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Population–employment dynamics in the European Union: Does innovation lead or follow?*

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Abstract

This article examines the interaction between innovation and employment and population dynamics through the development of a system of simultaneous equations. The model is applied to a panel dataset of 271 European NUTS-2 regions. The results reveal strong bidirectional feedbacks between innovation and employment, while population dynamics operate indirectly through employment rather than exerting a direct effect on innovation. Innovation is found to follow jobs rather than people, indicating that the concentration of economic activity and labor interactions, not demographic size per se, constitute the primary drivers of regional innovative capacity. These mutually reinforcing dynamics give rise to virtuous and vicious cycles that contribute to persistent regional disparities. By opening the black box of employment–population–innovation interactions, the paper provides a structural foundation for designing more effective population, innovation, and employment policies. In particular, the analysis demonstrates that policies targeting a single dimension, whether business climate, quality of life, or innovation support, are unlikely to succeed in isolation.

Key words and phrases: innovation, population-employment dynamics, European Union, NUTS2, spatial effects, territorial development

JEL Classifications: C3, O18, O21, R1, R23, R3

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1. Introduction

As Storper and Scott (2009, p.147) note, "one of the most complex enigmas of contemporary social science concerns the causes of urban growth and associated spatial patterns of population movement". Although this question can be framed in different ways, a popular approach focuses on how population–employment dynamics occur and, for more than fifty years, has asked whether people follow jobs or jobs follow people. Put simply, "people follow jobs" assumes that urban growth is directly related to the geography of production, while "jobs follow people" considers that individuals base their location choices on the presence of certain attractive amenities.

Although some of the earliest contributions date back to the 1960s and 1970s (Borts and Stein, 1964; Muth, 1971; Steinnes and Fisher, 1974), it was Carlino and Mills's 1987 paper that made a crucial methodological contribution to this literature. These authors proposed approaching the question as a dynamic adjustment process with a system of two equations, one for population growth and the other for employment growth. Since then, numerous scholars have attempted to address the population–employment causality question, but the evidence reported is not conclusive. A meta-analysis devoted to the issue (Hoogstra et al., 2017) revealed that all possible results (no interaction, dual causality, jobs follow people, people follow jobs) are found in significant proportions. Therefore, as Hoogstra et al. (2017, p.358) conclude, "the controversy has only deepened since the results obtained have apparently included greater variety and become more difficult to make sense of". Outcomes vary depending on the nature of the territorial unit chosen, the level of urbanisation, type of administrative unit, or the size of the territorial area. However, this long-standing literature has not yet considered the role of innovation, that is, how innovation may condition or influence the population–employment dynamics. There are at least three reasons why we should consider the role of innovation to understand the interplay between population and employment.

Firstly, innovation has been linked to both sides of the population–employment dynamic process. On the one hand, the creative class (Florida, 2002), which is assumed to have the relevant skills and capacities to innovate, is usually attracted to urban areas because of its lively and attractive environment (Florida, 2005). On the other hand, one of the key stylised facts in the geography of innovation is the tendency of innovation to cluster spatially more than general economic activity (Feldman and Kogler, 2010; Carlino and Kerr, 2015). Since innovation involves recombining a variety of knowledge into new ideas or solutions, the tendency to cluster is usually explained by the positive impact of geographical proximity to exchange knowledge and ideas and the geographically bounded scope of knowledge spillovers (Jaffe et al., 1993; Storper and Venables, 2004; Boschma, 2005), in particular tacit and complex knowledge (Maskell and Malmberg, 1999; Sorenson et al., 2006). This clustering leads to location-specific advantages, commonly conceptualised as agglomeration economies of the Marshallian (specialisation), Jacobian (diversification) or broader urbanisation types. In consequence, several empirical studies suggest that as urban populations grow, innovation tends to rise at a faster rate, revealing a super-linear scaling relationship between city size and innovative output (Balland et al., 2020; Broekel et al., 2023).

However, population and employment levels are usually strongly correlated. On this basis, the urban scaling literature often focuses on population, but the agglomeration economies that foster innovation are often more closely associated with employment, in the same or different sectors, than with overall population *per se*. Moreover, it is well established that innovation constitutes a key driver of long-run economic growth (Romer, 1986; Grossman and Helpman, 1994). At the firm level, innovation enhances competitiveness by increasing productivity, thus enabling cost reductions, and by facilitating the introduction of new or improved products that help firms differentiate themselves from competitors and adapt to evolving market conditions (Porter, 1990). From this perspective, employment and innovation would be positively related. However, a potential countervailing effect arises when innovation takes the form of labour-saving technologies, which may reduce the demand for certain types of jobs or tasks (Brynjolfsson and McAfee, 2014; Acemoglu and Restrepo, 2020).

Secondly, in recent years, a growing body of literature has emphasised that innovation is not a *magic bullet* inherently leading to only positive outcome; rather it can also produce undesired effects, often referred to as *the dark side of innovation* (Biggi and Giuliani, 2022; Coad et al., 2021). One such potential downside is the exacerbation of inequality. At the interpersonal level, Lee and Rodríguez-Pose (2013) provide evidence of a positive relationship between innovation and inequality across European regions, although they find only limited support for this relationship in the United States. Similarly, Breau et al. (2014), examining Canadian cities during the 1996–2006 period, find that those with higher levels of innovation tend to exhibit greater earnings inequality. There is also recent evidence pointing to the potential negative effects of innovation at the interregional level. Kemeny et al. (2025) adopt a historical perspective to examine the geography of disruptive innovations. Their findings reveal, first, that such innovations tend to exhibit a distinctive pattern of spatial concentration, and second, that they act as a force spurring growing regional inequalities. Similarly, Pinheiro et al. (2025) also found a differential geographical pattern for high and low complex activities. High-complex activities tend to concentrate in more economically advanced regions, while lagging regions tend to diversify into related low-complex activities. Given that more complex activities are generally associated with greater growth potential (Hidalgo and Hausmann, 2009), this uneven distribution of complex activities reinforces spatial inequality through a self-reinforcing feedback loop. The strength of these loops may affect and be affected by the population–employment dynamics.

Finally, gaining a better understanding of the dynamic relationship between innovation, population, and employment can provide valuable insights for policy design. The answer to *who follows whom* in the population–employment dynamics is associated with different policy recommendations designed to stimulate local growth: should policy-makers focus on improving the business climate of a place, or it would be better to cater to people's wishes and improve the people climate? Considering innovation introduces an additional layer of complexity, in particular to align innovation and regional policies, a coordination challenge that is especially important in the European context. On the one hand, the efficient design of innovation policies may call for the concentration of efforts, which frequently goes to the most developed areas (Pinheiro et al., 2025). Indeed, some scholars draw on urban scaling laws to argue that efforts to foster innovation in peripheral or non-urban regions tend to yield limited returns and may represent a misallocation of scarce resources (Glaeser and Hausman, 2020). On the other hand, concentrating innovative activity in a handful of metropolitan hubs would foster disparities through the above mentioned self-reinforcing feedback loops and exacerbate the difficult situation facing left-behind places and regions in development traps (Rodríguez-Pose, 2018; Diemer et al., 2022).

These spatial inequalities have been linked to the rise of populist voting behaviour in disadvantaged regions (Dijkstra et al., 2020; Rodríguez-Pose et al., 2024).

In this context, the present paper aims to examine the mediating role of innovation in population–employment dynamics. Inspired by De Graaff et al. (2012a), who extended the Carlino-Mills model by specifying each sector as a separate equation and thus introduce a jobs-follow-jobs mechanism, we also extend the canonical Carlino–Mills model by adding a third endogenous equation for innovation, thereby integrating it directly into the dynamic adjustment process. By adopting this dynamic adjustment formulation, we move beyond the framework typically used,[1] towards a modelling approach that explicitly distinguishes between short-run adjustment dynamics and long-run equilibrium relationships (allowing for gradual convergence towards the steady-state outcomes). In doing so, this framework enables us to address key questions such as which variables lead the cumulative processes observed over time in population, employment, and innovation, and which variables follow (i.e. who follows whom?).

The fundamental contribution of this paper lies in modelling population dynamics, employment evolution, and innovation processes as jointly determined phenomena, treating all three as endogenous variables that interact simultaneously within a dynamic adjustment framework. Moreover, most of the studies examining the people-follow-jobs vs. jobs-follow-people dynamic focus on specific countries and use fine-grained scales as their unit of analysis. Our contribution also expands this literature by extending the scope to a multi-country context. In particular, we conduct the study for the case of the NUTS2 regions in the European Union over the period 2002–2018. Thus, the analysis for a large set of countries comes at the expense of larger spatial units. The results reveals mutually reinforcing dynamics between population, employment, and innovation. Population and employment exhibit dual causality, generating virtuous and vicious regional cycles, while innovation primarily follows and reinforces employment rather than population size, creating an additional feedback loop that amplifies regional disparities.

