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ABSTRACT

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This paper examines the evolution and determinants of skill-specific internal mobility among Italian citizens by urban–rural origin. Using administrative data from the Registry of Transfer of Residence (ADELE), which records the universe of skill-specific bilateral moves across more than 700 millions potential municipality pairs between 2012 and 2022, we document distinct trends in residential mobility for college-educated and non-college-educated citizens. We then assess the role of economic and non-economic factors in shaping these flows, employing a Poisson Pseudo-Maximum Likelihood (PPML) estimator with an extensive set of destination and origin-by-nest fixed effects. Our findings show that low-skilled movers respond more strongly to economic factors, while high-skilled movers are respond more to non-economic ones, with the urban–rural divide at origin amplifying these differences. Moreover, we find that after the COVID-19 pandemic, economic drivers became less relevant, whereas non-economic factors gained importance. Overall, this study highlights that, similar to international migration, the drivers of internal mobility are inherently skill-specific.

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Keywords: migration, human capital, urban-rural, Italy, COVID-19

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1 Introduction

Internal migration has historically served as an important buffer against economic shocks and a mechanism to reduce spatial inequalities (Cadena and Kovak, 2016, Basso and Peri, 2020). However, despite rising inequality and recurring economic crises in recent decades (Piketty and Saez, 2014), evidence shows a decline in internal migration across many developed countries (Bell et al., 2015, Jia et al., 2023). Olney and Thompson (2024) documents a sustained downward trend in the United States, while Alvarez et al. (2021), analyzing internal migration in 18 OECD countries from 1996 to 2018, find that all non-European countries exhibit declining trends, whereas evidence for European countries are more mixed.

While these trends may seem surprising, two important caveats should be noted. First, much of the existing evidence on internal mobility is based on broad spatial units, such as commuting zones, regions, or provinces, thereby overlooking migration patterns across more granular levels, like municipalities. Second, internal migration is often examined at a population-wide level, without accounting for the individual movers' characteristics.[1] Existing research shows that both international and internal mobility decisions are shaped by individual educational attainment (Grogger and Hanson, 2011, Diamond, 2016). Moreover, preferences are also influenced by individual place of residence. For instance, the urban population hold distinctive voting stances compared to rural one (e.g, Beckett, 2016, Moriconi et al., 2025), due to the access to a distinct set of services and amenities (e.g. Glaeser et al., 2001, Glaeser, 2011).

This paper contributes to the literature by documenting internal mobility patterns across the entire universe of 8,202 Italian municipalities over the 2012–2022 period, and by examining the role of economic and non-economic factors in shaping bilateral internal mobility flows before and after the COVID-19 pandemic. Using registry data from the *Elementary Data Analysis Laboratory* on changes of residence by education level and municipality type, the paper provides novel evidence on the heterogeneous effects of internal migration, with a particular focus on the interaction between movers' educational attainment and the urban–rural context of origin.

Building on an empirical framework grounded in a Random Utility Model (RUM), we estimate the influence of economic and non-economic factors at the destination level on skill- and urbanization-specific bilateral mobility flows across more than 700 millions potential corridors between Italian municipalities. Given the prevalence of empty corridors, we employ a Poisson Pseudo-Maximum Likelihood (PPML) estimator. The model includes origin municipality-year, destination, and origin-nest fixed effects to control for origin-specific time-varying factors and to account for the potential substitutability among similar destinations (Beine et al., 2016, 2025).

Regarding the descriptive evidence, our novel findings show that, in aggregate, internal

[1] Cantoni and Pons (2022) shows that individual observable characteristics accounts for a substantial shares of the variability of individual preferences in the US context, such as voting preferences.

mobility flows have been largely stable in Italy, with low-skill individuals accounting for the majority of it across Italian municipalities. However, mobility among college-educated individuals has slightly increased, while it has remained relatively stable for low-skill movers. Residents of Southern regions and suburban areas exhibit a higher propensity to relocate, although most internal mobility flows occur within the same NUTS-2 region.

