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# Mobility patterns in Austrian and Italian municipalities in the decade before and during the COVID-19 era

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**Abstract**

In European countries, where the demographic transition has reached advanced stages and the natural increase has fallen below zero, migration constitutes a significant component of local population change. We investigate to what extent the dynamics of international migration and internal mobility changed during the first waves of the COVID-19 pandemic, compared to the previous decade. We focus on Austrian and Italian municipalities to assess the contribution of migration components to local population growth, using official data provided by National Statistical Institutes on inflows and outflows of migrant and native populations, from 2010 to 2020. The adoption of harmonized degrees of urbanization allows us to profile spatial and demographic patterns of mobility, in the Austrian and Italian territories. We apply Bayesian-Geostatistical models, and Artificial Neural-Networks to investigate the potential determinants of mobility variability. The results reveal Austrian and Italian population-specific migration trends. Overall, the trends observed in the decade before the pandemic were either confirmed or further accentuated during the COVID-19 era. Although rural-urban mobility generally persisted in both countries, counter-urbanization trends were detected among Austrian populations during the initial period of the COVID-19 pandemic. Conversely, urban and intermediate municipalities in Italy maintained their attractiveness and capacity to retain Italian populations. These findings offer new empirical insights into urbanization dynamics in a comparative perspective, which are particularly relevant for the definition of European regional policy aimed at matching local needs with national social cohesion goals.

## 1 | INTRODUCTION

Population ageing is visible throughout the European Union (EU), but comparable insights on the impacts of population movements, and their mutual interactions with other demographic components at local levels, remain rare (Bates-Eamer, 2019; Piguet, 2022; Willett & Sears, 2020). Recent urbanization dynamics have shown the heterogeneity of demographic profiles across territories (Newsham & Rowe, 2022), with the coexistence of shrinking cities, due to suburbanization, and revitalization of urban centers (Kabisch & Haase, 2011). These dynamics are tentatively explained by the differentiated migration[1] of population groups along the life cycle (Goujon, Natale, et al., 2021). Studies have revealed the plurality of age-specific net migration profiles across European municipalities, looking at contextual factors (e.g., availability of services) that may characterize the attractiveness of places (Ghio et al., 2022a). Overall, younger populations are mainly attracted by the services and amenities of urban settings (Kashnitsky et al., 2020): De Beer et al. (2011)

[1]Throughout the paper, and unless explicitly mentioned, migration (or alternatively mobility) refers to all kinds of mobility such as internal mobility and international migration, by all population groups, whether they are natives, EU-citizens, or third-country nationals.

  

found that urban regions have higher positive net migration of young adults than intermediate and rural regions, while families with children tend to move to the periphery of urban centers, and older adults are more likely to remain in or retire to rural areas. Thus, discrepancies between rural and urban age structures seem to be more driven by the ability of territories to retain youth than by their rural or urban configurations (Lerch, 2017). However, the COVID-19 pandemic disrupted patterns of mobility, and their potential role in population changes at the local level. When the containment measures adopted to limit the spread of the virus affected mobility, the COVID-19 pandemic also altered the definition of amenities, limiting access to specific locations, such as restaurants, cinemas, and cultural exhibits, and causing people to reconsider rural areas for their possible residential relocation. Since the transmission of infection was higher in the most densely populated areas and lockdown measures were more restrictive in cities, the pandemic may have pushed people out of urban areas. For instance, the increase in out-migration from the largest cities in the United States, such as New York, Chicago, and Washington DC, has been largely documented (Bellafante, 2020; Bowman, 2021; Dorsey, 2020). Looking at the migration decision making in the United States, Lei and Liu (2022) examined changes in mobility intentions before and during the COVID-19 pandemic. In Europe, similar trends have been studied in Paris (Le Monde, 2021), Stockholm (Vogiazides & Kawalerowicz, 2022), and Dublin (Cuthbertson, 2021; Weckler, 2020). In Germany, Stawarz et al. (2022) describe the impact of the COVID-19 pandemic on the intensity and spatial patterns of internal mobility, which appears to be more pronounced among young adults. Marsh (2021) refers to the increase in out-movements from cities that occurred in Great Britain as the COVID exodus. Nevertheless, Rowe et al. (2023) argue that COVID-19 merely generated temporary changes in the patterns of mobility in Great Britain, without significant impacts on population structures; González-Leonardo et al. (2022) infer the same conclusion for Spain, but it remains unclear to what extent this is applicable to all European territories.

The lack of harmonized data and complete time-series has limited the adoption of comparative approaches to migration trends before and during the COVID-19 pandemic, which is crucial for (a) understanding trends in different contexts and depicting their spatial path dependency; (b) assessing the impacts of the COVID-19 pandemic on population behaviors, in the short-term, and the implications of these changes on population structures, in the medium- to long-term. In this study, we tackle the issue in the context of Austria and Italy, which exhibit different patterns of migration and urbanization, with Austria experiencing a steady and moderate urbanization rate, relatively balanced across the country, while the urbanization phenomena in Italy have been concentrated in certain areas, with a persistent urban-rural divide between the North and the South. We use official figures provided by the National Statistical Institutes (NSIs) of age-specific migration and mobility flows available at the municipal level in both countries, to contrast the period of the first waves of the COVID-19 pandemic in 2020, with the previous period spanning from 2010 to 2019. Specifically, we address the following research questions: (1). How did mobility between urban centers and rural-intermediate areas change during the COVID-19 pandemic initial period compared to previous years? (2). To what extent did migration influence population change (and ageing) at the municipal level?

This paper contributes to advancing current knowledge of spatial-demographic trajectories in two key ways. First, we empirically confirm migration as a main component in the demographic process (Champion, 1994). Our assessment delves into the differentiated role played by international migration and internal mobility in population change at the municipal level. Moreover, while previous studies have focused on population growth (Alaimo et al., 2023) or net migration within the total population, we distinguish between inward and outward movements of native and migrant populations. Second, by adopting harmonized definitions, we improve comparability between urban and rural areas across countries. These interactions often remain obscured by national figures and affected by data collection and specificities in monitoring and statistical systems at the country level. Thus, we highlight differences in urbanization trajectories, explaining the variability in mobility patterns of populations living in cities during the COVID-19 period, in contrast to the predominant trends observed in the decade preceding the pandemic.

The remainder of the paper is structured as follows. The next section gives an overview of the main demographic conceptualizations of the relationship between migration and population changes, sketching how the COVID-19 pandemic may have upset population patterns across territories. Data and methods are presented in Sections 3 and 4. In Section 5, we analyze the impact of the COVID-19 pandemic on mobility patterns in Austria and Italy, compared to the pre-pandemic period, followed, in Section 6, by the exploration of the consequences of these trends on age structures at the municipal level in the two countries. In Section 7, we focus on Austria, looking at the variability of mobility patterns. We conclude by discussing the main findings and explaining the relevance of framing the COVID-19 pandemic within the context of spatial population analyses for policymaking.

## 2 | MIGRATION AND POPULATION CHANGES

Scholars have studied migration alongside population change (Parrish et al., 2020; Piguet, 2013). In his classic work, Zelinsky (1971) attempted to bring migration into the framework of the demographic transition. During the first demographic transition, emigration served as a stabilizing factor in Western industrialized countries (Van de Kaa, 1999), and also at present, in lower-income countries, where the youth bulge can lead to intensified out-movements. During the second demographic transition, the populations in higher-income countries reach low levels of fertility and mortality, and experience challenges of ageing, which increase the demand for social security benefits, and the provision of care and support to older populations, often generating a burden on the pension systems. In such circumstances, international migration becomes one of the most important demographic factors being potentially able to mitigate or counteract population decline in the host countries (Lesthaeghe, 2014). However, this has been disputed considering that international migrants tend to settle more in urban settings, and particularly in capital cities (Brezzi et al., 2010; Viñuela, 2022), than in the rural areas affected by depopulation. Yet, there are short (direct) and longer-term (indirect) effects of migration on population size, composition, and distribution that are undeniable "notably in situations where young immigrants contribute to natural increase after their arrival, but also in terms of altering pre-existing patterns of demographic behaviour within countries" (Champion, 1994, p.664).

