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Impact of broadband access on local population and employment: Evidence from Spain

Rafael González-Val

Universidad de Zaragoza, Facultad de Economía y Empresa, Departamento de Análisis Económico, Gran Vía 2, 50005 Zaragoza, Spain
Institut d'Economia de Barcelona (IEB), Facultat d'Economia i Empresa, John Maynard Keynes, 1-11, 08034 Barcelona, Spain

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A B S T R A C T

This paper investigates the role of broadband connectivity in driving local economic growth in Spain. Municipal-level data from 8023 municipalities between 2013 and 2020 are used to examine whether broadband availability positively impacts population and employment. The study makes two key contributions: first, it provides a comprehensive analysis over an extensive dataset, and second, it focuses on a country facing significant depopulation challenges in many regions. Fixed effects dynamic panel data models and spatial dynamic panel data models are employed to identify the relationship between high-speed broadband expansion and local growth. Specifically, the baseline regressions indicate that a 10 % increase in broadband access leads to a 0.15 % and 0.08 % increase in local population and employment, respectively, in the short-term. Notably, this effect is more pronounced in small municipalities compared to larger cities. Spatial models confirm a modest but significant short-term impact of broadband on local growth, while the long-term analysis highlights differing spillover dynamics: broadband's influence on employment is more localized, while its impact on population growth extends spatially. The findings highlight the importance of tailoring broadband expansion policies to the specific outcomes being targeted: adopting a regional perspective for population growth and localized approach to boost local employment.

1. Introduction

Many rural areas around the world have experienced a continuous demographic decline over the past few decades. This phenomenon is common in many developed countries, including Portugal, France, Italy, Germany, and Japan (Doignon et al., 2016; Wirth et al., 2016). Even in highly developed and densely populated nations, certain regions and settlements face persistent economic stagnation and population loss. Spain is no exception. One major concern in the Spanish context is the growing concentration of populations in large urban centres and the sustained depopulation of numerous small towns and municipalities.

Over the period from 1975 to the present, Spain's population has experienced a growth of approximately 37 %, rising from 34.2 million people to around 47 million. However, this population growth has not been evenly distributed across the country. Despite an overall 15.4 % increase in Spain's population since 2000, more than 60 % of municipalities and 13 provinces (NUTS 3 regions) have, in fact, witnessed declines in their population (Fundación BBVA, 2019).[1] These population losses have followed a distinct and consistent spatial pattern over time. Since the population census in 2011, the number of municipalities with 1000 or fewer inhabitants has increased, reaching 4997 in 2021 (source: Spanish Statistical Office, *Instituto Nacional de Estadística*, INE). This figure represents the highest proportion of Spanish municipalities (61.4 %) since 2000, although they only account for 3 % of the country's total population.

These small municipalities are primarily situated in rural and inland areas of Spain and have their own distinct spatial distribution. Depopulation in these municipalities is the result of a long process that began many decades ago. As González-Leonardo et al. (2023) explained, during the period of rapid industrialisation in the 1950–1960s, the rural areas recorded high levels of internal out-migration (Collantes & Pinilla, 2011) and, as a consequence, the outflow of young adults during this period has been linked to a subsequent fertility decline extending to the present (Del Rey & Cebrán, 2010; Recaño, 2017).

Wirth et al. (2016) referred to these small towns in the rural periphery as 'the chronic patients of regional policy,' as they are constantly in need of care but never truly recover. In Spain, residents of these small communities have initiated a social movement urging national, regional

E-mail address: rafaelg@unizar.es.

[1] NUTS regions are the European Union's standard classification of European regions at different geographical levels of aggregation.

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and local governments to devise solutions that ensure the economic and demographic sustainability of these regions. Broadband expansion is frequently put forward as one of the proposed solutions by politicians and mass media. This study makes a significant contribution to the literature by addressing the existing gap in research on this topic using local data. The analysis relies on yearly municipal data to examine the potential effects of broadband availability on socio-economic outcomes in less populated regions of Spain. Specifically, using municipal-level data from 2013 to 2020, the study assesses whether the expansion of broadband infrastructure yields positive impacts on two key indicators. The central research question guiding this investigation is: What are the effects of increasing the availability of high-speed broadband at the local level on:

(1) Population dynamics, particularly whether broadband access helps retain or attract residents in sparsely populated areas.

(2) Local employment, assessing whether broadband expansion contributes to job creation or supports existing employment in these municipalities.

While most existing studies on broadband and local/regional growth focus on its effects on GDP growth (Abrardi & Cambini, 2019; Gómez-Barroso & Marbán-Flores, 2020), generally finding a positive link, there is scarce evidence regarding its impact on population (an exception is Merino et al. (2024)), and findings on employment effects are often inconclusive. For example, the survey by Abrardi and Cambini (2019) reported several studies that could not find any significant effect of broadband on local job creation: Fabling and Grimes (2021), Bai (2017), Ford (2018) and Briglauer et al. (2019). To address this gap in the literature, this study provides new and robust evidence on the impact of broadband expansion on both population and employment in Spain, using panel data covering all municipalities in the country.

However, estimating the impact of broadband expansion on local growth using panel data poses challenges, largely due to omitted variable bias and endogeneity concerns arising from reverse causality and simultaneity (de Clercq et al., 2023; Kolko, 2012; Myovella et al., 2020). To deal with these potential issues, the quasi-maximum likelihood estimator for fixed effects dynamic panel data (Hsiao et al., 2002) is used, including a set of additional variables at the region and municipality levels to control for other relevant factors that may influence growth. Furthermore, several robustness checks considering different sub-samples were carried out, separating small and large municipalities and considering the young population aged 15 to 24. Finally, a dynamic spatial Durbin model is estimated to account for spatial effects. These methods yield a significant and robust link between broadband and local growth, with important policy implications.

The remainder of the paper is organised as follows. Section 2 reviews the relevant literature. Section 3 presents the data utilised in this study, while Section 4 outlines the methodology employed. Section 5 shows the main findings. Finally, Section 6 provides the conclusion of the study.

2. Literature review

The literature identifies several channels through which broadband can influence local growth. Firstly, broadband infrastructure facilitates economic growth by drawing businesses, encouraging entrepreneurship and enhancing firm productivity (Cambini et al., 2023; Chen et al., 2023; Holt & Jamison, 2009). Areas with well-established broadband networks have a greater ability to attract businesses in knowledge-oriented industries that heavily rely on digital technology, such as IT services, e-commerce and tech startups (Hasbi, 2020; Stephens et al., 2022). Consequently, this leads to job creation, elevated income levels and expanded opportunities for residents, thus contributing to population growth as individuals relocate to these places in pursuit of improved economic prospects (Kolko, 2012). Therefore, improving rural broadband access has been touted as a rural development strategy to attract new firms (Duvivier & Bussière, 2022; Kim & Orazem, 2017).

Secondly, reliable broadband empowers individuals with the flexibility to work remotely and telecommute (Pender et al., 2022). This enables people them to reside in cities of their choice while still working for companies elsewhere. Even before the COVID-19 pandemic, teleworking from home had steadily risen in many countries. The pandemic accelerated this trend, compelling many workers to adjust because of the 'stay at home' orders and quarantine practices (Zhang, 2021), and it is now an established and enduring working model. Access to high-speed internet enables employees to collaborate virtually, utilise cloud-based tools and participate in video conferencing, eliminating the need for physical proximity to the workplace. The availability of remote work options can attract professionals and families to regions with reliable broadband infrastructure, thereby stimulating population and economic growth (Gallardo & Whitacre, 2018). Notably, Ramani et al. (2024) provide global evidence that remote work has shifted economic activity away from urban cores—a phenomenon termed the 'donut effect'—which is significantly larger and more persistent in cities with high levels of remote work adoption. However, empirically the a priori impact of broadband on employment is indeterminate, because it depends on whether broadband complements or substitutes for local labour; therefore, studies have obtained mixed results (Abrardi & Cambini, 2019).

Thirdly, broadband access is crucial in supporting educational institutions and research centres. It facilitates online learning, grants access to digital resources and enables remote collaboration among students, teachers and researchers (Skinner, 2019; Yellowlees et al., 2006). Regions with well-connected educational institutions can attract students, researchers and academics in search of quality education and advanced research opportunities. Consequently, this can contribute to population growth as these individuals opt to reside near these esteemed institutions.

Fourthly, high-speed internet access has become a fundamental aspect of daily life, enabling various activities, such as online shopping, entertainment streaming, telemedicine and smart home automation (Firth & Mellor, 2005). In essence, broadband access has transformed into a crucial amenity, and regions that offer reliable connectivity grant their residents an improved quality of life and easy access to modern amenities (Xu et al., 2025). This enhanced appeal can make these cities more attractive places to live, contributing to population growth.

Finally, cities with advanced broadband infrastructure are better positioned to implement smart city initiatives. These initiatives utilise data and technology to enhance urban services, such as transportation, energy management, public safety and sustainability (Anthopoulos, 2017). By embracing smart city initiatives, cities can elevate their liveability and overall efficiency, making them more attractive to current residents and potentially drawing in new ones.

Any of these mechanisms could potentially explain the positive influence of broadband on local growth. However, the extent to which empirical literature has supported this relationship remains a subject of inquiry. Several studies in the economic literature have attempted to establish the economic gains derived from the impact of broadband. Notably, the relationship between broadband and economic development is multifaceted and contingent upon the specific economic outcomes under consideration and the perspective taken—whether local, national, or even global.

Several studies (Czernich et al., 2011; Datta & Agarwal, 2004; Jorgenson et al., 2008; Koutroumpis, 2009; Myovella et al., 2020; Wang et al., 2022) have documented a positive impact of broadband on various economic outcomes and urban concentration. However, most of these analyses have relied on cross-sectional (or panel) country data sets (see the survey by Gómez-Barroso and Marbán-Flores (2020)). Consequently, observations were measured at the national level, and the estimations evaluated the effects of broadband on the entire national economy.

The distinctive contributions of this paper lie in two main aspects: (1) the comprehensive scope of the analysis, focusing on a panel of local-level data and (2) the examination of a country grappling with significant depopulation patterns in various regions. As such, the local approach proposed in this paper stands out as relatively uncommon, although a growing number of recent studies have considered local data in recent years (a survey of the recent literature on the socio-economic impact of ultra-fast broadband on growth and local development was conducted by Abrardi and Cambini (2019)). One exception involves the United States, which has been studied on a disaggregated spatial scale, utilising data from states, counties, and metropolitan areas (Bai, 2017; Ford, 2018; Holt & Jamison, 2009; Kolko, 2012; Mossberger et al., 2022; Whitacre et al., 2014). In the case of the European Union, a recent study by de Clercq et al. (2023) considered a panel of 1348 regions across all EU member states between 2011 and 2018, and found that expansions in the provision of broadband access accelerated annual per capita growth in EU regions. For Germany, Briglauer et al. (2021) concluded that an increase in average bandwidth speed by one megabit per second (Mbps) stimulated a rise in the regional gross domestic product (GDP) of 0.18 % using data at the county level.

Other studies have analysed the impact of broadband on local economic growth focusing on the COVID-19 pandemic period, usually considering a cross-section of local or regional units. For instance, Abrardi and Sabatino (2023) determined that exposure to ultra-broadband mitigated the negative effect of the pandemic on local employment in Italy, considering a cross-section of 7485 municipalities from 2019 to 2020. Furthermore, Zhang (2021) analysed how broadband had affected China's economic growth during the pandemic period considering data from 31 provincial districts in Mainland China.

