THE EFFECTS OF AGING ON LABOR PRODUCTIVITY AND EMPLOYMENT: EVIDENCE FROM BRAZIL

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Abstract

This study evaluates the effects of population aging on economic growth in Brazil, decomposing its impacts into labor productivity and employment. Using data across 557 microregions from 2000 to 2022, I combine instrumental-variable estimators with spatial econometric models to address both endogeneity and cross-regional spillovers. I find no compelling evidence that population aging directly undermines economic growth or labor productivity. Instead, aging showed positive effects on employment in public-sector services and contributed to increased formalization in non-agricultural sectors. The findings reveal rising demand for public health and social-care services, while Brazil faces growing fiscal challenges in financing its public pension.

Keywords: population aging, economic growth, labor productivity, informal economy, development economics

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Developing countries have experienced sharp declines in fertility rates and substantial improvements in life expectancy, resulting in rapid population aging (United Nations, 2022). This demographic shift may pose major challenges, as population aging occurs in economies with relatively low per capita incomes and limited social inclusion, which usually would require sustained long-term growth. Some main concerns regarding the effects of population aging on economic growth include the potential reduction in labor supply, if the reduction in the share of the working-age population is not offset by higher labor-force participation rates (International Monetary Fund, 2025); slower productivity growth, as labor productivity tends to be higher among prime-aged workers (Feyrer, 2007); and greater fiscal pressure through higher lifetime spending on pensions and healthcare (Einav & Finkelstein, 2026), potentially reducing the public resources available for investment in productive capacity. Recent evidence remains mixed, with studies reporting either negative (Maestas et al., 2023) or no adverse effects of population aging on economic growth (Acemoglu & Restrepo, 2017). More research is still needed, particularly in developing countries, where empirical evidence remains comparatively limited.

I evaluate the effects of population aging on economic growth in Brazil, decomposing its effects into labor productivity and employment. Brazil provides a unique case for understanding the effect of population aging on growth. In addition to being one of the largest economies and most populous countries in the developing world, Brazil's demographic transition began later than in many other economies but has progressed rapidly. In early 2020, the country had one of the lowest total fertility rates (1.6 children per woman) worldwide (United Nations, 2022), and its elderly population is expected to account for more than one-third of the population by 2060

(Economic Commission for Latin America and the Caribbean, 2023). In parallel, the country has experienced successive years of modest economic growth following the domestic boom in the early 2000s (Organisation for Economic Co-operation and Development [OECD], 2025a).

I use a panel data set on 557 microregions from 2000 to 2022, providing a finely disaggregated spatial analysis of regional inequalities in Brazil. Building on recent developments in the literature (Maestas et al., 2023), the study extends previous empirical approaches by combining spatial panel data models with instrumental variables to address different sources of bias in estimates of the effect of population aging on economic dynamics. For example, local unobserved institutional and economic shocks can simultaneously affect growth and demographic processes, such as fertility and selective migration, thereby also altering the local age structure. The instrumental variable exploits variation in the share of the elderly population arising from predetermined cohort structures from earlier periods (relevance assumption) that are likely uncorrelated with contemporaneous economic shocks affecting growth (exclusion restriction). Another potential source of bias in regional growth models is spatial dependence in the data. The study accounts for the possibility that population aging in one locality may affect local economic growth and generate indirect effects in nearby localities, for example, through labor mobility or broader economic spillovers. After accounting for these potential sources of bias and time-varying confounders, such as initial demographic and economic characteristics, I find no strong evidence of a negative relationship between aging and economic growth.

The effects of population aging on growth are also decomposed into two major components: employment and productivity. Population aging is expected to reduce the economically active population and the total volume of hours worked (Bloom et al., 2001). All else being equal, a smaller working-age population would likely result in lower employment and

aggregate output growth rates (Maestas et al., 2023). However, the negative effects of population aging on employment can be offset by increasing employment and labor force participation among prime-age and older workers, a trend observed in many developed countries (Organisation for Economic Co-operation and Development [OECD], 2025b).

Another consequence of aging is a potential negative effect on labor productivity (Poplawski-Ribeiro, 2020). For example, the growth of the old-age dependency ratio would put pressure on public spending on pensions and healthcare, thereby reducing productive investment (Emerson et al., 2024). An aging labor force may also affect the generation of innovation by changing the age composition of inventors, since inventive activity and the characteristics of inventions vary over the life course (Kaltenberg et al., 2023). On the other hand, local economies may respond to population aging by adopting labor-saving technologies and increasing automation, particularly where aging creates shortages of workers performing manual production tasks (Acemoglu & Restrepo, 2018).

The magnitude and direction of the relationship between population aging, employment, and productivity may therefore vary according to the institutional and economic contexts. This is particularly relevant in developing economies, which are often characterized by dual labor market structures and substantial cross-sectoral differences in productivity and labor regulation. In Brazil, recent economic growth has been primarily driven by increases in agricultural productivity and the expansion of employment in the service sector (Arbache et al., 2016; Maia & Menezes, 2014). This trend suggests that the agricultural sector has relied more intensively on capital investment and technological adoption to offset a decreasing rural population. On the opposite side, some service sectors may have a more limited scope to offset workforce aging through labor-saving automation while simultaneously facing growing demand for care services.

Finally, I investigate how population aging shapes employment structures by examining whether it changes the composition of employment arrangements within economic sectors that may differ in their capacity to adapt to an aging population. Nearly half of the Brazilian labor force is engaged in informal employment (Roubaud et al., 2020), which usually has limited access to capital, technology, and organizational resources. In this context, population aging may shift employment toward more formally organized firms that are better able to adapt to a tightening labor supply. Population aging is also likely to increase demand for public-sector employment in health and social-care services in Brazil, mirroring the trend of substantial employment growth in these sectors across developed countries (Organisation for Economic Co-operation and Development [OECD], 2021). In Brazil, health and social-care services are predominantly provided by the public sector, where the Unified Health System provides universal public health-care coverage (Gadelha et al., 2023).

Material and Methods

Data and variables

I merge data from the Demographic Census and the System of National Accounts (SNA) to construct a longitudinal dataset covering 557 microregions for the years 2000, 2010, and 2022, provided by the *Instituto Brasileiro de Geografia e Estatística* (IBGE). Microregions are the second level of territorial organization in the Brazilian Administrative Division, grouping municipalities that share similar demographic, economic, historical, and geographical characteristics. In 2022, Brazil had 5,570 municipalities and 558 microregions. The island of Fernando de Noronha was excluded because it has no contiguous neighboring microregions and therefore cannot be incorporated into the spatial models described below.

The exploratory variable of interest is population aging, which is proxied by the share of the population aged 60 or older relative to the population aged 14 or older. The minimum retirement ages in Brazil are currently 62 for women and 65 for men. However, some individuals may retire earlier based on their contribution history and eligibility under the new rules introduced by the 2019 pension reform. I use the population aged 14 or older as a reference because this threshold corresponds to the minimum age for defining the employed population by the IBGE in the 2022 Demographic Census, as early entry into the labor market is relatively common in Brazil compared to other countries. Table 1 shows that the average share of people aged 60 or older was 12.4% in 2000 and increased by an average rate of 3.6 percentage points between consecutive censuses.

[Insert Table 1 here]

The three main dependent variables are: the log of gross value added (GVA) divided by the population aged 14 years or older (GVA per person); the log of GVA divided by the employed population (a proxy for labor productivity); and the log of employed population divided by the population aged 14 years or older (employment-to-population rate). GVA values are deflated to 2022 constant values using the implicit GDP (Gross Domestic Product) deflator from the SNA. Table 1 shows that GVA per capita increased by an average of 13.8% ($e^{0.129} - 1 = 0.138$) between consecutive censuses, driven by a 17.5% increase in labor productivity, while the employment-to-population rate declined slightly by 3.1%.

