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Original Article

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Is aging in the regional labor market wiping out localized external economies? Evidence from European manufacturing firms

Filippo Berti Mecocci [1] and Amir Maghssudipour [2,*]

[1]Department of Economics and Management, University of Florence, Via delle Pandette, 9, Firenze, Toscana 50127, Italy and [2]Department of Economics and Management "Marco Fanno", University of Padova, Via del Santo 33, Padua 35123, Italy

*Main author for correspondence.

Aging is an increasingly relevant phenomenon for several European countries. While endogenous adaptations of technology downsize concerns about possibly shrinking productivity, we know little about the pressures that aging exerts on the effects of localized external economies—such as the economies of specialization and urbanization—on productivity. On the one hand, as the regional labor market ages, we expect that labor pooling and knowledge spillovers decline due to a reduction in job hopping, and entrepreneurship shrinks due to a limited time horizon for future income flows. On the other hand, technological adaptation should be faster due to selection and competition in thick labor markets. To study these mechanisms, we use data on manufacturing firms across NUTS-2 regions in eight European countries. We deal with endogeneity in the correlation between productivity and localized external economies such as industry size and entrepreneurial quality, and we design a regional varying instrumental variable to deal with endogeneity in aging. Our results indicate that while the impact of aging on productivity is positive, the effects of localized external economies are positive for younger regions and negative for older ones. We identify a threshold in the workforce's age composition at which the positive effects of localized external economies on productivity vanish: 19.68% of workers in the older age group for specialization economies and 24.28% for urbanization economies.

JEL classification: J11, R11, D24, L60

1. Introduction

The increasing aging of the population is evident to all. Regional differences are present mainly because of differentials in demographic structures (Figure 1, panel B). Moreover, in the long run, the observed differentials depend on changes in people's localization preferences, which are also influenced by regional characteristics such as the endowment with amenities and public goods, living standards, and gender wage differentials (e.g., due to industry composition). Moreover, active participation of young and old people in our societies and labor markets are issues at the center of today's economic and political debate. For example, concerns about the availability of suitable workers, (un)employment of young people, and longer working lives typical of some places related to forms of late retirement are increasingly being discussed. In this scenario, the effect of age-related characteristics on labor productivity is a key issue for firms and policymakers,

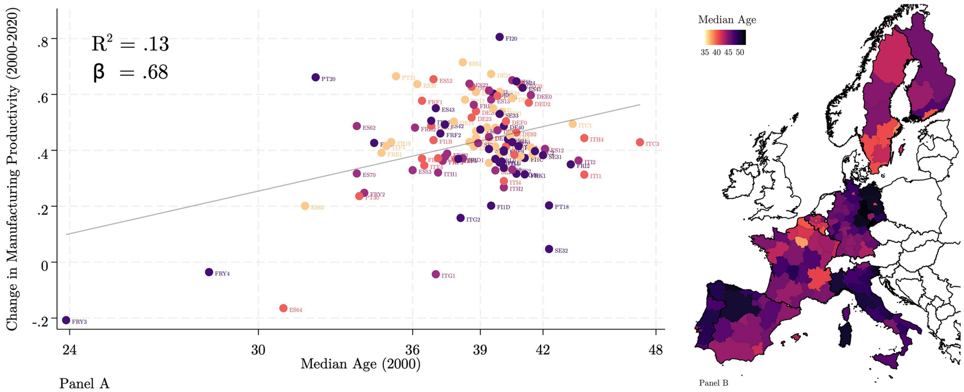

Figure 1. Change in manufacturing productivity (2000–2020) according to different levels of initial median age (panel A); median age in NUTS-2 regions (panel B). *Notes.* The sample includes Belgium, Germany, Italy, Spain, France, Portugal, Sweden, and Finland as in the econometric approach proposed in the following sections. Panel A focuses on manufacturing productivity in NUTS-2 regions and plots the simple correlation between past levels of median age (2000) and change in labor productivity (2000–2020). Increases in the lightness of colors in panel A stand for higher levels of manufacturing specialization across NUTS-2 regions under investigation. Specialization is computed as the logarithmic transformation of the ratio between hours worked in manufacturing and the area of the NUTS-2 region. The change in manufacturing productivity is estimated as the difference between the logarithmic transformation of both labor productivity in 2020 and that in 2000. The *x*-axis shows natural levels for sake of simplicity; however, it plots the logarithmic level. Panel B plots the level of median age in 2022 in NUTS-2 regions under study. Lighter to darker colors indicate an increase in the median age. *Source*: Authors' elaboration on Eurostat data.

which is also addressed by research by international organizations (Auer and Fortuny, 2000; OECD, 2006). Despite the risk regarding the ability of an aged workforce to fix its productivity level, unambiguous evidence has shown that aging does not necessarily have a negative impact on labor productivity (Acemoglu and Restrepo, 2017) (Figure 1, panel A).

In an aging scenario, although economic theory provides arguments to allay concerns about possible productivity slowdowns, some issues still need to be addressed. The impact of aging on productivity is not entirely independent of the role that geography plays in production processes. Because of the localized nature of the increasing returns to production in the manufacturing sector, different trends in aging could unevenly affect the sources of localized external economies, such as the economies of specialization and urbanization. We focus on manufacturing because it is more likely to be spatially clustered than other activities (Ellison and Glaeser, 1997).

In this paper, we aim to contribute to the previous literature by adding new insights into the effect of aging on productivity. However, we argue that there are more indirect effects in such a relationship that are properly geographical (we call them *localized external economies-related effects*). Thus, we seek to answer the following research questions: Does aging mediate the relationship between the sources of localized external economies and productivity? To what extent can aging wipe out the effects of localized external economies?

Studies of the relationship between age, aging, and productivity are well established in some branches of the economic literature. Findings are divergent. On the one hand, firm-level studies have found that age affects productivity along an inverted U-shaped curve (Lindh and Malmberg, 1999), with peaks in the middle age. On the other hand, studies at a more aggregate level have found positive associations between an aging population and GDP (Feyrer, 2007). Acemoglu and Restrepo (2017), with an investigation at the aggregate level, found that aging can also affect productivity through an indirect effect as an endogenous adaptation of technology (i.e., through automation). Thus, the scarcity of the labor factor caused by an aging workforce can increase GDP if the effect of increasing automation is greater than the effect of aging on productivity. In this case, endogenous technologies respond to structural-demographic trends by replacing declining productive forces.

Our work examines the possible moderating effect of aging on the impact of localized external economies[1] driven by regional specialization of manufacturing activities and urbanization economies on productivity. Although this is an increasingly hot topic in economics, research at the regional level is scarce. Therefore, we aim to fill such a gap. First, we theoretically elaborate on the relevant channels through which aging and agglomeration externalities interact to affect productivity. Then, we test our theoretical predictions using a firm-level manufacturing dataset covering eight countries in the European Union with information between 2014 and 2021. Our results suggest that there are thresholds of aging above which localized external economies (from both urbanization and specialization phenomena) have no effect on productivity.

The paper is organized as follows. The next section presents a theoretical perspective on the relationship between aging, localized external economies, and productivity. Section 3 presents the data sources, the methodology used, and the model. Section 4 presents and discusses the results, robustness tests, and heterogeneity analyses. Finally, Section 5 concludes with theoretical and policy implications.

2. Theory

2.1 Workers' age and productivity—a micro-perspective

Differences in productivity between workers of different ages are generally attributed to observable characteristics. First, age-related declines in health are a major contributing factor. Parameters such as average muscle strength, flexibility, visual acuity, and aerobic capacity tend to decline over time (Silverstein, 2008). Second, cognitive abilities, including reasoning capacity and perceptual speed, tend to decline with age. Conversely, other cognitive aspects, such as vocabulary size and semantic understanding, often remain high throughout an individual's working life cycle (Skirbekk, 2008). In addition, the stock of skills and knowledge acquired in the early stages of a worker's career may become obsolete, potentially affecting innovation and productivity (Dixon, 2003). Third, on-the-job training becomes less economically viable for older workers, given the shorter timeframe available to capitalize on acquired knowledge and skills compared to their younger counterparts. As a result, current knowledge tends to be more concentrated among younger and middle-aged workers (Bartel and Sicherman, 1998).