Finally, in relation to population dynamics, Merino et al. (2024) conducted cross-sectional regressions to examine how broadband services influence the population dynamics of small and medium-sized municipalities in Spain, concluding that connectivity in smaller localities (with populations of 101–10,000) plays a crucial role in shaping their demography.

3. Data

Unlike prior studies (Merino et al., 2024), the present analysis employs dynamic panel data models encompassing municipalities of all sizes, without restrictions. The panel data set covers 8023 municipalities over the period 2013 to 2020. These municipalities serve as the lowest spatial subdivision in Spain (LAU 2/NUTS 5 units), collectively representing the country's entire territory. They cover the total land area and account for the entire population, with two exceptions: the North African cities of Ceuta and Melilla, which have been excluded, and the municipalities of the Canary Islands, which are not included due to their geographical distance from the Iberian Peninsula.[2]

Beyond the full-sample analysis, separate models are estimated for subsamples defined by city size: the 296 largest cities with more than 25,000 inhabitants (4 % of all municipalities), the 961 municipalities with populations between 5000 and 25,000 inhabitants (12 %), and the smaller municipalities with fewer than 5000 inhabitants (84 %).

The 5000-inhabitant threshold is widely used in many countries to distinguish between urban and rural areas. According to the European definition, urban and rural areas are categorized as cities, towns, suburbs, or rural areas based on population density and size. Under this definition, a human settlement becomes 'urban' when it reaches 5000 inhabitants, a criterion applied in the Joint Research Centre's Global Human Settlement Layer data sets.[3] Additionally, as shown in Table 1, this value is roughly the mean population, so this sample includes below average population municipalities. Finally, the 5000-inhabitant limit is one of the reference values of a formula based grant in Spain to obtain higher per capita grant allocations, and Foremny et al. (2017) documented an excess mass of municipalities to the right of this threshold. Accordingly, selecting the 5000-inhabitant threshold helps to avoid municipalities affected by population over-reporting.

Distinguishing between large and small municipalities is crucial for two reasons. Firstly, as previously mentioned, the Spanish case is characterised by depopulation, with small municipalities experiencing a decline over many years and facing a high risk of disappearance. Consequently, the dynamics in these areas are markedly different from those observed in the largest cities. Secondly, a significant digital divide exists between urban and rural regions, encompassing municipalities across the European Union (de Clercq et al., 2023; Lucendo-Monedero et al., 2019). Horrigan et al. (2006) indicate that the utilisation of broadband is found to be greater in larger cities and in cities with large telecommunications-intensive economic sectors.

Data on broadband availability and download speed at the local level are sourced from the Spanish government's *Ministerio de Energía, Turismo y Agenda Digital*.[4] For each municipality, information is available on the proportion of households with access to broadband at speeds of 30 and 100 Mbps or higher. This proportion is calculated as the share of actual subscriptions at that speed over the total number of subscribers. However, the main analysis focuses on speeds of 100 Mbps or higher, as this represents the fastest speed for most of the years within the considered period. This category includes hybrid fibre coaxial (HFC) and fibre to the home (FTTH) networks.

Ovando et al. (2015) and Calzada et al. (2018) previously analysed the expansion of broadband coverage in Spain. The deployment of fibre networks in Spain began in 2008 when *Telefónica* initiated the rollout of its FTTH network in the most densely populated areas, such as Barcelona and Madrid (Calzada et al., 2018). Subsequently, the Digital Agenda for Europe (European Commission, 2010) played a crucial role in shaping the national broadband strategy in Spain (Spanish Ministerio de Industria, Energía y Turismo, 2013), with the 2011 broadband universal service commitment as its initial step. Since then, virtually the entire country has been covered (Ovando et al., 2015).

The present study focuses exclusively on fixed (fibre) broadband. Although data on mobile broadband are available for different technologies for the same period and from the same source, certain technical challenges preclude its inclusion in this paper. Specifically, the much higher and faster penetration rates of mobile broadband compared to fixed broadband pose significant difficulties.

For instance, the proportion of households with mobile connectivity through HSPA shows an average coverage exceeding 92 % across all municipalities in the sample as early as 2014. This leaves virtually no variation over time or across sections. In contrast, the data for Long Term Evolution (LTE, 4G) show the opposite scenario. In the early years

[2] Boundary modifications were very limited during the period analysed. Twelve municipalities that experienced a loss of population and area due to boundary changes remain in the sample, representing only 0.15 % of the total number of municipalities in the dataset. To ensure the robustness of the results, all models were re-estimated excluding these municipalities, and the results remained unchanged.

[3] From a global perspective, the UN Population Division provides definitions of 'urban' populations based on census data from 232 countries (Deuskar, 2015). Among these, 101 countries use minimum population thresholds to define settlements as 'urban,' with 2000 inhabitants (applied by 23 countries) and 5000 inhabitants (used by 21 countries —including Belgium, Cameroon, India, Qatar, Saudi Arabia, Slovakia, and Tunisia) being the most common.

[4] This dataset is publicly available at: https://avance.digital.gob.es/banda-ancha/cobertura/paginas/informacion-cobertura.aspx (accessed on July 23rd, 2025).

Table 1
Mean values by year.

Year	Population	Workers	Broadband (speed ≥100 Mbps)	Mean age	Regional inflation rate	Regional employment rate	Regional proportion of population with higher education
2013	5787.05	1978.44	0.06	48.55	1.41	0.44	0.26
2014	5742.68	2010.63	0.08	48.82	−0.24	0.45	0.26
2015	5723.12	2074.37	0.08	49.05	−0.70	0.46	0.26
2016	5710.51	2133.25	0.10	49.30	−0.29	0.47	0.27
2017	5713.01	2207.27	0.14	49.56	2.01	0.48	0.27
2018	5731.53	2276.51	0.19	49.80	1.72	0.49	0.28
2019	5763.93	2335.41	0.26	49.94	0.72	0.50	0.29
2020	5816.15	2278.67	0.37	50.08	−0.44	0.48	0.30

Notes: Sources: Spanish Government, INE and social security records. Broadband is the proportion of actual subscriptions at the speed of 100 Mbps or higher over the total number of subscribers (units: proportion of households). The regional (NUTS 3 level) inflation rate is the rate of change in the Consumer Price Index. The regional (NUTS 2 level) measure of educated people is the proportion of population older than 16 with higher education.

of the panel, most municipalities had zero coverage (e.g., 92 % in 2013 and 79 % in 2014). This abundance of zeros presents an econometric challenge. Moreover, many municipalities transitioned from 0 % to 100 % coverage within a single year, leading to an average coverage of 90 % or higher across all municipalities by 2018. This rapid growth could complicate the interpretation of results.

Overall, these data peculiarities prevent the inclusion of mobile broadband in the analysis. Consequently, all broadband-related results in this study refer to the impact of fixed broadband. While both fixed and mobile broadband enable internet connectivity, fixed broadband has several unique features that make it particularly important for local economic growth. For example, fixed broadband typically offers higher data transmission speeds and more stable connections than mobile broadband. It also supports larger bandwidths and higher data limits, making it indispensable for businesses and industries requiring extensive and continuous internet access. Finally, fixed broadband often complements mobile networks rather than substituting them. However, the question of whether these technologies are complementary or substitutes remains debated in the literature. Some studies have found weak substitution effects between the two technologies (Bae et al., 2014; Czajkowski et al., 2024; Srinuan et al., 2012), while others suggest complementarity, particularly in regions with robust fixed broadband infrastructure (Grzybowski & Verboven, 2016).

Fig. 1 presents the evolution of broadband coverage in Spain from 2013 to 2020. It displays the mean proportion of households with broadband access at speeds of 30 and 100 Mbps or higher across all municipalities and the national values for the entire country. Although both series show an increase in proportions over time, the differences are striking. While the majority of the country's population now has broadband access, especially in recent years, the average for municipalities is considerably lower, with only 37.44 % having access to speeds of 100 Mbps or higher in 2020. This discrepancy can be attributed to the urban–rural divide. A significant proportion of the Spanish population (69.6 % in 2020) resides in large cities with over 20,000 inhabitants (16 % in cities with more than 500,000 inhabitants), where broadband coverage is nearly universal, but these cities constitute only 5.1 % of the total municipalities. Consequently, most municipalities are sparsely populated areas with lower percentages of households accessing high-speed broadband. These figures underscore the uneven distribution of high-speed broadband access within Spain, which could worsen economic disparities, especially in rural and underserved communities (Lucendo-Monedero et al., 2019).

Figs. 2, 3 and 4 vividly illustrate this point. Fig. 2 displays the spatial distribution of the population across municipalities in 2013. The dark areas represent large cities, while the light blue municipalities, with populations of 1000 inhabitants or fewer, form the majority, mainly situated in the country's inner regions. Figs. 3 and 4 depict the spatial distribution of broadband coverage at speeds of 100 Mbps or higher in the first (Fig. 3) and final (Fig. 4) years of the sample period. A striking observation is the significant advancement in broadband coverage from 2013 to 2020, as evident from the comparison of Figs. 3 and 4. These maps provide compelling evidence of notable time and cross-sectional variations in the primary explanatory variable, the percentage of households with broadband access. Additionally, they reveal a distinct spatial pattern of low broadband access in the country's inner regions, aligning with the population distribution shown in Fig. 2.

For the remaining variables, annual population data at the municipal level were acquired from the yearly municipal register (*Padrón continuo*) published by the INE. The municipal register, which is mandatory, includes information on individuals who are regular residents in each municipality and is continually updated with data on births, deaths and migration flows. Official data regarding workers at the aggregate municipality level are available from social security records. The yearly number of workers is derived by averaging the monthly values. This measure of local total employment includes salaried workers (an average 75 % of total employment at the country level for the period considered), self-employees (18 % of total workers), workers in agriculture (4 % of total workers), or even housekeeping workers (2 % of total workers). Furthermore, salaried workers include public employment (17 % of workers in Spain are public employees).

As the empirical methods, specifically the spatial models, require a balanced panel data set, some missing values were filled using linear interpolation. Table 1 presents the mean values of all variables considered in the empirical analysis—population, workers and all the explicative variables—by year. Although there are fluctuations over time, the overall trend during the considered period shows an increase in the average value of the two outcome variables (population and employment). The summary statistics by year of all variables are presented in the Table A1 in Appendix A.