Consistency of patterns in mobility across regions, and how they can reflect common population trajectories (Davis, 1965) have been studied extensively in the context of urbanization (Lerch, 2017). The migration transition hypothesis has conceptualized a five-stage framework to model population distribution, where intra and inter-urban mobility increase over time, while international migration and rural to urban mobility first increase, become stable and then decline. The similarities with the demographic transition are evident: both models can be represented as a series of transition sequences, where migration incorporates spatial and temporal perspectives. With respect to the latter, time series capture the variability of migration, while age-selectivity represents the most prevalent migration pattern (Rogers and Castro, 1978).

Studies have revealed commonalities and divergences in population and (international and internal) migration trends that are at play in Italy and Austria (Champion, 1994).

Ghio et al. (2022b) noted that between 2015 and 2019, for most territories in Austria, net migration (including internal and international flows) was sufficient to offset the deficit in the working-age population caused by cohort turnover. This was not the case of Italy, where net migration of the 20–24 age-group recorded a negative balance in Southern municipalities and a positive one in Northern municipalities (Ghio et al., 2022b), but with a wide distribution across territories, while in Austria (like in Germany), positive net migration of the 20–24 age group was concentrated in the largest municipalities.

Looking at the age patterns of migration, the native population exhibits a peak in its young adult migration, at slightly older ages in Italy compared to Austria (Bonifazi et al., 2018).[2] For both countries, international and internal immigrants tend to gravitate toward urban centers, that are expected to offer more economic and service opportunities (Kabisch & Haase, 2011). In Italy, there is a persistent North-South divide in migration flows (Reynaud et al., 2020). In the 2001–2011 decade, 40% of Italian municipalities reported a population decline, in favor of the metropolitan areas situated in Northern-Central Italy that recorded higher migration gains compared to the cities located in the Southern Italian regions (Benassi, 2020). Moreover, based on the analysis of eight Italian urban agglomerations from 2001 to 2010, Strozza et al. (2016) demonstrated the relevance of migration as a driver of population growth in Turin, Milan, Verona, Bologna. Florence, and Rome (urban agglomerations situated in the Northern and Central Italian regions) while Naples and Palermo (situated in the Southern Italian regions) exhibited population stagnation during the same period.

In the case of Austria, Vienna and other provincial capital cities to a lesser extent, concentrate most migration flows, particularly of international migrants, since the 1990s. In 2022, the Austrian NSI estimated that 25% of the population living in Austria has a migration background (meaning both parents were born abroad). International migration has significantly contributed to urban growth in Austria in the past two decades as more than one-third of foreign-born immigrants settled initially in the capital (Statistik Austria, 2022). Goujon and Schinko (2023) calculated that if no international migrants had arrived in the country between 1971 and 2021, and only internal mobility from and to Vienna within Austria had been allowed, the discrepancy in absolute numbers would have been 883,000 by 2022 (1.05 million residing in Vienna without migration vs. 1.93 million with migration), with consequences for the mean age of the population.[3] Vienna, which also attracts young internal movers, records higher dispersion of migrant population when compared to the segregation patterns present in many European cities (Goujon, 2015; Premrov & Schnetzer, 2023; Skifter Andersen et al., 2016). As argued by Kadi and Suitner (2019), from high segregation levels, the Austrian capital has become one of the most livable cities in the world.

To summarize, while sharing many demographic and migration patterns, Austria and Italy differ by the urbanization patterns. Italy' share of urban population is higher than in Austria (in 2022,[4] 72% and 59% respectively), where most of the population and hitherto most of the mobility takes place in Vienna: nearly one out three people in Austria lives within the metropolitan area. Both countries are characterized by suburbanization and counter-urbanization[5] signals in the early 1980s, with increased outflows from peripherical and rural areas, followed by reverse trends in subsequent years (Champion, 1992). Suburbanization trends appear pronounced in Austria, particularly at the level of the broader surroundings of the capital city, which has a negative migration balance with its surrounding suburban areas (Geyer, 2009; Kakaš & Gruber, 2016), and in other state capitals, such as Graz and Linz. Suburbanization is also occurring in Italy around the major metropolitan cities in Northern-Central regions, such as Milan, Bologna and Rome (Buonomo et al., 2024). Counter-urbanization trends have been noticed in Austria (Schorn et al., 2024) particularly in Western Austria, in regions like Tyrol and Vorarlberg, in Southern

[2]Strong family ties and a weak social welfare system, which remain the prominent characteristics of Italian society, are recognized to favour immobility and discourage the younger generations from leaving their parental homes in the first years of adulthood (Dalla Zuanna, 2001).

[3]46 years versus 41 years, with a much higher dependency ratio: 70 personAs aged 0–19 and 65+ for every 100 people of working age (20–64) in Vienna without migration, compared to 56 in real Vienna (Goujon and Schinko, 2023).

[4]World Development Indicators, https://databank.worldbank.org/source/world-development-indicators [login on: 3/1/2024].

[5]Counter-urbanization is seen as the antithesis of urbanization and "implies a movement from a state of more concentration to a state of less concentration" (Berry, 1970, p.17).

Austria (Carinthia and Styria) and in the regions surrounding Vienna, while in Italy they are less pronounced (Bonifazi & Heins, 2003). For a long time, Italy's population movements have polarized around the Northern regions, more vivid economically than the Southern ones, with a significant dynamism of intermediate-size areas. Bonifazi and Heins (2003) noted that 'a genuine process of counter-urbanization has not yet taken place in Italy' and highlighted the central role of the intermediate-size areas, which coincided with 'the general trend in the national economy' when 'the industrial districts and the small and medium-sized enterprises are the driving forces' (Bonifazi & Heins, 2003, p:30). From a theoretical point of view, the authors advocated the approach proposed by Geyer and Kontuly (1993) to insert an intermediate stage of polarization reserve besides the counter-urbanization phase.

Against this context, in February 2020, Italy was the first European member state that started experiencing SARS-CoV-2 infections. The pandemic prompted an almost uniform policy response in all countries, with the adoption of lockdown measures aimed at flattening the infection curve. However, due to the easing of mobility restrictions, most European countries faced a resurgence of cases in early September 2020 (Hodcroft et al., 2021; Lemey et al., 2021). During this first wave, in Italy, the proportion of COVID-19 cases that required hospitalisation reached 32%, while in Austria the proportion was not more than 6% (Ghio et al., 2022c). Among men and women aged 50–59 years, the highest hospitalisation rates were recorded in Italy (187 and 103 per 100,000 respectively), while the lowest rates were observed in Austria (26 and 16 per 100,000 for men and women respectively) (Ghio et al., 2022c).

These differences contribute to making Austria and Italy interesting cases to study. Media and public opinion have debated the potential 'renaissance of rural areas' (Schorn et al., 2024). For instance, in Austria, Wisbauer et al. (2023) found an increase in movements from urban to rural areas in 2020 and 2021 compared to periods before the COVID-19 pandemic; similar trends were observed in Germany (Stawarz et al., 2022). For Italy, recent comparative studies have detected urban-rural disparities by COVID-19 wave, revealing that residents in Italian intermediate territories experienced a much lower probability of dying than residents in German rural territories (Bignami et al., 2024). In both countries, the COVID-19 pandemic may have accelerated the process of population redistribution, potentially revitalizing rural areas, whereas, in the post-globalization era, migration has been expected to stagnate (Fielding & Ishikawa, 2021).