A critical factor associated with both age and productivity is human capital. Becker's "Human Capital" theory supports the existence of an inverted U-shaped curve in human capital levels over time (Becker, 1964). It typically rises in the early stages of a career, declines toward the end, and peaks in the prime age (approximately between the ages of 30 and 50 years). While experience is a highly valued attribute by employers and increases over a worker's lifetime, it can have a positive impact on productivity in a mature workforce (Disney, 1996). Learning-by-doing mechanisms support increasing levels of productivity throughout the entire worker's life cycle. In cases where wages increase with age and workers are compensated at their marginal contribution level, productivity gains can be expected in older age groups (Feyrer, 2008). The two mechanisms (aging and learning-by-doing) are not perfect substitutes; in fact, the presence of increasing returns from age diversification of the workforce (different age cohorts working together) can stimulate the productivity of each age cohort (Malmberg *et al.*, 2008).

The empirical investigation of the age–productivity relationship in the existing literature yields contradictory results. Lindh and Malmberg (1999) found a positive effect of prime age and a negative effect of older cohorts on labor productivity (measured as real GDP per worker). Malmberg et al. (2008) confirmed the positive effect of the prime age cohort but observed a negative effect of younger workers on productivity (value added per employee) in a study of a steel plant in central Sweden. Mahlberg et al. (2013) found no negative association between Austrian firm-level productivity and a high share of older workers but found a negative association between the share of young workers and productivity (value added and wages per employee). Haltiwanger et al. (1999) reported a negative effect of older workers on labor productivity using a U.S. census

[1] We adopt the term "localized external economies" to identify economies external to the firm and internal to the region.

dataset (sales-to-employment ratio), while Lallemand and Rycx (2009) found a negative effect of a high share of older workers on productivity (value added per employee) using Belgian data.

Looking at sector-specific issues, Lallemand and Rycx (2009) found a differentiated effect of age cohorts; in particular, the contribution of younger employees to firm-level productivity is higher than that of the older employees in ICT sectors. Nevertheless, Göbel and Zwick (2012) found no difference in the level of productivity (value added per employee) between metal manufacturing and service sectors according to the age of employees. Moreover, Mahlberg et al. (2013) found regional productivity (value added per employee) variations across Austrian regions, with the main source of heterogeneity coming from industry differences.

In sum, existing research agrees on the existence of a productivity peak around middle age but remains ambiguous about productivity differentials between younger and older workers. In particular, previous empirical work often adopts either an industry or a regional perspective on the age–productivity relationship, often overlooking spillovers arising from the spatial concentration of firms and workers.

2.2 Agglomeration and increasing returns: tales of specialization and urbanization

Several contributions attempted to integrate the concept of increasing returns into the concept of perfect competition. This challenge was first taken up by Alfred Marshall, who incorporated external economies into his partial equilibrium framework. External economies arise from the concentration of activities within what he termed—in descriptive terms—"industrial districts" (Marshall, 1920; Sforzi, 2008; Bellandi and De Propris, 2015). In such districts, the collective knowledge and expertise within a set of very proximate activities in an industry become increasingly accessible, leading to a reduction in costs and an increase in efficiency (Bellandi, 2021). Three main mechanisms of agglomeration have been identified in the literature: knowledge spillovers, labor pooling, and the presence of specialized input suppliers (Rosenthal and Strange, 2004). These mechanisms lead to increasing returns even in the context of perfect competition. Subsequently, this line of research has developed in different branches of economics. Labor economists have focused on knowledge spillovers and labor pooling resulting from the movement of workers between different firms (Moretti, 2021). Industrial economists have focused on the role of the division of labor between firms operating at different stages of the production process (Stigler, 1951). The movement of goods between different firms gives rise to knowledge spillovers. Also, the existence of public goods shared by a group of producers generates savings in fixed and variable costs (Abdel-Rahman, 1994). Moreover, increasing returns emerge from increases in the total output of the local industry rather than in the output of the firm itself (Caballero and Lyons, 1990).

The so-called Marshallian external economies (Becattini, 1990) are often studied as a key factor affecting productivity and local growth. One mechanism that encourages firms to colocate in the same area is *labor market pooling*. This is due to the existence of a thick labor market that facilitates the matching of workers and employers (Puga, 2010). Krugman (1991) and Overman and Puga (2010) showed that spatial clustering is an optimal choice for firms in sectors with more heterogeneous productivity shocks (i.e., orthogonal across firms). The point here is that the availability of a pool of substitutable workers irons out firms' idiosyncratic shocks rather than reflecting them in wages. Overman and Puga (2010) tested this mechanism and found labor pooling is an important source of agglomeration.

Second, firms and workers benefit from *knowledge externalities* that facilitate learning mechanisms and imitation. The movement of workers in the labor market is one means by which the most innovative practices are diffused among localized firms (Combes and Duranton, 2006; Andini *et al*., 2013). The movement of knowledgeable workers among firms increases their ability to imitate and integrate ideas and knowledge bases (Storper and Venables, 2004). Serafinelli (2019) found that the movement of workers across firms accounts for 10% of the productivity gains that firms derive from being localized in thick labor markets.

In general, these externalities have different industrial scopes depending on the specificity of the knowledge used and the tasks performed by workers. The difference in the industrial scope of agglomeration allows the identification of two different modes of knowledge diffusion. When knowledge and tasks are industry-specific, economies arise from the geographical concentration of the same or very proximate activities. In this case, the external economies are external to the firms but internal to the industry of the region (or city) and are defined as specialization or localization economies. On the other hand, when the size, density, and diversity of the region are determinants, economies of urbanization are more likely to operate. In this case, the economies are external to firms and industries and internal to a region (or city). For example, Neffke et al. (2017) examined the extent to which workers move between different industries. They found that workers move between "distant" industries, but that most of the movement occurs between a narrow set of industry pairs.

Third, in the case of specialization, the presence of a pool of specialized suppliers can reduce transaction and transportation costs and generate relevant spillovers in locally integrated sectors. This sharing mechanism allows the local industry to benefit from increasing returns by reducing the cost of intermediate inputs, even in the presence of an upward-sloping individual cost curve (specialization economies) (Abdel-Rahman and Fujita, 1990). A similar mechanism works for urbanization economies and depends on the home market effect. The larger the size of the local market, the greater the demand for products (Domeque Claver *et al.*, 2011). As discussed by Abdel-Rahman (1988), the incentive for firms to move to large cities also arises from agglomeration economies of consumers in the form of product variety (urbanization economies).

Fourth, entrepreneurship is also an important source of knowledge spillovers that accelerate the formation of firm agglomerations (Holcombe, 1998; Glaeser *et al.*, 2010). Indeed, it facilitates the integration of new knowledge into available products and services (Acs and Plummer, 2005). Since external economies result from a large and competitive pool of firms, entrepreneurship is a major source of agglomeration economies.

2.3 Aging, localized external economies, and productivity

In this section, we build on the existing literature on aging and productivity to propose theoretical implications for the literature on localized external economies, as discussed in Section 2.2. Acemoglu and Restrepo (2017) suggest that an aging workforce does not necessarily have a negative impact on productivity. This is mainly due to the endogenous adaptation of technology. Two key effects are identified. First, the decline in the number of middle-aged labor units leads to a decline in aggregate output, reflecting the declining labor factor. Second, the scarcity of labor induces technological change (including automation). When the latter effect overcomes the former, lower labor input can generate positive effects on the aggregate output.

However, the presence of localized external economies, resulting from the concentration of activities, workers, and industries within a territorial setting, alters these effects. In the following paragraphs, we propose additional mechanisms which we define as "localized external economy-related effects."