The rest of the paper is organised as follows. Section 2 reflects on the arguments supporting the existence of all the possible mechanism at play. Section 3 presents the dataset

[1]For instance, in the scaling literature about (the super-linear or not) relationship between city size and innovation production (Bettencourt et al., 2007a; Bettencourt and Lobo, 2016).

used, and explains how the dynamic adjustment process is modelled for the regressions. Section 4 reports the results, Section 5 discusses the implications of the results, and Section 6 closes the paper with some concluding remarks.

2. Who follows whom? Conceptual issues

In this section, we review the arguments and examine the dynamics at play, first between population and employment, and second between these variables and innovation.

When explaining urban growth, one strand of the literature argues that firms' location decisions are paramount in the process. Economic activity tends to concentrate rather than be evenly distributed across space (Audretsch and Feldman, 1996b; Rodríguez-Pose and Crescenzi, 2008), and attractive locations often differ in the types of activities they host, that is, in their specialization profiles to produce different bundles of goods. The increasing strength of agglomeration forces, weather Marshallian, Jacobian or urbanization externalities, acts as a magnet for firms, although the relevance of each particular type may change throughout along the industry life cycle (Neffke et al., 2011; Duranton and Puga, 2001). These firm location choices set in motion the dynamics of urban growth. They create demand for additional labour, and due to specialisation, they demand labour with specific skills and capabilities. As a result, workers, especially those with relevant skills, will arrive in the region to seize emerging employment opportunities (Storper and Scott, 2009; Storper, 2010). From this perspective, population movements occur primarily in response to the availability of jobs (Tervo, 2016; Mulligan and Nilsson, 2020).

Of course, this explanation may face the chicken-and-egg problem concerning the origin of the externalities that attract firms in the first place. Evolutionary economic geographers introduced the concept of the window of locational opportunity (WLO) to address this conundrum (Storper and Walker, 1989; Boschma and Lambooy, 1999). When a new industry emerges, there is an initial phase in which location-specific externalities have not yet developed, and several places may potentially become the industry's dominant hub. The eventual selection among these locations is often triggered by a small event, frequently based on chance or on factors unrelated to pure economic reasoning.[2] This initial ad-

[2]For instance, one of the usual explanations about the birth of Silicon Valley as the locus of the semiconductor industry is William Shockley's decision to relocate there to be closer to his mother.

vantage can give rise to cumulative processes that generate external economies, thereby gradually closing the WLO (Arthur, 1990). Moreover, from this perspective, urban growth is not necessarily perpetual. It may come to a halt if employment opportunities vanish either because local firms lose competitiveness or as a result of relocation processes. These relocation processes, within the spatial model of the industry life cycle (Duranton and Puga, 2001; Audretsch and Feldman, 1996a), occur regularly and contribute to the redesign of the industrial landscape (Duranton, 2007; Crespo and Peiró-Palomino, 2025). Thus, the persistence of urban growth depends on the capacity of the city to successfully transition to new economic activities (Martin and Sunley, 2015, 2006).[3]

Alternatively, it has been argued that the driving force in processes of urban growth lies in the residential choices of individuals seeking to improve the quality of their lives. From this perspective, people relocate to specific areas attracted by features of the urban environment broadly known as *amenities*. Employers, in turn, follow these residential decisions, choosing to locate near workers. They are drawn by the abundance of labour supply as well as by the market potential offered by a growing population. This perspective reflects a case of supply-induced growth, where jobs follow people. The range of amenities that may trigger such dynamics is broad, and includes: (i) natural or exogenous factors such as climate (Glaeser, 2005); (ii) built urban amenities that address both basic needs (e.g. schools, healthcare services) and cultural or leisure preferences (e.g. parks, museums, restaurants, art galleries), aligning with conceptions of the city as an "entertainment machine" or a "consumer city" (Clark et al., 2002; Deller et al., 2001; Glaeser and Gottlieb, 2006); and (iii) socially constructed attractions such as safety, tolerance, or diversity (Florida, 2002).

We now extend the discussion by considering the role of innovation. Although, to the best of our knowledge, the effects of innovation on population–employment dynamics have not yet been explicitly addressed, they are implicitly linked to some of the arguments previously discussed. In particular, following the work of Florida (2002), the creative class, including scientists, engineers, artists, designers, and other knowledge-based professionals, is seen as a key driver of innovation through the generation of new ideas, products, and organisational practices. These individuals contribute to enhancing regional competitive-

[3] The case of Detroit vs. Silicon Valley is a well-known illustration of this situation. The former failed to reinvent itself after the maturation of the automotive industry, while the latter successfully transitioned from semiconductors to personal computing, then to the Internet—and beyond.

ness and adaptability. However, in line with the jobs-follow-people perspective, members of the creative class do not choose locations based solely on employment opportunities, but rather—primarily—on lifestyle conditions or, as noted above, amenities (Florida, 2005). In this sense, a city's innovative capacity may itself be considered a form of amenity, a signal of the dynamic and vibrant environment that the creative class is looking for, and thus attract (creative) people. In some cases, locational attraction is driven by mimetic behaviour, whereby individuals and firms observe the location choices of similar actors and decide to replicate them—*that place is the place to be*—thereby triggering a location cascade (Vicente and Suire, 2007). The intensity of this mimetic dynamic tends to be greater when the initial movers have a strong reputation or signalling power (Appold, 2005). This would constitute a direct channel through which people follow innovation. However, there may also be an indirect people-follow-innovation mechanism, whereby people follow innovation via the jobs it generates.[4] Innovation is widely recognised as a source of competitiveness because it allows firms to be more productive by increasing the value of their outputs and/or by reducing their production costs (Porter, 1990). Furthermore, innovation is usually associated with stronger adaptive capacity, allowing firms to sustain growth and live longer even in the face of external shocks or industrial maturity (Agarwal and Gort, 2002; Agarwal et al., 2002; Cefis and Marsili, 2005). As a result, the stronger and more sustained growth of innovative firms translates into more, and more stable, employment opportunities for workers. From this perspective, innovation would reinforce the people-follow-jobs mechanism.

Despite these arguments, there are also strong reasons to contend that the relationship between innovation and population may operate in the opposite direction, namely that innovation follows people. According to Feldman and Kogler (2010) and Carlino and Kerr (2015), one of the stylised facts of the geography of innovation is the tendency of innovation to spatially concentrate (Audretsch and Feldman, 1996b; Crespo and Peiró-Palomino, 2025). This pattern is largely explained by the strength of agglomeration economies. At the micro level, these agglomeration economies emerge from three primary mechanisms: sharing of resources, matching of labour and input markets, and learning through knowledge spillovers (Duranton and Puga, 2011). Each of these mechanisms is closely linked to city size: (i) larger local markets allow for more efficient sharing of specialised inputs and

[4] We discuss this in more detail below.

facilities like universities or public research institutes, enhancing economies of scale; (ii) thicker markets increase the likelihood of high-quality matches between firms and workers or suppliers of inputs and complementary services; (iii) learning relies on interaction, which is facilitated by densely populated environments where more individuals can engage in knowledge exchange through a variety of knowledge spillover mechanisms, such as labour flows, spin-offs and dense social networks. Consequently, populous and economically dense urban environments enhance the innovative capacity of both firms and individuals located within them. Several studies have shown that as the population of urban areas increases, innovation outcomes grow more than proportionally, reflecting a super-linear relationship between population size and innovation (Mewes, 2019; Balland et al., 2020; Broekel et al., 2023). This pattern is commonly attributed to the effects of agglomeration economies working either via an over-representation of inventors in large urban areas or via an environment that makes them more productive (Bettencourt et al., 2007b; Broekel et al., 2023). In either case, these mechanisms suggest a direction of causality in which innovation follows people. In contrast, Coccia (2014) explicitly focuses on the relationship between innovation growth and population growth, instead of using levels. Adopting a two-stage model strategy, he finds an inverted-U curve representing the relation between population and technological growth, thus validating the hypothesis that technological outputs of countries are negatively affected by both low/negative and high population growth rate.

Nevertheless, given that these arguments are rooted in the presence of agglomeration economies, they may also experience the innovation-follows-employment causality. Indeed, although urban scaling has linked innovation to urban size, proxied by population, most agglomeration economies primarily arise from a concentration of economic actors, whether firms or workers, in the same industry for Marshallian localisation economies or across various industries for Jacobian economies, rather than merely by population *per se*. As De Graaff et al. (2012a) argue, most of the micro-motives underlying agglomeration economies are sector-dependent. The numerous empirical studies that have tried to identify which particular mechanism lead to agglomeration economies have found that most of these mechanisms are sector-specific and determined by sectoral composition (Almeida and Kogut, 1999; Buenstorf and Klepper, 2009; Puga, 2010). Thus, De Graaff et al. (2012a) propose a jobs-follow-jobs mechanism to take into account intra- and inter-industry linkages. In parallel, we consider an innovation-follow-jobs mechanism. Hence, since sectoral composition is key for agglomeration economies to emerge, employment, rather than population, leads to innovation. Of course, while not all individuals are part of the workforce, all workers are individuals; thus, employment and population are closely related.