The primary aim of the analysis is to contextualize the COVID-19 pandemic within the complexity of the existing urban-rural gradient (Alaimo et al., 2023) and trends of population dynamics, in Austria and Italy. This presents a notable challenge for two main reasons. Firstly, the lack of migration and demographic data, distinguishing between age-specific internal and international movements of native and migrant populations at municipal levels. Secondly, the adoption of country-specific spatial definitions of urban, intermediate and rural areas, limiting cross-country comparability. Both limitations have been addressed in the analysis.

## 3 | DATA

We collected data on population, internal mobility, and international migration, by age, sex, and citizenship at the municipal level, from the NSIs. Only aggregate figures have been made public as part of official statistics; thus, ad-hoc requests (motivating the research objectives and defining the empirical strategy) were submitted and positively accepted by the NSIs.

In both countries, population movements are derived from administrative sources, mostly population registers, which record changes in residence and new registrations by municipality. Since these are administrative data, biases may limit their accuracy. For instance, registration procedure practices may vary across municipalities, and the reporting of changes in residence may be postponed or never communicated by individuals. Nevertheless, population registers are periodically aligned with the population census, using cross-sectional techniques to validate administrative sources with the enumeration of people, houses, firms, and other important items in a region at a given time (Britannica, 2023).

Following the NSI definitions, the categorization between the native and migrant population is based on the citizenship criterion. Therefore, native population include Austrian (Italian) citizens living in Austria (Italy); whereas, migrant population include persons without Austrian (Italian) citizenship living in Austria (Italy). Overall, we account for 10,124 municipalities, 22% in Austria and the remaining in Italy. To harmonize national categorizations, we adopt the classification of degrees of urbanization provided by Eurostat (2020), which distinguishes three predominant categories: (a) urban areas, where more than 80% of the population lives in urban agglomerations; (b) rural areas, where at least 50% of the population lives in rural agglomerations; and (c) intermediate areas, where more than 50% and up to 80% of the population lives in urban agglomerations. On this basis, we examine the age-specific patterns of international migration and internal mobility across urban rural and intermediate areas, by citizenship (native and migrant populations). When data are available, we conduct an in-depth analysis of the international migrant population focusing on extra-European citizens, namely migrants living in Austria (Italy) holding passports from countries outside the European Union.

To complement the datasets with further spatial variables, we add estimates of the travel time to the nearest urban center as proxy for detecting accessibility to services offered by cities (Perpiña Castillo et al., 2021). The map in Supporting Information S1: Annex 1 illustrates the distribution of the variable within each country.

## 4 | METHODS

We adopt a three-step strategy to investigate our research questions.

### 4.1 | Migration behaviors

To address the first research question, we use the out-migration rates categorized by population target, age-group, and degree of urbanization. Our aim is to assess the spatial distribution of both native and migrant populations, during the COVID-19 pandemic in comparison to previous years. To generalize, we assume that only the population $P$ living in region $i$ during the annual period between $t_0$ and $t_1$ was at risk of emigrating. It was calculated as follows:

$$e_{i,(t_0-t_1)} = \frac{E_{i,(t_0-t_1)}}{(P_{t_0} + P_{t_1})/2}$$

Thus, the rates of annual internal mobility and international migration $e$ are derived as the proportion of outflows $E$ in -region $i$ between $t_0$ and $t_1$ to the stock of average population (average of populations $P$ living in -region $i$ at the beginning ($Pt_0$) and end of the period ($P\ t_1$)) by citizenship, age-group, and place of residence.

## 4.2 | The role of migration as a component of population change

For the second research question, we explore the demographic contribution of mobility and migration to population change at the local level using the share of migration and mobility in population turnover.

$$MST_{i,(t_0-t_1)} = \frac{I_{i,(t_0-t_1)} + E_{i,(t_0-t_1)}}{B_{i,(t_0-t_1)} + D_{i,(t_0-t_1)} + I_{i,(t_0-t_1)} + E_{i,(t_0-t_1)}}$$

The Migration Share of Turnover (MST) is derived from the amount of immigrants and emigrants $I_{i,(t_0-t_1)} + E_{i,(t_0-t_1)}$ and the components of changes (births, deaths $B_{i,(t_0-t_1)} + D_{i,(t_0-t_1)}$) in the region $i$ during the reference period $(t_0–t_1)$ (Billari, 2022). By definition, it ranges between 0 and 100 percent. The MST measures the contribution of migration to population growth/decline. A similar approach was followed by Rees et al. (2017) who assessed the impact of internal migration at the national level to measure the role of migration in population change.

## 4.3 | The link between migration and demographic components

As explained above (Section 2), the conceptualization of the migration transition (Skeldon, 1990; Zelinsky, 1971) and differential urbanization (Champion, 2001; Geyer & Kontuly, 1993) sketches the stages of societal transformation from predominantly rural to urban. In the first stages, urban centers tend to attract people seeking employment opportunities. In later stages, with the regional redistribution of economic development, subnational income disparities diminish, and, as society becomes urban, population movements shift toward intermediate or rural areas.

We report on the different phases of urbanization of Austria in comparison to Italy. Furthermore, focusing on Austrian urban municipalities, we model the interactions between migration and the other demographic components adopting a machine learning approach to examine how both rural-to-urban flows decrease, and counter-urban-to-rural migration increases, over two periods: (a) from 2010 to 2019; (b) from 2010 to 2020, including the COVID-19 first waves.

The application of a machine learning approach allows the disclosure of nonlinear correlations among variables that remain hidden using traditional regression models. The proposed approach is data-driven, and the algorithm drives the identification of relationships between variables. First, we adopt the Bayesian Geostatistical model (BGS) to unveil how local demographic factors intertwin differently to shape urban-to-rural mobility during COVID-19 waves, compared to the previous decade. Second, we adopt artificial neural networks (ANNs) to enhance robustness and improve the accuracy of outcomes.

BGS is a statistical technique (Gelman & Hill, 2007; Press, 2002) integrating a hierarchical analysis of observed data with spatial information. BGL models allow us to identify potential associations between variables across the range of geographical coordinators (latitude and longitude), revealing the relative contribution of demographic determinants to mobility over specific time intervals, with the measurement of uncertainties.

We opt for the Integrated Nested Laplace Approximations (INLA) approach, available in the GNU R (R Core Team, 2020) package called R-INLA (Martins et al., 2013), because of its computational efficiency at approximating a classic Markov Chain Monte Carlo method. This approach belongs to the category of Latent Gaussian models, which encompasses linear, mixed, spatial, and temporal models. The combination with the stochastic partial differential equation allows the modelling of all kinds of georeferenced data. A summarized form of these models can be represented as:

$$z(s) = x(s)\beta + \zeta(s) + \varepsilon(s)$$

where z(s) are realizations of the process linked to a structured predictor in an additive way, x(s) represents a set of covariates with β coefficients, ζ(s) is a first-order autoregressive dynamics with spatially correlated innovations and ε (s) is the measurement error.

ANNs use an architecture inspired by the human brain that acquires knowledge through a learning process and stores the acquired information within inter-neuron connection forces. An ANN is implemented through a system of interconnected nodes; the information propagates through the nodes, transforming the inputs into intermediate derived signals until generating the final outputs. The nodes are connected to each other by weighted input functions. The internal nodes, called neurons, define the hidden layers of ANNs. Considering the relationship between nodes does not need to be linear or even continuous, the architecture of ANNs' can more easily take advantage of the complex relationships between the covariates and the independent variable. Each of the processing neurons calculates the weighted sum of all the interconnected signals from the previous layer plus a bias term and then produces an output through the activation function. The effective incoming signal $s_j$ to node $j$ is:

$$S_j = \sum_{i=0}^{n_0} W_{ij} x_i + b_j$$

where $W_{ij}$ is the connection weight, $x_i$ is the input to the network and $b_j$ is the bias term. The activation function associating individual nodes typically has a sigmoid shape. The sigmoid function most often used for ANN is the logistic function:

$$Y_j = f(S_j) = \frac{1}{1 + \exp(-S_j)}$$

in which $s_j$ can vary in the interval $\pm \infty$ but $y$ is bounded between 0 and 1.