Our estimated results on the determinants of internal mobility flows yield three key findings. First, consistent with Diamond (2016), we identify an education-specific gradient: low skill movers are more influenced by economic factors, whereas high skill movers respond more strongly to non-economic factors, such as amenities. Second, the urban–rural divide amplifies this pattern: the influence of economic (non-economic) factors is stronger for low skill (high skill) individuals moving from rural areas compared to those from urban areas. Third, in the post-COVID-19 period, economic factors at destination have become less relevant in shaping residential choices, while non-economic factors have gained importance (Peri and Zaiour, 2023).

This paper contributes to two main strands of the literature. First, it adds novel empirical evidence to the growing body of work on internal mobility trends and dynamics (Bell et al., 2015, De la Roca, 2017, Basso and Peri, 2020, Alvarez et al., 2021, Jia et al., 2023, Olney and Thompson, 2024, Bellodi et al., 2024). In contrast to the majority of existing studies — particularly those focused on Italy (Piras, 2017, 2021) — we are the first to provide skill-specific insights at the municipal level. Second, by examining the determinants of mobility, we show the presence of an education gradient, which is further shaped by an urban–rural divide. Additionally, we show how a major shock like the COVID-19 pandemic altered the influence of destination-specific pull factors.

Second, our paper provides novel insights on the role and interaction of individual characteristics, such as education and urban-rural residence, in shaping individual residential choices.[2] While the role of education in shaping mobility has been well documented (e.g., Grogger and Hanson, 2011, Diamond, 2016, De la Roca, 2017), and the urban-rural divide has been explored separately in internal migration studies (e.g., Selod and Shilpi, 2021, Choumert-Nkolo and Le Roux, 2024), our findings show that the educational gradient shaping migration choices is amplified by the urban-rural context of origin.

The remainder of the paper is structured as follows. Section 2 describes the data sources and presents stylized facts on skill-specific internal mobility patterns, along with economic and non-economic characteristics at the municipal level. Section 3 outlines the theoretical framework and its empirical counterpart, discussing key econometric challenges. Section 4 presents the main empirical findings, and Section 5 concludes.

[2]Studies that aim to disentangle the role of individual characteristics from contextual factors in explaining spatial variation in preferences and outcomes find that individual attributes account for a substantial share of this variation (e.g., Card et al., 2013, Chetty et al., 2014, Finkelstein et al., 2016). For example, Cantoni and Pons (2022) shows that individual characteristics explain 63% of the variability in voter turnout in the U.S. context.

2 Data and Stylized Facts

In this section we present our data sources, as well as providing descriptive evidence covering the universe of Italian municipalities between 2012 and 2022. Section 2.1 describes our source of skill-specific internal bilateral flows of Italian citizens, and provides facts of its evolution and geographical distribution. Section 2.2 outlines the economic and non-economic characteristics of Italian municipalities that may influence individuals' mobility choices.

2.1 Skill-Specific Internal Mobility

The main focus of our study is the analysis of the skill-specific determinants of internal mobility choices of Italian residents. To this end, we were granted access to confidential data gathered by the *Elementary Data Analysis Laboratory* (hereafter ADELE), collected by the Italian National Statistics Institute (ISTAT). To the best of our knowledge, this dataset provides the most detailed and fine-grained information (i.e., municipal-level) of the skill-specific mobility of residents in the Italian context.

The administrative information available from ADELE comes from the annual collection of "Registrations and cancellations to the registry for transfer of residence" (ISCAN), carried out by ISTAT. Registrations represent individuals who register their residence to a municipality, therefore capturing an inflow of new residents. Cancellations, instead, refer to those who have canceled their residence from a municipality, therefore capturing the outflows from that specific municipality. To better relate with the existing literature, we will refer to the municipality where individuals cancel their residence as *origin*, while we define the new municipality of residence as *destination*. Using the ADELE data, we can therefore construct comprehensive matrices of bilateral mobility flows between the 8,202 Italian municipalities that existed between years 2012-2022. Given our interest in understanding the drivers of internal mobility patterns (Jia et al., 2023), we exclude from our sample flows associated to movement from or to abroad.