Finally, we shift our focus to the reverse causal relationship between innovation and employment. In examining the employment-follows-innovation dynamic, it is essential to distinguish between product innovation and process innovation. On the one hand, product innovations allow firms to sustain or reinforce their competitive position by adding value to differentiate their products through new features and functionalities, and by introducing new products that renew the array of activities and markets in which the firm is involved to avoid maturity and decline. Accordingly, this sustains the firm's survival and growth, and then a positive effect on employment is expected (Freeman et al., 1982; Freeman and Soete, 1987). On the other hand, process innovations often have a labour-saving aspect. In the past, mechanisation mainly affected routine jobs, but more recent technical advances on robotization and artificial intelligence may also impact more skilled and creative jobs (Frey and Osborne, 2017). From this perspective, innovation may have a negative impact on employment. However, a variety of mechanisms may be at work to compensate for the *a priori* negative effect of process innovation on employment. These compensation mechanisms include employment shifts across sectors, output expansion and demand increase due to price reduction derived from the cost reduction obtained from the process innovation, or due to higher wages paid to more productive workers (Vivarelli, 2014; Calvino and Virgillito, 2018) .

Montobbio et al. (2023) and Hötte et al. (2023) have recently reviewed the empirical literature on the impact of innovation (or technical change) on employment. Their conclusions point to a wide variety of findings depending on the level of analysis (firm, sector, or macro), the measure of technological change, the geographical scale, the country and the time dimension of the analysis. In general, studies at the firm and sector level show that product innovation has a positive but limited effect on job creation, mostly benefiting high-tech and knowledge-intensive sectors, both in manufacturing and in services. In contrast, process innovation can lead to job losses, especially in the more traditional and downstream sectors. For instance, Harrison et al. (2014) used an original methodology on a sample of about 20000 companies from different European countries, concluding that process innovation tends to displace employment, while product innovation is a strong force behind employment creation. Other scholars have found consistent results when replicating the same methodology (Crespi et al., 2019; Cirera and Sabetti, 2019). This positive effect is also found by Van Reenen (1997) and Piva and Vivarelli (2005) with longitudinal panel data for Italian and UK manufacturing firms. At the sectoral level, Pianta (2000) finds a negative effect of innovation on employment in manufacturing industries across five European countries, while Evangelista and Savona (2002) show a positive effect when considering the most innovative and knowledge-intensive service sectors. In turn, Piva and Vivarelli (2018) show that R&D expenditures significantly contribute to job creation, although this effect is limited to medium- and high-tech sectors. In contrast, capital formation is associated with job losses, likely reflecting labour-saving effects stemming from technological change embedded in investment. At the aggregate (national/regional) level, the impact varies depending on market conditions and institutions. Innovation can have a negative effect on employment in the short term (Feldmann, 2013), but with time, employment gains occur and are more likely where product innovation is common and price-related compensation effects are strong (Vivarelli, 1995). Capello and Lenzi (2013) examine the relationship between innovation and employment growth at the regional level in Europe. Their findings indicate that the direct effects of product and process innovation are contingent upon specific structural characteristics of regions. In particular, product innovation tends to have a positive impact on employment in regions with a strong presence of production activities, whereas the impact of process innovation is negative in regions with large urban centres.

3. Methods and data

3.1. Method

The analytical approach of this study is based on the specification proposed by Carlino and Mills (1987), who modeled a dynamic adjustment process through a system of two equations. In this framework, both population change and employment change are treated as jointly determined processes, with each considered an endogenous variable.

In their model, population dynamics are influenced by employment opportunities, and employment dynamics are related to population decisions. Equation (1) shows Carlino and Mills's (1987) system of equations:

$$\begin{aligned} \Delta P_{i,t} &= \mathbf{X}^P_{i,t}\gamma + \Delta E_{i,t}\delta_1 + P_{i,t-1}\delta_2 + u^P_{i,t} \\ \Delta E_{i,t} &= \mathbf{X}^E_{i,t}\beta + \Delta P_{i,t}\alpha_1 + E_{i,t-1}\alpha_2 + u^E_{i,t} \end{aligned} \tag{1}$$

In this two-equation system, $\Delta P_{i,t}$ represents the change in population in region i at time t, while $\Delta E_{i,t}$ denotes the corresponding change in employment. Both equations incorporate vectors of exogenous variables, $\mathbf{X}^P_{i,t}$ and $\mathbf{X}^E_{i,t}$, capturing region-specific socioeconomic and structural characteristics. The parameters δ_1 and α_1 measure the interdependence between employment and population change, whereas δ_2 and α_2 account for the influence of lagged population and employment levels, respectively. Finally, the error terms $u^P_{i,t}$ and $u^E_{i,t}$ represent unobserved shocks affecting each process.

The central objective of this study is to disentangle the relationship between employment, population, and innovation dynamics. Building on Carlino and Mills (1987), we extend the original two-equation framework by endogenously linking population, employment, and innovation within a unified system. In our specification, population growth, employment growth, and innovation growth are jointly determined, allowing us to analyse how innovation dynamics interact with demographic and labour market adjustments and how these three dimensions adjust simultaneously over time.

Variants of this modelling strategy have been applied in different empirical contexts. For instance, Deller et al. (2001) incorporate income as an additional endogenous variable, and De Graaff et al. (2012a) and Alamá-Sabater et al. (2025b) add n sector-specific equations to disaggregate employment dynamics.

The long-run equilibrium for population, employment, and innovation is characterised by the following system of equations:

$$\begin{aligned} P^*_{i,t} &= g_P\left[X^P_{i,t}, E^*_{i,t}, I^*_{i,t}\right] \\ E^*_{i,t} &= g_E\left[X^E_{i,t}, P^*_{i,t}, I^*_{i,t}\right] \\ I^*_{i,t} &= g_I\left[X^I_{i,t}, P^*_{i,t}, E^*_{i,t}\right] \end{aligned} \tag{2}$$

Here, $P^*_{i,t}$, $E^*_{i,t}$ and $I^*_{i,t}$ represent the equilibrium levels of population, employment and innovation in region i at time t. Each equation relates the equilibrium level of a given variable to its relevant controls and to the remaining endogenous variables. We assume that the functions g_P, g_E and g_I are linear, allowing the equilibrium relationships to be expressed as linear functions of their explanatory variables.

Building on this equilibrium structure, we introduce dynamics through a partial-adjustment mechanism, following Carlino and Mills (1987). Under this framework, population, employment and innovation adjust gradually toward their long-run equilibrium values:

$$\begin{aligned} \Delta P_{i,t} &= \lambda_P(P^*_{i,t} - P_{i,t-1}) \\ \Delta E_{i,t} &= \lambda_E(E^*_{i,t} - E_{i,t-1}) \\ \Delta I_{i,t} &= \lambda_I(I^*_{i,t} - I_{i,t-1}) \end{aligned} \tag{3}$$

where λ_P, λ_E and λ_I measure the speed of adjustment toward equilibrium. Values between 0 and 1 indicate partial adjustment and ensure dynamic stability.

Assuming linear equilibrium functions with additive disturbances[5] and combining them with the adjustment mechanism in Equation (3), we obtain the following dynamic system:

$$\begin{aligned} \Delta P_{i,t} &= \lambda_P\alpha_1 X^P_{i,t} + \lambda_P\alpha_2\tfrac{1}{\lambda_E}\Delta E_{i,t} + \lambda_P\alpha_2 E_{i,t-1} + \lambda_P\alpha_3\tfrac{1}{\lambda_I}\Delta I_{i,t} + \lambda_P\alpha_3 I_{i,t-1} - \lambda_P P_{i,t-1} + u^P_{i,t} \\ \Delta E_{i,t} &= \lambda_E\beta_1 X^E_{i,t} + \lambda_E\beta_2\tfrac{1}{\lambda_P}\Delta P_{i,t} + \lambda_E\beta_2 P_{i,t-1} + \lambda_E\beta_3\tfrac{1}{\lambda_I}\Delta I_{i,t} + \lambda_E\beta_3 I_{i,t-1} - \lambda_E E_{i,t-1} + u^E_{i,t} \\ \Delta I_{i,t} &= \lambda_I\gamma_1 X^I_{i,t} + \lambda_I\gamma_2\tfrac{1}{\lambda_P}\Delta P_{i,t} + \lambda_I\gamma_2 P_{i,t-1} + \lambda_I\gamma_3\tfrac{1}{\lambda_E}\Delta E_{i,t} + \lambda_I\gamma_3 E_{i,t-1} - \lambda_I I_{i,t-1} + u^I_{i,t} \end{aligned} \tag{4}$$

Rearranging and simplifying yields the estimable model in Equation (5).

$$\begin{aligned} \Delta P_{i,t} &= \delta_0 + \delta_1 X^P_{i,t} + \delta_2\Delta E_{i,t} + \delta_3 E_{i,t-1} + \delta_4\Delta I_{i,t} + \delta_5 I_{i,t-1} - \lambda_P P_{i,t-1} + u^P_{i,t} \\ \Delta E_{i,t} &= \rho_0 + \rho_1 X^E_{i,t} + \rho_2\Delta P_{i,t} + \rho_3 P_{i,t-1} + \rho_4\Delta I_{i,t} + \rho_5 I_{i,t-1} - \lambda_E E_{i,t-1} + u^E_{i,t} \\ \Delta I_{i,t} &= \theta_0 + \theta_1 X^I_{i,t} + \theta_2\Delta P_{i,t} + \theta_3 P_{i,t-1} + \theta_4\Delta E_{i,t} + \theta_5 E_{i,t-1} - \lambda_I I_{i,t-1} + u^I_{i,t} \end{aligned} \tag{5}$$

As a benchmark, we also estimate the two-equation specification indicated in Expression (1) and originally proposed by Carlino and Mills (1987), which focuses on the adjust-

[5]Where u_{it} are random disturbance terms (normally and independently distributed with zero mean and constant variance).

ment dynamics between population and employment while abstracting from innovation. This baseline estimation ensures comparability with the original framework and provides a benchmark for our results. Building on this baseline, we extend the specification by incorporating innovation as a third endogenous variable, yielding the three-equation system reported in Equation (5).