2.3.1 Effect of aging on labor pooling

As proposed by Acemoglu and Restrepo (2017), in a labor market with an increasing share of older workers, the probability of hiring middle-aged workers (who are more likely to be more productive) is reduced, which subsequently leads to a decline in overall productivity. In a dense labor market, the effects of aging also affect labor pooling. An aging population can constrain the size of the labor market, thereby reducing the ability of firms to adjust to idiosyncratic shocks. This impact is experienced equally by firms that derive their productivity gains from specialization or urbanization economies. Thus, we can expect that the impact of population aging on labor pooling and its subsequent effect on productivity to be negative.

2.3.2 Effect of aging on knowledge spillovers

Knowledge transfer benefits colocated firms. In the labor market, knowledge is diffused through job-hopping, the movement of workers between firms. As the labor force ages, fluidity shrinks, meaning that fewer workers move from job to job (Davis and Haltiwanger, 2014). In an aging labor market, the contribution of knowledge spillovers to productivity growth and innovation declines. However, such a process depends on the structure of the labor market. When knowledge and skills are industry-specific (workers mainly move between firms in the same industry), the reduced effect of knowledge externalities on productivity is mainly experienced in specialized regions through specialization economies. Conversely, when labor demand is homogeneous across industries, the diminished effects are via urbanization economies. Thus, aging reduces the positive effect of knowledge externalities on productivity.

2.3.3 Effect of aging on entrepreneurship

The aging of the labor market affects not only productivity through labor shortages but also entrepreneurship. As individuals age, starting a new business becomes less desirable because the opportunity cost of time increases with age. That is, while the value of time increases with age, the present value of future income flows is lower for older individuals (Lévesque and Minniti, 2006). For this reason, older individuals prefer wage employment rather than starting new businesses. Empirically, there is evidence of a negative (Glaeser and Kerr, 2009) and U-shaped relationship (Bönte *et al.*, 2009) between regional age and the decision to start a new business. Thus, aging reduces the sources of external economies via reduced entrepreneurship in both large (more related to urbanization economies) and specialized regions.

2.3.4 Effect of agglomeration on technological change

As firms face an aging workforce, they can endogenously adjust production technology by substituting machines for human tasks where labor inputs are scarce in order to maintain their productivity levels. Although this may be the case for specialized regions where the potential for automation is higher due to the intensity of the division of labor (Crowley *et al.*, 2021),[2] it is not the case for diverse and large regions. However, both specialized and large diverse regions also face high levels of local competition (Combes *et al.*, 2012). Head-to-head competition among firms promotes technological change and innovation (Aghion *et al.*, 2005, 2018); in agglomeration, competition leads workers to work more (Rosenthal and Strange, 2008) and firms to innovate more: "firms that do not advance technologically are bankrupted by their innovating competitors" (Glaeser *et al.*, 1992: 7). Thus, agglomeration affects technological change and innovation via (I) a true effect of innovation by encouraging innovative practices and (II) firm selection, as noninnovators are less likely to survive in an agglomeration than elsewhere (Fang, 2020).

This study aims to show that the combined effects of aging and productivity are more complex when local interactions are considered. We identified three relevant mechanisms that may negatively affect productivity and a moderating effect of agglomeration vis-à-vis technological change. We defined these mechanisms as localized external economies-related effects. Woodward (2017) notes that agglomeration advantages may diminish in the "machine age," a term he coined to describe a future in which artificial intelligence, robots, and machines do not require spatial spillovers to achieve productivity gains. While agglomeration may promote the speed of adoption of such automated factors through higher levels of competition, localized external economies-related effects exacerbate the negative effects of aging. This section has provided a main testable prediction: the effect of aging tends to reduce the positive effects of specialization/urbanization economies on productivity.

3. Data, identification strategy, and model

Firm-level data were collected from the Amadeus-Bureau Van Dijk database between 2014 and 2021. The dataset includes firms operating in eight European countries and is geographically disaggregated to the NUTS-3 level. However, due to data availability, the analysis is performed at the NUTS-2 level. We used data on manufacturing activities in Belgium, Germany, Spain, Finland, France, Italy, Portugal, and Sweden. Each firm is linked to its respective four-digit sector within the manufacturing industry, identified by Nomenclature statistique des activités

[2] However, the empirical evidence rejects this hypothesis (Crowley *et al.*, 2021).

économiques dans la Communauté européenne (NACE) codes ranging from 10 to 33. The data collected include key metrics such as value added, fixed assets, prime materials, energy costs, labor costs, and number of employees.

Given the potential endogeneity issues in our study, we adopt a two-step approach to identify the relationship between localized external economies, aging, and productivity, following the methodology proposed by Combes et al. (2011) and Combes and Gobillon (2015). Our estimation strategy is designed to address several sources of endogeneity identified in the literature, focusing on total factor productivity (TFP) in the context of localized external economies (Combes *et al.*, 2011):

1. *Endogenous size of local industry*: more productive local industries attract more firms/workers.
2. *Endogenous productivity of firms*: The productivity of a firm (via management or workers) is directly influenced by the main industry of the location. Individuals born in such regions are likely to acquire higher skills due to the presence of industry-specific schools and similar institutions.
3. *Shocks*: Certain shocks have uneven impacts on firms across regions and industries. Another concern relates to aging, as explained by Aiyar and Ebeke (2016).
4. *Higher sensitivity of specific age cohorts to cyclical shocks*: Certain age cohorts may be more sensitive to cyclical shocks, potentially leading to increased labor force participation during productivity-related cyclical shocks.

To address these concerns, we use the methodology proposed by Combes et al. (2011) for localized external economies and employ an instrumental variable approach to mitigate concerns associated with the sensitivity of the old cohort to cyclical shocks.

Following Combes and Gobillon (2015), the first step in obtaining unbiased estimates of aging, regional specialization, and their interactions is to extrapolate local industry-time fixed effects from the firm-level production function estimation. We do this by following the Wooldridge–Levinsohn–Petrin (WLP) method (Wooldridge, 2009; Petrin and Levinsohn, 2012). Endogeneity in firm-level TFP estimation arises from the possibility that inputs are chosen in response to past and current productivity shocks. It is addressed by considering variations in the use of material and energy costs as proxies for firms' own unobservable time-varying productivity (Levinsohn and Petrin, 2003; Rovigatti and Mollisi, 2018). Following Wooldridge (2009), we use a Generalized Method of Moments estimation method that allows us to identify the capital (K) and labor (L) parameters as in Petrin and Levinsohn (2012) and add another local industry time-varying fixed effect to the model specification:

$$\log(VA_{it}) = \log(K_{it}) + \log(L_{it}) + \eta \sum_{r}\sum_{s}\sum_{t} D^{r}_{it} D^{s}_{it} D^{t}_{it} + \varepsilon_{it} \tag{1}$$

where i refers to the generic firm, t to time, r to region, and s to sector. To account for possible variations in local endowments over time, we compute a set of regional industry fixed effects for each period. They can be visualized as the combination of three dummies: a regional dummy (D^{r}_{it}), a three-digit industry dummy (D^{s}_{it}), and a year dummy (D^{t}_{it}). This approach allows us to examine the factors influencing productivity variation that cannot be explained by observable firm characteristics. In doing so, we control at the firm level for unobserved local shocks that may be correlated with firm variables, as highlighted by Combes and Gobillon (2015). We proceed by saving the estimated coefficient for the combination of the three dummies, namely η_{rst}, which is a time-varying local industry fixed effect. We then use these estimates as the dependent variable in an estimation of local industry characteristics. Appendix Figure A1 shows the relative values of the regional TFP residuals estimated using the proposed method. Table A2 shows the two-digit industry levels of the regional TFP residuals. The former suggests regions where local factors are relevant to TFP, while the latter suggests industries that rely more on the same local factors.

Adapting the rationale established by Combes et al. (2011) to our estimation framework improves our understanding of endogeneity issues related to localized external economic indicators. Let's consider, for example, the inclusion of traditional fixed effects (not time-varying) in the production function. It is plausible that certain regional-industry characteristics, represented by unobservable regional-industry effects, may change during the period under study, such as the construction of a new railroad. This could significantly reduce the transportation costs to access the local industrial cluster, a factor not accounted for in the fixed effects. In such cases, the use of traditional fixed effects could exacerbate the bias. The introduction of the new rail line could explain a substantial portion of the variation in the productivity residual of clustered local firms by reducing transportation costs. This, in turn, increases the ability of the area to attract other firms and more productive skilled workers who were previously inaccessible due to their travel time preferences. These changes can also have spillover effects on specialization indices, influencing firm growth in terms of employment and the overall increase in the number of firms in the region.