Empirical strategy

Identification. The benchmark model is a first-difference (FD) model, given by:

$$\Delta \ln \left(\frac{\mathrm{GVA}_{it}}{\mathrm{N}_{it}}\right) = \alpha_t + \delta \Delta \frac{\mathrm{A}_{it}}{\mathrm{N}_{it}} + \mathbf{x}'_{it}\boldsymbol{\beta} + \varepsilon_{it}, \qquad (1)$$

where the dependent variable, $\Delta \ln \left(\frac{\mathrm{GVA}_{it}}{\mathrm{N}_{it}}\right) = \ln\left(\frac{\mathrm{GVA}_{i,t+10}}{\mathrm{N}_{i,t+10}}\right) - \ln\left(\frac{\mathrm{GVA}_{i,t}}{\mathrm{N}_{i,t}}\right)$, is the change in the logarithm of GVA per person aged 14 or older (N) in the microregion i over the intercensal period t, which is a proxy for changes in the output per capita. The explanatory variable of interest, $\Delta \frac{\mathrm{A}_{it}}{\mathrm{N}_{it}} = \frac{\mathrm{A}_{i,t+10}}{\mathrm{N}_{i,t+10}} - \frac{\mathrm{A}_{i,t}}{\mathrm{N}_{i,t}}$, represents the change in the share of the population aged 60 or older (A) over the population aged 14 or older. The parameter δ represents the marginal effect of population aging on log GVA per person. Equation (1) is estimated in first difference, which removes time-invariant microregion-specific characteristics and therefore controls for persistent regional heterogeneity (such as historical differences in socioeconomic development). The period fixed-effects, α_t, additionally capture shocks common to all microregions in each intercensal interval (such as macroeconomic crises); and ε is the idiosyncratic error (such as local labor and demographic shocks).

The vector $\mathbf{x}$ contains variables with baseline values representing three main demographic confounders in the relationship between population aging and growth (Table A.1 in Appendix A). The first confounder is the log of population density (people per km^2), which controls for differences in urbanization, agglomeration, and population concentration. The second is net migration, which can affect economic growth and alter the age structure of the population. This factor is controlled by the cohort survival ratio, a proxy for net migration, computed as the population of individuals aged 15-59 at the current census (t) divided by the population aged 5–49 at the preceding census. To compute the cohort survival ratio for 2000, I use population data from the 1991 Census. The third confounder is education, as population aging affects the rate at which a new and better-educated cohort enters the labor market. This factor is controlled by two variables representing the share of people aged 25 or older with less than primary education, and with higher education or more (the share of those with primary or

secondary education is the reference category). In our robustness check, we additionally control for lagged ln $(\frac{\mathrm{GVA}_{i,t-15}}{\mathrm{N}_{i,t-15}})$, which accounts for differences in the initial level of regional development and conditional convergence. We measure this variable at 15 years before each growth interval to limit potential simultaneity.

One key challenge to estimating equation (1) is that population aging may also respond to economic dynamics, i.e., the variable $\frac{\mathrm{A}_{it}}{\mathrm{N}_{it}}$ may be endogenous. A key source of endogeneity is selective migration. Low economic dynamism is a main driver of out-migration of high-skilled individuals to more dynamic regions in Brazil, leaving an elderly population concentrated in less dynamic ones (Maia & Buainain, 2015). This trend may lead to downward bias in FD estimates, making the effect of aging on growth appear more negative than it actually is.

I follow Maestas et al. (2023) and define an instrumental variable (IV) based on the predicted share of the population aged 60 or older in a microregion i and year t, calculated by projecting the population aged 30 or older from year $t-30$ forward by 30 years using national survival rates. I use data from the Census at $t-30$ (1970 for 2000, 1980 for 2010, and 1991 for 2022) to forward-project age cohorts 0 or older ($N_{i,t-30}$) and 30 or older ($A_{i,t-30}$) by 30 years later, obtaining the predicted populations aged 30 or older ($\widehat{N}_{it}$) and 60 or older ($\hat{A}_{it}$) at year t. The predicted populations are obtained by applying age- and sex-specific survival rates from the IBGE life tables (Instituto Brasileiro de Geografia e Estatística [IBGE], 2026).

The change in the predicted share of the population aged 60 or older, $\Delta\frac{\widehat{\mathrm{A}}_{it}}{\widehat{\mathrm{N}}_{it}} = \frac{\widehat{\mathrm{A}}_{i,t+10}}{\widehat{\mathrm{N}}_{i,t+10}} - \frac{\widehat{\mathrm{A}}_{i,t}}{\widehat{\mathrm{N}}_{i,t}}$, is then used as an IV for $\Delta\frac{\mathrm{A}_{it}}{\mathrm{N}_{it}}$ to estimate equation (1) using first-difference two-stage least squares (FD-2SLS) (Berge, 2018). For analytical simplicity, I use the population aged 30 or older as the denominator, rather than 14 or older, to estimate the share of the predicted population aged

60 or older ($\hat{A}_{it}/\widehat{N}_{it}$). Estimating the population aged 14 or older would require combining cohorts from different censuses with little empirical benefit. As shown in the results section, the predicted populations based on national survival rates are strong predictors of the population 30 years later, satisfying the relevance condition. At the same time, because it is based on predetermined cohort structures and national survival rates, it is likely exogenous to contemporaneous local shocks that may simultaneously affect economic growth and population aging, satisfying the exclusion restriction.

Spatial dependence. The effects of population aging may extend beyond the boundaries of the locality in which demographic change occurs. Labor commuting, for example, creates spatial connections between local labor markets, as workers residing in one municipality may supply labor in another. Aging may also generate economic spillovers, as demographic change may directly affect economic activity in one locality and indirectly affect nearby localities through trade and other economic linkages. FD–2SLS estimates that ignore such spatial dependence may therefore underestimate the geographical reach of aging on economic dynamics.

I tested for the robustness of the estimates by using spatial panel data models (Elhorst, 2003). These models allow economic growth in each locality to depend on economic growth in neighboring localities while also accounting for unobserved shocks that may be spatially correlated across localities. A more general specification of the growth model with spatial dependence is:

$$\Delta \ln \left(\frac{\mathrm{GVA}_{it}}{\mathrm{N}_{it}}\right) = \alpha + \rho \mathbf{w}_i' \Delta \mathbf{y}_t + \delta \Delta \frac{\mathrm{A}_{it}}{\mathrm{N}_{it}} + \mathbf{x'}_{it}\boldsymbol{\beta} + \xi_{it}, \quad (2)$$

$$\text{where } \xi_{it} = \lambda \mathbf{w}_i' \boldsymbol{\xi}_t + \varepsilon_{it}$$

The spatial neighborhood matrix $\mathbf{w}_i'$ contains positive values for microregions with common boundaries, including vertices (queen contiguity criterion), and zero otherwise. I

normalize the matrix rows to smooth the data and facilitate the interpretation of spatial weights (Almeida, 2012). The same row-standardized neighborhood matrix $\mathbf{w}_i'$ is repeated for each intercensal period *t*, allowing spatial dependence within periods but not across periods.

The vector $\mathbf{y}_t$ contains the values of log GVA/N for all microregions at census *t*. The term $\boldsymbol{w}_{\mathrm{i}}'\Delta\mathbf{y}_t$ is the spatial lag of the dependent variable and represents the weighted average of the changes in log GVA/N across all microregions neighboring microregion *i*. Similarly, the vector $\boldsymbol{\xi}_t$ contains the errors for all microregions in intercensal interval *t*, while $\mathbf{w}_i'\boldsymbol{\xi}_t$ is the spatial lag of the error and represents the weighted average of errors across neighboring microregions. The spatial coefficients ρ and λ represent the degree of spatial dependence in the dependent variable and in the error, respectively.

Equation (2) represents the spatial autoregressive combined (SAC) model, which allows economic growth in one microregion to be affected by economic growth in neighboring microregions while also accounting for unobserved shocks across neighboring microregions. As a robustness check, I also estimate two simpler spatial specifications: the spatial autoregressive (SAR) model, which allows the spatial dependence only in the dependent variable through $\rho\mathbf{w}_i'\Delta\mathbf{y}_t$; and the spatial error model (SEM), which allows for spatial dependence only in the error through $\lambda\mathbf{w}_i'\boldsymbol{\xi}_t$.