These multilayer feed-forward networks (also known as multi-layer perceptron) are the basis of many applications of ANNs (Bosco et al. 2013, 2017a, 2017b; Bosco, 2019; de Rigo et al., 2001; Secomandi, 2000), due to their universal approximation properties (Hornik et al., 1989; Kreinovich, 1991). The architecture, written in MATLAB language, is developed using the Neural Network Package (Schmid, 2009) available in GNU Octave (Eaton et al., 2008).

### 4.4 | Modelling urban mobility

The choice of covariates is a fundamental step to maximize the predictive accuracy of a model: including too few informative covariates could result in loss of explanatory power, while including too many could cause the resulting high-dimensional multivariate model to overfit the data, especially when ANN models are applied.

To identify the most appropriate set of covariates, we employ a sensitivity analysis using a jackknife approach (Bosco, 2019; Tukey, 1958). This technique involves the systematic exclusion of observations from the data set and re-estimation of the outcome multiple times. Throughout this iterative process, the covariates are assessed: with each step, the least impactful covariate is gradually removed, thereby improving the model's performance. Jackknife methods aid in preventing overfitting and maximizing the model's explanatory potential. Additionally, this method reduces the risk of missing nonlinear correlation patterns among numerous covariates. Upon completing the covariate selection, we utilized the root mean square error (RMSE) and mean absolute error (MAE) metrics, derived from the final iteration of the jackknife approach, to assess the most significant variables.

The set of variables is described in Supporting Information S1: Annex 2. This covers the annual changes in the following covariates collected at the municipal level by both native and migrant populations: population size, demographic components such as rates of international migration and internal mobility (as described in Section 4.1), crude birth rates and mortality rates, and spatial covariates including geographic coordinates (latitude and longitude), areas in $km^2$, travel time (as outlined in Section 3), and population density.

Previous studies have shown that urban spatial factors, such as population density, have increased vulnerability to COVID-19 (Boterman, 2022; Geng et al., 2021; Gonzàlez-Val and Sanz-Gracia, 2021; Goujon, Natale, et al., 2021).

We define 8 models (4 Bayesian models and 4 ANN models) using out-mobility rates and in-mobility proportions as dependent variables, for the period 2010–2019 and the period 2010–2020 to include the COVID-19 first waves. Supporting Information S1: Annex 3 reports the variable composition of each model. Using these variables, the main modelling challenge is the leveraging multicollinearity, which can have a significant impact on the stability and quality of the results. We apply the variance inflation factor (VIF) to control multicollinearity, considering that the larger the VIF, the greater the multicollinearity. Multicollinearity is tested among all covariates.

To obtain the best performance for each of the modelled variables, we compare the prediction capacities of models. Then, to get a more stable model with reduced overfitting and better predictive capacity over time, we apply a nonrandom method to select the training and validation variables.

We utilize repeated random sub-sampling cross-validation on the data set to train models, identifying the best set of hyperparameters (tuning). A two-step validation approach is followed. First, we apply a cross-validation on the training data set (70% of the data) to tune each of the tested modelling architectures. The model performance is estimated using the mean absolute error (MAE), the root mean square error (RMSE) and the explained variance of the model (expressed in proportional terms). By calculating the RMSE, we quantified the accuracy of the models (the relationship between predicted and observed values). The models with the lowest RMSE value are selected. Although some authors suggest that inter-comparisons of average model-performance should be based on MAE (Willmott & Matsuura, 2005), we also consider RMSE because of its sensitivity to occasional large predictive errors. Second, we use the remaining data (30%) to evaluate model performance of the same metrics. We calculate the explained variance (pseudo – $R^2$) as follows (Bosco et al., 2017a):

$$\text{Pseudo} - R^2 = 1 - \frac{MSE}{\text{var}(obs)}$$

The validation results are presented and discussed in the following sections. Finally, the results are compared to the outcomes obtained by running a *trivial* model, replacing each variable using its mean value. The scope of this modelling exercise is to certify that the model performs better than a basic *trivial* model, which implies that the efforts made to develop the model are reasonable. On the contrary, when the model and the *trivial* model achieve similar performance levels, there is no reason to continue developing the model.

## 5 | MOBILITY CHANGES DURING THE COVID-19 PANDEMIC

We depict the in- and out-mobility rates (Section 4.1) over the period 2010–2020 across municipalities in Austria and Italy by degree of urbanization (Figure 1). Mobility patterns differed consistently in the two countries. The mobility rates were higher in Austrian urban municipalities compared to the Italian ones, while we observe the preeminence of in-mobility to intermediate areas in Italy. This reflects

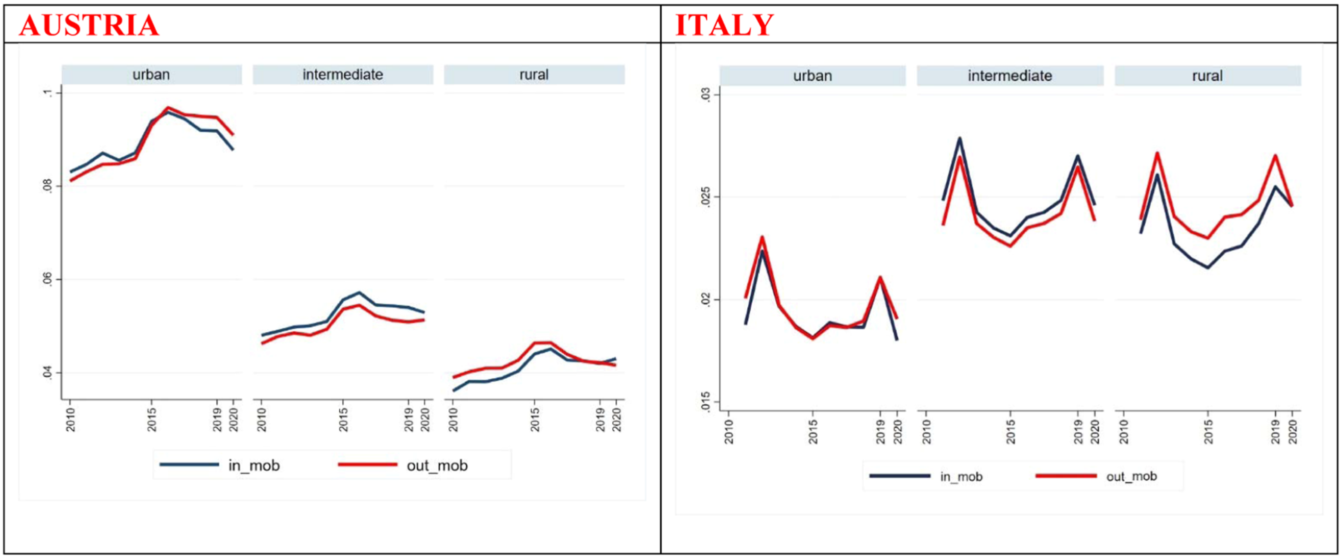


**FIGURE 1** Mobility trends by degree of urbanization in Austria (2010–2020) and Italy (2011–2020). Legend: Blue lines show in-mobility rates; red lines show the proportion of out-movements on populations living in the areas.

the differences between the Austrian and Italian settlement systems: while in Austria, the capital has played a polarization role, alternatively Italy is characterized by a more deconcentrated[6] configuration, with ongoing trends of higher mobility levels to the intermediate-sized centers (Mitchell, 2004).