To reduce the bias, the approach suggested by Combes et al. (2011) is to use time-varying fixed effects. In this way, a large part of this endogeneity problem is eliminated. Firms that move to a city because they expect to achieve higher levels of TFP are no longer a source of bias. Similarly, the fact that some firms would be more productive because they are located in a specialized area is partially eliminated by the WLP method with time-varying fixed effects. Bias due to shocks that affect firms in some regions and industries at each time point is resolved using the WLP method with time-varying fixed effects. Interestingly, this also partially addresses endogeneity concerns regarding the aging index. If shocks affecting both firms' TFP and the participation of specific age cohorts occur at the regional–industrial level, then the estimation of time-varying regional–industrial effects also eliminates such concerns.

Thus, we use the estimated parameters of the time-varying fixed effects as our main left-hand-side variable in an estimation of regional and industry characteristics:

$$\eta_{rst} = \alpha SE_{rst} + \beta Aging_{rt} + \gamma (SE * Aging)_{rst} + \phi X + \tau_t + \chi_s + \varepsilon_{rst} \tag{2a}$$

$$\eta_{rst} = \alpha UE_{rt} + \beta Aging_{rt} + \gamma (UE * Aging)_{rt} + \phi X + \tau_t + \chi_s + \varepsilon_{rst} \tag{2b}$$

Where the model aims at identifying three main coefficients:

1. α, which is the parameter associated with agglomeration economies, which we analyzed through the lens of specialization and urbanization mechanisms. The former (SE_{rst}) is measured by the location quotient, which is the ratio of local three-digit manufacturing employment to regional manufacturing employment (Groot *et al.*, 2014) to the same ratio calculated at the national level. The latter (UE_{rt}) is the population density:

$$SE_{rst} = \frac{e_{rst}/e_{rt}^{M}}{e_{st}/e_{t}^{M}} \tag{3}$$

$$UE_{rt} = \frac{Population_{rt}}{Area_r} \tag{4}$$

2. β, which is the parameter associated with the effect of aging on the local industrial component of TFP. We use data on the composition of the labor force and construct a proxy variable measured as the ratio of workers aged over 54 years and under 64 years to those aged under 54 years (Acemoglu and Restrepo, 2017):

$$Aging_{rt} = \frac{e_{rt}^{54-64}}{e_{rt}^{15-54}} \tag{5}$$

3. γ, which is the parameter associated with the interaction effect between specialization/urbanization economies and aging. It identifies the mechanisms presented in Section 3 through which aging affects the benefits of specialization and urbanization.

We also include several control variables, identified by the vector of parameters (ϕ), which may affect the relationships between our core variables (aging and regional specialization/urbanization) and the local industrial component of TFP. The vector X includes the following variables:

1. Average size of firms in the local industry to proxy for internal economies of scale calculated as the ratio of the number of employees to the number of firms.
2. The inverse of a Herfindahl–Hirschman Index (HHI^{-1}) computed using firm-level employment as a measure of local industrial competition (Groot *et al.*, 2014). It can be interpreted as the number of symmetric firms producing the observed concentration.
3. Old-age dependency ratio and youth-dependency ratio calculated, respectively, as the ratio of persons aged over 65 years to the total population and the ratio of persons aged under 15 years to the total population.
4. As further controls, we include population density in the case of specialization economies (Eq. (2a)) and a location quotient for three-digit manufacturing specialization in the case of urbanization economies (Eq. 2(b)).

While the average size of firms is included to rule out sources of economies that are not external to firms, if there are dimensions other than productivity on which firms are heterogeneous, the inverse HHI provides a way to deal with the bias. The old and young dependency ratios are included to control for other channels through which aging eventually affects TFP's local industrial component such as an increase in longevity, pressures on public finance, greater aggregate volatility, lower aggregate savings and investment rates, and structural transformation (Aiyar and Ebeke, 2016; Poplawski-Ribeiro, 2020). When included in a regression, time-varying region-industry fixed effects help to disentangle possible sources of bias due to different statutory retirement ages. Finally, we log-transform all our variables. We also include a vector of year effects to capture trends (Combes *et al.*, 2011), as well as three-digit industry fixed effects. Table A1 in the Appendix presents the summary statistics and the correlation matrix.

3.1 The instrumental variables

We use an instrumental variable approach to go beyond the endogeneity issues identified in Aiyar and Ebeke (2016), Acemoglu and Restrepo (2017), and Poplawski-Ribeiro (2020) to deal with our index of aging. We use demographic instruments to capture the effect of aging on productivity. However, the available data at the NUTS-2 level do not allow us to capture changes in the age cohort of interest. Therefore, we use a computational method to construct external instruments. We use a national series of live births from 1960 to 1970 to proxy our aging variable. Excluding migration and mortality, the share of the labor force aged 55–64 years is determined by the number of live births 55 and 64 years ago. We regionalize these series by multiplying the number of national live births (lb_n) by the share of the national population of each NUTS-2 region in 1960, 1965, and 1970:

$$lb_{rn}^{1960} = lb_n^{1960} * \frac{pop_r^{1960}}{pop_n^{1960}} \tag{6}$$

For each value in the series from 1960 to 1970, the same operation is performed. We then calculate the logarithmic transformation of the instruments. Since the instruments are not time-varying, the first stage is identified using only inter-regional variations.

We use the series of live births every 5 years from 1960 to 1970 as an external instrument to measure the aging of the labor force. The series of instruments is expected to be highly correlated with the share of the population up to 55 years later, but orthogonal to future technological shocks that affect the labor force participation of specific age cohorts. If the national childbearing decision in 1960/1970 and the regional population in 1960/1970 are not correlated with current shocks in the local industry residuals of TFP, then the instruments are exogenous. In addition, our econometric design includes an interaction term between the endogenous aging variable and the specialization index. To complement this, we include the interaction of each demographic instrument with indexes of external economies as additional instruments.[3]

4. Results

Table 1 presents the results of our estimation strategy for specialization economies; Table 2 does the same for urbanization economies. Each table is organized as follows: columns (1)–(5) present the baseline results, estimated using Ordinary Least Squares (OLS) and including two vectors of fixed effects (year and three-digit industry fixed effects) and control variables. Due to the endogeneity issues discussed in Section 3, the aging variable presents a biased estimate. Similarly, the interactions between the external economies indexes (which are assumed to be exogenous after partialling out time-varying regional-industry fixed effects) and aging would also be biased because it interacts with an endogenous variable (aging). Our dependent variable in each column is η_{rst}, which is the time-varying regional-industry effects. Thus, each observation represents the pair of NUTS-2 regions by three-digit manufacturing industries over the period 2014–2021. Column (6) presents the Instrumental Variable (IV) result without control variables, and column (7) adds control variables. Column (8) uses the instrumental variable technique to estimate the interaction term without control variables, and column (9) adds control variables.

Column (1) shows that there is a positive effect of aging on productivity; the older the labor force employed in regional manufacturing, the higher the industrial TFP. Looking at the magnitude and sign, TFP increases by 0.15 percentage points (p.p.) when the cohort of workers aged 55–64 years increases by 1 p.p. Column (2) estimates the index of specialization to measure localized external economies. The results again show a positive and statistically significant coefficient. A one percentage point increase in the concentration of activities in the same three-digit industry in a region, holding the national industrial concentration constant, leads to an increase in local industrial TFP of 0.01 p.p. Interestingly, this effect changes when the aging variable is added, as in column (3). Local external economies disappear when the effect of aging is ruled out. That is, when aging is introduced as a control variable, the effect of specialization changes from positive to not statistically different from 0. Asymmetrically, the effect of aging does not change even when conditioned on the average level of specialization.