As previously mentioned, one of the distinctive features of the ADELE database is the possibility of constructing disaggregated matrices based on respondents' characteristics. Concerning education, ADELE collects the educational attainment of Italian movers, distinguishing them between those that have a tertiary education degree (hereafter, *high skill*) and those who have an high-school or lower degree (hereafter, *low skill*).[3] Therefore, we construct the yearly skill-specific bilateral flow from each municipality $i \in I$ to each municipality $j \in J$, which is calculated as the total number of persons who cancel their residence in municipality i and register in municipality j in a specific year.[4]

Table 1 provides an overview of internal migration flows within Italy. The dataset encompasses over 700 million observations across 8,202 municipalities, and the descriptive

[3]Additionally, the data can be decomposed by: (a) citizenship (Italian vs. foreign), and (b) age. Data on the educational attainment of foreign-born movers are not collected.

[4]The origin-destination matrix is a squared matrix, given the fact that I is equal to J by construction.

Table 1: Summary statistics by DEGURBA level

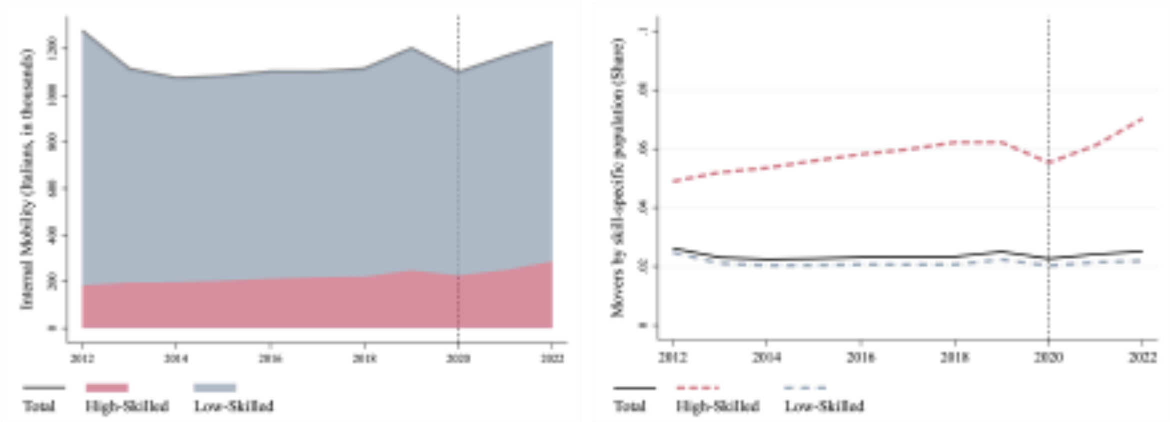
Panel A: Total Sample					
Variable	Obs	Mean	Std. Dev.	Min	Max
Total	702,579,012	0.0179	0.9764	0	1971
High Skill	702,579,012	0.0035	0.2299	0	945
Low Skill	702,579,012	0.0144	0.7937	0	1794
Income pc	702,579,012	10.4278	0.2194	9.7135	11.0910
Amenity index	702,579,012	0.0857	1.0327	-2.4471	2.5798
Number of municipalities	8,202				
Panel B: Urban					
Variable	Obs	Mean	Std. Dev.	Min	Max
Total	22,422,913	0.1702	4.1989	0	1971
High Skill	22,422,913	0.0379	1.0768	0	945
Low Skill	22,422,913	0.1322	3.3560	0	1794
Income pc	22,422,913	10.5784	0.2236	10.0137	11.0910
Amenity index	22,422,913	0.8368	1.0411	-1.7588	2.4350
Number of municipalities	256				
Panel C: Suburban					
Variable	Obs	Mean	Std. Dev.	Min	Max
Total	231,228,091	0.0276	1.0417	0	1220
High Skill	231,228,091	0.0051	0.2086	0	221
Low Skill	231,228,091	0.0225	0.8652	0	1049
Income pc	231,228,091	10.5152	0.2010	9.7144	11.0910
Amenity index	231,228,091	0.5403	0.9444	-2.3358	2.4513
Number of municipalities	2,680				
Panel D: Rural					
Variable	Obs	Mean	Std. Dev.	Min	Max
Total	448,928,008	0.0052	0.2262	0	311
High Skill	448,928,008	0.0009	0.0485	0	50
Low Skill	448,928,008	0.0043	0.1923	0	280
Income pc	448,928,008	10.3754	0.2103	9.7135	11.0910
Amenity index	448,928,008	-0.1860	0.9731	-2.4471	2.5798
Number of municipalities	5,266				