In Austria, from 2010 to 2014, in-mobility rates exceeded out-mobility rates, in urban and intermediate municipalities, whereas in rural areas, the out-mobility prevailed, suggesting a dominant tendency toward increased urbanization. However, starting from 2015, mobility trends have shown a shift within urban municipalities, marked by a simultaneous increase in out-mobility levels from urban municipalities, and in-mobility levels to rural areas. These counter-urbanization trends presented higher proportions of outbound mobility from cities compared to rural and intermediate areas. While the specific extent of these occurrences varied across areas, this trend has persisted over time. As reported in Section 2, from 2015 onward, Austrian mobility patterns seemed to contribute to the slowdown of the urbanization process.

Conversely, Italy experienced more mobility towards intermediate areas during the observed periods. This trend reflects the outward movements from urban areas, with a predominance of mobility between intermediate and rural areas compared to mobility from/to urban areas, as described above (Section 2). Similar peaks were recorded across the three areas, in 2012–2013, when the increase of internal mobility was related to the general intensification of international migration movements, and the Arab Spring in the early 2010s; and in 2018, when the peak may likely result from changes to the statistical system.[7] Nevertheless, out-mobility rates prevail in rural areas throughout the observed period.

Although the intensity of mobility differed between the two countries, urban mobility changed in 2020, the first year of the pandemic, for both populations.

As shown in Figure 1, the mobility of Austrian populations living in urban areas dropped in 2020, but the decrease appears to be smaller compared to Italy. In Italy, mobility declined across intermediate and rural municipalities, while in Austria, incoming mobility to rural municipalities increased, when outgoing mobility decreased. Movements from/to intermediate areas remained relatively stable in Austria, whereas in Italy, the decline was, in terms of intensity, comparable to the other areas. Whether or not the lower number of movements is attributable to the pandemic-related closure measures adopted during the lockdown, it is evident that Austrian urban municipalities have experienced an increase in outbound mobility rates versus inward mobility rates from 2015 onward. By contrast, in Italy, higher rates of out-mobility than in-mobility were reported in rural municipalities. In both countries, intermediate areas attracted more internal migrants than rural areas. The tendency to leave urban municipalities in Austria, and rural municipalities in Italy, is confirmed when looking at the mean values (Figure 2). Further evidence for this finding is derived from examining the distribution scatter of mobility rates across municipalities. Estimated regression slopes (predicting future trends in mobility rates, with 95% confidence interval) by degree of urbanization suggest that a different impact on the

[6]With respect to Mitchell's work (2004), here the attribute 'deconcentrated' is firstly derived from the population distribution, then from population movements. According to the ISTAT's classification, metropolitan cities in Italy are: Bari, Bologna, Cagliari, Catania, Florence, Genoa, Messina, Milan, Naples, Palermo, Reggio Calabria, Rome, Turin, and Venice. Nevertheless, it is worth noting that to ensure comparability, Austrian and Italian municipalities are categorized as urban, intermediate and rural based on the Eurostat's harmonized definition (Section 3).

[7]In 2018, the Italian NSI has introduced the 'permanent' population census; thus, as of 2018, the resident population figures have been aligned with results from the permanent population census.

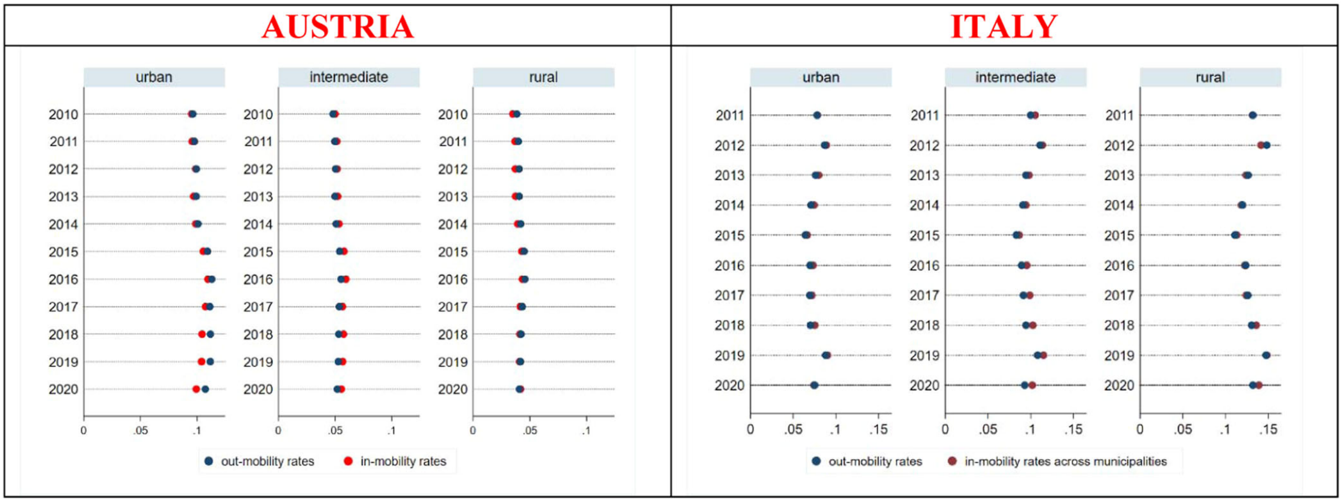


**FIGURE 2** Mean values of out- and in-mobility rates by degree of urbanization in Austrian (2010–2020) and Italian municipalities (2011–2020). Legend: Blue circles show mean values of out-mobility rates; red circles show mean values of in-mobility rates.

spatial redistribution of Austrian and Italian populations during the COVID-19 pandemic between urban and rural areas. Austrian populations may have accelerated their propensity to leave urban areas and move towards rural and intermediate areas; on the contrary, Italian populations have retained their preference for living in urban or intermediate areas, also during the pandemic.

We explore international migration and mobility patterns, comparing native to migrant populations, revealing important differences between the two countries. In Italy, migrant populations were more evenly distributed between municipalities than in Austria where they were mainly concentrated in urban areas. It should be noted that in 2015–2016, when more than 80,000 asylum seekers entered Austria from Syria, Iraq and Afghanistan, the Austrian government tried to distribute them in refugee centers located all over the country; after 2016, most migrants opted for resettlement in urban centers (mainly Vienna). Austria's native population showed a trend of counter-urbanization among family age-groups, consisting of young parents and children, who were more likely to move from urban to intermediate and rural areas. By contrast, urban areas remained more attractive for immigrant populations.

Figure 3 shows the age-specific mobility rates of native populations across municipalities. As a general trend, age-specific mobility rates in Austria were much more stable than in Italy. In Austria, youth (15-29 age-groups) had the highest mobility rates over the whole period, while in Italy, young adults (30–44 age-groups) showed the highest propensity to move. In 2015–2016 (migration crisis), the effects were limited to the youth in Austria. By contrast, in Italy the mobility of all age-groups appeared to be affected. Similarly, during the COVID-19 pandemic, mobility declined among Austrian youth living in urban areas, likely due to lockdowns that have postponed movements from rural to urban areas for education- or employment-related reasons. Nevertheless, urban municipalities in Austria were losing attractiveness for Austrian young adults: from 2012 onwards, their out-mobility rates increased steadily, driving the increased mobility of children (0–14). This may imply that families formed by young parents often decided to move to the countryside, as evidenced by the increase in in-mobility rates. This counter-urbanization trend was evident in Italy, where inward-mobility in urban areas remained higher than outward-mobility for the 15–44 age-groups, then decreased among older age-groups linked to life course events, such as retirement (60+). Although intermediate areas played an important role in both countries, Italian intermediate municipalities were able to retain more youth than Austrian ones. This may reveal a different pace of the urbanization transition between the two countries, with Italian rural areas experiencing more emigration of younger populations than Austrian ones, and Italian intermediate municipalities representing a valid alternative to an urban resettlement. The overall decline observed in Italy during 2020 indicates how the COVID-19 pandemic strongly affected mobility rates at all ages.