4. Methods

A first approach to testing the relationship between population and employment levels and broadband coverage at the city level is to estimate a simple linear dynamic model, incorporating time and city fixed effects and including additional explanatory variables to account for omitted variable bias:

$$ln(Y_{it}) = \mu_i + \tau ln(Y_{it-1}) + \pi \cdot Broadband_{it} + \sum_{i=1}^{m} \gamma_m X_{mit} + \phi_t + u_{it}, \quad (1)$$

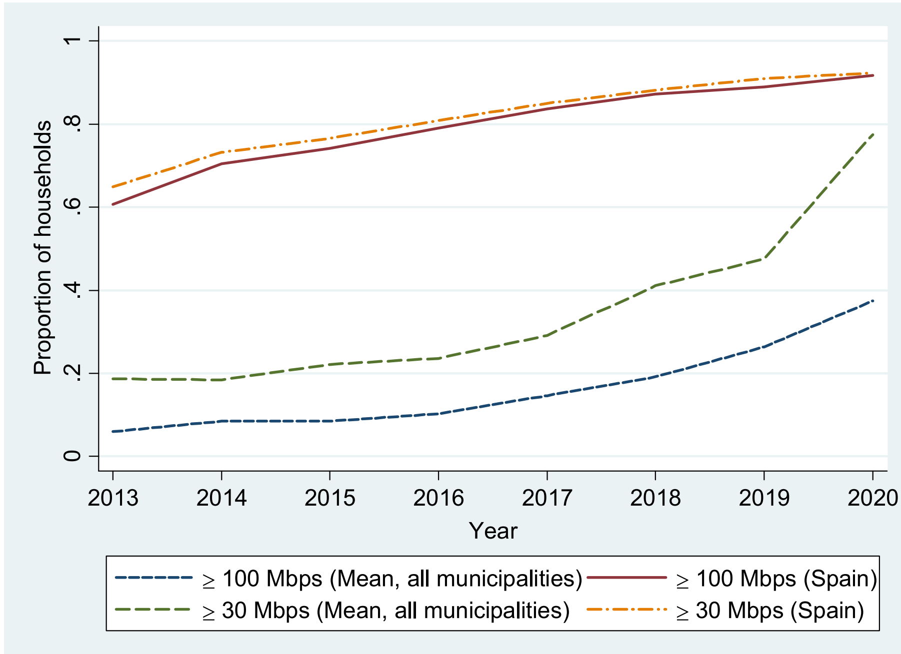


Fig. 1. Mean broadband coverage by year.
Notes: Data from the Spanish government and the European Commission. Units: Proportion of actual subscriptions at the speeds of 30 and 100 Mbps or higher over the total number of subscribers (units: proportion of households). Mean values across all municipalities vs. national values for the entire country.

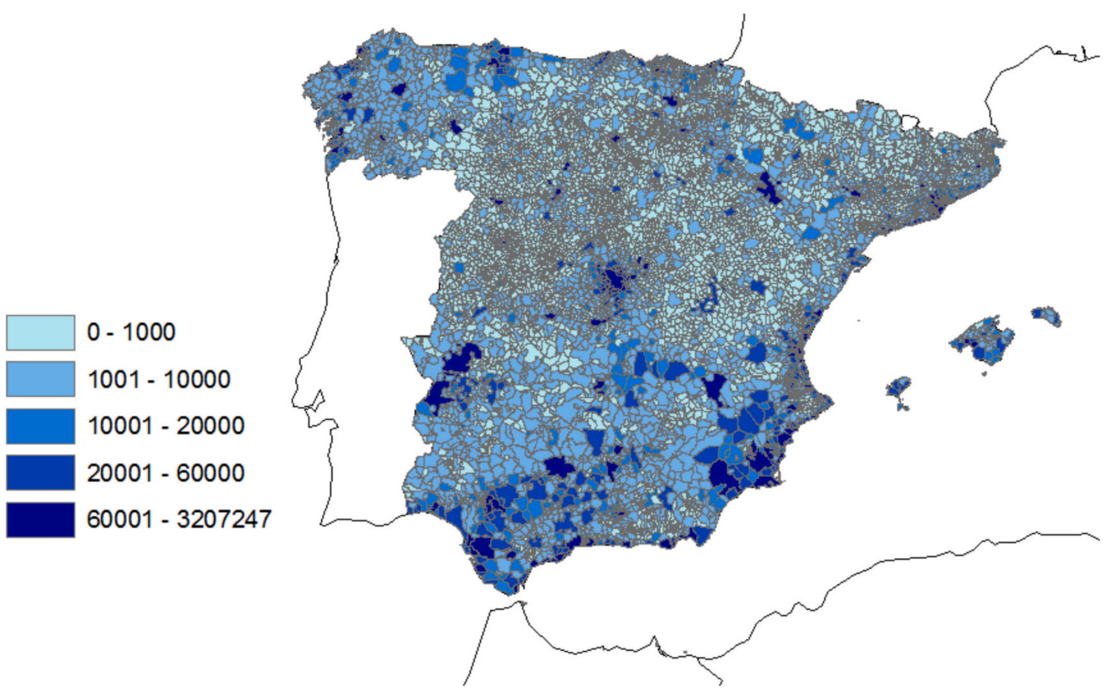


Fig. 2. Spatial distribution of population in 2013.
Source: Own elaboration based on INE data. Unit: inhabitants. The North African cities of Ceuta and Melilla, as well as the municipalities of the Canary Islands, are excluded.

where $ln(Y_{it})$ is the logarithmic value in municipality i at time t for any of the two outcome variables Y_{it} at the municipality level ($Y =$ population and workers). The term Y_{it-1} represents the first lag of the outcome variable. A dynamic specification is adopted due to the strong persistence of these variables over time.

X_{mit} represents a set of additional regional and municipal factors

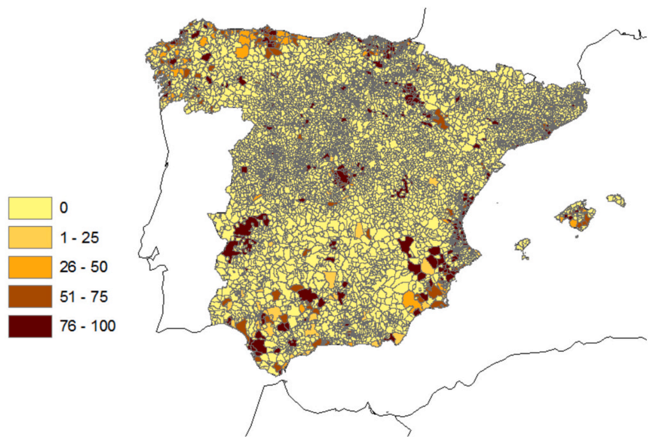


Fig. 3. Broadband coverage (≥100Mbps) in 2013.
Notes: Own elaboration based on data from the Spanish government. Proportion of actual subscriptions at the speed of 100 Mbps or higher over the total number of subscribers (unit: % of households). The North African cities of Ceuta and Melilla, as well as the municipalities of the Canary Islands, are excluded.

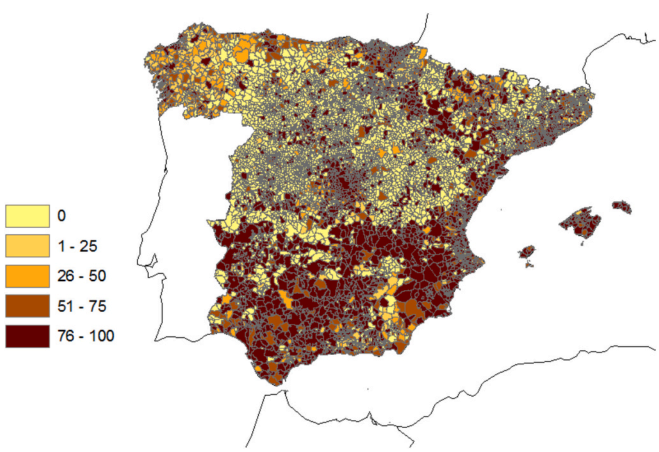


Fig. 4. Broadband coverage (≥100Mbps) in 2020.
Notes: Own elaboration based on data from the Spanish government. Proportion of actual subscriptions at the speed of 100 Mbps or higher over the total number of subscribers (unit: % of households). The North African cities of Ceuta and Melilla, as well as the municipalities of the Canary Islands, are excluded.

selected to avoid omitted variable bias.[5] In the population model, these controls include the logarithm of the mean age of population by municipality and the provincial value (NUTS 3 regions) of the inflation rate. The local mean age captures possible demographic pre-trends, because population growth could be driven by fertility decisions that are unlikely to be related to broadband access. Regarding the regional control, inflation is related to the standard of living. Furthermore, high inflation can generate economic uncertainty. The inflation rate is measured as the annual the rate of change in the Consumer Price Index. In the employment model, the controls are the provincial value (NUTS 3 regions) of the employment rate and the NUTS 2 regional proportion of population with higher education. The employment rate is included as a possible determinant of economic growth (de Clercq et al., 2023). The education variable controls the consistent positive relationship between higher education and employment in Spain (de la Fuente & Smith, 1995; Mora et al., 2000). Finally, municipality and time (year) fixed effects are also included, represented by μ_i and ϕ_t, respectively. u_{it} is the error term.

The key variable is $Broadband_{it}$, measuring the proportion of households in municipality i at time t with access to broadband at the speed of 100 Mbps or higher. Therefore, π captures the effect of broadband on local growth, measuring the impact of an increase in broadband access on local population or employment.

As Gómez-Barroso and Marbán-Flores (2020) noted in their survey, ad hoc growth regressions are commonly used in the literature examining the relationship between telecommunications and economic development. However, in this case, theoretical economic foundations for a linear equation such as Eq. (1) can be found in the urban growth model proposed by Glaeser et al. (1995) and further developed by Glaeser (2000) and Glaeser and Shapiro (2003). This model of spatial equilibrium, similar to Roback's (1982) framework, suggests that population and employment growth is influenced by changes in the demand for aspects of a city's initial endowments in production or consumption, or by the effects of these characteristics on productivity growth. This framework can be naturally combined with the model developed by Czernich et al. (2011) to explain the relationship between broadband and economic growth, assuming that broadband infrastructure fosters the generation and dissemination of decentralized information and ideas. Consequently, broadband availability directly enhances total factor productivity through externality-driven growth effects, from both the production and consumption sides (Briglauer et al., 2021), ultimately influencing the log-equilibrium levels of city population and employment.

Some authors have pointed out endogeneity as a primary concern in this kind of analysis (de Clercq et al., 2023; Kolko, 2012; Myovella et al., 2020). Although the model in Eq. (1) included fixed effects and time fixed effects to control for possible unobserved characteristics at the municipality level and year-specific shocks, some potential issues still remained, including the possible persistence in the trend in the dependent variable (log levels of population and employment), related to dynamic issues of the variable, endogeneity concerns and reverse causality. Kolko (2012, p. 101) indicated that "a positive relationship between broadband expansion and economic growth does not, in itself, mean that broadband expansion *causes* economic growth." He argued that the reverse might be true, where broadband providers choose to offer or expand service in areas with faster employment growth. Additionally, population growth could be driving both broadband expansion and employment growth, meaning that broadband expansion might follow population growth. As a result, the estimates may be subject to bias due to endogeneity and reverse causality.

To solve both potential issues, Myovella et al. (2020) and de Clercq et al. (2023) recommended estimating by using the GMM estimator (Arellano & Bond, 1991; Blundell & Bond, 1998). In this estimator, unobserved individual fixed effects are removed by taking first differences of all dependent and independent variables, and then the deeper lags in levels are used as instruments to estimate the equations. This estimator not only allows for reverse causality, but also addresses measurement error and omitted variables (de Clercq et al., 2023). However, this method is not well suited for highly persistent variables, as is the case with broadband, the main explicative variable. Furthermore, the structure of the panel with a large number of elements and a short time period (a short T, large N specification of the panel data) could also be an issue. In dynamic panel data models where the time dimension T is short, the presence of lagged dependent variables among the regressors makes standard panel estimators inconsistent, and complicates statistical inference on the model parameters considerably (Hayakawa & Pesaran, 2015).