Due to the simultaneity among the endogenous variables, we estimate the model using three-stage least squares (3SLS), which accounts for cross-equation correlations and endogeneity. The model is estimated using panel data for European regions over the period 2002–2018 (see below). We control for unobserved heterogeneity with year and national fixed effects,[6] which absorb country-specific time-invariant characteristics.

3.2. Data

Our empirical analysis focuses on European regions over the period 2002–2018. In particular, we examine 271 NUTS-2 regions (2016 classification) across 28 European countries.[7] While previous studies on population–employment dynamics often rely on smaller spatial scales, this choice tends to restrict the geographical scope of the analysis. By focusing on NUTS-2 regions, we are able to examine these dynamics across a broader and more heterogeneous set of territorial contexts within Europe

The key variables in this analysis are annual growth of employment, population and innovation. Employment (in levels) is measured as the total number of individuals employed, while population (in levels) refers to the total working-age population. We choose working-age population instead of total population because the likelihood of being affected by labour market dynamics (De Graaff et al., 2012a). Both the employment and the working-age population indicators are sourced from the AMECO database.

To capture regional innovation (in levels), we use patent data drawn from the OECD's REGPAT database. Patents are a widely used, albeit imperfect, proxy for innovative activity.

[6]We use national fixed effects to account for the fact that formal and informal institutional factors—such as labour regulation, culture or language—are typically defined at this level in Europe.

[7]Hence, the sample includes all European Union countries plus the UK, which was a member during the analysed period—the UK did not formally leave the European Union until January 31, 2020. In addition, although the 28 countries in the sample would correspond to the EU-28 composition that existed from July 2013 (when Croatia joined) until the UK's departure in 2020, for the earlier years of the study (2002–2013), the EU had fewer member states.

In particular, the innovation level of a region is the number of patents granted to inventors located in a region in one year. If a patent has several inventors living in different regions, fractional counting is applied. From these annual levels for population, employment and innovation we compute the annual growth rates that are used as key endogenous variables of the model.

In addition to changes in the levels and growth rates of the regional population, employment and innovation, we have considered other factors attracting firms and people to particular regions that may also influence the observed adjustment dynamics. First, to account for the population structure of the region, we include the shares of the population under 15 and over 65 years of age. Second, we control for the level of regional development using per capita gross domestic product (in purchasing power standards). Third, to capture the degree of urbanisation, we use population density (inhabitants per kmkm^2); in this case, we also include a squared term to allow for potential non-linear effects, such as saturation or urban diseconomies of scale. In the employment equation, we account for the economic conditions and the degree of economic dynamism of the region by including the growth rates of GDP and investment. Additionally, we control for the economic structure of the region. Specifically, we calculate the revealed comparative advantage (RCA)[8] of regions based on sectoral employment data across six broad sectors. We also include a measure of economic diversity, captured through the Shannon index[9] constructed from employment data too. Finally, in the innovation equation, we control for both the resources that regions dedicate to innovative activities by including a variable for the growth of R&D expenditure, and a variable for the growth of human resources dedicated to science and technology. Data on total and sectoral employment are obtained from AMECO database, while the other variables on population structure, population density, economic indicators

[8]The revealed comparative advantage corresponds to the expression $\mathrm{RCA}_{rs} = \frac{\frac{E_{rs}}{\sum_s E_{rs}}}{\frac{\sum_r E_{rs}}{\sum_r \sum_s E_{rs}}}$, where E_{rs} denotes employment in region r and sector s; $\sum_s E_{rs}$ is total employment in region r across all sectors; $\sum_r E_{rs}$ is total employment in sector s across all regions; and $\sum_r \sum_s E_{rs}$ represents total employment across all regions and sectors. The numerator thus captures the share of sector s in region r's total employment, while the denominator represents the share of sector s in total employment across all regions. An RCA value greater than one indicates that region r is relatively specialized in sector s compared to the European average.

[9]It is defined as the negative sum of the shares of each sector multiplied by the natural logarithm of those shares, with higher values indicating greater economic diversity. The index equals zero when all economic activity is concentrated in a single sector, and it increases as activities become more diversified.

(GDP per capita, GDP and investment growth) and resources to innovation activities (R&D expenditure and human resources in science and technology) are sourced from Eurostat. Table 1 reports the definition of the variables and Table 2 presents the main summary statistics.

4. Results

4.1. Descriptive results

Before examining the regression results, we first analyze and visualize the relationships between employment, population, and innovation, considering both their levels and growth rates. Figure 1 illustrates these relationships through a series of scatter plots.

The contrast between these two perspectives provides some relevant insights about the dynamics we aim to investigate. When examined in levels, all three variables (employment, population, and innovation) exhibit strong positive correlations with one another. Regions with larger populations tend to have higher employment levels, and both population and employment are positively associated with innovation output (measured by patents). These positive relationships in levels are consistent with well-established findings in the urban scaling literature, which documents that larger cities and regions tend to produce more innovation in absolute terms (Bettencourt et al., 2007b; Balland et al., 2020).

However, the picture changes considerably when we shift our focus to growth rates. The bottom panels of Figure 1 reveal much weaker and more dispersed relationships between the growth rates of these variables. This dispersion suggests that the question of causality (who follows whom in the dynamic adjustment process) is far from straightforward and cannot be inferred simply from the positive correlations observed in levels. While levels tell us about the accumulated outcomes of past processes, growth rates capture the ongoing dynamics and adjustment mechanisms that generate these outcomes over time.

As noted in the introduction, the long-standing debate about whether "people follow jobs" or "jobs follow people" is fundamentally a question about growth dynamics—i.e., about the direction of causation in the adjustment process. Similarly, to understand the role of innovation we must examine how changes in innovation relate to changes in employment and population, rather than simply observing that innovative regions tend to be populous and economically active. The regression analysis that follows is designed to disentangle these dynamic relationships and identify the mechanisms driving regional growth trajectories.[10]

The maps in Figures 2, 3 and 4 illustrate the regional distribution of growth in population, employment, and innovation growth (measured with patent registration) in European NUTS 2 regions. Given the time-series nature of the data (2002–2018), we opted to represent the maps using the average levels of the growth rates for each variable corresponding to the 2002–2018 period. This approach facilitates the visualisation of a stable mean trend throughout the entire study period, smoothing out year-to-year fluctuations that might obscure longer-term patterns. While this averaging necessarily masks some of the temporal variation in growth rates—including the impact of the 2008–2009 financial crisis and subsequent recovery—it provides a clearer picture of the underlying growth trajectories that characterize different regions over the full period of analysis. These maps provide a complementary spatial perspective on the relationships examined in the scatter plots, revealing the geographical patterns underlying the statistical associations, with several patterns emerging from their visual inspection. First, there is considerable spatial heterogeneity in growth rates across Europe, with some regions experiencing rapid expansion, while other regions stagnate or decline. Second, there appears to be some degree of spatial clustering, with high-growth regions often located near other high-growth regions, suggesting the potential importance of spatial spillovers and inter-regional dynamics. Third, the geography of innovation growth (Figure 4) shows a somewhat different spatial pattern from population or employment growth, with concentrations in certain metropolitan areas and industrial regions (particularly in Central and Eastern Europe), as well as in parts of Spain and Portugal. This distinct geography of innovation growth provides initial visual evidence that innovation dynamics may not simply mirror population or employment dynamics, but may follow their own spatial logic shaped by factors such as knowledge infrastructure, industrial specialisation, and regional innovation systems.

Overall, the maps complement the scatter plots by adding a geographical dimension to

[10]In the approach proposed in this paper, the levels of population, employment, and innovation are interpreted as the accumulated outcomes of past processes, whereas their growth rates capture the short-run partial adjustment dynamics through which these variables respond gradually to deviations from their long-run equilibrium, thereby enabling convergence toward steady-state levels over time.

our understanding of the relationships between population, employment, and innovation growth, setting the stage for the more formal econometric analysis that follows.