Notes: Authors' elaborations. The table reports the number of observations, means, standard deviations, minimum, and maximum values for each variable across the total sample and by DEGURBA classification: Urban (Panel B), Suburban (Panel C), and Rural (Pandel D). The count of municipalities includes all municipalities that existed at any time between 2012 and 2022. Income per capita values are winsorized at the 0.1st and 99.9th percentiles to reduce the influence of extreme outliers. The reported means for Income per capita and the Amenity index refer to the municipalities of origin and are expressed using the inverse hyperbolic sine (arcsinh) transformation.

statistics reveal distinct mobility patterns. When considering the total sample (Panel A), the mean migration flow by bilateral corridor for low skill individuals (0.0144) is consistently higher than that for high skill individuals (0.0035), suggesting that a significant proportion of internal mobility in Italy is driven by individuals with lower skill sets.[5] When considered alongside the degree of urbanisation of Italian municipalities (Panels

[5]The numbers are below unity since we measure the average bilateral migration flow over the full square matrix origin-destination.

Figure 1: Evolution of Internal mobility across Italian municipalities



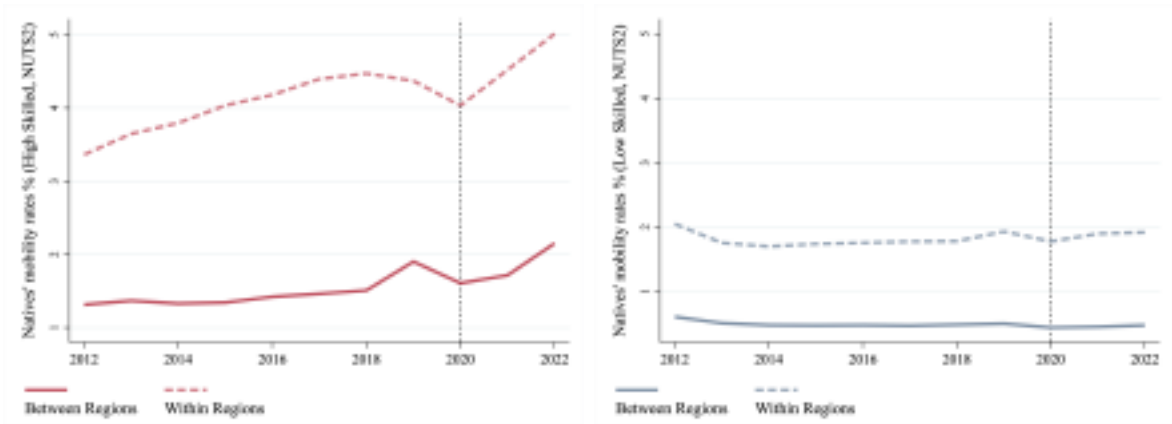
(a) Number (b) Share

Notes: Authors' calculations based on ISTAT data. Panel (a) shows the number of movers for total (black), high skill (red), and low skill (blue). Panel (b) shows the share of movers relative to group-specific population for total (black, solid line) high skill (red, dashed), low skill (blue, dash-dot). The vertical line indicates 2020, the year of the outbreak of COVID-19.

B, C and D), these skill-based disparities persist. In urban areas, despite comprising a significantly smaller number of municipalities, the mean migration flow for low skill individuals (0.1322) is higher than for high skill individuals (0.0379). A similar trend is observed in suburban areas, where low skill migration (0.0225) outweighs high skill migration (0.0051). Even in rural areas, which generally experience lower mobility, the flow of low skill individuals (0.0043) is still more pronounced than the flow of high skill individuals (0.0009).

In Figure 1, we show the evolution of Italian citizens' internal mobility over time. Figure 1(a) displays the total and skill-specific number of movers in thousands. Figure 1(b), on the other hand, shows the group-specific shares of the two groups (high skill vs. low skill) over the population residing in the origin municipality with the same level of education. These figures reveal some interesting empirical facts. First, out of the 1.1 millions of Italians that change residence every year on average, only 17% of them are highly-skilled. Therefore, the general trends are influenced by the movements of low skill residents, who represent the majority. However, the relative mobility within each skill group shows a marked difference. Once adjusted by the skill-specific size of the population, Figure 1(b) reveals that mobility patterns for low skill residents remain fairly constant, with only about 2% relocating each year. In contrast, the mobility rate for high skill individuals is higher and has shown an upward trend over time. These patterns are in line with the international migration literature, where returns from migration or relocation are generally higher for highly educated individuals (Clemens and Mendola, 2024), and highlight the importance of examining mobility patterns by skill group. Lastly, it can be seen that the COVID-19 pandemic influenced differently the skill-specific mobility trends.