The spatial models are estimated combining generalized spatial two-stage least squares (GS2SLS) and generalized moments estimation, instrumenting the spatial lag for the dependent variable (in the SAC and SAC models) and the endogenous ageing variable (Drukker et al., 2013; Piras, 2010).

Decomposing productivity and employment. The change in the log output per capita in equation (1) can be decomposed into two components:

$$\Delta \ln\left(\frac{\mathrm{GVA}_{it}}{\mathrm{N}_{it}}\right) = \Delta \ln\left(\frac{\mathrm{GVA}_{it}}{\mathrm{L}_{it}} \times \frac{\mathrm{L}_{it}}{\mathrm{N}_{it}}\right) = \Delta \ln\left(\frac{\mathrm{GVA}_{it}}{\mathrm{L}_{it}}\right) + \Delta \ln\left(\frac{\mathrm{L}_{it}}{\mathrm{N}_{it}}\right), \qquad (2)$$

where L is the employed population aged 14 or older. The first component of this decomposition – $\Delta \ln\left(\frac{\mathrm{GVA}_{it}}{\mathrm{L}_{it}}\right)$ – is the change in the log of GVA per employed person, a proxy for changes in labor productivity, while the second component – $\Delta \ln\left(\frac{\mathrm{L}_{it}}{\mathrm{N}_{it}}\right)$ – is the change in the log of employment-to-population ratio (employed population divided by the working-age population, defined as individuals 14 years or older), a proxy for changes in employment levels. I estimate equation (1) separately for each component, using the same strategies described above (FD-2SLS and GS2SLS). These strategies decompose the effects captured by the coefficient δ into the labor productivity and employment channels.

Heterogeneous effects. I develop separate analysis by economic sector and employment status to better understand the mechanisms explaining the effects of population aging. First, I decompose the effects on labor productivity and employment separately for the three main economic sectors: agriculture, which includes agriculture, livestock, forestry, fishing, and aquaculture (ISIC Rev. 4 Section A); industry, which includes mining and quarrying, manufacturing, utilities—electricity, gas, water, and waste management—and construction (Sections B–F); and services, which include trade, transportation and storage, accommodation and food services, information and communication, financial and insurance activities, real estate, professional and administrative services, public administration, education, health, and other services (Sections G–U).

Agriculture was the most dynamic sector over the period, combining the largest increases in labor productivity and decline in employment-to-population ratio. Table 1 indicates that average agricultural labor productivity increased by 64.9% per intercensal period, while the share

of people working in the sector declined by 34.9%. In the same period, labor productivity in the industry sector grew more modestly (10.5% per intercensal period), while it remained relatively stable in the service sector (2.8% increase).

To examine how population aging may affect the employment structure, I also evaluate the effects of changes in the share of people aged 60 or older on changes in the log of employment-to-population ratio across five employment-status categories: formal employment, which represents the share of private employees with registered labor contracts; informal employment, which represents the share of private employees without formally registered contracts; public employment, which represents the share of workers employed in the public sector, including civil servants, employees of state-owned enterprises, and military personnel; employers, defined as the share of individuals with at least one employee; and self-employment, which represents the share of self-employed workers.

The period of analysis coincides with a wider formalization of the labor market. The average proportion of the population in informal employment declined by 21.0% per intercensal period, while the proportion in formal employment increased by 9.4% (Table 1). Public-sector employment, which accounted for 3.1% of the population in 2000, increased by 64.8% per intercensal period.

Results

Main estimates. The estimates in Table 2 indicate the effects of population aging, defined by the intercensal change in A/N, on three dependent variables: changes in the output per capita (Panel A, where the dependent variable is the change in log of GVA/N), labor productivity (Panel B, which uses the change in log of GVA/L), and employment (Panel C, which uses the change in log of L/N). The estimates are derived from five different model

specifications. Model (1) uses FD estimators, while models (2)-(5) use FD-2SLS estimators. Models (1) and (2) include only period fixed effects. Models (3)–(5) are nested extensions of model (2): model (3) adds the CSR and log population density; model (4) additionally controls for educational composition; and model (5) further includes lagged log GVA per capita. Estimates from Model (1), which do not account for endogeneity, are presented for comparison and should be interpreted descriptively regarding the direction of potential bias. The IV (change in the predicted share of the population aged 60 or older) used in models (2)-(5) is strongly correlated with the change in the observed share (with R^2=0.478), as shown in Figure B1 (Appendix B). The complete set of model estimates reported in Table 2, including covariates, is presented in Tables C.1–C.3 of Appendix C.

[Insert Table 2 here]

The FD-2SLS estimate without time-varying controls (Model 2) suggests a negative effect of population aging on output per capita (–1.780, p=0.007). However, this effect diminishes and becomes statistically insignificant after controlling for time-varying sociodemographic characteristics associated with both aging and regional economic performance, including population density and cohort survival (Model 3, p= 0.494), as well as educational composition (Model 4, p=0.828). The estimate is also insignificant in Model 5, which additionally accounts for prior output per capita (p=0.914).

The FD-2SLS in Table 2 also suggest two opposite effects of population aging: a negative effect on labor productivity and a positive effect on employment. While the positive effects on employment remain strongly significant in all five specifications (p<0.001), the negative effect of aging on labor productivity diminishes and becomes insignificant after accounting for educational composition (Model 4, p=0.253) and prior output per capita (Model 5, p=0.194).

Taken together, these preliminary findings suggest a stronger and positive effects of population aging on employment, while its negative effects on labor productivity tend to be explained by concurrent sociodemographic processes. As a result, the overall negative associations between aging and output per capita observed in the parsimonious specifications appear to be primarily mediated by concurrent sociodemographic processes.

Regional spillovers. Table 3 compares the FD-2SLS estimates from model (5) with three spatial model specifications estimated by GS2SLS: SAC, SAR, and SEM. The idea is to assess whether the FD-2SLS estimates are robust to spatial dependence arising from economic and demographic dynamics across neighboring regions. The complete set of estimates, including those for the spatial-dependence parameters, is presented in Tables D.1–D.3 of Appendix D.

[Insert Table 3 here]

The effects of aging on productivity and its overall impact on output per capita remain statistically insignificant across all spatial specifications, SAC (p=0.513 and p=0.380, respectively), SAR (p=0.621 and p=0.276), and SEM (p=0.252 and p=0.790). In turn, the negative effects of aging on employment, observed in the FD-2SLS estimates, remain statistically significant in the SEM specification (1.125, p=0.020), they become statistically insignificant in the SAC (p=0.693) and SAR (p=0.398) models. However, by accounting only for spatial dependence in the error term, the SEM may be inadequately specified, and its estimates should therefore be interpreted with caution. The statistically significant spatial-lag coefficients reported for the SAC and SAR specifications in Table D.3 ($p < 0.001$ in both models) indicate that spatial dependence also operates through the dependent variable.

In summary, the GS2SLS estimates for the spatial models reinforce the FD-2SLS estimates indicating no statistically detectable effects of aging on labor productivity or output per

capita when analyzing the economy as a whole. The positive effects on employment are sensitive to model specification, suggesting the presence of economic spillovers across neighboring regions.

Heterogeneous effects. I now examine the heterogeneous effects of population aging by economic sector. As the SAC model accounts for both spatial-lag and spatial-error dependence, I focus on its estimates in the subsequent analyses. Table 4 reports the GS2SLS estimates of SAC models for effects of population aging on the three main economic sectors: agriculture, industry, and services. Tables E.1–E.3 (Appendix E) provide the complete set of estimates.

[Insert Table 4 here]

The estimates indicate that the effects of aging are statistically significant only on employment in the service sector. The estimate indicates a positive effect (0.570, p=0.009), suggesting growing demand for service jobs in regions with higher concentration of older people.