Column (4) adds all control variables to column (3), which reduces the effect of aging on TFP by about 0.01 percentage points. The effect of specialization is still not statistically different from 0. Finally, column (5) adds the interaction term between regional specialization and aging as well as control variables. The effect of regional specialization and the interaction term are not statistically significant, while the effect of aging is still positive with a stronger magnitude. In this preliminary part, we show the main effects and how they change the conditioning on the control variables. However, the effect of aging is still biased due to its residual endogeneity with the term η_{rst}. Thus, the effect of the interaction is also biased. From column (6) to column (9), we address such concerns by implementing the instrumental variable approach described in Section 3.

Column (6) re-estimates the specification of column (3) including the three instrumental variables for aging. Its effect changes from 0.15 to 0.31. This does not affect the estimate of regional specialization, which is still not statistically different from 0. The Hansen J-stat is weak, that is, the exogeneity of the instruments cannot be taken for granted, and the first-stage F-stat shows their relevance (39.14). Column (7) adds the control variables to the specification in column (6). The effect of aging increases by 0.11 percentage points. The Hansen J-stat increases accordingly. Column (8) examines the effect of the interaction between the index of aging and the index of regional specialization unconditionally. The coefficients change because their interpretation changes when the interaction term is included. The effect of aging is 0.31. Rather, the effect of regional specialization goes from 0 to positive. Column (9) adds the control variables. The result confirms what was already suggested by the estimate in column (8). This is because the effect of aging on the local industrial component of TFP is closely related to the presence of localized

[3] A minimum approach when incorporating an interaction as an additional endogenous regressor is to include an additional instrument for the interaction term.

Table 1. Regressions results for specialization economies

	OLS					IV			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Aging	0.15***		0.15***	0.14***	0.14***	0.31***	0.42***	0.31***	0.41***
	(0.03)		(0.03)	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)	(0.05)
SE		0.01*	0.00	0.00	0.04	0.00	0.00	0.18**	0.19**
		(0.00)	(0.00)	(0.00)	(0.04)	(0.00)	(0.00)	(0.09)	(0.09)
Aging × *SE*					−0.01			−0.06**	−0.06**
					(0.01)			(0.03)	(0.03)
Observations	39,625	39,445	39,445	39,445	39,445	39,176	39,176	39,176	39,176
No. of clusters	133	133	133	133	133	128	128	128	128
Controls				√	√		√		√
Year fixed effects (FE)	√	√	√	√	√	√	√	√	√
Industry FE	√	√	√	√	√	√	√	√	√
First-stage *F*-stat						39.14	41.64	18.26	26.88
Hansen J-stat						0.04	0.08	0.06	0.15

Notes: From columns (1) to (9), firms' data are aggregate at the three-digit industry (s) and the NUTS-2 level (r). The dependent variable is η_{rst} that is the time-varying regional industrial FE estimated from the production function. From columns (1) to (5), OLS including industry FE and yearly FE are employed. From columns (6) to (9), we adopt an instrumental variable technique. Excluded instruments are regional *log*(*LiveBirth*) in 1960, 1965, and 1970 computed as described in Section 3.1. Column (9) also uses the interaction between indexes of specialization and the three log(*LiveBirth*) instruments as additional instruments and includes the interaction between the index of specialization and aging as endogenous regressor as well. Columns (4), (5), (7), and (9) include as control variables: old dependency ratio, young dependency ratio, average size of firms, an index of local competition, and population density. From columns (6) to (9) the number of regions reduces to 128 because we remove all regions from overseas departments due to the instrumental variable. All specifications include year and industry FE.

$^{***}P < 0.01$,
$^{**}P < 0.05$, and
$^{*}P < 0.1$.

Table 2. Regressions results for urbanization economies

	OLS (1)	(2)	(3)	(4)	(5)	IV (6)	(7)	(8)	(9)
Aging	0.15***		0.16***	0.14***	0.44***	0.34***	0.42***	0.74***	0.67***
	(0.03)		(0.03)	(0.04)	(0.09)	(0.04)	(0.05)	(0.18)	(0.19)
UE		0.00	0.01	0.00	0.20***	0.01***	0.01**	0.27**	0.19
		(0.01)	(0.00)	(0.01)	(0.06)	(0.00)	(0.00)	(0.12)	(0.14)
Aging × *UE*					–0.06***			–0.08**	–0.06
					(0.02)			(0.04)	(0.04)
Observations	39,625	39,625	39,625	39,445	39,445	39,328	39,176	39,328	39,176
No. of clusters	133	133	133	133	133	128	128	128	128
Controls				√	√		√		√
Year fixed effects (FE)	√	√	√	√	√	√	√	√	√
Industry FE	√	√	√	√	√	√	√	√	√
First-stage *F*-stat						34.09	41.64	14.12	11.30
Hansen J-stat						0.07	0.08	0.56	0.39

Notes: From columns (1) to (9), firms' data are aggregate at the three-digit industry (s) and the NUTS-2 level (r). The dependent variable is η_{rst} that is the time-varying regional industrial FE estimated from the production function. From columns (1) to (5), OLS including industry FE and yearly FE are employed. From columns (6) to (9), we adopt an instrumental variable technique. Excluded instruments are regional $log(LiveBirth)$ in 1960, 1965, and 1970 computed as described in Section 3.1. Column (9) also uses the interaction between population density and the three $log(LiveBirth)$ instruments as additional instruments and includes the interaction between the index urbanization economies and aging as endogenous regressor as well. Columns (4), (5), (7), and (9) include as control variables: old dependency ratio, young dependency ratio, average size of firms, an index of local competition, and the location quotient as index of specialization. From columns (6) to (9), the number of regions reduces to 128 because we remove all regions from overseas departments. Standard errors are clustered at the regional level (NUTS-2). All specifications include year and industry FE.
*** $P < 0.01$,
** $P < 0.05$, and
* $P < 0.1$.

external economies, as shown theoretically in Section 2. At the average level of aging, the benefits of regional specialization are zero; however, when the aging index is zero—that is, when the 55–64-year-old workers are out of the labor market or only younger workers are working—the effect of regional specialization becomes positive.[4]

To better assess the implications of such a specification, we plot the average marginal effect of both aging (panel A) and specialization (panel B). At low levels of specialization, the effect of aging is positive, as is the average effect found in columns (7) and (9), because the index of regional specialization has its mean around 0. When the value of specialization is lower than the mean, aging has a stronger positive effect on the local industrial component of TFP. When the specialization index is higher than the mean, the effect of aging is reduced to zero. The negative shift of aging occurs at high levels of specialization. On the other hand, panel B shows that the marginal effect of specialization is also negative when interacting with aging. In this case, the statistically insignificant coefficient of aging (found in column (7)) coincides with the average level of aging. At lower levels, the effects of specialization economies are positive, generating localized external economies. When aging reaches its higher values, the positive effects of specialization economies disappear. At very high levels of aging, specialization economies become external diseconomies. The two dynamics are then symmetric. Our results confirm previous research in the literature, which suggests that the effect of aging is non-negative when the average level of specialization economies is taken into account (Acemoglu and Restrepo, 2017).

Table 2 replicates the specification of Table 1, replacing the index of specialization economies with an index of urbanization economies. It is perfectly symmetric with the previous one, and the results partially overlap. In the following, we focus on the main differences with respect to the previous results. First, the effect of aging is confirmed in all specifications. Second, the effect of population density is not statistically significant in the OLS regressions, but it is significant in the case of the interaction term. When the interaction term is included, as in the case of specialization economies, the effect of urbanization economies becomes positive, suggesting that aging affects urbanization economies through the distribution of the age composition of the labor force. Using the instrumental variable technique, the effect of urbanization economies becomes positive at the average level of the aging variable. Finally, columns (8) and (9) include the interaction term as an endogenous variable, which leads to an overlap with the results for specialization economies.

As explained earlier, we included the marginal effects to examine the varying impact of population density as a function of the level of the old-age share of the labor force (Figure 4). The effect of aging is positive when urbanization economies are weak and reach zero at high levels of them (panel A). Like specialization, urbanization economies have a positive effect on manufacturing TFP at low levels of aging. After a certain threshold, the positive effect due to external economies of urbanization becomes zero. Overall, the trend for urbanization economies is similar to that observed for specialization economies. However, the threshold at which the external economies fade out differs between the two. This will be discussed in the next section.