For these reasons, the quasi-maximum likelihood estimator for fixed effects dynamic panel data (QML-FE henceforth), developed by Hsiao et al. (2002), is employed. This estimator is appropriate when the

[5] Due to the limited availability of information at the municipal level, most control variables are incorporated using regional-level data. Nevertheless, the main results concerning broadband's effect hold if the set of controls is excluded.

number of cross sections is large and the time dimension is fixed. Furthermore, this method takes account of initial conditions to correct for short-T bias but does not rely on instrument use. The QML-FE estimator maximises the transformed likelihood function after a first-difference transformation of the model in Eq. (1), thus removing the individual specific unobserved effects. Then, the estimated model is:

$$\Delta ln(Y_{it}) = \tau \Delta ln(Y_{it-1}) + \pi \cdot \Delta Broadband_{it} + \sum_{i=1}^{m} \gamma_m \Delta X_{mit} + \phi_t + \nu_{it}. \quad (2)$$

This specification in first-differences is similar to the empirical model used by de Clercq et al. (2023), based on the empirical work from Datta and Agarwal (2004) and Myovella et al. (2020).

The estimator is consistent as $N \to \infty$ for fixed T, unlike traditional methods, which may fail in this scenario. However, it relies on two strong assumptions (Hsiao et al., 2002; Kripfganz, 2016). First, the QML-FE estimator assumes that the regressors are strictly exogenous, meaning they are uncorrelated with current, past, and future values of the error term. Second, the errors are assumed to be independently and identically distributed. If the error terms exhibit serial correlation or heteroscedasticity, these assumptions may no longer hold, potentially leading to inefficient or inconsistent results. Serial correlation is tested using the second-order (AR(2)) test on the first-differenced residuals proposed by Arellano and Bond (1991), as well as the test developed by Wooldridge (2002).

Another potential source of bias is spatial correlation. To explicitly account for the influence of neighbouring municipalities on local population and employment, a dynamic spatial Durbin model (Debarsy et al., 2012) is also estimated. There are likely spatial effects of broadband (Briglauer et al., 2021): Consider an isolated municipality with good high-speed broadband but zero presence in the surrounding municipality compared to an equal spread of broadband over space. Broadband access in one municipality can have a local effect on population and/or employment in that municipality, whose impact may depend on the broadband access in neighbouring municipalities, but also on the population or employment in the surrounding municipalities.

The specification of the dynamic spatial Durbin model includes five components (Elhorst, 2021): a spatial lagged dependent variable, the time lagged value of the dependent variable, a spatial lag of the first-time lag of the dependent variable, a set of explanatory variables, and a set of spatial lagged explanatory variables. This can be expressed as:

$$\begin{aligned} ln(Y_{it}) = {} & \mu_i + \rho \sum_{j=1}^{n} W_{ij} ln(Y_{it}) + \tau ln(Y_{it-1}) + \eta \sum_{j=1}^{n} W_{ij} ln(Y_{it-1}) \\ & + \pi \cdot Broadband_{it} + \theta \sum_{j=1}^{n} W_{ij} Broadband_{it} + \sum_{i=1}^{m} \gamma_m X_{mit} + \sum_{j=1}^{n} \\ & \times \sum_{i=1}^{m} W_{ij} \varphi_m X_{mit} + \varepsilon_{it}, \end{aligned} \quad (3)$$

with ρ being the spatial autoregressive parameter measuring the effect on the response variable of the local variable level Y_{it} (Y = population and workers) in neighbouring municipalities, τ being the autoregressive parameter capturing the temporal dependence in the response variable, and η is the parameter measuring the spatiotemporal dependence. θ and φ_i are the parameters capturing the effects of the spatial lagged explanatory variables, while μ_i denotes the municipality fixed effects and ε_{it} is the error term.[6]

W_{ij} are the elements of the $N \times N$ spatial weight matrix W, built using the k-nearest neighbouring municipalities, where k is set to 7.[7] The nearest neighbouring municipalities are identified using each municipality's longitude and latitude. Finally, the spatial weight matrix is row normalised.

5. Results

5.1. Baseline results

The first-difference model in Eq. (2) was estimated using the QML-FE estimator.[8] Fig. 5 presents the short-run estimates of the impact of broadband on local population and employment (see Table A2 in Appendix A for the full set of coefficient estimates, tests, and statistics). For both outcome variables, panel data models are estimated using four distinct samples of municipalities: all municipalities, the 296 largest cities with more than 25,000 inhabitants, the 961 municipalities with populations between 5000 and 25,000 inhabitants, and the remaining municipalities (almost seven thousand) with fewer than 5000 inhabitants.

In all cases, the lagged value of the outcome variable is significantly positive, supporting persistence and a dynamic behaviour of the dependent variable across all specifications. This persistence is stronger in large cities than in smaller ones. The set of regional and municipal controls, included to account for observable differences across regions and to mitigate omitted variable bias, is significant in most cases. Nevertheless, the primary finding is the positive relationship between broadband expansion and local growth for both population and employment.

The results demonstrate a significant positive impact of broadband expansion on local population, measured as the proportion of households with broadband access at speeds of 100 Mbps or higher, with an estimated coefficient of 0.015. The interpretation of this coefficient is that a 10 % increase in broadband access implies roughly a 0.15 % increase in local population, holding other variables constant. However, this effect is not uniform across all municipalities; the results for the subsamples reveal significant differences by city size. In less populated municipalities, a significant positive effect of broadband on population is observed, with a point estimate of 0.020—similar to the coefficient estimated for the whole sample. In contrast, the estimate drops to 0.003 for the municipalities with a population between 5000 and 25,000 inhabitant, although the effect remains significant. Nevertheless, the effect is not significant for the most populated municipalities. Additionally, when exploring non-reported results obtained by considering different broadband speeds (30 Mbps or higher), the estimated coefficient shows an increasing trend with higher connection speeds.[9] This suggests that a higher speed corresponds to a greater impact on population.

The impact of broadband expansion on employment yields mixed results. The effect is negative in large cities, not significant in medium-sized cities with populations between 5000 and 25,000 inhabitants, and positive and significant in small municipalities, with a point estimate of 0.030. When considering all municipalities, the effect remains positive and significant. However, it is noteworthy that the value of the estimated coefficient for the full sample (0.008) is substantially smaller than that for small municipalities. This suggests that the impact of broadband diminishes with city size and that the overall effect for the overall sample reflects a balance between the negative impact observed in large

[6] Note that the model in Eq. (3) does not include time fixed effects; Elhorst (2021, p. 2149) recommended not including time dummies to avoid (near) perfect multicollinearity. Multicollinearity can be an issue especially for large panel data sets.

[7] Alternative values of k (k = 8, 9, and 10) yield similar results. The estimated spatial models for these values of k are available from the author upon request.

[8] Models were estimated using the xtdpdqml command in Stata (Kripfganz, 2016), with default options applied and no parameter restrictions imposed.

[9] The results for alternative slower broadband speeds (30 Mbps or higher) are available from the author upon request.

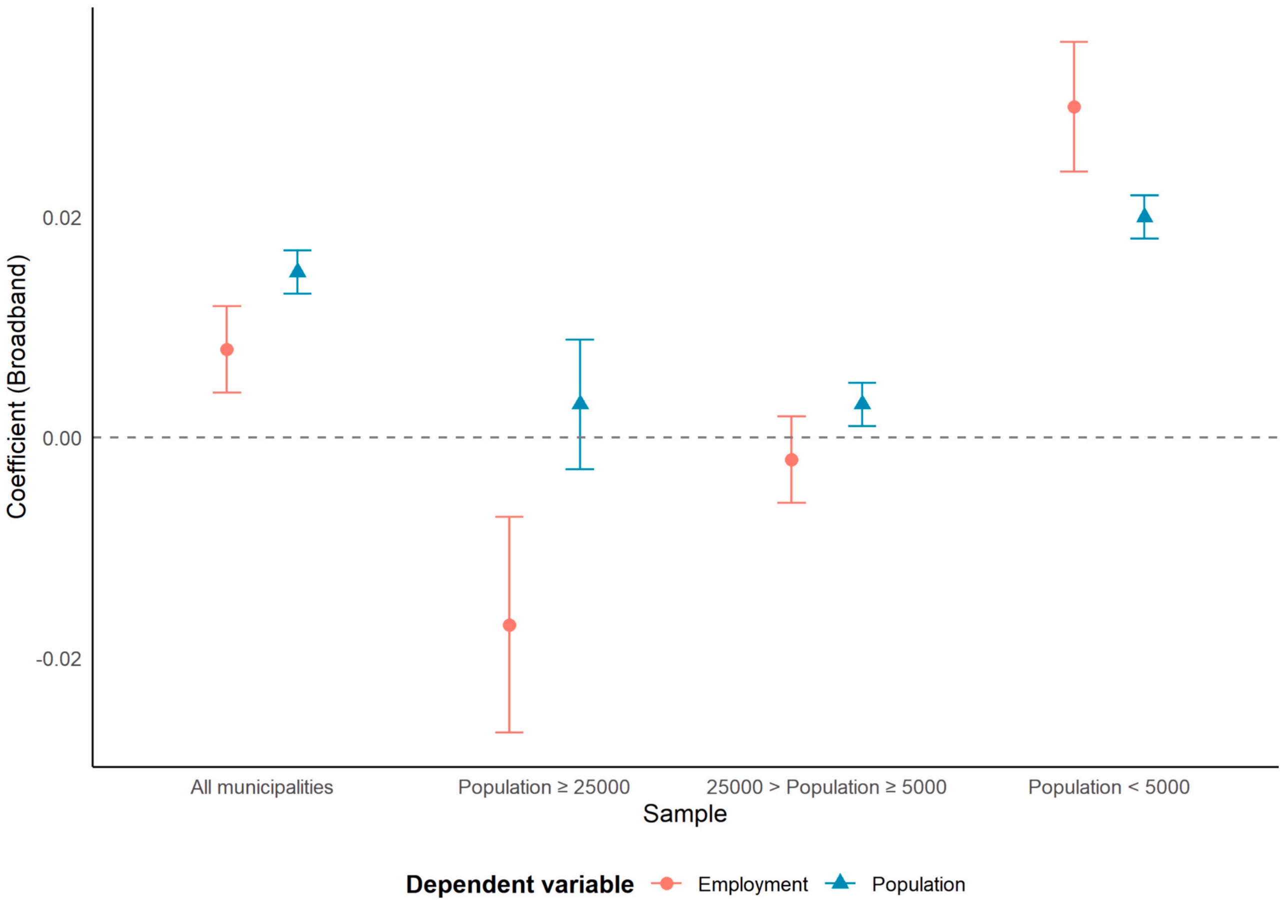


Fig. 5. Local effects of broadband, QML-FE results.
Notes: The figure reports the estimated coefficients for the broadband variable, defined as the proportion of actual subscriptions at the speed of 100 Mbps or higher over the total number of subscribers (units: proportion of households). The model is estimated using a quasi-maximum likelihood estimator for dynamic panel data with fixed effects (QML-FE). Estimations in first differences. Sample: All municipalities, municipalities with more than 25,000 inhabitants, municipalities with a population between 5000 and 25,000 inhabitants, and municipalities with less than 5000 inhabitants. Period: 2013–2020. Dependent variable: Logarithm of population and logarithm of employment. All models include the lag of the dependent variable, year fixed effects, and a set of municipal and regional control variables. For the population models, controls include mean age (in logs) and the regional inflation rate. For the employment models, controls include the regional employment rate and the regional share of population with higher education. Robust standard errors are used to compute 95 % confidence intervals.

cities and the positive impact in small municipalities. This point estimate suggests that a 10 % increase in the broadband variable means roughly a 0.08 % increase in local employment, holding other variables constant. This effect is half the size of that obtained for the local population variable. Additionally, non-reported findings regarding slower broadband speeds suggest that the effect on employment becomes significant only for higher connection speeds (100 Mbps or higher), which are more closely associated with business activities.