4.2. Regression results

We begin with the baseline two-equation model in Equation (1), examining the adjustment dynamics between population and employment, and which does not take into account the effect of innovation. Results are presented in Table 3. The coefficients on the lagged endogenous variables are critical for model validity and, in our case, both the lagged log population and log employment coefficients fall between -1 and 0 and are statistically significant. This confirms that the system is dynamically stable, and converges to equilibrium (hence, it is possible to proceed with confidence in interpreting the remaining coefficients).

The control variables display the expected effects. In the population equation (first equation in Model (1)), younger population structures ($SHARE\_POP15$) tend to be more conductive to population growth, whereas regions with a higher share of older individuals ($SHARE\_POP65$) experience a negative impact. The coefficients are significant (1%) in both cases. As for GDP per capita (LOG_GDPpc), the effect is positive and significant, indicating that richer regions tend to exhibit higher population growth rates, which would suggest that people are attracted to areas with higher levels of development. Finally, the signs of the population density coefficients (LOG_POP_DENS and $LOG\_POP\_DENS^2$) reveal an inverted U-shaped relationship, implying that urbanization economies foster population attraction up to a certain threshold, beyond which congestion and saturation effects dominate, exerting a negative influence on population growth.

In the employment equation (second equation in Model (1)), GDP and investment growth (GDP_GROWTH and $INVEST\_GROWTH$, respectively) coefficients are positive and significant implying, as one may expect, that in expansion periods the region will create more employment and in recession times it will destroy. Finally, concerning the effect of productive structure, we find that specialisation in the service sector (RCA_SERV) has a positive impact on employment, but specialisation in other sectors has no impact (agriculture, RCA_AGRI, and non-market sector, $RCA\_NONMARKET$) or a negative one (industrial, RCA_IND, and financial, RCA_FIN). The degree of diversification ($SHANNON$)

is not significant for employment growth. All this might imply that regional employment growth in Europe is increasingly tied to the service economy, while traditional industrial specialisation may have become a drag on job creation. This pattern is consistent with the broader literature documenting how process innovation in manufacturing tends to be labour-saving, whereas product innovation and service activities tend to be more labour-absorbing (Harrison et al., 2014; Calvino and Virgillito, 2018). The absence of a significant effect for diversification, however, might suggest that the composition of economic activity matters more than its variety for employment dynamics at the regional level.

Nevertheless, the main variables of interest for this study are employment growth (EMP_GROWTH) and population growth (POP_GROWTH). They are both positive and significant, implying that we have a dual causality phenomenon in which "people follow jobs" and "jobs follow people". This implies the existence of a double-edged sword leading to polarization. On the one hand are the regions in a virtuous cycle in which population drives employment and employment drives population, in a process that is continuously reinforced. On the other hand, are the regions in a vicious cycle in which losses of population reduce employment, and less employment further reduces population growth. This dual causality result is partly consistent with the mixed findings reported by Hoogstra et al. (2017) who, as indicated earlier, found that all possible outcomes (no interaction, dual causality, jobs follow people, people follow jobs) appeared in significant proportions across different studies. Hence, beyond the explorations done for specific European countries such as Finland (Tervo, 2016) and the Netherlands (De Graaff et al., 2012a), our findings for the EU-28 suggest that the dual causality pattern may be a general feature of regional dynamics in Europe with potential implications for the persistence of spatial inequalities across the continent (Alamá-Sabater et al., 2025a).

In Table 4, we extend the previous model by incorporating innovation in order to examine whether it alters or reinforces the observed dynamics. Specifically, we add a third equation for innovation to simultaneously model the endogenous interdependence between population, employment and innovation. As in the case of the two-equation model, the values of the coefficients of the lagged endogenous variables in levels (LOG_POP_{t-1}, LOG_EMP_{t-1} and LOG_INNOV_{t-1}) across the three equations show that the model is stable and converges to equilibrium. The coefficients of the control variables in the employment and population equations (columns 2 and 3 in Table 4) remain consistent with the previous ones in both sign and significance. Regarding the innovation equation (column 4), growth in funding dedicated to innovation ($INNOV\_GROWTH$) enhances patent production. For its part, R&D expenditure growth ($R\&D\_GROWTH$) positively affects patent production, whereas growth in tertiary-educated population ($HKAP\_GROWTH$) does not have a significant effect—a somewhat surprising finding.

Focusing on the three endogenous variables of interest in this study, we find that the dual causality between population and employment persists, since employment growth and population growth maintain their positive and significant effect on the population and employment equations respectively. However, the coefficients for innovation ($INNOV\_GROWTH$) are negative but not significant (-0.00077) in the population equation, and positive (0.00576) and significant (5%) in the employment equation. On the one hand, the negative coefficient of innovation in the population equation indicates that a region's innovative performance does not directly attract more people. According to the arguments discussed in Section 2, innovation therefore does not act as a signal of a region's creative environment with the potential to attract other *creative* individuals. On the other hand, the positive effect of innovation growth on employment growth suggests that the employment-creation effect of innovation outweighs its employment-saving alternative. The positive coefficient thus suggests that innovation enhances firms' performance and competitiveness, ultimately leading to higher job creation. Moreover, as previously discussed, there is a virtuous cycle between population and employment, implying that the positive impact of innovation on employment indirectly contributes to population growth too, even though the direct effect remains insignificant.

Finally, the results from the innovation equation (column 4 in Table 4) indicate that population growth does not have a statistically significant effect on innovation growth. By contrast, employment growth exerts a positive and significant impact, suggesting that innovation follows jobs rather than people. In line with the theoretical discussion in Section 2, this finding implies that innovation emerges not from population size *per se*, but from the concentration and interaction of workers, which generate matching advantages and learning opportunities within and across sectors. These results reveal a dual causality relationship between innovation and employment, whereby "innovation follow jobs" and "jobs follow innovation". As a consequence, regions engaged in a *virtuous cycle* experience mutually reinforcing dynamics in which employment growth stimulates innovation and innovation further promotes employment. Conversely, regions trapped in a *vicious cycle* face declining innovative capacity that leads to job losses, which in turn further constrain both employment and innovation growth. Although innovation and population dynamics are not directly linked, they are indirectly connected through employment, implying that the employment–population and innovation–employment cycles are interdependent and jointly contribute to the amplification of regional disparities.

5. Discussion

Our results, therefore, reveal a relatively convoluted system of interconnected dynamics linking population, employment, and innovation in European regions, yielding some implications for understanding spatial polarisation and providing some helpful insights for policy design.

On the one hand, the baseline model confirms dual causality between population and employment: people follow jobs and jobs follow people simultaneously. This finding, consistent with the mixed evidence in the literature (Hoogstra et al., 2017), has implications for regional development. It creates both virtuous and vicious cycles—regions with employment growth attract workers who stimulate further job creation, while declining regions experience reinforcing downward spirals. The coexistence of both cycles help to explain the persistence, even the increase, of regional inequalities across Europe (Iammarino et al., 2019a; Alamá-Sabater et al., 2025a).

On the other hand, introducing innovation into the framework reveals some additional interesting patterns. First, innovation does not directly attract population: the coefficient is negative and non-significant. This finding suggests that patent-based technological innovation does not act *per se* as an amenity capable of attracting new residents. Although this conclusion should be interpreted with caution given the innovation measure and territorial scale employed, it nonetheless challenges Florida's (2002, 2005) creative class thesis. However, innovation significantly affects employment: regions experiencing higher innovation growth also see higher employment growth. This confirms that employment-creation effects dominate any labor-saving impacts (Harrison et al., 2014; Crespi et al., 2019), implying that innovation indirectly boosts population through the employment channel.

Second, innovation follows jobs rather than people. In other words, innovation growth is driven by employment growth, not by population growth. This finding challenges the urban scaling literature, which emphasises population size as a key driver of innovation (Bettencourt et al., 2007b; Balland et al., 2020). When focusing on dynamics rather than levels, it is the concentration of employment (namely, workers interacting within and across sectors) that fuels innovation growth. This interpretation is consistent with the view that agglomeration economies arise from sector-specific interactions among economic actors (De Graaff et al., 2012b; Duranton and Puga, 2004). The underlying mechanisms (sharing of specialized resources, matching in thick labour markets, and learning through knowledge spillovers) depend on the concentration of economic activity rather than on population size *per se*. This perspective also aligns with the nuanced argument in the scaling literature that scaling effects may arise because of the larger share of resources available to R&D in highly populated areas, rather than by the greater productivity of those resources simply due to their location in large cities (Bettencourt et al., 2007b; Fritsch and Wyrwich, 2021).