In the Appendix, Table A2 reports estimated TFP for 2-digit industries. Table A3 tests the same specifications in column (9) for both urbanization and specialization economies using different independent variables. This serves to show that the results are not affected by the choice of the measure of specialization and urbanization. Table A4 averages all v (Glaeser and Kerr, 2009) ariables over time and re-estimates columns (7) and (9) of Tables 1 and 2. It is a robustness test showing that (I) identification in the first stage using only interregional variation is not a source of bias and (II) using different dependent variables for urbanization and specialization does not change the results in this case either. The estimates strongly confirm the previous results.

5. Discussion

We discuss aging and agglomeration economies separately. The discussion concerns columns (7) and (9) of Tables 1 and 2. Our interpretation of the results follows the theoretical model (Figure 2) so that the aging effect operates through three different linkages:

[4] Being the index of aging a log-transformation, it is more precise to say that the log(or) is 0. Then, the correct percentage of the workforce aged 55–64 years is at least 1%.

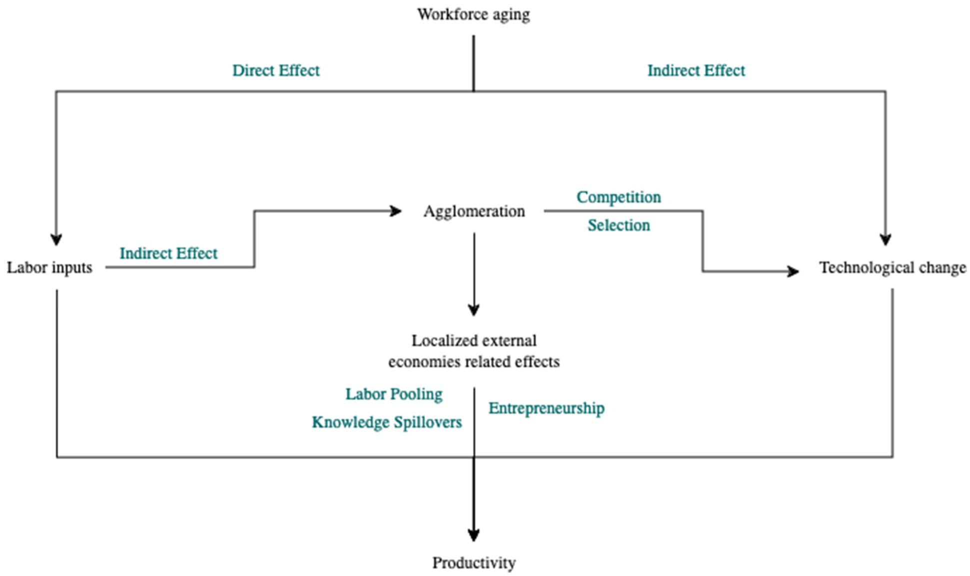

Figure 2. Graphical representation of the proposed mechanisms. *Notes.* This is a stylized representation of the main mechanisms described in Section 2.3. Arrows indicate the direction of the relationship. Blue words indicate key working channels. *Source*: Authors' elaboration.

1. direct effect (labor shortage),
2. indirect effect (technological change), and
3. localized external economies-related effects (on the one hand, due to labor shortage—reduction of labor pooling, knowledge spillovers, and entrepreneurship; on the other hand, via competition and firm selection).

Our results suggest some insights into the proposed mechanisms. First, the aging coefficient tells us something about the direct (point 1) and indirect (point 2) effects. The overall effect of aging on productivity is positive on average, suggesting that the indirect effect (technological change) is on average larger than the direct effect (aging). The estimated parameter of specialization economies suggests a zero average effect on the local industrial component of TFP conditional on aging and other control variables included in column (7), while the effect due to urbanization economies is positive. In other words, the estimated coefficients for agglomeration economies (specialization and urbanization economies) are the average effect of both the traditional external effects and part of the variability due to the aging-related effect of localized external economies (point 3). When we deal with endogeneity in columns (8) and (9) of both tables, the coefficients of the interacting terms also change, since part of the bias is eliminated by the interaction term. By including the interaction of the two terms in column (9), we explicitly model point 3, which was previously partially absorbed by the aging and agglomeration coefficients. In other words, the estimated coefficient of the interaction term excludes the effects of the coefficient of specialization/urbanization economies and aging in point 3. Once the effects of aging are partialled out, the result for specialization economies is positive and that for urbanization economies is not statistically significant. The estimation of the interaction term suggests that the localized external economies-related effects are negative in both cases (see marginal effects in Figures 3 and 4). So, when localized external economies-related effects are partialled out, aging does not threaten benefits from agglomeration, and specialization is positive. Aging is still positive. Urbanization economies have a not statistically significant prediction out of sample. As shown in Figures 2 and 3, their marginal effects change when higher levels of the other variable included in the interaction are taken into consideration. At higher levels of aging, benefits from agglomeration crowd out because localized external economies-related effects of aging are

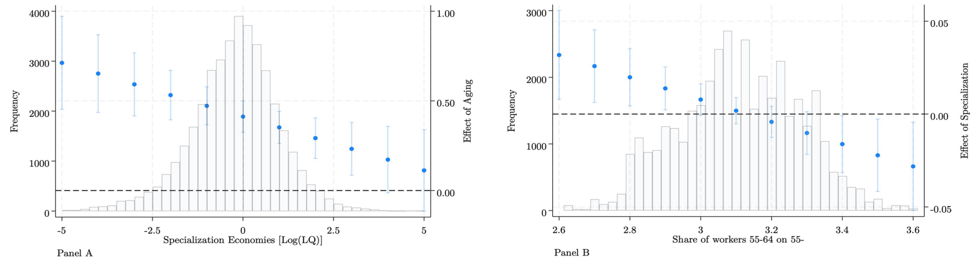

Figure 3. The average marginal effect of interaction terms presented in column (9) of Table 1 on the pairs of NUTS 2 manufacturing NACE-3 TFP. *Source*: Authors' elaboration on Amadeus-Bureau Van Dijk and Eurostat data.

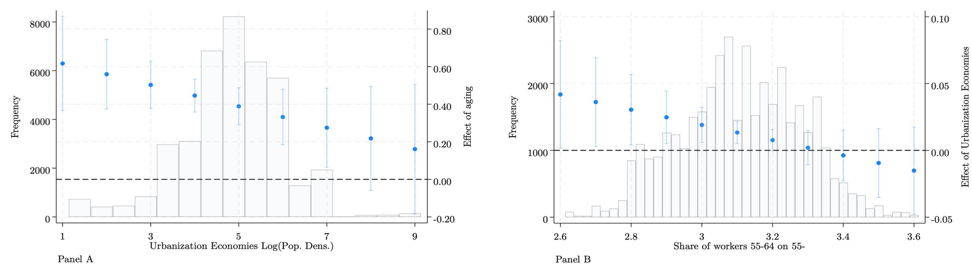

Figure 4. The average marginal effect of interaction terms presented in column (9) of Table 2 on the pairs of NUTS 2 manufacturing NACE-3 TFP. *Source*: Authors' elaboration on Amadeus-Bureau Van Dijk and Eurostat Data.

greater than benefits. At higher levels of specialization/urbanization, the direct effect of aging and the localized external economies-related effects of aging are equal to the indirect effect suggesting an overall null effect.

Finally, we identify two specific thresholds:

1. The aging effect on the local industry component of TFP goes from positive to zero when the log location quotient of a local industry is higher than 3.8 or when the log population density is higher than 7.5.
2. The positive effect of specialization economies becomes zero and then negative when the share of old workers (age cohort 55–64 years) is higher than 19.68%. On the other hand, urbanization economies disappear when the share of old workers is higher than 24.28%.