5.2. Robustness checks

Several robustness checks were performed to validate the results. First, additional lags of the dependent variable were included, and the estimated coefficient for broadband did not change substantially. Second, alternative population thresholds of 1000, 2000 and 3000 inhabitants were used to define small municipalities, and the findings remained consistent. The commonly used 10,000-inhabitant threshold (e.g., Collantes & Pinilla, 2011; González-Leonardo et al., 2023) was also considered and the results still held. Similarly, using alternative thresholds for large cities, such as 50,000 or 100,000 inhabitants, produced similar results. Third, the potential influence of the COVID-19 pandemic, the 2020 lockdown, and the subsequent economic crisis on the results was examined. The pandemic's impact on internal migration is well documented across several countries—including Australia (Perales & Bernard, 2023), Germany (Stawarz et al., 2022), Japan (Fielding & Ishikawa, 2021), Sweden (Vogiazides & Kawalerowicz, 2023), and the United Kingdom (Rowe et al., 2023)—and Spain was no exception. González-Leonardo et al. (2022) reported a 2.5 % decline in internal migration moves in Spain, particularly during the early stages of the pandemic, followed by a return to pre-pandemic levels by late 2020. Their findings also indicated unusually large net migration losses in core cities and gains in rural areas. To test for potential bias, the models were re-estimated excluding data from 2020, and the results remained unchanged.[10]

Another potential issue affecting the results is simultaneity. Considering both population and employment could be troublesome to interpret because both variables can be strongly related: Jobs might follow people and people might follow jobs (Boarnet, 1994). As Kolko (2012) points out, a positive relationship between broadband and local employment growth does not by itself answer the question of who benefits from broadband. Whether the final beneficiaries are the local residents empirically depends on labour mobility.

However, internal mobility within European countries tend to be moderate. Bell and Charles-Edwards (2013) found that migration

[10] The results of all these robustness checks are available from the author upon request.

intensities are highest in 'new world' countries such as Australia, Canada, New Zealand, and the United States, and lowest in Asia, with Europe, Latin America, and Africa exhibiting intermediate levels. Similarly, Cheshire and Magrini (2006) estimated that the population mobility in the US is 15 times higher than that in Europe. Within Europe, Spain stands out for its particularly low internal mobility. Bell et al. (2015), analyzing migration intensities across nearly 100 countries, ranked Spain among the lowest based on two distinct measures. Bentolila (1997) also documented a significant decline in interregional migration within Spain since the 1970s, despite persistent and widening regional disparities in unemployment rates.

Other authors have provided additional evidence of the low migration movements within Spain. González-Val (2021) used information from the 2011 population census to show that only 15 % of residents in Spanish municipalities were born in a different NUTS 2 region, while 44 % lived in the same city where they had been born and 27 % came from other cities within the same region. Some large cities in particular received a high number of people from other regions (e.g. 28 % in Madrid and 20 % and 19 % in Barcelona and Valencia, respectively), though the 15 % average value held for cities with more than 25,000 inhabitants. This pattern has been persistent over time. Romero Valiente (2003) found evidence of low internal migrations in previous censuses; from 1981 to 2001, the percentage of people living in the city of their birth was always higher than 50 %, and the share of residents coming from other places within the same NUTS 2 region oscillated between 25 % and 30 %.

Thus, in Spain, even if employment growth actually raises wages, the low mobility should mitigate the concern of simultaneous population growth following employment and/or wage growth, at least for middle-sized and small municipalities. Furthermore, the pairwise correlation between population and employment growth at the municipality level is low in the sample: 0.045 for the full sample of all municipalities, −0.072 for cities with more than 25,000 inhabitants, −0.003 for cities with populations between 5000 and 25,000 inhabitants, and 0.039 for cities with fewer than 5000 people.

One simple test to determine whether the employment results are merely driven by population change is to include the municipality population as an additional explanatory variable in the employment model. After rerunning the models, the results hold similarly. The effect of log population on log employment is found to be positive and significant, with an estimated elasticity of approximately 0.05 for the full sample, 0.14 for medium-sized cities, and 0.15 for small municipalities with fewer than 5000 inhabitants. No significant relationship was observed for the largest cities. This means that, for the full sample, a 1 % increase in population implies a rise of 0.05 % in local employment. In small municipalities, a 1 % increase in population corresponds to a 0.15 % increase in local employment while in medium-sized cities, it corresponds to a 0.14 % increase. These effects are statistically significant but modest in magnitude. Furthermore, the positive effect of broadband on local employment remains positive and significant except for the largest municipalities, and the magnitude of the broadband parameter is similar to those coefficients reported in Fig. 5.[11]

Nevertheless, there are more sophisticated methods to address this issue. Ihlanfeldt and Sjoquist (1998) reviewed methods for dealing empirically with the simultaneity between employment and residential location. They concluded that the most popular approach to handling the simultaneity between employment and residential location was to focus the analysis exclusively on the young still living at home, on the assumption that their residential location is exogenously determined by their parents or guardians (Raphael, 1998).[12] Following this literature (e.g., Holzer et al., 1994; Ihlanfeldt & Sjoquist, 1998), the estimations are repeated using a subsample of population including only young people aged 15 to 24 to avoid any potential simultaneity issues.[13] The minimum age to work in Spain is 16, but the average age at which young Spaniards get their first job is 23 years old.[14] Fig. 6 presents the results of the QML-FE estimations of the impact of broadband on population considering this subsample of young people; Table A3 in Appendix A reports all coefficient estimates, tests, and statistics. The results are similar to those reported in Fig. 5, confirming that the main findings are not driven by simultaneity.

A positive and significant effect of broadband on the young population is observed in both the full sample and in small municipalities, whereas the effect was not significant for large and medium-sized cities. However, the magnitude of the coefficients differed significantly. The effect of broadband on the young population was greater than its effect on the overall population. Specifically, a 10 % increase in the broadband variable corresponded to approximately a 0.5 % increase in the local young population, holding other variables constant. Consistent with the main findings, the effect of broadband appears to be primarily driven by small municipalities.

5.3. Long-term effects of broadband

The long-term effects of broadband are also of interest. While the estimated coefficients (π) reported in Figs. 5 and 6 represent the immediate short-term effects observed in the following year, conditional on the initial level of population or employment, in dynamic panel data models the corresponding long-term effects can be computed as $\pi/(1-\tau)$ (Kripfganz, 2016).[15] Short-term effects are typically smaller than the long-term coefficients because the latter capture the total cumulative impact after the system has fully adjusted over time, accounting for the persistence caused by the lagged dependent variable, which amplifies the influence of broadband on population or employment growth. Moreover, the long-term effect provides a more comprehensive indication of the overall importance of the explanatory variable, as it reflects the sustained and cumulative impact of broadband coverage on population or employment dynamics.

Fig. 7 graphically presents the long-term effects of broadband shown in Table A4 in Appendix A, derived from the QML-FE results in Figs. 5 and 6.[16] According to these estimates, a 10 % increase in broadband coverage is associated with an approximate 0.79 % increase in population in the long term for the overall population. The effect on the young population is approximately double that, with a 10 % increase in broadband coverage linked to a 1.8 % increase in the young population. Long-term effects in small municipalities are similar to those for the overall sample of municipalities. However, in medium-sized and large cities, no significant long-term effects were found.

For employment, a significant long-term effect is identified only in small municipalities. In the full sample, the long-term effect is not significant, despite the short-term effect being significant. One possible explanation is the strong persistence in the dependent variable (τ is close to 1, as reported in Table A2 in Appendix A). In contrast, for small municipalities, the long-term coefficient suggests a strong relationship between broadband coverage and employment growth. Specifically, a

[11] Again, these results are available from the author upon request.

[12] This empirical approach also shows some weaknesses; see Ihlanfeldt and Sjoquist (1998).

[13] When considering the population aged 15 to 19, the results are similar to those obtained using the sample of young people aged 15 to 24. These results are available from the author upon request.

[14] Spain tended to have the highest young unemployment rate in Europe in the last decades; unemployment among Spanish workers under 25 years of age reached peaks above 50 % in 2012, 2013 and 2014 (Verd et al., 2019).

[15] Estimating long-term effects from dynamic models with lagged dependent variables is a common practice in economics. However, in some cases, this approach may be subject to bias caused due to various factors (Reed & Zhu, 2017).

[16] Long-term values estimated using the nlcom command in Stata.