Hence, when innovation is incorporated into the analysis, the mutual reinforcement between innovation and employment gives rise to a second dual causality loop, again with a virtuous side and a vicious side, operating alongside the population-employment cycle. As both causality loops operate through employment, they are also interconnected. These interconnected feedback loops amplify some of the initial advantages: regions gaining employment attract people and develop innovation capacity, which further stimulates job creation.[11]

This integrated framework helps explain the persistence (and widening) of regional inequalities. In doing so, it connects with a growing body of research documenting enduring spatial imbalances in economic development, while adding a dynamic perspective to this debate. In particular, recognising the mutually reinforcing (virtuous or vicious) feedback loops between employment and population, as well as between innovation and employment, is essential to understand how the risk of being caught in a regional development

[11]Or disadvantages if we consider a negative starting point: regions destroying employment will lose population and weaken their innovative capacity, which further weakens their capacity to stimulate job creation.

trap raises (Diemer et al., 2022), and the structural challenges faced by lagging and left-behind places (Rodríguez-Pose, 2018). The innovation-related feedback loop is especially relevant, as it aligns with recent evidence showing that more economically advanced regions tend to generate more complex and more disruptive forms of innovation; that is, those with the greatest potential to foster new growth trajectories (Pinheiro et al., 2025; Kemeny et al., 2025). The effect that innovation can reinforce spatial inequalities through self-perpetuating feedback loops is one of the dark sides of innovation identified by the literature (Biggi and Giuliani, 2022).

Taking these mechanisms into consideration also has implications for policy (Fratesi, 2023). According to Rodríguez-Pose (2018), there is a well-established narrative arguing that cities are engines of growth, and the spatial inequalities they may generate are temporary. They will eventually dissipate as agglomeration benefits diffuse from core to peripheral regions and automatic adjustment mechanisms operate (Glaeser, 2011; Duranton and Puga, 2004). From this perspective, the efficient allocation of resources would involve innovation policies emphasizing excellence and concentration in core areas, where greater returns are expected (Glaeser and Hausman, 2020; Balland et al., 2020) and from where they will spread. However, the existing empirical evidence, including this study, points to a more complex and heterogeneous reality. The higher efficiency of larger cities has been questioned as giving rise to sterile agglomerations (Grover et al., 2022), there may be several barriers for knowledge spillovers from core to peripheral regions (Boschma, 2005), and the automatic adjustment mechanisms, such as migration, might be not that strong. As a consequence, the outcome of this concentration policy, based on an efficiency argument that entails virtuous cycles, but also vicious cycles, would be rising polarisation. This creates an obvious tension with cohesion policies seeking to reduce disparities (Di Caro and Fratesi, 2022, 2023). Based on our results, policymakers may reduce regional polarisation by transforming vicious development cycles in lagging regions into virtuous ones. However, previous large-scale projects or redistributive transfers have not consistently delivered the expected results. If innovation follows employment, policies aimed at fostering innovation in lagging regions may need to prioritise strengthening the local employment base. Investing in R&D infrastructure in the absence of a critical mass of economic activity is likely to generate limited returns. At the same time, innovation does stimulate employment once it takes hold, meaning that successfully building innovative capacity can trigger virtuous cycles, the central challenge lies in reaching the necessary thresholds. The existence of dual causalities further suggests that effective regional policies cannot focus on a single dimension. Improving the business climate without attracting workers is unlikely to succeed, just as enhancing amenities without generating employment is insufficient. Instead, successful strategies must simultaneously promote job creation and improve quality of life. Our findings therefore indicate that lagging regions may escape development traps if they are given support to strengthen both their employment and innovation bases in areas aligned with their comparative advantages. Therefore, given the strength of the feedback mechanisms identified, interventions must be sustained, substantial and tailored to the specific conditions and capabilities of each region—that is, they must be place-sensitive (Rodríguez-Pose, 2018; Iammarino et al., 2019b).

6. Conclusions

In this study, we attempt to examine the interaction between innovation and the dynamic processes of employment and population. To this end, we adopt a slightly different stance to that found in the existing literature by extending the traditional Carlino-Mills framework to incorporate innovation as a third endogenous variable. By doing so, we move to a dynamic framework that explicitly models population, employment and innovation as endogenous and simultaneous processes within the regional system to uncover the causal mechanism linking them.

Our analysis therefore helps to bridge the gap between to strands of the regional science and economic geography literature that have traditionally evolved in parallel. On the one hand, we enrich the long-standing "people follow jobs" versus "jobs follow people" debate (Carlino and Mills, 1987; Hoogstra et al., 2017) by considering the endogenous role of innovation. On the other hand, we enrich the urban scaling literature that has analysed the positive effects of larger cities on economic outcomes in general (Bettencourt and Lobo, 2016) and innovation in particular (Bettencourt et al., 2007a; Balland et al., 2020) by focusing on the dynamics of the process that lead to those scaling effects. Moreover, based on our findings, the paper contributes to the emerging literature on the dark side of innovation (Biggi and Giuliani, 2022; Kemeny et al., 2025; Pinheiro et al., 2025). Our integrated framework identifies the simultaneous existence of virtuous and vicious feedback loops between innovation and employment, as well as between employment and population. In doing so, it helps explain why some regions thrive while others decline, sheds light on the growing risk of polarisation, and it provides further insight into the persistence of regional disparities in Europe despite decades of cohesion policy efforts.

Our analysis of 271 European NUTS-2 regions over the period 2002–2018, yields three main results. First, we confirm dual causality between population and employment: both mechanisms operate simultaneously in European regions. This creates conditions for self-reinforcing virtuous and vicious cycles, contributing to the persistence of regional inequalities. Second, innovation does not directly attract population but strongly stimulates employment growth, suggesting that employment-creation effects dominate any labour-saving impacts of technological change—in our specific context. Third, and most notably, innovation follows employment rather than population, indicating that the concentration of economic activity—not demographic size *per se*—drives innovative capacity. The combination of innovation following employment and employment following innovation creates an additional feedback loop that operates alongside and interconnects with the population-employment cycle. These interconnected dynamics form an integrated system where causality runs in multiple directions simultaneously. Regional development cannot be understood by examining population, employment, or innovation in isolation, but requires acknowledgment of how these dimensions co-evolve through mutually reinforcing processes. Initial advantages or disadvantages are amplified over time as regions become trapped in either growth-enhancing or growth-inhibiting trajectories.

From a policy perspective, our findings underscore the need for integrated approaches that can disentangle the interconnections among population, employment, and innovation. Policies targeting only one dimension (whether business climate, quality of life, or innovation support) are unlikely to succeed in isolation. The threshold effects implied by our results suggest particular challenges for lagging regions attempting to escape development traps, as interventions must be substantial and sustained enough to overcome self-reinforcing negative dynamics. The tension between efficiency-oriented innovation policies that concentrate resources (Aghion et al., 2023) and equity-oriented cohesion policies that seek to reduce disparities reflects genuine trade-offs that require careful policy coordination at the European level. Understanding the interconnections between population, employment and innovations, and the cumulative processes they generate, constitutes therefore an additional tool for both theory and policy in dealing with Europe's spatial inequalities. As these inequalities have been linked to political discontent and support for populist movements (Dijkstra et al., 2020; Rodríguez-Pose, 2018), addressing them effectively requires moving toward integrated strategies that acknowledge how population, employment, and innovation dynamics jointly determine regional trajectories.

Our study has several limitations and raises new questions that open avenues for future research. One natural avenue would be to analyse finer spatial scales, which would allow researchers to examine whether these dynamics operate differently in urban versus rural contexts or across different city sizes. Another promising direction involves a more refined measurement of innovation. This may include measures of regional innovation that goes beyond patents which focus on technological innovation but may miss other important forms such as organisational type/style or services. Moreover, it may also be important to distinguish between types of innovation (product vs. process) and examining sectoral heterogeneity, as this would provide richer insights into how different forms of technological change affect employment and population. It would also be valuable to extend the temporal scope of the analysis to reveal whether these relationships vary across business cycles or have evolved with recent technological transformations such as digitalisation and artificial intelligence. Finally, incorporating additional dimensions such as income inequality, skills composition, or environmental sustainability would offer a more comprehensive view of regional development and its multiple facets.