Thus, our analyses also shed light on the overall effect of aging by hypothesizing the presence of unobservable technological adaptation. On the one hand, our estimates suggest that the direct negative effects of aging are magnified in regions dominated by external economies, as their interaction generates a further effect (the localized external economies-related effect of aging). Accordingly, aging cancels out positive effects of external economies. As suggested by Woodward (2017), this dual relationship poses a serious threat to agglomeration effects.

6. Further analyses

In Table 3, we decompose the effect of external economies of agglomeration into the main mechanisms identified in the theoretical framework: (I) labor market pooling, measured as in Krugman (1991) and more recently in Dellisanti (2023), (II) knowledge spillovers, measured as the average number of patents in each NUTS-2 region, similar to Rosenthal and Strange (2001), and (III) entrepreneurship, measured as the yearly net change in the population of manufacturing firms, similar to Glaeser and Kerr (2009).

The results are consistent with previous findings. There is an overall decrease in the source of external economies due to aging. The proxy for labor pooling shows a positive coefficient in both

Table 3. Regressions distinguishing by sources of localized external economies

	(1)	(2)	(3)	(4)	(5)	(6)
Aging	0.47***	0.58***	0.47***	0.47***	0.31***	0.60**
	(0.09)	(0.13)	(0.09)	(0.09)	(0.10)	(0.24)
Labor pooling	0.01*	0.34***				
	(0.01)	(0.12)				
Entrepreneurship			0.00	0.25**		
			(0.01)	(0.11)		
Knowledge spillovers					0.01*	0.31**
					(0.00)	(0.14)
Aging × *Labor pooling*		−0.11***				
		(0.04)				
Aging × *Entrepreneurship*				−0.08**		
				(0.03)		
Aging × *Knowledge spillovers*						−0.10**
						(0.04)
Observations	39,176	39,176	39,176	39,176	28,838	28,838
No. of clusters	128	128	128	128	106	106
Controls	√	√	√	√	√	√
Year fixed effects (FE)	√	√	√	√	√	√
Industry FE	√	√	√	√	√	√
First-stage *F*-stat	12.41	12.10	13.31	13.31	10.37	2.90
Hansen J-stat	0.15	0.12	0.18	0.18	0.72	0.49

Notes: The dependent variable is η_{rst}. Columns (1) and (2) use an index of labor pooling as the main explanatory variable to interact with aging. Columns (3) and (4) use a measure of entrepreneurship and columns (5) and (6) use a measure of knowledge spillovers. Labor pooling is estimated as $LP_{rst} = \sum_i \left|(\Delta e_{(it)} - \Delta e_{rst})\right| / n$. Knowledge spillovers are gauged as the overall sum of patents in each region r for each year from 2014 to 2022. Entrepreneurship is the yearly growth rate in the count of firms in each region and industry. All the columns add competition, size, young and old dependency ratios, population density, and a location quotient for specialization as control variables. Standard errors are clustered at the regional level (NUTS-2). All specifications include year and industry FE.
***$P < 0.01$,
**$P < 0.05$, and
*$P < 0.1$.

columns (1) and (2). Entrepreneurship has a not statistically significant coefficient in column (3) and a positive and statistically significant coefficient in column (4). Knowledge spillovers have a positive coefficient in both columns (5) and (6). On the other hand, looking at the three interaction terms, as aging increases, the effect of the three sources of external economies decreases. The result for all interaction terms is negative and statistically significant. Our estimation suggests that, given the average level of aging, the only source of external economies that no longer affects manufacturing productivity is entrepreneurship. It is positive and statistically significant at lower levels of aging. On the other hand, knowledge spillovers and labor pooling work at the average empirical level of the old-age share of the labor force (i.e., 22.45% across all countries and regions).

However, it is important to remember that the measure of knowledge spillovers used, even if it is the one currently available, is not the most appropriate one. Several studies have measured labor market fluidity as a source of knowledge spillovers by looking at the mobility of workers between firms. As in our case, we argued that aging affects labor market mobility by reducing job-to-job transitions and then the component of knowledge spillovers due to worker mobility is also reduced. We recognize that this could be a valuable choice for the mechanism presented, but it cannot be explicitly included due to a lack of data.

7. Conclusions

Our work sheds light on the implications of aging for the impact of local external economies on productivity. Some recent contributions suggest that concerns about productivity declines due to an aging workforce should be tempered because of endogenous technological adaptation (Acemoglu and Restrepo, 2017). We add novel qualifications to such a stream of research. On the one hand, aging affects the impact of external economies on productivity. On the other hand, the impact of aging on a relevant economic factor as productivity changes according to regional specialization/urbanization.

Our paper contributes to the extant literature in several ways. On the one hand, it originally extends the well-established literature on the relationships between the mechanisms driving localized external economies and the economic structure and performance of regions (here measured by productivity) (Rosenthal and Strange, 2001; Puga, 2010), including the simultaneous role of aging. On the other hand, it provides further reasons to reconsider the model of Acemoglu and Restrepo (2017) in production dominated by localized external economies. Recent studies, such as those by Crowley et al. (2021) and Prenzel and Iammarino (2021), have explored themes closely related to our paper. Crowley et al. (2021) examined automation across European regions, focusing on how local industrial structures influence regional vulnerability to automation. Their findings indicate that specialization has no significant effect on such vulnerability. Moreover, aging has been linked to the regional composition of human capital. Prenzel and Iammarino (2021) highlight that regions with older populations tend to exhibit lower levels of tertiary education. Given the importance of human capital externalities, aging may also impact economic performance through its influence on the composition of human capital. Building on this body of research, our study complements these contributions by offering a distinct perspective.

We focus on the productivity (dis)advantages of aging, theoretically considering technological change (such as automation, digitization, artificial intelligence, and robotics) as its countervailing force (unobservable in our data). We show that aging has positive effects on productivity on average and tends to zero at higher levels of specialization/urbanization. However, like Crowley et al. (2021), we expect faster technological change in (I) specialized local industries due to firm division of labor, competition, and selection and (II) high-density regions due to firm competition and selection. Our results suggest that, on average, specialization economies do not operate at average levels of aging: the positive indirect effect of aging (i.e., technological change) exactly offsets its negative effect (i.e., labor shortage) (Woodward, 2017). Rather, urbanization economies operate at average levels of aging. However, when heterogeneous effects of specialization and urbanization economies on productivity at different levels of aging are considered, some important negative spillovers emerge (i.e., localized external economies-related effects). This paper finds that specialization and urbanization economies have negative (positive) effects in old (young) regions. We identify two thresholds above which aging threatens the effects of external economies on productivity. For specialization economies, the threshold is when the regional share of old workers (55–64) exceeds 19.68%; for urbanization economies, it is 24.28%.

The benefits of agglomeration are important for firms and industries, providing insights into the spatial distribution of economic activity and the urban structure of the economy. Our results show that aging poses a threat to these benefits, revealing a negative feedback loop that affects firms and regional productivity. As a result, there is an urgent need for place-sensitive policies to rapidly address aging trends. These policies should not only target the well-known age-related structural shifts across sectors in national economies and their adverse effects on public finances but also recognize their role in constraining positive externalities from agglomerations. There are also important implications for firms, managers, and recruitment strategies, as well as for decisions on the optimal level of a firm's investment in technological change.

Despite these contributions, certain limitations remain. First, a more detailed geographical level of analysis could improve our ability to detect knowledge spillovers, which tend to diminish in larger geographic areas. In our case, data at the NUTS-2 level represent the highest level of detail possible. Moreover, our measure of knowledge spillovers may not be the most appropriate for measuring labor market fluidity, as argued in Ehrl (2013). Future studies could explicitly consider a measure of inter-firm mobility, which is not currently available at the level of analysis implemented. Second, as in Acemoglu and Restrepo (2017), we elaborate on the possible role of technological change (such as automation, digitization, artificial intelligence, and robotics) as a countervailing force to aging, even if unobservable due to a lack of direct and reliable data. We maintain that technological change is a possible explanation, but we cannot provide direct evidence. Once available, researchers can design a comprehensive specification that includes both effects to capture their overall interaction.

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Appendix.