I further examine the employment effects of population aging across five employment statuses: formal employment, informal employment, public-sector employment, employer status, and self-employment. Table 5 presents the GS2SLS estimates from the SAC models. The dependent variables measure changes in the log employment-to-population ratio for each employment status. The models are also segmented by economic sector: the total economy (panel A), agriculture (panel B), industry (panel C), and services (panel D).

The positive effect of aging on employment in the service sector observed in Table 4 is primarily driven by three types of employment: formal (1.622, p=.003), informal (1.052, p=.003), and public employment (3.244, p=.005). The effect is stronger among public employees, which may indicate that an aging population is pressuring the demand for services provided by the public sector in Brazil.

Results also indicate that population aging increases formal employment in the industry sector (3.503, p<.001) and informal employment in the agricultural sector (2.057, p=.004). On the one hand, the findings suggest that formal-sector industries may be better positioned to adapt to population aging. On the other hand, some rural regions may experience demographic and economic stagnation, with older workers concentrated in traditional and often informal agricultural activities.

Concluding remarks

I found no consistent evidence that population aging itself is undermining economic growth or labor productivity in Brazil. Instead, population aging seems to, at least temporarily, boost employment, particularly in public-sector services. Aging regions have also seen an increase in the formalization of the labor force in both the industrial and service sectors, while the agricultural workforce remaining in these localities has been disproportionately concentrated in informal employment.

While estimates from more parsimonious specifications suggest that population aging is negatively associated with output per capita and labor productivity, these relationships are primarily mediated by contemporaneous demographic changes and economic dynamics. For example, population aging has been more pronounced in highly urbanized and developed regions in Brazil, where economic growth has also been slower. Similarly, the positive association between population aging and employment is partially mediated by the economic dynamics of neighboring regions. One possible explanation is that economic changes associated with population aging spill over into surrounding localities, leading to a redistribution of employment effects across local labor markets, for example, through labor mobility and interregional trade.

In response to an aging labor force, economies may adapt by adopting labor-saving technologies and shifting labor to strategic sectors where labor cannot easily be automated. Brazil provides a compelling illustration of this dynamic, where rapid agricultural mechanization sustained robust output growth despite a shrinking agricultural labor force in rural areas. This process may have facilitated the expansion of growth and employment in specific service sectors nationwide. One notable example is the expansion of public employment in the service sector, which has been more pronounced in aging regions. This result also aligns with the expectation that population aging increases the demand for health and social care services, which are predominantly provided by the public sector in Brazil.

The findings also highlight a dual labor market shift in aging regions: non-agricultural sectors experiencing an expansion of formal employment, while the agricultural sector is experiencing a rise in informality. One possibility is that the positive effect of aging on formal employment in non-agricultural sectors may be associated with structural transformation in the economy, where less productive and informally organized firms are gradually being replaced by more capital-intensive and formalized firms that can more readily adopt labor-saving technologies (Acemoglu & Restrepo, 2018). On the other hand, the increase in informality in regions experiencing faster population aging may reflect the relative stagnation of some rural areas, where older workers remain concentrated in labor-intensive and informal agricultural activities (Maia & Buainain, 2015).

While this study indicates positive effects of population aging on employment in specific service activities, this effect may be temporary. During this period, Brazil benefited from a demographic window in which the working-age population increased relative to dependent age groups, creating the potential for a larger labor supply and the expansion of employment-based

growth in non-agricultural activities, particularly services (Maia & Menezes, 2014). This process was reinforced by the growing participation of women in the labor market, which accounted for an important share of the increase in employment during the most favorable phase of the demographic bonus (Alves, 2020). However, as population aging progresses, the working-age population will begin to grow more slowly than the older population, potentially undermining the supply of the labor force while simultaneously increasing the demand for health and social care services.

Another challenge related to population aging in Brazil is how to sustain the growing demand for health and social-care services in the public sector while also financing a growing public pension system. While Brazil has achieved quasi-universal old-age benefit coverage, this comes with a high financial cost, as pension expenditures already accounted for nearly 13% of the GDP in 2019, higher than the average of developed countries (Zviniene & Raquel, 2024).

References

Acemoglu, D., & Restrepo, P. (2017). Secular Stagnation? The Effect of Aging on Economic Growth in the Age of Automation. *American Economic Review*, *107*(5), 174–179. https://doi.org/10.1257/aer.p20171101

Acemoglu, D., & Restrepo, P. (2018). *Demographics and Automation* (No. W24421; p. w24421). National Bureau of Economic Research. https://doi.org/10.3386/w24421

Alves, J. E. D. (2020). Bônus demográfico no Brasil: Do nascimento tardio à morte precoce pela Covid-19. *Revista Brasileira de Estudos de População*, *37*, 1–18. https://doi.org/10.20947/S0102-3098a0120

Arbache, J., Rouzet, D., & Spinelli, F. (2016). *The Role of Services for Economic Performance in Brazil* (OECD Trade Policy Papers No. 193; OECD Trade Policy Papers, Vol. 193). https://doi.org/10.1787/5jlpl4nx0ptc-en

Berge, L. (2018). *Efficient estimation of maximum likelihood models with multiple fixed-effects: The R package FENmlm* (No. 23; CREA Discussion Papers). Center for Research in Economics and Management.

Bloom, D., Canning, D., & Sevilla, J. (2001). *Economic Growth and the Demographic Transition* (No. W8685; p. w8685). National Bureau of Economic Research. https://doi.org/10.3386/w8685

Drukker, D. M., Egger, P., & Prucha, I. R. (2013). On Two-Step Estimation of a Spatial Autoregressive Model with Autoregressive Disturbances and Endogenous Regressors. *Econometric Reviews*, *32*(5–6), 686–733. https://doi.org/10.1080/07474938.2013.741020

Economic Commission for Latin America and the Caribbean. (2023). *Social Panorama of Latin America 2023*. ECLAC. https://www.cepal.org/en/publications/48568-ageing-latin-america-and-caribbean-inclusion-and-rights-older-persons

Einav, L., & Finkelstein, A. (2026). *Elderly Health and Longevity in the US: Evidence and Implications* (No. W35346; p. w35346). National Bureau of Economic Research. https://doi.org/10.3386/w35346

Elhorst, J. P. (2003). Specification and Estimation of Spatial Panel Data Models. *International Regional Science Review*, *26*(3), 244–268. https://doi.org/10.1177/0160017603253791

Emerson, P., Knabb, S., & Sirbu, A.-I. (2024). Does the old-age dependency ratio place a drag on secular growth? *Economic Analysis and Policy*, *82*, 1056–1070. https://doi.org/10.1016/j.eap.2024.04.026

Feyrer, J. (2007). Demographics and Productivity. *Review of Economics and Statistics*, *89*(1), 100–109. https://doi.org/10.1162/rest.89.1.100

Gadelha, C. A. G., Gimenez, D. M., Cajueiro, J. P. D. M., & Moreira, J. D. D. (2023). The Health Economic-Industrial Complex (HEIC): A strategic area for both the modernization of the Unified Health System (SUS) and the creation of future jobs. *Ciência & Saúde Coletiva*, *28*(10), 2833–2843. https://doi.org/10.1590/1413-812320232810.10672023en

Instituto Brasileiro de Geografia e Estatística [IBGE]. (2026). *Estatísticas do Séc. XX*. https://seculoxx.ibge.gov.br

International Monetary Fund. (2025). The Rise of the Silver Economy: Global Implications of Population Aging. In *World Economic Outlook, April 2025: A Critical Juncture amid Policy Shifts* (pp. 1–26). International Monetary Fund. https://doi.org/10.5089/9798400289583.081

Kaltenberg, M., Jaffe, A. B., & Lachman, M. E. (2023). Invention and the life course: Age differences in patenting. *Research Policy*, *52*(1), 104629. https://doi.org/10.1016/j.respol.2022.104629