Further analyses are presented in Supporting Information S1: Annex 4 depicting the share of immigrant populations with extra-EU citizenship in the municipalities of both countries.

## 6 | HOW MIGRATION CONTRIBUTES TO LOCAL POPULATION CHANGES

Adopting the MST approach detailed in Section 4.2, we obtain an indicator between 0 and 100 to assess the effects of mobility and migration on the annual population change during the reference period.

In Austria, internal mobility and international migration determined population change in all municipalities (Figure 4) over the observed periods, with a dominance of the internal mobility component when looking at the magnitude. Distinguishing between inbound and outbound components, the average percentage share of turnover due to in-mobility was lower than out-mobility in urban

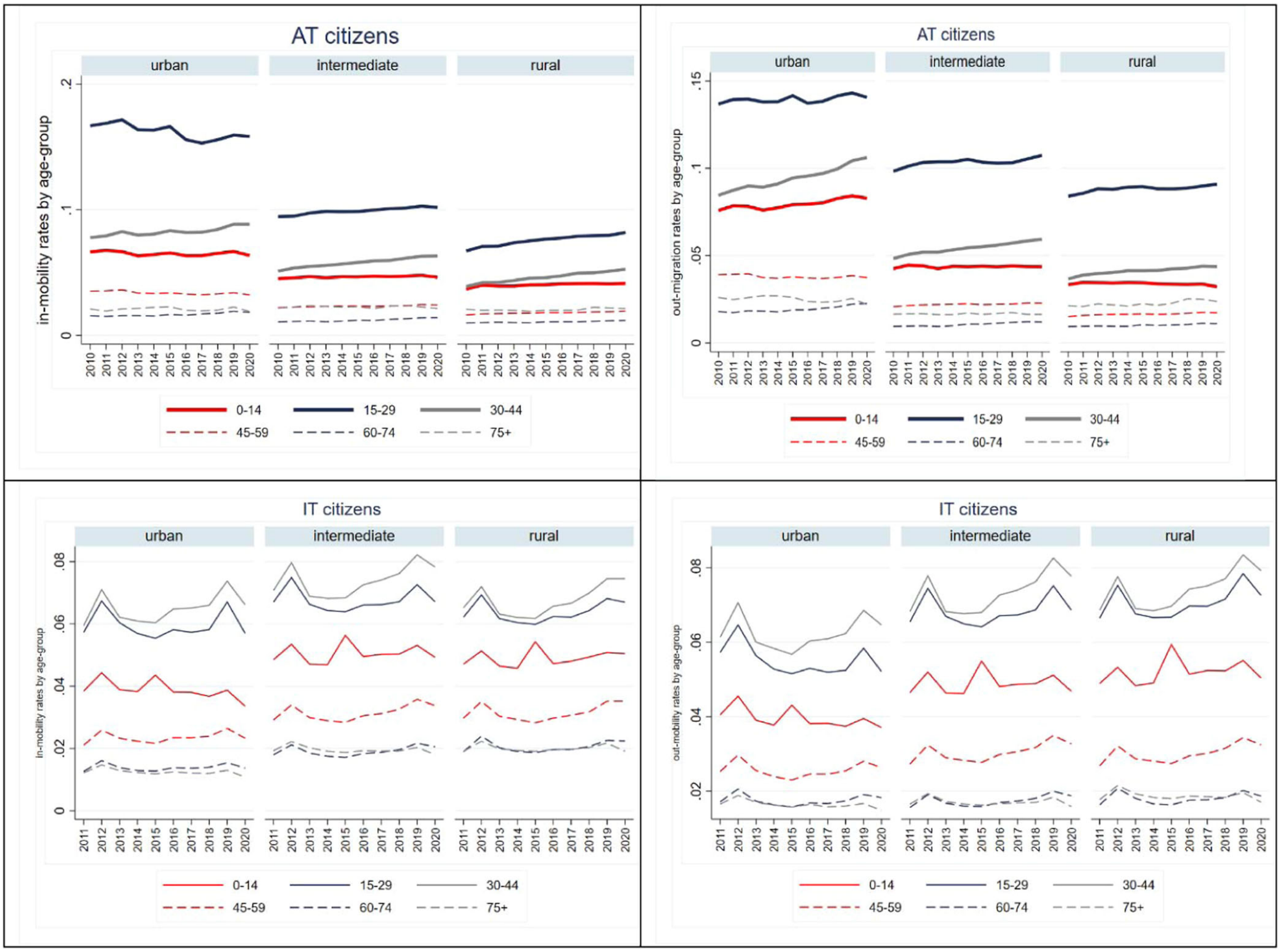


FIGURE 3 Age-specific mobility rates of native populations by degree of urbanization, Austria (2010–2020) and Italy (2011–2020).

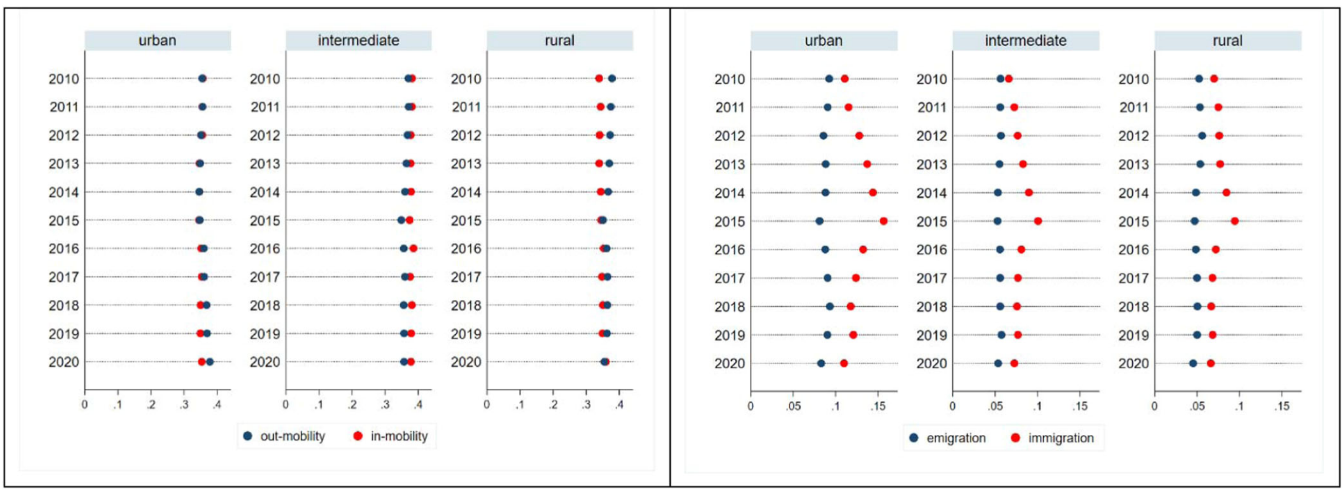


FIGURE 4 Average percentage share of population turnover due to mobility and migration by degree of urbanization in Austria, 2010-2020.

areas, and higher in intermediate areas. By adopting a similar distinction between immigration and emigration components, the analysis shows that the average percentage share of turnover due to immigration consistently surpassed that of emigration. This confirms the key-role played by international migration in driving population change within Austrian urban centers.

