis that economies of scale have a significant impact on enhancing agricultural productivity. Mechanization is a significant determinant that exhibits a positive correlation with labor productivity. This relationship underscores the significance of innovative equipment and technology in enhancing agricultural efficiency. Likewise, the assertion that irrigation exerts a positive impact on agricultural productivity emphasizes the critical importance of effective water management in ensuring consistent yields in dry and semi-arid regions of southern Europe. This study also emphasized the importance of investments in human capital, which not only improve farmers' practices, but also their capacities to adapt to evolving market dynamics and advancements in technology.

The study also uncovered a notable impact of geography on labor productivity. Communities characterized by a significant presence of Mediterranean crops, such as orchards, vineyards, and horticulture, exhibit enhanced levels of labor productivity. This observation implies the existence of a mutually beneficial relationship between specific crops and labor efficiency, which may be associated with factors such as crop suitability, specialized knowledge, and effective management practices.

Overall, the research contributes to the existing body of knowledge on agricultural labor productivity by reaffirming previous associations and providing insights into the unique impact of regional production systems. The implications of the findings are relevant for policymakers, agricultural practitioners, and researchers, as they provide a foundation for implementing specific interventions aimed at achieving sustainable improvements in agricultural productivity. As agriculture undergoes transformations in response to climate variations, market dynamics, citizen demands, and technological advancements, the findings presented here offer significant insights into enhancing labor productivity and safeguarding the resilience of food systems. Upon analyzing the various factors affecting agricultural productivity, it becomes evident that the implementation of a comprehensive agricultural policy is imperative. These policies should enhance land accessibility, ensure the productivity of Mediterranean agricultural systems and small-to-medium farms, promote irrigation access, and mitigate the risks of over-extraction and adverse environmental impacts. In addition, the implementation of initiatives aimed at promoting the establishment of young farmers is critical to revitalizing local agriculture and ensuring its long-term viability.

Nonetheless, several research limitations must be highlighted. Agricultural systems are complex and are impacted by a number of elements that are outside the scope of this study. Due to a lack of commune-level data, variables such as weather patterns, insect incidence, access to financing, market circumstances, and agricultural policy restraints and incentives that may have affected labor productivity were not evaluated. It is also worth noting that this research depends on aggregated data, such as averages and proportions, which may not accurately reflect the nuances and variety seen in individual farmers' experiences and practices. In addition, potential spatial autocorrelation and the possibility that endogeneity may have affected the true causal relationships remain as concerns.

Further investigation using both quantitative and qualitative research methods has the potential to enhance the findings of this study, particularly within the framework of various production systems. By integrating quantitative and qualitative methodologies, researchers have the ability to uncover the intricate complexities of labor productivity dynamics, enabling policymakers to develop interventions that effectively tackle the unique challenges encountered by each system. Holistic research initiatives that concentrate on diverse production systems are imperative for formulating well-informed strategies that effectively enhance agricultural productivity and bolster the overall resilience of the food system.

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Appendix A

Table A1. Correlation coefficients.

	lnL	*lnK*	*lnT*	*fruit*	*olives*	*vine*	*cereals*	*horticulture*	*cattle*	*sheep*
lnL	1.0000									
lnK	0.3218	1.0000								
lnT	0.1528	0.1691	1.0000							
fruit	0.1096	0.0197	−0.2847	1.0000						
olives	−0.3509	−0.1679	−0.0974	−0.0806	1.0000					
vine	0.1507	−0.1742	−0.3088	0.0166	−0.0376	1.0000				
cereals	0.1103	0.2643	−0.1548	−0.0879	−0.2159	−0.0544	1.0000			
horticulture	0.1565	0.1699	−0.1975	0.1400	−0.1515	−0.0310	0.1048	1.0000		
cattle	0.2188	0.2622	−0.0391	−0.0817	−0.2663	−0.1334	−0.0617	−0.0044	1.0000	
sheep	−0.1017	−0.0101	−0.2042	−0.0550	0.0870	−0.0675	0.0235	−0.0122	−0.1765	1.0000
goat	−0.0861	−0.0537	−0.3618	0.0370	0.1700	−0.0606	0.0122	0.1228	−0.0896	0.2163
irrigation	0.3441	0.3329	−0.4557	0.3080	−0.3374	0.1328	0.4063	0.2828	0.2998	0.0353
tenure	−0.2478	−0.2220	−0.2665	0.0642	0.3235	0.1525	−0.0922	−0.1234	−0.4440	0.0895
no training	−0.2568	−0.3284	0.1378	−0.0929	0.1420	−0.2116	−0.1926	−0.1282	−0.1653	0.0354
education	0.0595	0.0142	0.3424	0.0650	0.0522	0.1037	−0.0516	−0.0297	−0.1619	−0.0885
age	−0.2386	−0.0279	−0.1623	−0.0340	0.3806	0.0713	0.0632	−0.1020	−0.3415	0.1176
gender	−0.0164	−0.1996	−0.1637	−0.0376	−0.0753	0.0175	0.0197	−0.1051	−0.1150	0.0073
part time	−0.4970	−0.1725	−0.0557	0.0125	0.2904	0.0708	−0.0354	−0.0811	−0.3383	0.0876
population	0.0038	−0.1915	−0.4641	0.2809	−0.1033	0.3654	0.0032	0.1911	0.0892	−0.0334

	goat	*irrigation*	*tenure*	*no training*	*education*	*age*	*gender*	*part time*	*population*
goat	1.0000								
irrigation	0.0890	1.0000							
tenure	0.1384	−0.1729	1.0000						
no training	−0.0055	−0.2780	0.1048	1.0000					
education	−0.1688	−0.0845	−0.0656	0.0145	1.0000				
age	0.0153	−0.0518	0.3877	0.1649	−0.1221	1.0000			
gender	0.0445	0.0752	0.3297	0.1897	−0.1800	0.1121	1.0000		
part time	0.0665	−0.2344	0.2364	0.1252	0.1535	0.2742	−0.0261	1.0000	
population	0.0379	0.2616	0.0887	−0.1147	−0.1249	−0.0526	0.1326	−0.0192	1.0000

Table A2. Variance Inflation Factor (VIF).

	VIF	*1/VIF*
lnL	1.94	0.515936
lnK	1.63	0.612567
lnT	3.43	0.291479
fruit	1.39	0.720966
olives	1.61	0.622537
vine	1.87	0.534925
cereals	1.65	0.604276
horticulture	1.23	0.812474
cattle	2.05	0.487405
sheep	1.18	0.848591
goat	1.33	0.750764
irrigation	2.67	0.374897
tenure	1.68	0.596843
no training	1.39	0.719409
education.	1.52	0.658342
age	1.52	0.656035
gender	1.50	0.665869
part time	1.53	0.653200
population	1.73	0.578215
Mean VIF	1.73	

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