Maestas, N., Mullen, K. J., & Powell, D. (2023). The Effect of Population Aging on Economic Growth, the Labor Force, and Productivity. *American Economic Journal: Macroeconomics*, *15*(2), 306–332. https://doi.org/10.1257/mac.20190196

Maia, A. G., & Buainain, A. M. (2015). O novo mapa da população rural brasileira. *Confins*, *25*. https://doi.org/10.4000/confins.10548

Maia, A. G., & Menezes, E. (2014). Economic growth, labor and productivity in Brazil and the United States: A comparative analysis. *Revista de Economia Política*, *34*(2), 212–229. https://doi.org/10.1590/S0101-31572014000200003

Organisation for Economic Co-operation and Development [OECD]. (2021). *Health at a Glance 2021: OECD Indicators*. OECD Publishing. https://doi.org/10.1787/ae3016b9-en

Organisation for Economic Co-operation and Development [OECD]. (2025a). *OECD Economic Outlook, Volume 2025 Issue 2: Resilient Growth but with Increasing Fragilities* (Vol. 2025). OECD Publishing. https://doi.org/10.1787/9f653ca1-en

Organisation for Economic Co-operation and Development [OECD]. (2025b). *OECD Employment Outlook 2025: Can We Get Through the Demographic Crunch?* OECD Publishing. https://doi.org/10.1787/194a947b-en

Piras, G. (2010). sphet: Spatial Models with Heteroskedastic Innovations in R. *Journal of Statistical Software*, *35*(1). https://doi.org/10.18637/jss.v035.i01

Poplawski-Ribeiro, M. (2020). Labour force ageing and productivity growth. *Applied Economics Letters*, *27*(6), 498–502. https://doi.org/10.1080/13504851.2019.1637509

Roubaud, F., Razafindrakoto, M., Saboia, J., Simões, A., Hallak Neto, J., & Botelho, L. (2020). Conceitos, definições e mensuração do trabalho informal no Brasil. *IE-UFRJ - Texto Para Discussão*, (031). https://www.ie.ufrj.br/publicacoes-j/textos-para-discussao.html

United Nations. (2022). *World Population Prospects 2022*. United Nations, Department of Economic and Social Affairs, Population Division. https://www.un.org/development/desa/pd/sites/www.un.org.development.desa.pd/files/wpp2022_summary_of_results.pdf

Zviniene, A., & Raquel, T. (2024). *The Brazilian Pension System Under an Equity Lens: Technical Note*. Washington, DC: World Bank. https://doi.org/10.1596/41521

Tables

Table 1. Descriptive statistics at baseline and intercensal changes

	Baseline year (2000)		Intercensal change	
Variable	Mean	SD	Mean	SD
A/N (proportion and Δp.p.)				
Share people 60+	0.124	(0.027)	0.036	(0.016)
GVA/N by sector (R$1,000 and Δln)				
Total	33.5	(25.0)	0.129	(0.238)
Agriculture	5.4	(6.3)	0.071	(0.469)
Industry	8.6	(14.3)	0.134	(0.534)
Services	19.5	(12.1)	0.125	(0.140)
GVA/L by sector (R$1,000 and Δln)				
Total	62.7	(45.6)	0.161	(0.266)
Agriculture	36.7	(40.6)	0.500	(0.648)
Industry	82.1	(133.3)	0.100	(0.510)
Services	73.9	(28.4)	0.028	(0.147)
L/N by sector (proportion and Δln)				
Total	0.528	(0.062)	-0.032	(0.114)
Agriculture	0.175	(0.093)	-0.429	(0.342)
Industry	0.095	(0.046)	0.034	(0.188)
Services	0.252	(0.071)	0.097	(0.079)
L/N by employment status (proportion and Δln)				
Formal	0.139	(0.081)	0.090	(0.321)
Informal	0.142	(0.038)	-0.211	(0.232)
Public	0.031	(0.013)	0.500	(0.576)
Employer	0.013	(0.007)	0.136	(0.579)
Self-employed	0.137	(0.038)	0.018	(0.184)

Notes: Changes are measured as first differences in logarithms, except for the share of the population aged 60 or older, which is expressed in percentage points. SD is standard deviation.

Table 2. First-difference estimates of the association between population aging, economic growth, labor productivity, and employment-to-population ratio

	(1)	(2)	(3)	(4)	(5)
(A) Δ log GVA/N					
Δ share people 60+	-1.136*	-1.780**	-0.435	0.170	0.085
	(0.504)	(0.658)	(0.637)	(0.783)	(0.784)
	p = 0.024	p = 0.007	p = 0.494	p = 0.828	p = 0.914
(B) Δ log GVA/L					
Δ share people 60+	-3.036***	-4.660***	-2.936***	-0.924	-1.055
	(0.529)	(0.742)	(0.684)	(0.807)	(0.811)
	p = 0.000	p = 0.000	p = 0.000	p = 0.253	p = 0.194
(C) Δ log L/N					
Δ share people 60+	1.899***	2.880***	2.501***	1.094***	1.139***
	(0.214)	(0.294)	(0.288)	(0.294)	(0.300)
	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000

Notes: The table reports the estimated coefficient for Δ share aged 60+. Panel A reports estimates for Δ log GVA/N, Panel B for Δ log GVA/L, and Panel C for Δ log L/N. All models are estimated in first differences and include period fixed effects. Model (1) is a non-instrumented first-difference specification without additional controls. Models (2)-(5) treat the change in the share aged 60+ as endogenous and instrument it with the predicted change in the share aged 60+. Model (3) controls for the cohort survival ratio and log population density. Model (4) adds educational composition. Model (5) further controls for lagged log GVA/N. Standard errors clustered by microregion are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3. Spatial estimates of the association between population aging, economic growth, labor productivity, and employment-to-population ratio

	(1) Non-spatial IV	(2) SAC-IV	(3) SAR-IV	(4) SEM-IV
(A) Δ log GVA/N				
Δ share people 60+	0.085 (0.784) p = 0.914	0.705 (0.804) p = 0.380	0.782 (0.719) p = 0.276	-0.326 (1.222) p = 0.790
(B) Δ log GVA/L				
Δ share people 60+	-1.055 (0.811) p = 0.194	-0.897 (1.369) p = 0.513	-0.443 (0.897) p = 0.621	-1.414 (1.234) p = 0.252
(C) Δ log L/N				
Δ share people 60+	1.139*** (0.300) p = 0.000	0.136 (0.343) p = 0.693	0.286 (0.338) p = 0.398	1.125* (0.483) p = 0.020

Notes: Panel A reports estimates for Δ log GVA/N, Panel B for Δ log GVA/L, and Panel C for Δ log L/N. The change in the share aged 60+ is treated as endogenous and instrumented by the predicted change in the share aged 60+. All models are estimated in first difference and include period effects, cohort survival ratio, log population density, educational composition, and lagged log GVA/N. The spatial weights matrix is block diagonal, with one queen-contiguity matrix for each intercensal growth interval. SAC-IV is the general spatial model incorporating both spatial lag and spatial error dependence, while SAR-IV and SEM-IV are the corresponding restricted models with spatial lag and spatial error dependence, respectively. The non-spatial IV model reports standard errors clustered by microregion, whereas the spatial models report heteroskedasticity-robust GMM standard errors. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 4. Sectoral SAC-IV estimates of the association between population aging, economic growth, labor productivity, and employment-to-population ratios

	(1) Agriculture	(2) Industry	(3) Services
(A) Δ log GVA/N			
Δ share people 60+	0.433 (0.881) p = 0.623	1.803 (1.160) p = 0.120	0.625 (0.447) p = 0.162
(B) Δ log GVA/L			
Δ share people 60+	0.011 (0.867) p = 0.990	1.212 (0.906) p = 0.181	0.128 (0.289) p = 0.657
(C) Δ log L/N			
Δ share people 60+	-0.676 (1.227) p = 0.582	0.628 (0.414) p = 0.130	0.570** (0.217) p = 0.009