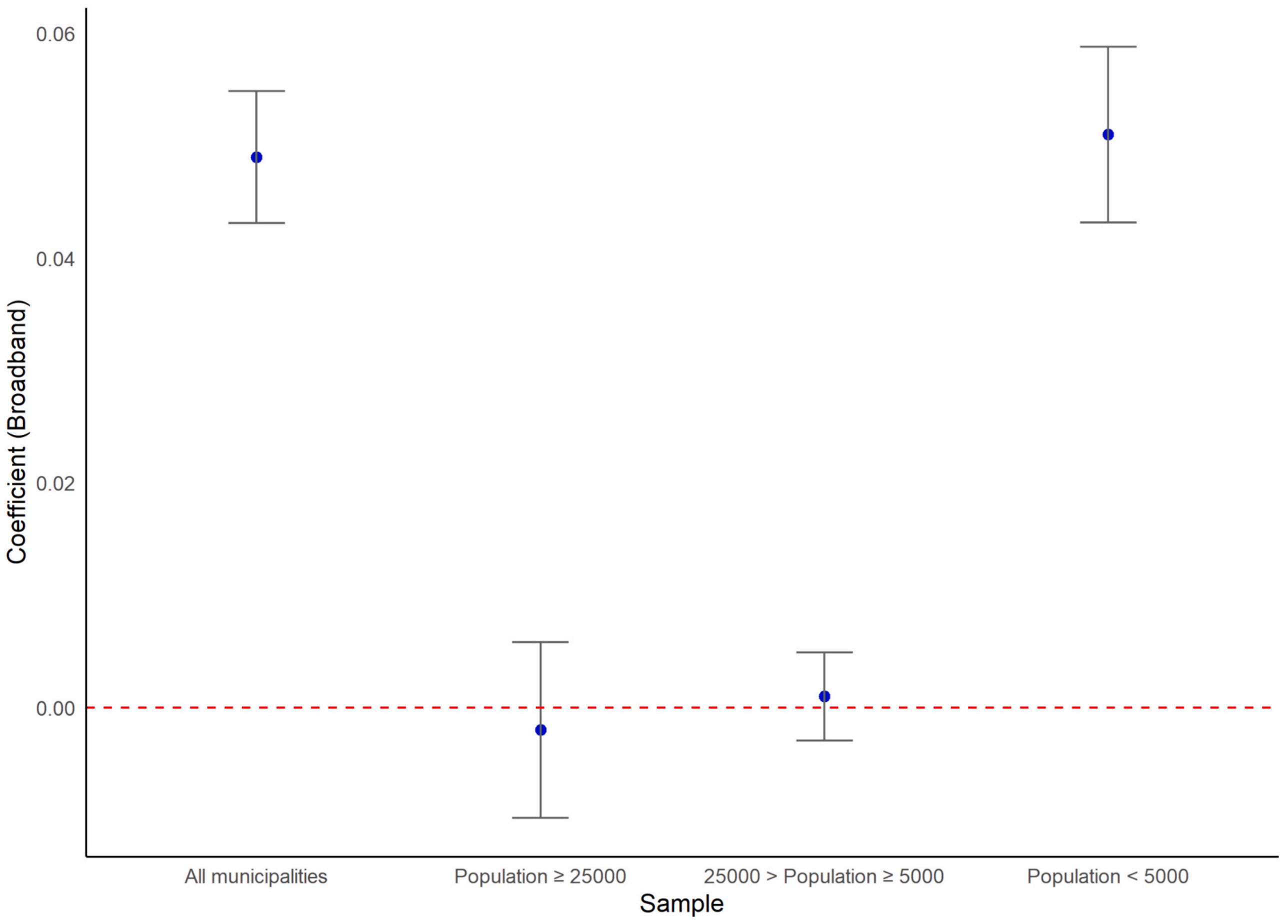


Fig. 6. Local population and broadband, people aged 15–24.
Notes: The figure reports the estimated coefficients for the broadband variable, defined as the proportion of actual subscriptions at the speed of 100 Mbps or higher over the total number of subscribers (units: proportion of households). The model is estimated using a quasi-maximum likelihood estimator for dynamic panel data with fixed effects (QML-FE). Estimations in first differences. Sample: All municipalities, municipalities with more than 25,000 inhabitants, municipalities with a population between 5000 and 25,000 inhabitants, and municipalities with less than 5000 inhabitants. Period: 2013–2020. Dependent variable: Logarithm of population aged 15–24. All models include the lag of the dependent variable, year fixed effects, and a set of control variables including mean age (in logs) and the regional inflation rate. Robust standard errors are used to compute 95 % confidence intervals.

10 % increase in broadband coverage is associated with an approximate 9.73 % increase in employment in the long term. This finding indicates that broadband access has a substantial cumulative impact on employment dynamics over time in small cities.

5.4. Spatial models

Finally, possible spatial interactions are analysed by estimating a dynamic spatial Durbin model (Eq. 3) for the two dependent variables using maximum likelihood.[17] The coefficient estimates are presented in Tables A5 and A6 in Appendix A. In both tables, ρ and τ are positive and significant in the two models, indicating that the spatial and temporal dependences of population and employment have significantly increased the concentration of these variables at the local level in Spain. However, differences arise in the estimated η parameter, which is significant only in the population model. The $\widehat{\eta}$ parameter is positive in the population model (Table A5), implying that the spatiotemporal dependence of population has favoured the concentration of local population. In contrast, it is not significant in the employment model, indicating no significant spatiotemporal dependence of local employment. Consequently, the final specification estimated for the employment model, shown in Table A6, excludes the η parameter.[18]

However, the coefficient lag estimates reported in Tables A5 and A6 must be interpreted with caution, because in spatially lagged models, the estimated coefficient of an independent variable does not directly reflect its marginal effect on the dependent variable (Golgher & Voss, 2016). LeSage and Pace (2009) indicated that using the point estimation method of the spatial regression model to test the spatial spillover effect leads to bias, because the coefficient estimate of the explanatory variable does not represent the true partial regression coefficient. They suggested that the direct, indirect and total effects of a change in an independent variable should be calculated.

According to Elhorst (2014), the effects have the following interpretation: a change in broadband access in a particular municipality not only has a direct effect on that municipality, but also an indirect effect on neighbouring municipalities via the spatial spillover, and the sum of the direct and indirect effects is the total effect of a change in broadband access. These effects are calculated as partial derivatives (Elhorst, 2014; LeSage, 2014), and the dynamic specification of the model enables the distinction between short- and long-term effects.

[17] The spatial models were estimated using the SDPDm package in R.

[18] The estimation of the employment model, including the not significant spatiotemporal parameter, produces results similar to those presented in Table A6 in Appendix A. These results are available from the author upon request.

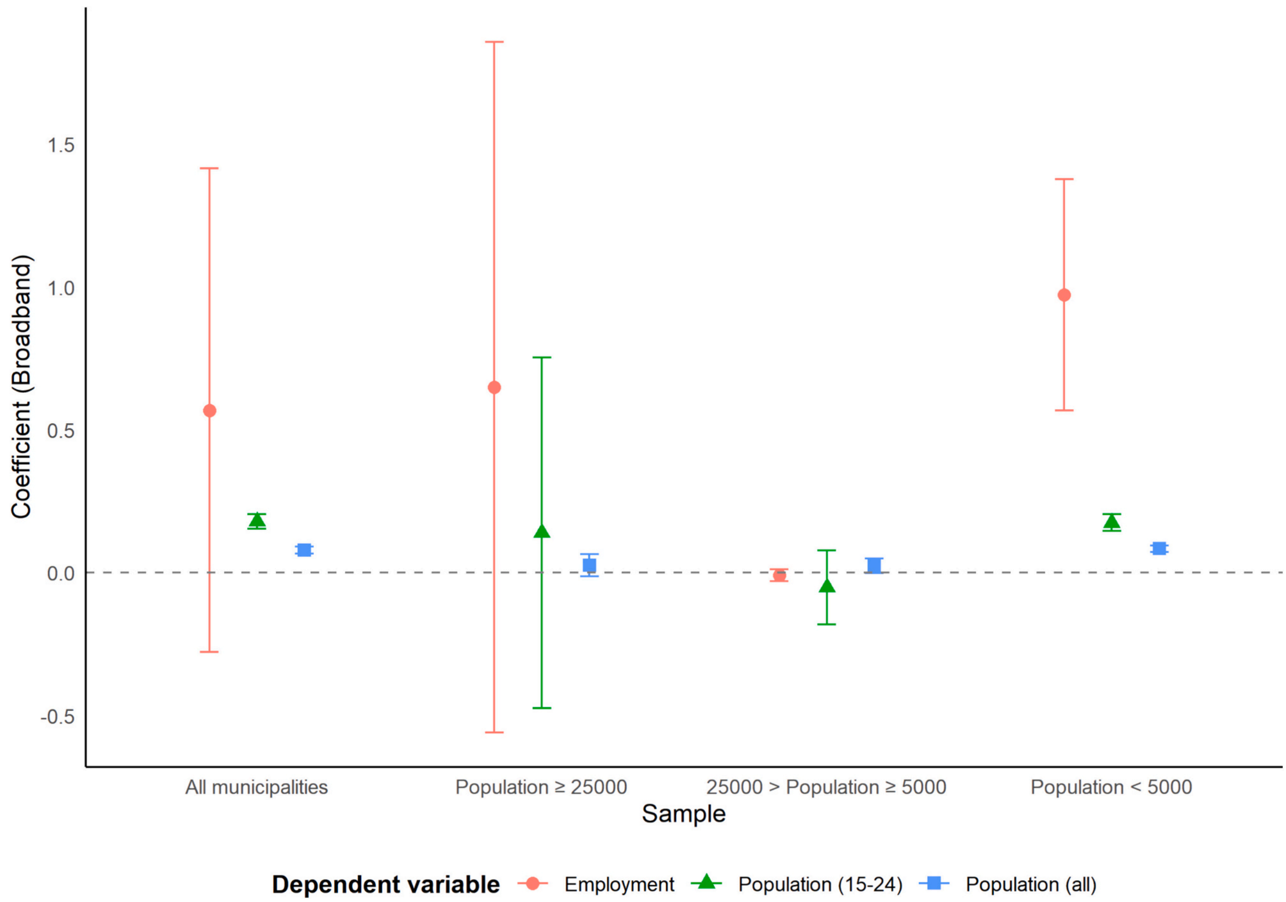


Fig. 7. Long-term effects of broadband, QML-FE results.
Notes: Long-term effects of broadband obtained using the QML-FE results reported in Figs. 5 and 6 (see Tables A2, A3 and A4 in Appendix A). The broadband variable is the proportion of actual subscriptions at the speed of 100 Mbps or higher over the total number of subscribers (units: proportion of households). The long-term effect is obtained as $\pi/(1-\tau)$. Sample: All municipalities, municipalities with more than 25,000 inhabitants, municipalities with a population between 5000 and 25,000 inhabitants, and municipalities with less than 5000 inhabitants. Period: 2013–2020. Dependent variable: Logarithm of population, logarithm of population aged 15–24, and logarithm of employment. The delta method is used to calculate the standard errors. Robust standard errors are used to compute 95 % confidence intervals.

Fig. 8 presents the direct, indirect and total effects of broadband from the dynamic spatial Durbin model, estimated using Eqs. 4.7 and 4.8 in Elhorst (2014, p. 106). Note that the y-axis scale differs across the graphs. A key finding is that the total spatial effects of broadband are positive and significant in the short-term for both population and employment. However, the nature of these effects differs between the two variables.

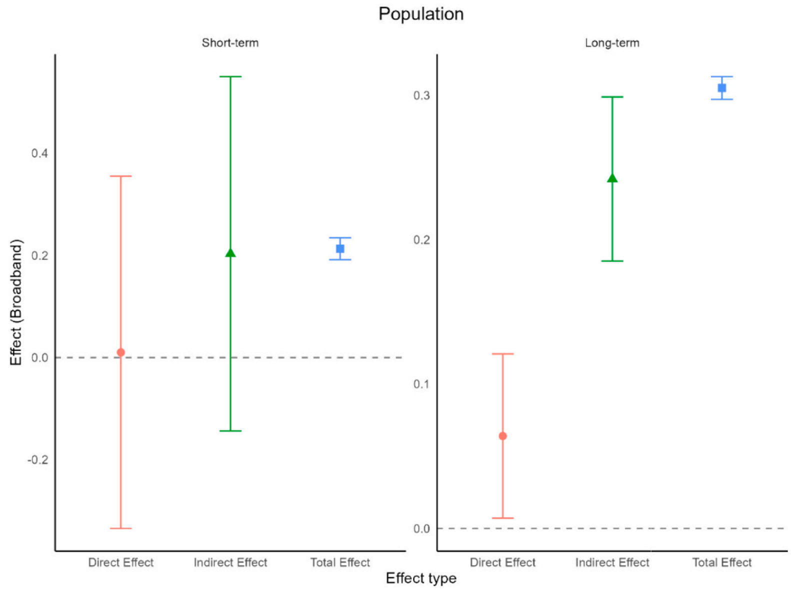
For population, while the total short-term effect is significant, neither the direct nor the indirect effects are individually significant (Fig. 8(a)). This outcome is plausible because, in the short-term, the aggregation of direct and indirect effects can yield a significant total effect even when individual components are not significant. Such results may arise due to multicollinearity between spatial lags and explanatory variables or the presence of dynamic feedback loops. Additionally, the total effect often has a smaller standard error compared to its individual components, enhancing its statistical significance.