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Table 1: Description of the variables

Variable	Variable name	Description	Source
Population growth	*POP_GROWTH*	Growth of total population	AMECO
Employment growth	*EMP_GROWTH*	Growth of total employment	AMECO
Innovation growth	*INNOV_GROWTH*	Growth in the number of patents obtained by inventors	OECD RegPat
Log population	LOG_POP_{t-1}	Log of total population (lagged)	AMECO
Log employment	LOG_EMP_{t-1}	Log of total employment (lagged)	AMECO
Log innovation	LOG_INNOV_{t-1}	Log of the number of patents (lagged)	OECD RegPat
Share pop <15	$SHARE\_POP15$	Share of population below 15	Eurostat
Share pop >65	$SHARE\_POP65$	Share of population above 65	Eurostat
Log GDPpc	LOG_GDPpc	Log of GDP per capita (PPS)	Eurostat
Log pop density	*LOG_POP_DENS*	Log of inhabitants per km^2	Eurostat
GDP growth	*GDP_GROWTH*	Growth of the GDP (constant)	Eurostat
Investment growth	*INVEST_GROWTH*	Growth of gross investment (constant)	Eurostat
Sector diversification	*SHANNON*	Shannon index based on sectoral employment	AMECO
RCA agriculture	*RCA_AGRI*	Relative comparative advantage of the region in sector 1	AMECO
RCA industry	*RCA_IND*	Relative comparative advantage of the region in sector 2	AMECO
RCA construction	*RCA_CONS*	Relative comparative advantage of the region in sector 3	AMECO
RCA services	*RCA_SERV*	Relative comparative advantage of the region in sector 4	AMECO
RCA financial	*RCA_FIN*	Relative comparative advantage of the region in sector 5	AMECO
RCA non-market	*RCA_NONMARKET*	Relative comparative advantage of the region in sector 6	AMECO
R&D expenditure growth	*R&D_GROWTH*	Growth of R&D expenditure	Eurostat
Human capital growth	*HKAP_GROWTH*	Growth of tertiary-educated population	Eurostat

Table 2: Summary statistics of the variables

Variable name	# Obs	Mean	Std. Dev.	Min	Max
POP_GROWTH	4,529	0.003	0.008	-0.110	0.056
EMP_GROWTH	4,529	0.006	0.023	-0.156	0.217
INNOV_GROWTH	4,529	-0.013	0.558	-1.000	4.820
LOG_POP_{t-1}	4,529	14.166	0.759	12.116	16.318
LOG_EMP_{t-1}	4,529	6.447	0.777	2.811	8.771
LOG_INNOV_{t-1}	4,529	3.046	1.917	-4.382	8.116
*SHARE_POP*15	4,529	0.158	0.022	0.097	0.235
*SHARE_POP*65	4,529	0.179	0.033	0.078	0.285
LOG_GDPpc	4,529	10.066	0.414	8.456	12.209
LOG_POP_DENS	4,529	5.083	1.226	1.194	9.861
GDP_GROWTH	4,529	0.016	0.033	-0.163	0.358
INVEST_GROWTH	4,529	0.028	0.126	-0.481	1.759
SHANNON	4,529	1.434	0.070	0.964	1.542
RCA_AGRI	4,529	1.130	1.408	0.000	10.754
RCA_IND	4,529	0.366	0.456	0.000	3.306
RCA_CONS	4,529	0.879	0.542	0.000	8.208
RCA_SERV	4,529	0.223	0.279	0.000	2.179
RCA_FIN	4,529	0.403	0.509	0.000	4.310
RCA_NONMARKET	4,529	0.210	0.263	0.000	2.076
R&D_GROWTH	4,529	0.067	0.313	-0.879	9.403
HKAP_GROWTH	4,529	0.030	0.060	-0.286	1.834

Table 3: Regression results: Two-equation model

This table presents the results of the baseline two-equation system of simultaneous equations estimated using Three-Stage Least Squares (3SLS). The model examines the dynamic adjustment process between population and employment growth in 271 NUTS-2 regions across 28 European countries over the period 2002–2018. The first column shows the results for the population equation, where population growth is the dependent variable, while the second column presents the results for the employment equation, with employment growth as the dependent variable. The key endogenous variables of interest are employment growth in the population equation and population growth in the employment equation, which test the "people follow jobs" and "jobs follow people" hypotheses, respectively. The model includes year and country fixed effects (not reported). The coefficients on the lagged dependent variables indicate the speed of adjustment toward equilibrium and confirm that the model is dynamically stable.

	Population Eq.	Employment Eq.
POP_GROWTH		0.80858***
		(0.089)
EMP_GROWTH	0.07775***	
	(0.013)	
LOG_POP_{t-1}	−0.00609***	0.00935***
	(0.002)	(0.002)
LOG_EMP_{t-1}	0.00554***	−0.00933***
	(0.002)	(0.002)
$SHARE\_POP15$	0.03393***	
	(0.010)	
$SHARE\_POP65$	−0.05691***	
	(0.007)	
LOG_GDPpc	0.00427***	
	(0.001)	
LOG_POP_DENS	0.00266***	
	(0.001)	
$LOG\_POP\_DENS^2$	−0.00025***	
	(0.000)	
GDP_GROWTH		0.17818***
		(0.012)
$INVEST\_GROWTH$		0.03212***
		(0.003)
$SHANNON$		0.00370
		(0.008)
RCA_AGRI		0.01436
		(0.016)
RCA_IND		−0.28057***
		(0.107)
RCA_CONS		−0.00780
		(0.011)
RCA_SERV		1.25787**
		(0.500)
RCA_FIN		−0.18958***
		(0.065)
$RCA\_NONMARKET$		−0.53560
		(0.367)
Constant	0.00787	−0.07589***
	(0.025)	(0.020)
# obs.	4,188	4,188
R^2	0.398	0.289

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Regression results: Three-equation model

This table presents the results of the full three-equation system of simultaneous equations estimated using Three-Stage Least Squares (3SLS). The model extends the baseline specification by incorporating innovation as a third endogenous variable, examining the dynamic adjustment processes between population, employment, and innovation growth in 271 NUTS-2 regions across 28 European countries over the period 2002–2018. The first column shows the results for the population equation (population growth as dependent variable), the second column presents the employment equation (employment growth as dependent variable), and the third column displays the innovation equation (innovation growth, measured by patent applications, as dependent variable). The key endogenous variables of interest are the growth rates and lagged levels of the three main variables: employment growth and innovation growth in the population equation (testing whether jobs and innovation attract people), population growth and innovation growth in the employment equation (testing whether people and innovation attract jobs), and population growth and employment growth in the innovation equation (testing whether people and jobs drive innovation). The model includes year and country fixed effects (not reported). The coefficients on the lagged dependent variables confirm dynamic stability and convergence to equilibrium across all three equations.

	Population Eq.	Employment Eq.	Innovation Eq.
POP_GROWTH		0.93603***	−1.56100
		(0.088)	(2.009)
EMP_GROWTH	0.09232***		2.52340***
	(0.012)		(0.893)
INNOV_GROWTH	−0.00077	0.00576**	
	(0.001)	(0.002)	
LOG_POP_{t-1}	−0.00633***	0.01085***	−0.00678
	(0.002)	(0.002)	(0.050)
LOG_EMP_{t-1}	0.00606***	−0.01139***	0.01700
	(0.002)	(0.002)	(0.050)
LOG_INNOV_{t-1}	−0.00017***	0.00045***	−0.02786***
	(0.000)	(0.000)	(0.004)
*SHARE_POP*15	0.03358***		
	(0.010)		
*SHARE_POP*65	−0.05603***		
	(0.007)		
LOG_GDPpc	0.00420***		
	(0.001)		
LOG_POP_DENS	0.00264***		
	(0.001)		
$LOG\_POP\_DENS^2$	−0.00025***		
	(0.000)		
GDP_GROWTH		0.17171***	
		(0.012)	
INVEST_GROWTH		0.03083***	
		(0.003)	
SHANNON		0.00473	−0.43039***
		(0.008)	(0.153)
RCA_AGRI		0.01366	
		(0.016)	
RCA_IND		−0.26869**	
		(0.105)	
RCA_CONS		−0.00702	
		(0.011)	
RCA_SERV		1.19743**	
		(0.494)	
RCA_FIN		−0.18126***	
		(0.065)	
RCA_NONMARKET		−0.50679	
		(0.363)	
R&D_GROWTH			0.04205*
			(0.023)
HKAP_GROWTH			−0.09376
			(0.124)
Constant	0.00958	−0.08906***	0.86351**
	(0.025)	(0.020)	(0.434)
# obs.	4,188	4,188	4,188
R^2	0.385	0.267	0.311

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure 1: Employment, population and innovation: growth rates and levels

This figure illustrates the relationships between employment, population, and innovation across 271 NUTS-2 regions in the European Union over the period 2002–2018. The top three panels show these relationships when measured in levels (logarithmic scale), while the bottom three panels display the corresponding relationships when measured as annual growth rates. The left panels show the employment-population relationship, the center panels show the population-innovation relationship, and the right panels show the employment-innovation relationship. The weak correlations in growth rates indicate that the direction of causality—whether people follow jobs, jobs follow people, or innovation leads or follows either—cannot be determined from simple bivariate relationships and requires the more sophisticated simultaneous equations approach presented in the regression analysis. Each point in the scatter plots represents a region-year observation.