Notes: The table reports the estimated coefficient for Δ share aged 60+. Panel A reports SAC-IV estimates for sectoral Δ log GVA/N, Panel B for sectoral Δ log GVA/L, and Panel C for sectoral Δ log L/N. The change in the share aged 60+ is treated as endogenous and instrumented by its predicted change. All models are estimated in first differences and include period effects, the cohort survival ratio, log population density, educational composition, and lagged log GVA/N. Period effects are removed through within-period demeaning. The spatial weights matrix is block diagonal, with one queen-contiguity matrix for each intercensal growth interval. All models incorporate both spatial-lag and spatial-error dependence. Heteroskedasticity-robust GMM standard errors are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 5. Estimates of the association between population aging and employment status by economic sector

	(1) Formal	(2) Informal	(3) Public	(4) Employer	(5) Self-employed
(A) Total employment					
Δ share people 60+	1.292** (0.466) p = 0.006	0.401 (0.309) p = 0.194	3.423** (1.216) p = 0.005	0.556 (0.959) p = 0.562	-1.374*** (0.359) p = 0.000
(B) Agriculture					
Δ share people 60+	1.616 (0.990) p = 0.103	2.057** (0.707) p = 0.004	9.103 (13.801) p = 0.509	-0.022 (6.985) p = 0.998	-0.468 (0.399) p = 0.241
(C) Industry					
Δ share people 60+	3.503*** (0.731) p = 0.000	0.875 (0.523) p = 0.094	-1.218 (5.407) p = 0.822	0.668 (4.397) p = 0.879	0.492 (0.585) p = 0.400
(D) Services					
Δ share people 60+	1.622** (0.553) p = 0.003	1.052** (0.360) p = 0.003	3.244** (1.150) p = 0.005	1.164 (1.293) p = 0.368	-0.458 (0.276) p = 0.097

Notes: The table reports the estimated coefficient for Δ share aged 60+. Panel A reports SAC-IV estimates for total employment, Panel B for agriculture, Panel C for industry, and Panel D for services. The dependent variables are the first differences in the log employment-to-population ratios for formal workers, informal workers, public-sector workers, employers, and self-employed workers. The change in the share aged 60+ is treated as endogenous and instrumented by its predicted change. All models are estimated in first differences and include period effects, the cohort survival ratio, log population density, educational composition, and lagged log GVA/N. Period effects are removed through within-period demeaning. The spatial weights matrix is block diagonal, with one queen-contiguity matrix for each intercensal growth interval. All models incorporate both spatial-lag and spatial-error dependence. Heteroskedasticity-robust GMM standard errors are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

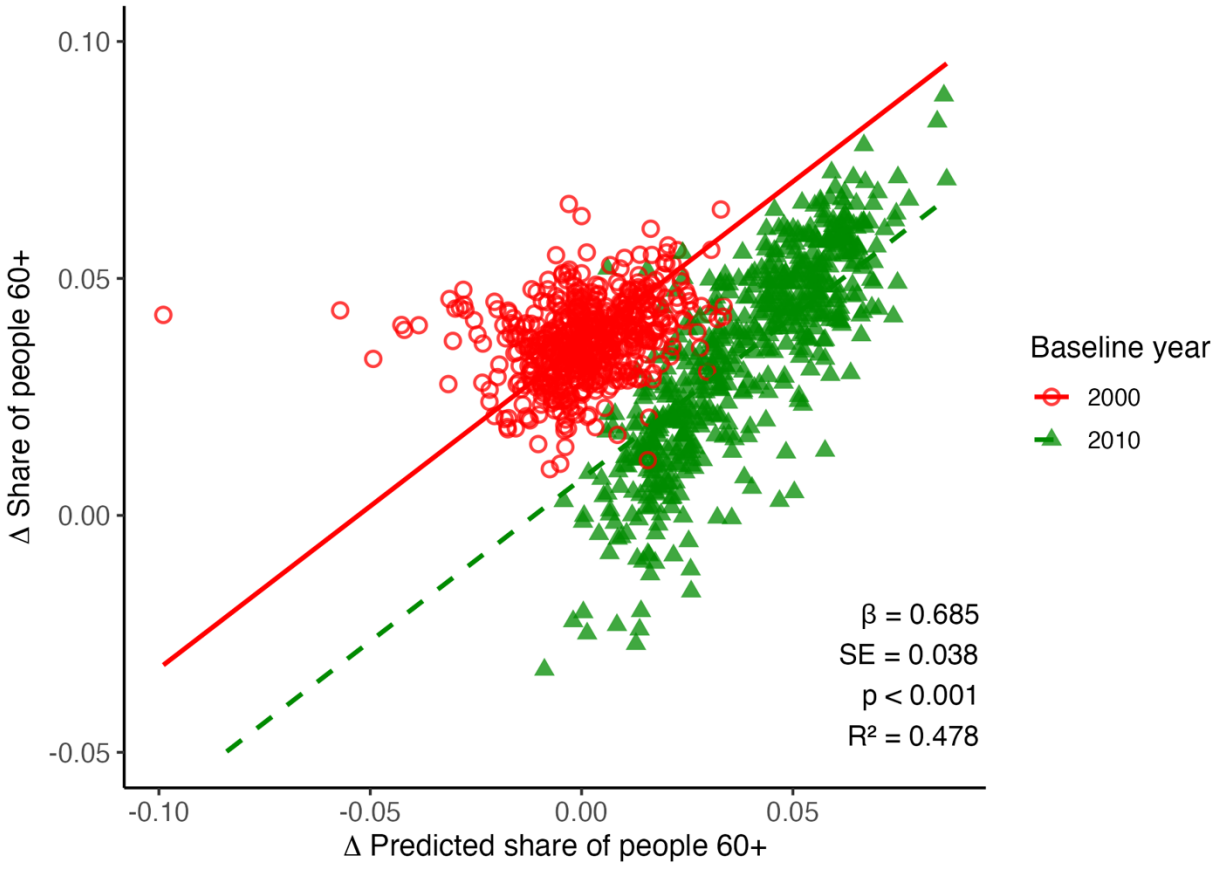
Appendices

Table A.1. Descriptive statistics for baseline control variables

	2000		2010	
Variable	Mean	SD	Mean	SD
Cohort survival ratio	0.913	(0.149)	0.956	(0.107)
Population density	66.2	(246.9)	81.7	(294.6)
Share less than primary education	0.695	(0.094)	0.609	(0.114)
Share superior education or more	0.043	(0.030)	0.073	(0.037)

Notes: The years 2000 and 2010 represent the baseline years of the 2000–2010 and 2010–2022 intercensal intervals, respectively. Population density is reported in inhabitants per square kilometer. SD is standard deviation.

Figure B.1. Relationship between first difference of the predicted and observed share of people 60 or older



Notes: The model is estimated in first differences and include period fixed effects.