Looking at Italy (Figure 5), the average shares of in- and out-mobility in population turnover were similar in urban and in

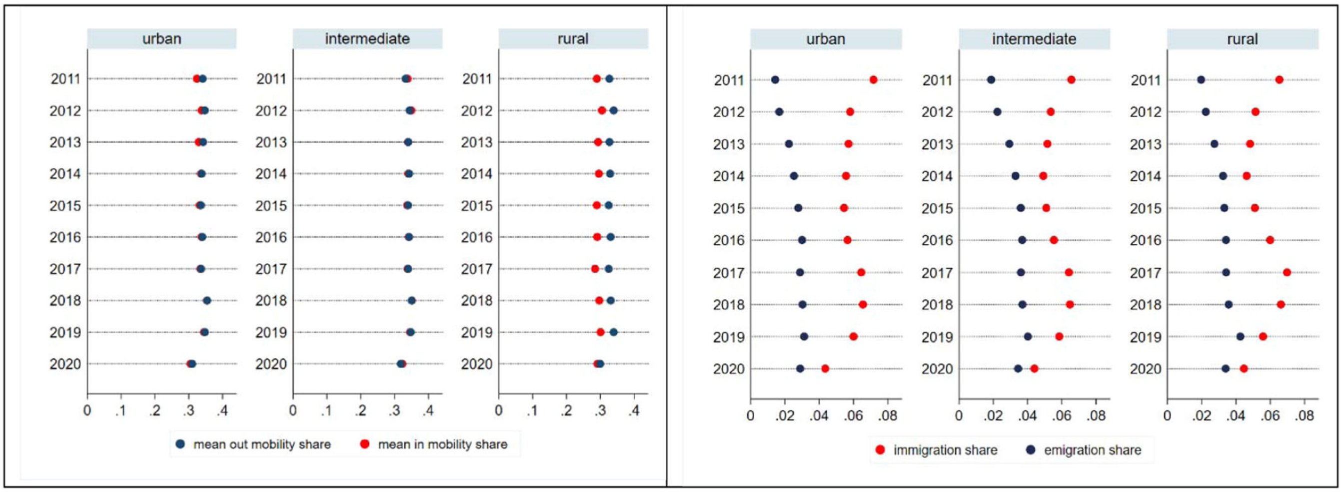


**FIGURE 5** Average percentage share of population turnover due to mobility and migration by degree of urbanization in Italy, 2011–2020.

intermediate areas, while in rural areas, out-mobility share prevailed over in-mobility share in all years, except in 2020, when both shares stood at 30%. As observed in Austria, the shares of migration components on population turnover were lower, yet the immigration components peaked at 7% in 2017 in all municipalities. Then, the trajectory differed across municipalities, remaining around 6%,. in urban areas until 2019 and then falling to 4% in 2020.

We complete the analysis by looking at the contribution of natural increase to population change (Supporting Information S1: Annex 5). The contribution of natural components tended to be lower when population growth was negative, and higher when population growth was positive. Despite the fact that the incidence of births and deaths was modest in all municipalities, the contribution of natural growth was double in rural municipalities compared to urban ones. In Italy, where COVID-19 fatalities were particularly high in 2020, we detect an increase in the share of the mortality component in rural municipalities and intermediate areas, increasing the gap between the two natural components.

## 7 | VARIABILITY OF MOBILITY PATTERNS IN AUSTRIA

The bivariate relationship between mobility share and population changes is examined using the lowess (locally weighted scatterplot smoothing) method with a 95% confidence interval (Supporting Information S1: Annex 6). The technique allows us to compare the contribution of native and migrant mobility by degree of urbanization over time. It shows how the mobility of native populations in rural areas differed from intermediate and urban areas stabilizing trends. This relative lower volatility indicates the relevance of mobility patterns as contributors to population changes in rural areas. These patterns gradually escalated during the initial intervals, stabilizing and persisting as an ongoing trend that endured even during the initial COVID-19 period.

Contrarily, the mobility of migrant populations shows decreasing patterns in all territories, regardless of the degree of urbanization. Yet, a larger decline is reported in cities, likely due to restriction measures adopted during the pandemic. These insights motivate our modelling strategy in selecting Austrian urban municipalities to better understand the variability of mobility patterns and the intertwined demographic dynamics of native and migrant populations.

We start by presenting the covariates selected by the models, as potential predictors of inward and outward mobility. Both BGS and ANNs identify the same group of variables, meaning that the selected covariates, as a whole, are relevant in explaining mobility variability for Austrian urban municipalities. Among the spatial covariates, the models excluded population density and travel time. These findings should be interpreted in context rather than as isolated factors; selected covariates identify the main intertwined features that are able to explain the variance in mobility across territories, while most studies have examined the role played by each determinant in isolation (Basellini & Camarda, 2022). According to the analysis, neither the population density nor the accessibility of urban services are determinant per se for movements across Austrian urban municipalities.

We detail the results of the out-mobility models (Table 1), over the period 2010–2019 (Ref. Models 1, 5) and including the COVID-19 pandemic (Ref. Models 2, 8). The out-mobility models give insights into the ability of municipalities to retain populations showing that out-mobility patterns of the Austrian population are explained by the following demographic components: in-mobility, emigration and population size of the Austrian native population and size of migrant population living in municipalities. Supporting Information S1: Annex 8 displays the variance explained by each covariance.

When comparing the out-mobility models in 2010–2019 (Ref. Models 1, 5) with the out-mobility models in 2010–2020 (Ref. Models 2, 6), the inclusion of crude death rates becomes evident. This indicates that mortality played a different role in the modelling of the period 2010–2020. The COVID-19 pandemic increased the significance of mortality impacts in urban areas; this interpretation is in line with previous studies during the COVID-19 first waves, that examined disparities in excess mortality across territories (Goujon, Jacobs, et al., 2021).

**TABLE 1** Models of out-mobility, Austrian urban municipalities, selected variables.

| Ref. | Model | Year | Dep variable | Selected variables |
|---|---|---|---|---|
| 1 | BGS | 2010–2019 | out-mobility | in-mobility of native population, emigration of native population, population size of native population, population size of migrant population, latitude, and longitude. |
| 2 | | 2010–2020 | | in-mobility of native population, emigration of native population, population size of native population, population size of migrant population, latitude and longitude, crude death rates of native population. |
| 5 | ANNs | 2010–2019 | out-mobility | in-mobility of native population, emigration of native population, population size of native population, population size of migrant population, latitude, and longitude. |
| 6 | | 2010–2020 | | in-mobility of native population, emigration of native population, population size of native population, population size of migrant population, latitude and longitude, crude death rates of native population. |

Abbreviations: ANNs, artificial neural networks; BGS, Bayesian Geostatistical model.

**TABLE 2** Models of in-mobility, Austrian urban municipalities, selected variables.

| Ref. | Model | Year | Dep variable | Selected variables |
|---|---|---|---|---|
| 3 | BGS | 2010–2019 | in-mobility | out-mobility of native population, in-mobility of migrant population, emigration of native population, population size of migrant population, latitude and longitude |
| 4 | | 2010–2020 | | out-mobility of native population, in-mobility of EU migrant population, immigration of EU migrant population, population size of migrant population, latitude, and longitude |
| 7 | ANN | 2010–2019 | in-mobility | out-mobility of native population, in-mobility of migrant population, emigration of native population, population size of migrant population, latitude and longitude |
| 8 | | 2010–2020 | | out-mobility of native population, in-mobility of EU migrant population, immigration of EU migrant population, population size of migrant population, latitude, and longitude |

Abbreviations: ANN, artificial neural network; BGS, Bayesian Geostatistical model.

By examining in-mobility patterns (Table 2), the models highlight the ability of municipalities to attract populations and select the following demographic covariates: out-mobility and emigration of the native population, in-mobility and population size of the migrant population. It is worth noting the variability of territorial contexts by mobility type: in-mobility of Austrian population was more responsive to the presence of migrant populations in cities than out-mobility trends. This indicates that migrant neighborhoods may be more a deterrent for native in-mobility than for pushing the native population out of cities. This does not necessarily imply residential segregation that largely depends on the initial stock of residents living in the areas. However, Sievers et al. (2014) raised the issue of migrant discrimination in Vienna. According to Riederer et al. (2019), Vienna has experienced an urban social transformation over the past two decades, finding evidence of suburbanization dynamics in the Austrian middle-class. Exploring the relevance of changes in migrant composition for the transformation of Vienna's social stratification system, the authors show that 'the rise in the share of EU-15 migrants and those from other EU countries has had an inequality-reducing effect' (Riederer et al., 2019, p.9). For instance, the increasing share of highly educated migrants, representing the second generation of the migrant population in the city, has counteracted the shrinking of the middle class.