The total effect coefficient of 0.213 in the short-term indicates that a 10 % increase in broadband access would result in a 2.13 % increase in a municipality's population, assuming other factors remain constant. In the long-term, however, all effects of broadband on population are significant, with the indirect effect (0.242) substantially larger than the direct effect (0.064), accounting for 79 % of the total long-term effect. This finding suggests that broadband access primarily influences population growth through spillover mechanisms rather than directly within the municipality.

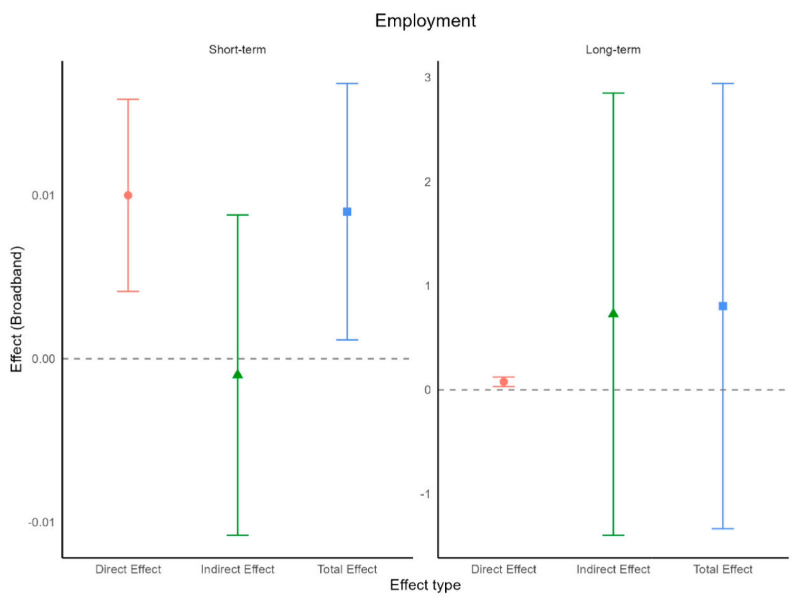
For instance, a 10 % increase in broadband access in a municipality and its neighbours results in a 0.64 % increase in the local population due to the direct effect and a 2.42 % increase due to indirect effects, combining for a total population growth of 3.05 %. Notably, the long-term direct effect coefficient (0.064) closely aligns with the estimate obtained from the dynamic panel data model without spatial effects (0.079, Fig. 7), underscoring the robustness of this finding. These results highlight the role of neighbouring broadband access as a critical driver of long-term population dynamics.

For employment, the short-term total effect is entirely driven by the direct effect, as the indirect effect is not significant (Fig. 8(b)). Specifically, a 10 % increase in broadband access within a municipality is associated with a 0.1 % increase in local employment. The total effect, which is nearly identical at 0.09 %, reflects the limited influence of neighbouring municipalities' broadband access on local employment during the short-term. These small effects suggest that while broadband access positively influences employment, its magnitude is modest. Notably, this short-term total effect is consistent with the estimate obtained from the dynamic panel data model without spatial effects (0.008, see Fig. 5).

In the long-term, however, neither the indirect nor the total effects of broadband on employment are significant, a result consistent with that obtained from the dynamic panel data model without spatial effects (Fig. 7). The only significant long-term effect is the direct effect, indicating that broadband access primarily impacts employment within the



(a) Population



(b) Employment

Fig. 8. Dynamic Spatial Durbin Model results.
Notes: The figure presents the decomposition of direct and indirect effects of broadband based on estimates from the Dynamic Spatial Durbin Model (see Tables A5 and A6 in Appendix A). The broadband variable is the proportion of actual subscriptions at the speed of 100 Mbps or higher over the total number of subscribers (units: proportion of households). Data transformed according to Yu et al. (2008) and Lee and Yu (2010) approach. Sample: All municipalities. Period: 2013–2020. Dependent variable: Logarithm of population and logarithm of employment. The models include municipality fixed effects and a set of municipal and regional control variables. In the population model, controls include mean age (in logs) and the regional inflation rate; in the employment model, they include the regional employment rate and the regional share of population with higher education. Standard errors are used to compute 95 % confidence intervals.

municipality itself, with no statistically significant spillover effects on neighbouring municipalities. A 10 % increase in broadband access is associated with a 0.77 % increase in local employment over the long-term, while neighbouring municipalities experience no significant impact. The magnitude of this long-term direct effect suggests that broadband fosters employment growth primarily through localized mechanisms such as business expansion, remote work opportunities, and enhanced productivity. The absence of significant indirect effects implies that the benefits of broadband do not extend meaningfully to neighbouring municipalities, potentially due to low worker mobility in Spain, which creates barriers to spatial spillovers in local employment.

6. Conclusions

This study investigates broadband positively influences local population and employment in Spain, using panel data from 8023 municipalities spanning the years 2013 to 2020. Fixed effects dynamic panel data models and spatial models are employed to identify the relationship between broadband expansion and local growth. In particular, the baseline regressions shown that a 10 % increase in broadband access leads to a 0.15 % and 0.08 % increase in local population and employment, respectively, in the short-term. However, in the long term, the effect on employment becomes not significant, while the impact of a 10

% increase in broadband access on population rises to a 0.79 %.

The spatial models confirmed that the positive effect of broadband access on local growth is robust even in the presence of spatial spillovers, revealing a modest but significant total short-term impact on both population and employment. In the long-term, however, the dynamics differ: while broadband's impact on employment remains highly localized—only the direct effect is significant—the influence on population growth extends more broadly, with the indirect effect exceeding the direct effect. These results highlight the contrast between employment and population responses: broadband's impact on employment is cumulative but localized, whereas for population, broader spatial spillover effects emerge over time.

Although studies examining the impact of broadband on population are scarce, the estimated effects on employment are consistent with findings from the literature. For instance, Abrardi and Sabatino (2023) found that one additional year of ultra-broadband exposure increased local employment by 1.3 percentage points in Italian municipalities during the COVID-19 pandemic period, and Hasbi and Bohlin (2022) concluded that broadband quality was positively correlated with unemployment reduction for low-skilled workers in small cities with broadband over 100 Mbps in Sweden.

The urban growth model developed by Glaeser et al. (1995) combined with the model developed by Czernich et al. (2011), provides a theoretical basis for understanding the mechanisms through which broadband expansion may exert a positive influence on local growth. According to this theoretical model, broadband access could have contributed to the increase in the technological growth rate, facilitating the exchange of knowledge about products, processes and innovations (knowledge spillovers) (see Tranos and Mack (2016) and Keene et al. (2024)). Broadband might become more important in the production process, as more businesses from many activity sectors (especially services) could incorporate e-commerce and online services. Pérez-Amaral et al. (2021) found that digital gaps were small and decreasing in Spain, nearing convergence in many services, and this convergence occurred despite a more limited deployment of internet-related infrastructure in rural areas.

Notably, small municipalities primarily drive this effect, with minimal significant impact observed in large cities. This finding aligns with de Clercq et al. (2023) in their analysis of a panel of EU regions. Their study indicated that high-speed broadband coverage significantly correlated with rural economic growth but had no discernible impact in urban areas. However, it is essential to note that their analysis was conducted at the EU region level, whereas the present investigation focuses on comparisons between municipalities within a single country.

The persistent depopulation of numerous small towns and municipalities in Spain has become a pressing concern, sparking intense debate within Spanish society. The findings of this study suggest that high-speed broadband access can serve as a valuable tool in addressing this demographic challenge. Specifically, the results indicate that broadband expansion contributes positively to both population growth and local employment, although the underlying mechanisms differ across outcomes and time horizons.

For population, the long-term effects are primarily driven by indirect spillovers from neighbouring municipalities. This highlights the importance of regional coordination in broadband infrastructure deployment: policies targeting single municipalities in isolation may fall short of maximizing demographic impact. In contrast, for employment, the long-term effect is direct and localized, with no evidence of spillover benefits. This suggests that broadband expansion influences job creation through mechanisms that remain largely confined within municipal boundaries.

These findings carry important policy implications. Broadband policies aimed at reversing rural depopulation should be designed at the regional level, promoting simultaneous infrastructure development across networks of municipalities to harness spatial spillovers. Conversely, policies intended to foster employment growth should focus on municipal-level improvements in broadband access, possibly complemented by measures to enhance local entrepreneurship, digital skills, and remote work opportunities.

Moreover, the absence of employment spillovers may reflect structural barriers such as low worker mobility across municipalities. To unlock broader labour market effects, broadband policies could be integrated with investments in transport connectivity or incentives that facilitate inter-municipal commuting.

In sum, bridging the urban–rural digital divide could provide many small municipalities with a critical lifeline, helping them adapt to demographic and economic transitions. A nuanced policy approach that differentiates between regional and local dynamics is essential to maximize the benefits of digital infrastructure and foster more balanced territorial development across Spain.

CRediT authorship contribution statement

Rafael González-Val: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

Table A1
Descriptive statistics by year.

Population					Workers				
Year	Mean	Standard deviation	Maximum	Minimum	Year	Mean	Standard deviation	Maximum	Minimum
2013	5587.90	46,846.46	3,207,247	1	2013	1917.31	23,375.30	1,654,467	1
2014	5544.64	46,364.40	3,165,235	3	2014	1946.95	23,746.50	1,682,181	1
2015	5526.48	46,152.83	3,141,991	5	2015	2008.38	24,571.27	1,744,011	1
2016	5517.05	46,364.18	3,165,541	5	2016	2066.18	25,368.67	1,800,954	1
2017	5518.08	46,575.86	3,182,981	5	2017	2136.62	26,228.17	1,860,970	1
2018	5534.43	46,961.64	3,223,334	5	2018	2203.45	27,171.64	1,935,905	1
2019	5567.56	47,475.86	3,266,126	3	2019	2257.82	28,082.42	2,008,988	1
2020	5617.65	48,285.69	3,334,730	3	2020	2206.60	27,584.14	1,981,414	1

Broadband (speed ≥100 Mbps)					Mean age				
Year	Mean	Standard deviation	Maximum	Minimum	Year	Mean	Standard deviation	Maximum	Minimum
2013	0.06	0.21	1	0	2013	48.55	7.36	76.17	30.58
2014	0.08	0.25	1	0	2014	48.82	7.33	78.47	30.79
2015	0.08	0.25	1	0	2015	49.05	7.26	79.50	30.93
2016	0.10	0.28	1	0	2016	49.30	7.26	79.00	31.24
2017	0.14	0.32	1	0	2017	49.56	7.26	77.00	31.55
2018	0.19	0.36	1	0	2018	49.80	7.26	77.07	31.96
2019	0.26	0.38	1	0	2019	49.94	7.20	78.43	32.30
2020	0.37	0.43	1	0	2020	50.08	7.11	75.13	32.76
Regional proportion of population with higher education					Regional inflation rate				
Year	Mean	Standard deviation	Maximum	Minimum	Year	Mean	Standard deviation	Maximum	Minimum
2013	0.26	0.04	0.39	0.20	2013	1.41	0.24	2.14	1.01
2014	0.26	0.04	0.38	0.20	2014	−0.24	0.21	0.28	−0.67
2015	0.26	0.04	0.38	0.20	2015	−0.70	0.30	−0.01	−1.35
2016	0.27	0.04	0.38	0.19	2016	−0.29	0.18	0.17	−0.62
2017	0.27	0.04	0.38	0.20	2017	2.01	0.21	2.50	1.55
2018	0.28	0.04	0.38	0.20	2018	1.72	0.16	2.02	1.09
2019	0.29	0.04	0.40	0.21	2019	0.72	0.21	1.19	0.19
2020	0.30	0.04	0.41	0.21	2020	−0.44	0.21	−0.01	−0.98

Regional employment rate				
Year	Mean	Standard deviation	Maximum	Minimum
2013	0.44	0.05	0.52	0.34
2014	0.45	0.05	0.52	0.33
2015	0.46	0.05	0.54	0.36
2016	0.47	0.05	0.56	0.37
2017	0.48	0.04	0.56	0.39
2018	0.49	0.05	0.59	0.40
2019	0.50	0.05	0.59	0.41
2020	0.48	0.04	0.55	0.39

Notes: Sources: Spanish Government, INE and social security records. Broadband is the proportion of actual subscriptions at the speed of 100 Mbps or higher over the total number of subscribers (units: proportion of households). The regional (NUTS 3 level) inflation rate is the rate of change in the Consumer Price Index. The regional (NUTS 2 level) measure of educated people is the proportion of population older than 16 with higher education.