Table C.1. First-difference estimates for GVA per person aged 14 or older

	(1)	(2)	(3)	(4)	(5)
Δ share people 60+	-1.136*	-1.780**	-0.435	0.170	0.085
	(0.504)	(0.658)	(0.637)	(0.783)	(0.784)
	p = 0.024	p = 0.007	p = 0.494	p = 0.828	p = 0.914
Cohort survival ratio			-0.230**	-0.148	-0.174
			(0.081)	(0.098)	(0.093)
			p = 0.005	p = 0.129	p = 0.062
Log population density			-0.028***	-0.025***	-0.022***
			(0.005)	(0.006)	(0.007)
			p = <0.001	p = <0.001	p = <0.001
Share less than primary				0.333*	0.256
				(0.169)	(0.197)
				p = 0.049	p = 0.194
Share superior or more				0.387	0.434
				(0.458)	(0.447)
				p = 0.398	p = 0.332
Lagged log GVA/N					-0.008
					(0.010)
					p = 0.401
R^2	0.007	0.008	0.062	0.067	0.068
N	1114	1114	1114	1114	1114

Notes: The dependent variable is Δ log GVA/N. All models are estimated in first differences and include period fixed effects. Model (1) is a first-difference specification without additional controls. Models (2)-(5) treat the change in the share people 60+ as endogenous and instrument it with the predicted change in the share people 60+.Standard errors clustered by microregion are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table C.2. First-difference estimates for GVA per employed person

	(1)	(2)	(3)	(4)	(5)
Δ share people 60+	-3.036***	-4.660***	-2.936***	-0.924	-1.055
	(0.529)	(0.742)	(0.684)	(0.807)	(0.811)
	p = <0.001	p = <0.001	p = <0.001	p = 0.253	p = 0.194
Cohort survival ratio			-0.422***	-0.185*	-0.224*
			(0.085)	(0.093)	(0.089)
			p = <0.001	p = 0.048	p = 0.012
Log population density			-0.031***	-0.019***	-0.016*
			(0.005)	(0.006)	(0.006)
			p = <0.001	p = <0.001	p = 0.012
Share less than primary				0.847***	0.730***
				(0.168)	(0.195)
				p = <0.001	p = <0.001
Share superior or more				0.629	0.700
				(0.462)	(0.453)
				p = 0.174	p = 0.122
Lagged log GVA/N					-0.012
					(0.010)
					p = 0.208
R^2	0.115	0.119	0.201	0.241	0.244
N	1114	1114	1114	1114	1114

Notes: The dependent variable is Δ log GVA/L. All models are estimated in first differences and include period fixed effects. Model (1) is a first-difference specification without additional controls. Models (2)-(5) treat the change in the share people 60+ as endogenous and instrument it with the predicted change in the share people 60+.Standard errors clustered by microregion are reported in parentheses. * p < 0.05, ** p < 0.01, *** p < 0.001.

Table C.3. First-difference estimates for the employed-to-population ratio

	(1)	(2)	(3)	(4)	(5)
Δ share people 60+	1.899***	2.880***	2.501***	1.094***	1.139***
	(0.214)	(0.294)	(0.288)	(0.294)	(0.300)
	p = <0.001	p = <0.001	p = <0.001	p = <0.001	p = <0.001
Cohort survival ratio			0.191***	0.036	0.050*
			(0.035)	(0.023)	(0.024)
			p = <0.001	p = 0.125	p = 0.035
Log population density			0.003	-0.005*	-0.006**
			(0.002)	(0.002)	(0.002)
			p = 0.125	p = 0.011	p = 0.003
Share less than primary				-0.515***	-0.474***
				(0.056)	(0.058)
				p = <0.001	p = <0.001
Share superior or more				-0.242	-0.267
				(0.142)	(0.142)
				p = 0.089	p = 0.060
Lagged log GVA/N					0.004*
					(0.002)
					p = 0.027
R^2	0.424	0.430	0.477	0.575	0.577
N	1114	1114	1114	1114	1114

Notes: The dependent variable is Δ log L/N. All models are estimated in first differences and include period fixed effects. Model (1) is a first-difference specification without additional controls. Models (2)-(5) treat the change in the share people 60+ as endogenous and instrument it with the predicted change in the share people 60+.Standard errors clustered by microregion are reported in parentheses. * p < 0.05, ** p < 0.01, *** p < 0.001.

Table D.1. Spatial estimates for output per capita

	(1) Non-spatial IV	(2) SAC-IV	(3) SAR-IV	(4) SEM-IV
Δ share people 60+	0.085 (0.784) p = 0.914	0.705 (0.804) p = 0.380	0.782 (0.719) p = 0.276	-0.326 (1.222) p = 0.790
Cohort survival ratio	-0.174 (0.093) p = 0.062	-0.205* (0.084) p = 0.014	-0.166 (0.085) p = 0.052	-0.229** (0.085) p = 0.007
Log population density	-0.022*** (0.007) p = 0.001	-0.015 (0.008) p = 0.069	-0.017* (0.008) p = 0.034	-0.018 (0.010) p = 0.076
Share less primary	0.256 (0.197) p = 0.194	0.103 (0.197) p = 0.602	0.204 (0.198) p = 0.304	0.056 (0.213) p = 0.794
Share superior more	0.434 (0.447) p = 0.332	-0.060 (0.458) p = 0.895	0.174 (0.458) p = 0.704	-0.019 (0.544) p = 0.972
Lagged GVA/N	-0.008 (0.010) p = 0.401	-0.014 (0.011) p = 0.200	-0.010 (0.010) p = 0.318	-0.014 (0.011) p = 0.181
Spatial lag of Y		0.266 (0.215) p = 0.216	0.241 (0.225) p = 0.285	
Spatial lag of error		0.206 (0.218) p = 0.346		0.572*** (0.039) p = 0.000
N	1114	1114	1114	1114

Notes: The dependent variable is Δ log GVA/N. The change in the share people 60+ is treated as endogenous and instrumented by the predicted change in the share people 60+. The spatial weights matrix is block diagonal, with one queen-contiguity matrix for each intercensal growth interval. All models are estimated in firs difference and include period effects. SAC-IV is the general spatial model incorporating both spatial lag and spatial error dependence, while SAR-IV and SEM-IV are the corresponding restricted models with spatial lag and spatial error dependence, respectively. The spatial lag coefficient measures dependence in the dependent variable across neighboring microregions, while the spatial error coefficient measures spatial dependence in the disturbance term. The non-spatial IV model reports standard errors clustered by microregion, whereas the spatial models report heteroskedasticity-robust GMM standard errors. Standard errors are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table D.2. Spatial estimates for labor productivity

	(1) Non-spatial IV	(2) SAC-IV	(3) SAR-IV	(4) SEM-IV
Δ share people 60+	-1.055 (0.811) p = 0.194	-0.897 (1.369) p = 0.513	-0.443 (0.897) p = 0.621	-1.414 (1.234) p = 0.252
Cohort survival ratio	-0.224* (0.089) p = 0.012	-0.267*** (0.077) p = 0.001	-0.209* (0.083) p = 0.012	-0.261** (0.084) p = 0.002
Log population density	-0.016* (0.006) p = 0.012	-0.010 (0.009) p = 0.304	-0.014* (0.006) p = 0.026	-0.011 (0.010) p = 0.228
Share less primary	0.730*** (0.195) p = 0.000	0.579** (0.206) p = 0.005	0.707*** (0.194) p = 0.000	0.588** (0.217) p = 0.007
Share superior more	0.700 (0.453) p = 0.122	0.360 (0.503) p = 0.475	0.612 (0.458) p = 0.181	0.461 (0.548) p = 0.400
Lagged GVA/N	-0.012 (0.010) p = 0.208	-0.018 (0.011) p = 0.092	-0.013 (0.010) p = 0.193	-0.017 (0.011) p = 0.108
Spatial lag of Y		0.033 (0.178) p = 0.851	0.107 (0.138) p = 0.436	
Spatial lag of error		0.557*** (0.090) p = 0.000		0.532*** (0.039) p = 0.000
N	1114	1114	1114	1114

Notes: The dependent variable is Δ log GVA/L. The change in the share people 60+ is treated as endogenous and instrumented by the predicted change in the share people 60+. The spatial weights matrix is block diagonal, with one queen-contiguity matrix for each intercensal growth interval. All models are estimated in firs difference and include period effects. SAC-IV is the general spatial model incorporating both spatial lag and spatial error dependence, while SAR-IV and SEM-IV are the corresponding restricted models with spatial lag and spatial error dependence, respectively. The spatial lag coefficient measures dependence in the dependent variable across neighboring microregions, while the spatial error coefficient measures spatial dependence in the disturbance term. The non-spatial IV model reports standard errors clustered by microregion, whereas the spatial models report heteroskedasticity-robust GMM standard errors. Standard errors are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table D.3. Spatial estimates for employment