When the COVID-19 pandemic is included in the analysis, two covariates become relevant to explain in-mobility of the Austrian population: the in-mobility and immigration of EU citizens, which may reflect the common policies adopted at EU level to lower the spread of the virus, such as lockdowns and obligatory testing for travel.

The following section documents the performance of the models. Table 3 attests to a good general performance of all the statistical methods applied to measure both in- and out-mobility. The explained variance is higher than 80% for all models and the mean absolute error is relatively low. Here we present the VIF, the larger the VIF, the greater the multicollinearity. Multicollinearity was tested among the independent variables. Some authors suggest excluding variables with a VIF greater than 5, here it was decided to safely keep only variables with a VIF less than 4.

The level of variance explained by the models is particularly high in the case of out-mobility models, over both periods of analysis, (around 0.91 and 0.87 respectively). RMSE is around 0.006–0.007 and the MAE ranges between 0.004 and 0.006. We report RMSE resulting from the trivial model, which is nearly three times higher than the RMSE obtained by the models. Finally, Supporting Information S1: Annex 7 reports the validation between the observed and predicted values of out-mobility (dependent variable) for the models referred to the 2010–2019 and 2010–2020 intervals.

TABLE 3 Model performance indicators.

| Ref. | Model | Year | Dep variable | Explained variance Validation | RMSE Validation | RMSE Trivial model | MAE Validation | VIF |
|---|---|---|---|---|---|---|---|---|
| 1 | BGS | 2010–2019 | out-mobility | 0.91 | 0.006 | 0.025 | 0.0054 | 3.8 |
| 2 | | 2010–2020 | | 0.87 | 0.0056 | 0.0023 | 0.0043 | 3.1 |
| 3 | | 2010–2019 | in-mobility | 0.84 | 0.0079 | 0.023 | 0.006 | 1.6 |
| 4 | | 2010–2020 | | 0.87 | 0.0077 | 0.025 | 0.0063 | 4 |
| 5 | ANNs | 2010–2019 | out-mobility | 0.92 | 0.0057 | 0.025 | 0.0044 | 3.8 |
| 6 | | 2010–2020 | | 0.88 | 0.0073 | 0.025 | 0.0061 | 4 |
| 7 | | 2010–2019 | in-mobility | 0.84 | 0.0079 | 0.023 | 0.006 | 1.6 |
| 8 | | 2010–2020 | | 0.91 | 0.006 | 0.023 | 0.0046 | 3.1 |

Abbreviations: ANNs, artificial neural networks; BGS, Bayesian Geostatistical model; MAE, mean absolute error; RMSE, the root mean square error.

## 8 | DISCUSSION AND CONCLUSIONS

The COVID-19 pandemic was a sudden event with a substantial impact on the movements of people. Prior works had shown that the decision to migrate (temporary, permanent, mobility or international migration) is associated with a mix of demographic, economic, political, socio-cultural and environmental factors (Black et al., 2013). During the COVID-19 pandemic, motivations for leaving were likely to differ across territories, populations and age-groups. It is possible that the adoption of teleworking, which increased dramatically during the pandemic, made mobility to urban areas, where workplaces are commonly located, less significant. However, as migration is inherently contextual, the strength of the impacts could vary considerably across regions and the consequences depend strongly on the demographic characteristics of the local populations living in the areas concerned. We develop a comparative analysis between Austrian and Italian municipalities, grounded on common definitions of urban, intermediate and rural areas, to contrast COVID-19's first waves with previous trends. Our study gives new insights into demographic differences and the role played by international migration and internal mobility as components of local population changes. We demonstrate that in Austria, the COVID-19 pandemic has accentuated already existing counter-urbanization and suburbanization trends, in Vienna and other state capitals. The findings are consistent with previous studies that have shown net migration losses for largest cities (Fielding & Ishikawa, 2021 Stawarz et al., 2022;). Moreover, results capture variability in mobility patterns by population living in urban centers. In line with a large literature, Austrian capitals have kept their attractiveness to immigrants (Massey, 2008), while the out-mobility of the native population increased during the COVID-19 pandemic. In this context, results demonstrate the significance of mortality impacts in urban areas. Because of higher mortality in urban than in rural centers, Austrians have moved to less populated areas, likely to protect their vulnerable family members, children or grandparents, from the spread of the virus, and to benefit from the possibility to be outside congested areas. Although this trend is relevant, its magnitude has not qualified as an exodus. Nevertheless, effects on local population changes have been accentuated by a large decline in in-mobility to urban areas. This combination demonstrates the importance of period-effects for urban areas and explains why the COVID-19 pandemic was not able to reshape the spatial patterns of mobility in the country, rather it boosted the incidence of existing trajectories at local levels. These effects are particularly evident for places where the demographic transition has reached advanced stages (deficit in natural components); consistently, the contribution of natural increase to population growth was larger in rural municipalities than in the urban ones.

In Italy, where prevailing migration trends have been from Southern to Northern regions, individuals tend to concentrate in urban and intermediate areas. The impact of the COVID-19 pandemic was prominently observed across all age-groups, with intermediate areas continuing to retain the Italian young population better than rural ones. Specifically, we found that, in Italian rural areas, population decline was accelerating, increasing the gap between the two natural components, and marking considerable demographic challenges for these areas.

Findings provide evidence that the impacts of the COVID-19 pandemic were sensitive to local contextual specificities which vary between native and migrant populations. The COVID-19 affected differently migration in Austria and Italy, primarily because the trends differed already before the pandemic. Like other countries, during the COVID-19 pandemic, Austria experienced an acceleration of pre-pandemic counter-urbanization trends. Yet, while the urban-rural dichotomy remained more evident in Austria, Italian rural municipalities were more likely to be affected by aging than Austrian rural municipalities. Results give empirical evidence that could be useful for future and more extended analyses rethinking the conceptualization of local population changes across the urban-rural gradient. Urban transition does not follow linear developmental pathways (Bonifazi & Heins, 2003; Geyer & Kontuly, 1993), as framed for fertility and mortality by the demographic transition model. In Italy, the interplays between historical conditions and local contingencies have furtherly differentiated intermediate areas, not only with distinct population trajectories but also shaping their influence in the urbanization process at the national level. These findings emphasize the need for a policy response tailored to local requirements. Some countries are implementing strategies to regenerate depopulated areas[8] and overcrowded urban environments, notably by improving public infrastructures and social cohesion (Musterd & Ostendorf, 2008). Nevertheless, more attention needs to be paid to the causes of mobility of native populations, especially when they are related to the immobility of migrant populations. To address this concern, systematic monitoring and comparative approaches are of fundamental importance for the governance of urban transformations and implementation of adaptive measures.

Our analysis presents some limitations. The main limitation is the temporal coverage, from 2010 to 2020. It remains unclear whether the increase in outflows from urban areas observed over the first waves of the COVID-19 pandemic was driven by temporary relocations (as shown in Spain by González-Leonardo et al., 2022) or permanent population resettlements. Large outflows from urban areas may have future relevant economic implications such as reduced demand for services and increased unemployment rates. Therefore, the study of mobility and urbanization trends should continue to include more recent time periods to ascertain whether the mobility patterns observed during the pandemic are temporary (period effects) or, persisting over time, become stable.

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## CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

## DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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## SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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