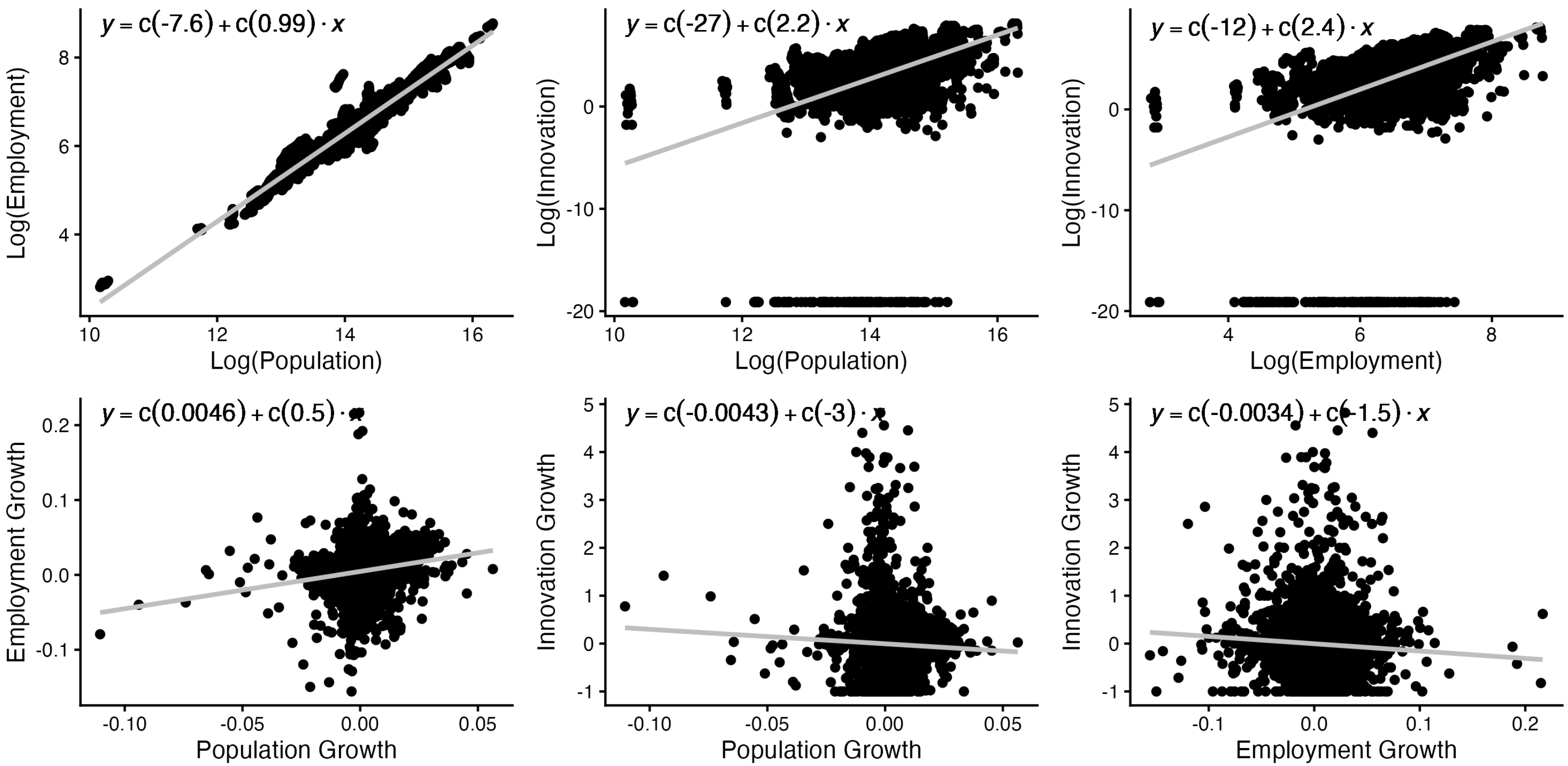

Figure 2: Average population growth, 2002–2018. NUTS 2 regions of the European Union

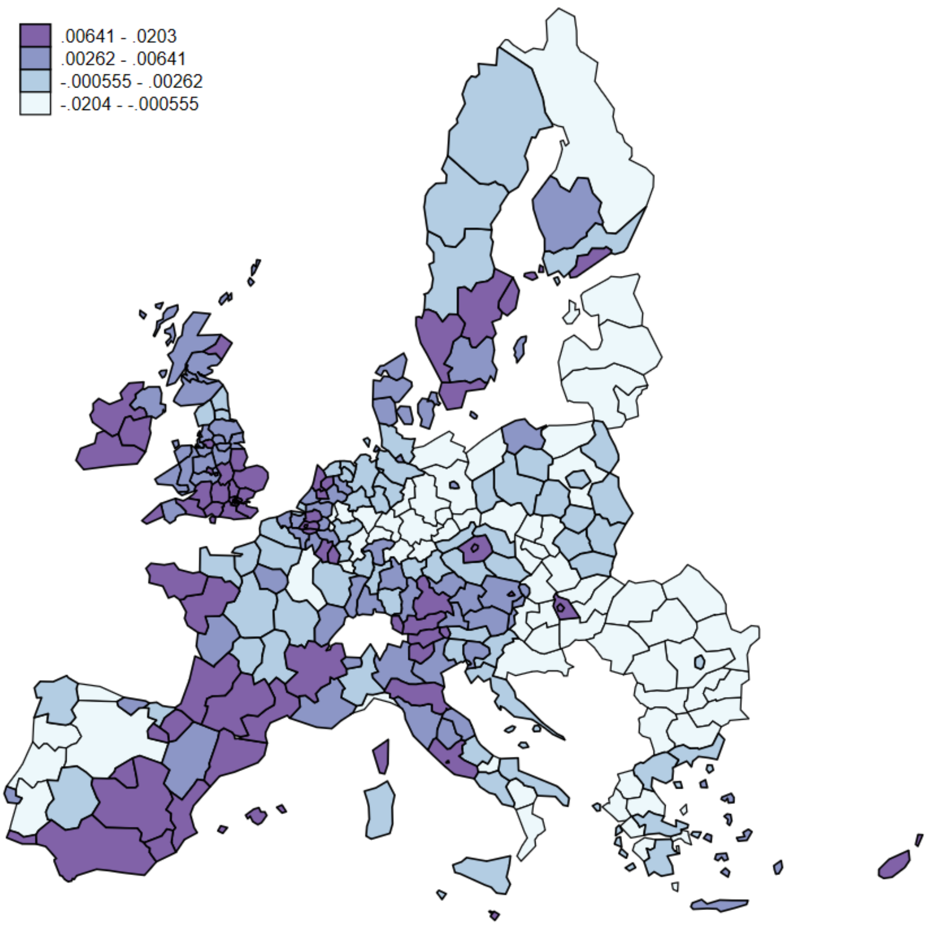

Figure 3: Average employment growth, 2002–2018. NUTS 2 regions of the European Union.

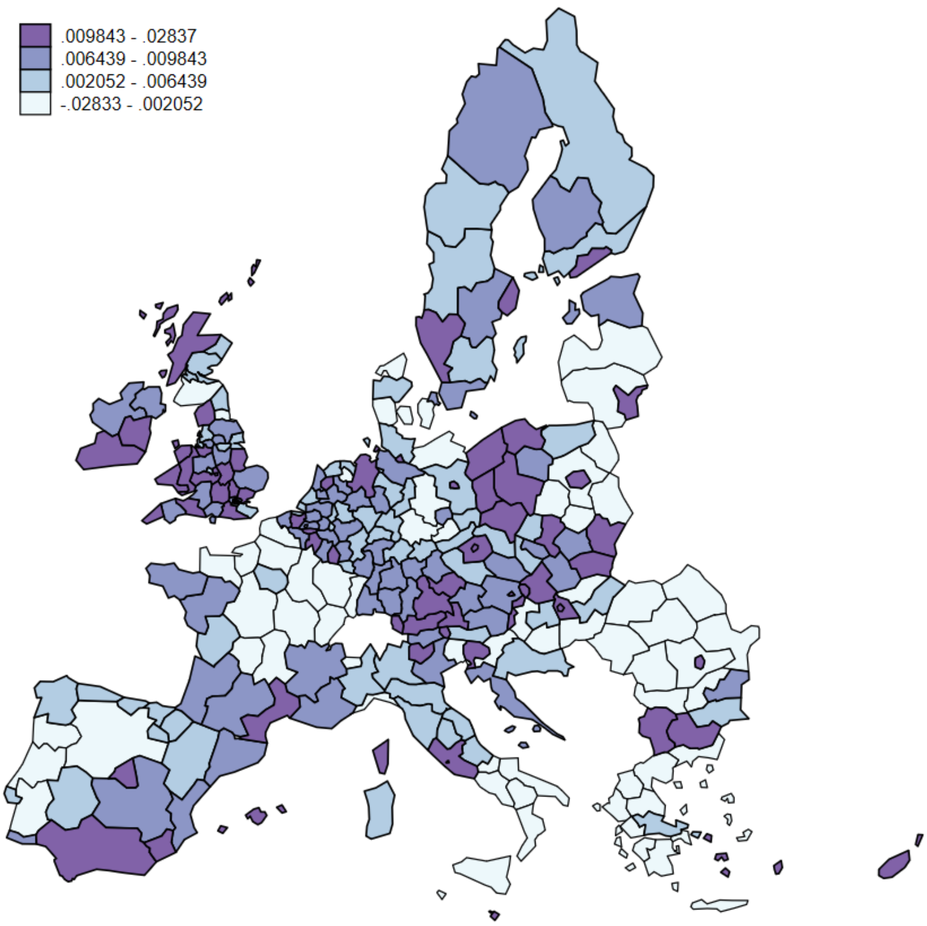

Figure 4: Innovation growth (patent applications), 2002–2018. NUTS 2 regions of the European Union.