	(1) Non-spatial IV	(2) SAC-IV	(3) SAR-IV	(4) SEM-IV
Δ share people 60+	1.139***	0.136	0.286	1.125*
	(0.300)	(0.343)	(0.338)	(0.483)
	p = 0.000	p = 0.693	p = 0.398	p = 0.020
Cohort survival ratio	0.050*	0.007	0.015	0.034
	(0.024)	(0.020)	(0.021)	(0.023)
	p = 0.035	p = 0.733	p = 0.474	p = 0.135
Log population density	-0.006**	-0.003	-0.004*	-0.007*
	(0.002)	(0.002)	(0.002)	(0.003)
	p = 0.003	p = 0.071	p = 0.047	p = 0.038
Share less primary	-0.474***	-0.481***	-0.461***	-0.523***
	(0.058)	(0.050)	(0.049)	(0.064)
	p = 0.000	p = 0.000	p = 0.000	p = 0.000
Share superior more	-0.267	-0.464***	-0.403***	-0.470**
	(0.142)	(0.120)	(0.118)	(0.148)
	p = 0.060	p = 0.000	p = 0.001	p = 0.001
Lagged GVA/N	0.004*	0.003	0.003*	0.003*
	(0.002)	(0.001)	(0.001)	(0.002)
	p = 0.027	p = 0.065	p = 0.045	p = 0.043
Spatial lag of Y		0.458***	0.405***	
		(0.073)	(0.074)	
		p = 0.000	p = 0.000	
Spatial lag of error		0.067		0.577***
		(0.101)		(0.034)
		p = 0.506		p = 0.000
N	1114	1114	1114	1114

Notes: The dependent variable is Δ log L/N. The change in the share people 60+ is treated as endogenous and instrumented by the predicted change in the share people 60+. The spatial weights matrix is block diagonal, with one queen-contiguity matrix for each intercensal growth interval. All models are estimated in firs difference and include period effects. SAC-IV is the general spatial model incorporating both spatial lag and spatial error dependence, while SAR-IV and SEM-IV are the corresponding restricted models with spatial lag and spatial error dependence, respectively. The spatial lag coefficient measures dependence in the dependent variable across neighboring microregions, while the spatial error coefficient measures spatial dependence in the disturbance term. The non-spatial IV model reports standard errors clustered by microregion, whereas the spatial models report heteroskedasticity-robust GMM standard errors. Standard errors are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table E.1. Spatial estimates for sectoral GVA per capita

	(1) Agriculture	(2) Industry	(3) Services
Δ share people 60+	0.433 (0.881) p = 0.623	1.803 (1.160) p = 0.120	0.625 (0.447) p = 0.162
Cohort survival ratio	-0.297*** (0.081) p = 0.000	-0.155 (0.117) p = 0.188	-0.107* (0.051) p = 0.035
Log population density	-0.037** (0.012) p = 0.002	-0.008 (0.010) p = 0.385	-0.001 (0.004) p = 0.733
Share less primary	0.329 (0.211) p = 0.119	0.236 (0.304) p = 0.436	0.218* (0.107) p = 0.042
Share superior more	1.627** (0.576) p = 0.005	0.055 (0.673) p = 0.934	-0.166 (0.261) p = 0.526
Lagged GVA/N	0.004 (0.007) p = 0.590	-0.024 (0.014) p = 0.074	-0.005 (0.004) p = 0.209
Spatial lag of Y	0.722*** (0.115) p = 0.000	0.724*** (0.191) p = 0.000	0.317* (0.145) p = 0.028
Spatial lag of error	-0.432*** (0.120) p = 0.000	-0.666*** (0.130) p = 0.000	0.102 (0.171) p = 0.550
N	1114	1114	1114

Notes: The dependent variables are Δ log agriculture GVA/N, Δ log industry GVA/N, and Δ log services GVA/N. All models are SAC-IV specifications estimated in first differences and include period effects. The change in the share aged 60+ is treated as endogenous and instrumented by its predicted change. All models control for the cohort survival ratio, log population density, educational composition, and lagged log GVA/N. Period effects are removed through within-period demeaning. The spatial weights matrix is block diagonal, with one queen-contiguity matrix for each intercensal growth interval. All models incorporate both spatial-lag and spatial-error dependence. Heteroskedasticity-robust GMM standard errors are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table E.2. Spatial estimates for sectoral labor productivity

	(1) Agriculture	(2) Industry	(3) Services
Δ share people 60+	0.011 (0.867) p = 0.990	1.212 (0.906) p = 0.181	0.128 (0.289) p = 0.657
Cohort survival ratio	-0.175 (0.092) p = 0.057	-0.057 (0.125) p = 0.649	-0.084* (0.041) p = 0.040
Log population density	-0.014 (0.008) p = 0.084	0.007 (0.008) p = 0.406	0.001 (0.002) p = 0.563
Share less primary	0.512* (0.219) p = 0.019	0.044 (0.248) p = 0.859	-0.089 (0.077) p = 0.244
Share superior more	1.569** (0.578) p = 0.007	0.138 (0.572) p = 0.810	-0.062 (0.209) p = 0.767
Lagged GVA/N	-0.004 (0.008) p = 0.669	-0.019 (0.011) p = 0.094	-0.007 (0.004) p = 0.075
Spatial lag of Y	0.894*** (0.093) p = 0.000	1.167*** (0.161) p = 0.000	0.881*** (0.123) p = 0.000
Spatial lag of error	-0.487*** (0.099) p = 0.000	-0.900*** (0.111) p = 0.000	-0.649*** (0.099) p = 0.000
N	1114	1114	1114

Notes: The dependent variables are Δ log agriculture GVA/L, Δ log industry GVA/L, and Δ log services GVA/L. All models are SAC-IV specifications estimated in first differences and include period effects. The change in the share aged 60+ is treated as endogenous and instrumented by its predicted change. All models control for the cohort survival ratio, log population density, educational composition, and lagged log GVA/N. Period effects are removed through within-period demeaning. The spatial weights matrix is block diagonal, with one queen-contiguity matrix for each intercensal growth interval. All models incorporate both spatial-lag and spatial-error dependence. Heteroskedasticity-robust GMM standard errors are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table E.3. Spatial estimates for sectoral employment-to-population ratios

	(1) Agriculture	(2) Industry	(3) Services
Δ share people 60+	-0.676 (1.227) p = 0.582	0.628 (0.414) p = 0.130	0.570** (0.217) p = 0.009
Cohort survival ratio	-0.050 (0.073) p = 0.491	-0.117* (0.055) p = 0.035	0.048* (0.021) p = 0.024
Log population density	-0.002 (0.006) p = 0.707	0.001 (0.003) p = 0.678	-0.004* (0.002) p = 0.048
Share less primary	-0.183 (0.112) p = 0.102	0.111 (0.107) p = 0.299	0.304*** (0.045) p = 0.000
Share superior more	-0.293 (0.297) p = 0.324	-0.011 (0.235) p = 0.964	0.011 (0.103) p = 0.916
Lagged GVA/N	0.004 (0.006) p = 0.448	-0.010** (0.004) p = 0.005	0.005* (0.002) p = 0.019
Spatial lag of Y	1.021*** (0.175) p = 0.000	0.727*** (0.120) p = 0.000	0.617*** (0.097) p = 0.000
Spatial lag of error	-0.279 (0.158) p = 0.077	-0.530*** (0.118) p = 0.000	-0.289* (0.134) p = 0.031
N	1114	1114	1114

Notes: The dependent variables are Δ log agriculture L/N, Δ log industry L/N, and Δ log services L/N. All models are SAC-IV specifications estimated in first differences and include period effects. The change in the share aged 60+ is treated as endogenous and instrumented by its predicted change. All models control for the cohort survival ratio, log population density, educational composition, and lagged log GVA/N. Period effects are removed through within-period demeaning. The spatial weights matrix is block diagonal, with one queen-contiguity matrix for each intercensal growth interval. All models incorporate both spatial-lag and spatial-error dependence. Heteroskedasticity-robust GMM standard errors are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.