Table A2
Local effects of broadband, QML-FE results.

Sample:	All municipalities		Population ≥ 25,000		25,000 > Population ≥ 5000		Population < 5000	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	Population	Employment	Population	Employment	Population	Employment	Population	Employment
$Ln(Y_{it-1})$	0.814***	0.986***	0.871***	1.027***	0.893***	0.771***	0.758***	0.969***
	(0.020)	(0.011)	(0.044)	(0.028)	(0.047)	(0.028)	(0.019)	(0.007)
Broadband (speed ≥100 Mbps)	0.015***	0.008***	0.003	−0.017***	0.003***	−0.002	0.020***	0.030***
	(0.001)	(0.002)	(0.003)	(0.005)	(0.001)	(0.002)	(0.001)	(0.003)
Ln(Mean age)	−0.616***		−0.497***		−0.263***		−0.587***	
	(0.024)		(0.090)		(0.053)		(0.026)	
Regional inflation rate	−0.004***		−0.001		0.001		−0.007***	
	(0.001)		(0.001)		(0.001)		(0.001)	

(continued on next page)

Table A2 (*continued*)

Sample:	All municipalities		Population ≥ 25,000		25,000 > Population ≥ 5000		Population < 5000	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	Population	Employment	Population	Employment	Population	Employment	Population	Employment
Regional employment rate		−0.043		0.429***		0.366***		−0.158***
		(0.070)		(0.108)		(0.076)		(0.060)
Regional proportion of pop. With higher education		−0.161*		−0.390***		−0.111		0.254***
		(0.095)		(0.141)		(0.117)		(0.085)
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	56,161	56,154	2022	2022	6590	6590	47,480	47,473
Municipalities	8023	8022	296	296	961	961	6801	6800
Log-likelihood	98,603.849	35,672.017	6397.255	4165.063	17,995.257	7777.752	80,093.323	27,342.448
Arellano-Bond test, AR(2), p-value	0.023	0.001	0.101	0.214	0.189	0.262	0.025	0.001
Wooldridge (2002) test, p-value	0.225	0.124	0.000	0.050	0.019	0.000	0.285	0.002

Notes: Quasi-maximum likelihood estimator for dynamic panel data with fixed effects (QML-FE). Estimations in first differences. Sample: All municipalities (Columns 1 and 2), municipalities with more than 25,000 inhabitants (Columns 3 and 4), municipalities with a population between 5000 and 25,000 inhabitants (Columns 5 and 6) and municipalities with less than 5000 inhabitants (Columns 7 and 8). Period: 2013–2020. Dependent variable: Logarithmic population (Columns 1, 3, 5 and 7), and logarithmic employment (Columns 2, 4, 6 and 8). $Y_{(it-1)}$ is the first lag of the outcome variable (Y = population and workers). The broadband variable is the proportion of actual subscriptions at the speed of 100 Mbps or higher over the total number of subscribers (units: proportion of households). Robust standard errors are reported in parentheses. Significant at the *10 %, **5 %, and ***1 % levels.

Table A3
Local population and broadband, people aged 15–24.

	(1)	(2)	(3)	(4)
Sample:	All municipalities	Population ≥ 25,000	25,000 > Population ≥ 5000	Population < 5000
Ln(Y_{it-1})	0.725***	1.014***	1.028***	0.707***
	(0.011)	(0.020)	(0.016)	(0.011)
Broadband (speed ≥100 Mbps)	0.049***	−0.002	0.001	0.051***
	(0.003)	(0.004)	(0.002)	(0.004)
Ln(Mean age)	−2.026***	−0.531***	−0.365***	−2.206***
	(0.091)	(0.140)	(0.071)	(0.095)
Regional inflation rate	−0.015***	−0.003	−0.002	−0.009**
	(0.004)	(0.002)	(0.002)	(0.005)
Year fixed effects	Y	Y	Y	Y
Observations	53,211	2022	6590	44,530
Municipalities	7727	296	961	6505
Log-likelihood	11,475.647	5487.808	13,542.063	5904.968
Arellano-Bond test, AR(2), p-value	0.013	0.221	0.602	0.014
Wooldridge (2002) test, p-value	0.047	0.000	0.001	0.097

Notes: Dependent variable: Logarithmic population aged 15–24. Estimator: Quasi-maximum likelihood estimator for dynamic panel data with fixed effects (QML-FE), estimations in first differences. Sample: All municipalities (Column 1), municipalities with more than 25,000 inhabitants (Column 2), municipalities with a population between 5000 and 25,000 inhabitants (Column 3) and municipalities with less than 5000 inhabitants (Column 4). Period: 2013–2020. $Y_{(it-1)}$ is the first lag of the outcome variable (Y = population aged 15–24). The broadband variable is the proportion of actual subscriptions at the speed of 100 Mbps or higher over the total number of subscribers (units: proportion of households). Robust standard errors are reported in parentheses, clustered at the municipality level in Columns 1 to 4. Significant at the *10 %, **5 %, and ***1 % levels.

Table A4
Long-term effects of broadband, QML-FE results.

Sample:	All municipalities			Population ≥ 25,000		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Population (all)	Population (15–24)	Employment	Population (all)	Population (15–24)	Employment
Broadband (speed ≥100 Mbps)	0.079***	0.180***	0.569	0.026	0.140	0.649
	(0.006)	(0.013)	(0.432)	(0.020)	(0.313)	(0.617)

Sample:	25,000 > Population ≥ 5000			Population < 5000		
	(7)	(8)	(9)	(10)	(11)	(12)
Dependent variable:	Population (all)	Population (15–24)	Employment	Population (all)	Population (15–24)	Employment
Broadband (speed ≥100 Mbps)	0.024*	−0.051	−0.009	0.084***	0.175***	0.973***
	(0.013)	(0.066)	(0.011)	(0.006)	(0.015)	(0.207)

Notes: Long-term effects of broadband obtained using the QML-FE results reported in Tables A2 and A3. The long-term effect is obtained as $\pi/(1-\tau)$. Sample: All municipalities (Columns 1, 2 and 3), municipalities with more than 25,000 inhabitants (Columns 4, 5 and 6), municipalities with a population between 5000 and 25,000 inhabitants (Columns 7, 8 and 9) and municipalities with less than 5000 inhabitants (Columns 10, 11 and 12). Period: 2013–2020. Dependent variable: Logarithmic population (Columns 1, 4, 7 and 10), logarithmic population aged 15–24 (Columns 2, 5, 8 and 11), and logarithmic employment (Columns 3, 6, 9 and 12). The broadband variable is the proportion of actual subscriptions at the speed of 100 Mbps or higher over the total number of subscribers (units: proportion of households). The delta method is used to calculate the standard errors. Robust standard errors are reported in parentheses. Significant at the *10 %, **5 %, and ***1 % levels.

Table A5
Local population and broadband, Dynamic Spatial Durbin Model.

			Short-term			Long-term		
	Coefficient Estimate	Coefficient Lag Estimate	Direct Effect	Indirect Effect	Total Effect	Direct Effect	Indirect Effect	Total Effect
Broadband (speed ≥100 Mbps)	−0.069***	−0.340***	0.010	0.203	0.213***	0.064**	0.242***	0.305***
	(0.011)	(0.056)	(0.176)	(0.177)	(0.011)	(0.029)	(0.029)	(0.004)
Ln(Mean age)	7.499***	1.840	4.073	−8.664	−4.591***	−15.728***	9.222***	−6.507***
	(0.954)	(2.965)	(7.064)	(7.244)	(1.551)	(4.344)	(2.953)	(2.019)
Regional inflation rate	0.059	−0.064	−0.026	0.029	0.003**	−0.348	0.352	0.004**
	(0.914)	(0.912)	(0.757)	(0.758)	(0.001)	(2.566)	(2.564)	(0.002)
ρ	2.902***							
	(0.220)							
τ	1.558***							
	(0.021)							
η	−2.123***							
	(0.009)							
Municipality fixed effects	Y							
Observations	64,184							
Municipalities	8023							
Log-likelihood	124,858.4							
R^2	0.688							

Notes: Sample: All municipalities. Period: 2013–2020. Dependent variable: Logarithmic population. The broadband variable is the proportion of actual subscriptions at the speed of 100 Mbps or higher over the total number of subscribers (units: proportion of households). Coefficient estimates of the Dynamic Spatial Durbin Model and decomposition estimates of the direct and indirect effects. Data transformed according to Yu et al. (2008) and Lee and Yu (2010) approach. Standard errors are reported in parentheses. Significant at the *10 %, **5 %, and ***1 % levels.

Table A6
Local employment and broadband, Dynamic Spatial Durbin Model.

			Short-term			Long-term		
	Coefficient Estimate	Coefficient Lag Estimate	Direct Effect	Indirect Effect	Total Effect	Direct Effect	Indirect Effect	Total Effect
Broadband (speed ≥100 Mbps)	0.010***	−0.002	0.010***	−0.001	0.009**	0.077***	0.727	0.804
	(0.003)	(0.004)	(0.003)	(0.005)	(0.004)	(0.023)	(1.084)	(1.091)
Regional employment rate	1.559***	−1.601***	1.544***	−1.595***	−0.051	8.080***	−13.242	−5.162
	(0.186)	(0.188)	(0.184)	(0.187)	(0.033)	(1.007)	(11.065)	(11.124)
Regional % pop. With higher education	0.181	−1.112**	0.135	−1.263***	−1.127***	−2.292	−97.813	−100.105
	(0.455)	(0.459)	(0.458)	(0.465)	(0.054)	(2.102)	(158.176)	(158.584)
ρ	0.174***							
	(0.005)							
τ	0.814***							
	(0.003)							
Municipality fixed effects	Y							
Observations	64,176							
Municipalities	8022							
Log-likelihood	51,272.44							
R^2	0.450							

Notes: Sample: All municipalities. Period: 2013–2020. Dependent variable: Logarithmic employment. The broadband variable is the proportion of actual subscriptions at the speed of 100 Mbps or higher over the total number of subscribers (units: proportion of households). Coefficient estimates of the Dynamic Spatial Durbin Model and decomposition estimates of the direct and indirect effects. Data transformed according to Yu et al. (2008) and Lee and Yu (2010) approach. Standard errors are reported in parentheses. Significant at the *10 %, **5 %, and ***1 % levels.

Data availability

Data will be made available on request.

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