Table A1. Descriptive statistics and correlations among variables

	Min.	Mean	SD	Max.	1.	2.	3.	4.	5.	6.	7.	8.
1. η_{rst}	−2.34	1.20	0.32	6.45	–							
2. LE_{rst}	−7.39	−0.31	1.46	7.07	0.02***	–						
3. or_{rt}	2.28	3.12	0.19	3.83	0.08***	0.06***	–					
4. ODR_{rt}	1.80	3.58	0.18	4.03	0.04***	−0.02***	0.50***	–				
5. YDR_{rt}	2.88	3.23	0.17	4.63	−0.06***	0.03***	−0.44***	−0.36***	–			
6. $Size_{rst}$	−1.79	3.63	1.56	11.00	0.01	0.51***	0.04***	−0.06***	−0.08***	–		
7. $Comp_{rst}$	0.00	1.05	1.06	6.50	0.01**	0.08***	−0.12***	0.03***	−0.07***	−0.25***	–	
8. $PDens_{rt}$	1.10	4.92	1.18	8.93	0.01**	0.03***	−0.18***	−0.36***	−0.15***	0.31***	−0.03***	–

Note: All variables are log transformed.
***$P < 0.01$,
**$P < 0.05$, and
*$P < 0.1$.

Table A2. Regional fixed effects (FE) according to two-digit industries

Two-digit industry	TFP residuals
10	1.112
31	1.136
24	1.141
14	1.149
29	1.15
13	1.179
15	1.184
30	1.188
17	1.189
16	1.189
11	1.195
23	1.20
18	1.20
27	1.214
22	1.22
32	1.223
25	1.23
28	1.23
20	1.252
33	1.265
26	1.269
19	1.319
21	1.338
12	1.451

Notes: This table was obtained by averaging η_{rs} over time and regions. It suggests which are the two-digit industries that leverage more on regional characteristics to grow.
Source: Authors' elaboration from Amadeus-Bureau Van Dijk data.

Table A3. Robustness test using different independent variables for urbanization and specialization economies

	(1)	(2)	(3)
Aging	0.41***	0.56***	0.64***
	(0.05)	(0.15)	(0.16)
SE	0.22***	0.08	
	(0.07)	(0.07)	
Aging × *SE*	–0.07***	–0.02	
	(0.02)	(0.02)	
UE			0.21
		(0.14)	
Aging × *UE*			–0.06
		(0.04)	
Observations	39,176	39,176	39,176
No. of clusters	128	128	128
Year FE	√	√	√
Industry FE	√	√	√
Controls	√	√	√

(continued)

Table A3. (Continued)

	(1)	(2)	(3)
First-stage *F*-stat	21.16	20.95	12.00
Hansen J-stat	0.01	0.05	0.46

Notes: Columns (1) and (2) re-estimate the specification in column (9) of Table 1, while column (3) re-estimates the specification in column (9) of Table 2. Data are aggregate at the three-digit industry (s) and the NUTS-2 level (r). The dependent variable is η_{rst} that is the time-varying regional industrial FE estimated from the production function. All columns use OLS and include industry and year FE. All columns adopt instrumental variables as explained in Section 3. 1. Excluded instruments are regional Log(*live birth*) in 1960, 1965, and 1970. Column (1) uses the log ratio between the s's sector and all regional manufacturing sectors as the specialization index. Column (2) exploits the log transformation of the total number of employees as the specialization index. Column (3) uses the employment (in all sectors of the economy) as an index of urbanization economies. All columns include the interaction between the indexes of specialization/urbanization and the three Log(*live birth*) instruments as additional instruments and include the interaction between the index of specialization and aging as endogenous regressor. Standard errors are clustered at the regional level (NUTS-2). All specifications include industry and year FE.
$^{***}P<0.01$,
$^{**}P<0.05$, and
$^{*}P<0.1$.

Table A4. Robustness test averaging all variables over time and using different independent variables for urbanization and specialization economies

	(1)	(2)	(3)	(4)	(5)
Aging	0.42***	0.41***	0.66***	0.69***	0.66***
	(0.05)	(0.06)	(0.17)	(0.20)	(0.17)
SE	0.20*	0.27***	0.13		
	(0.11)	(0.08)	(0.08)		
Aging × *SE*	−0.06*	−0.09***	−0.03		
	(0.04)	(0.03)	(0.03)		
UE				0.19	0.21
				(0.14)	(0.14)
Aging × *UE*				−0.06	−0.06
				(0.04)	(0.05)
Observations	6034	6034	6034	6034	6034
No. of clusters	128	128	128	128	128
Year fixed effects (FE)	√	√	√	√	√
Industry FE	√	√	√	√	√
Controls	√	√	√	√	√
First-stage *F*-stat	27.35	20.48	26.78	9.92	10.79
Hansen J-stat	0.81	0.22	0.09	0.88	0.90

Notes: This table partial-out time effects by averaging values over the span of time taken into consideration. Column (1) re-estimates the specification in column (9) of Table 1. Columns (2) and (3) re-estimate the specification in column (9) of Table 1 implementing a different independent variable for specialization (the same used in Table A3). Column (4) re-estimates the specification in column (9) of Table 2. Column (5) uses a different proxy for urbanization economies (the same used in Table A3). Standard errors are clustered at the regional level (NUTS-2). All specifications include industry and year FE.
$^{***}P<0.01$,
$^{**}P<0.05$, and
$^{*}P<0.1$.

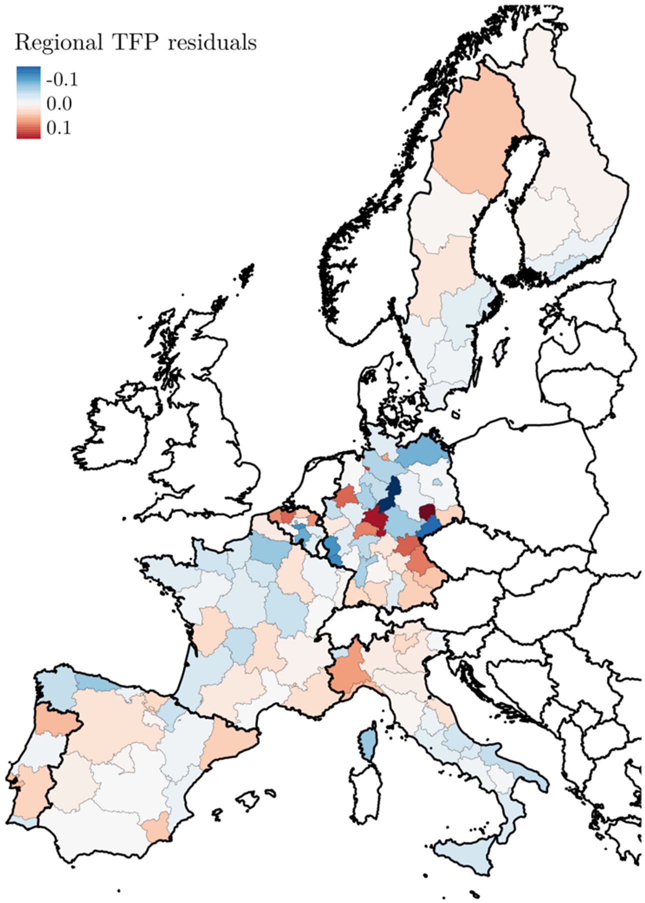

Figure A1. Spatial distribution of manufacturing regional TFP residuals. *Notes.* The map illustrates the levels of η_r among the countries included in this study. η_r is calculated as η_{rst}, which is described in detail in Section 3. However, to represent this variable on a map, it was necessary to reduce its dimensionality. Initially, η_{rt} was obtained by saving time-varying region fixed effects rather than region-industry fixed effects in the production function, in addition to separated two-digit industry fixed effects. Second, we average such variable over time. Subsequently, the variable was demeaned with respect to the national mean to illustrate the discrepancies within countries. The regions depicted in red exhibited higher levels of TFP than the national mean. White regions indicate a TFP level that is comparable to the national mean. *Source*: Authors' elaboration from Amadeus-Bureau Van Dijk data.

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