Figure 2: Mobility between- and within-NUTS2 regions



(a) High skill (b) Low skill

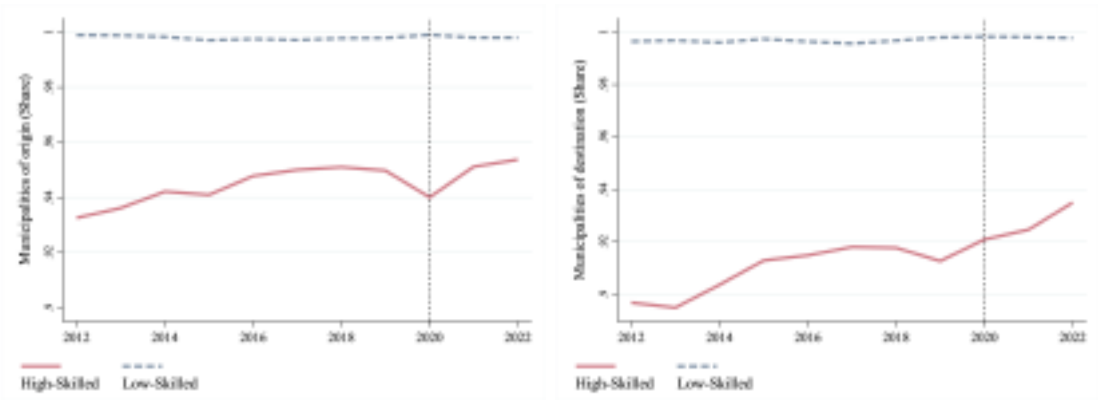
Notes: Authors' elaboration based on ISTAT data. The figures show the percentage of Italians moving between and within regions (NUTS2), relative to the resident population, in each year by education level. The vertical line indicates 2020, the year of the outbreak of COVID-19.

While the share of high skill movers increased after the outbreak of the pandemic, the share of low skill ones remained more or less constant, neither increasing nor decreasing significantly compared to previous years. Overall, these evidence suggest that the response to shocks may be different across skill-groups.

To explore the skill-specific distinctive features of mobility patterns, Figure 2 decomposes the evolution of the change of residence within NUTS2 regions (i.e., short distance movements) and between NUTS2 regions (i.e., long distance movements). As in the US context (Basso and Peri, 2020), Figure 2 shows that for both high skill (a) and low skill (b) movers, the mobility rate was consistently higher within regions (dashed line), nearly twice as large as between-region moves (solid line). Figure 2(b) reveals that for low skill movers, mobility trends remained stable throughout the period, regardless of intra- or inter-regional distinctions. Concerning high skill movers, Figure 2(a) suggests that the positive trend is mainly driven by the rising intra-region change of residence. Additionally, high skill mobility rose more sharply than low skill mobility in the post-pandemic period, for both between- and within-region moves.

To analyze the scope of skill-specific mobility and the number of municipalities involved, Figure 3 plots the evolution of the share of municipalities that experienced at least one skill-specific cancellation (a) or registration (b). Overall, the share of municipalities affected by skill-specific mobility remains high, close to one for low skill movers, indicating that almost all Italian municipalities were involved in low skill movements throughout the period in analysis. Concerning high skill individuals, not all Italian municipalities are involved in their mobility choices. On average 5% of municipalities of origin did not experience any cancellation of high skill citizens, largely due to smaller populations of

Figure 3: Share of municipalities with at least one registered or cancelled individual



(a) Origin

(b) Destination

Source: Authors' elaboration based on ADELE data. The figure shows the share of municipalities with at least one cancelled individual (Panel a) and at least one registered individual (Panel b), for high skill (red, solid line) and low skill (blue, dashed line). The vertical line indicates 2020, the year of the outbreak of COVID-19.

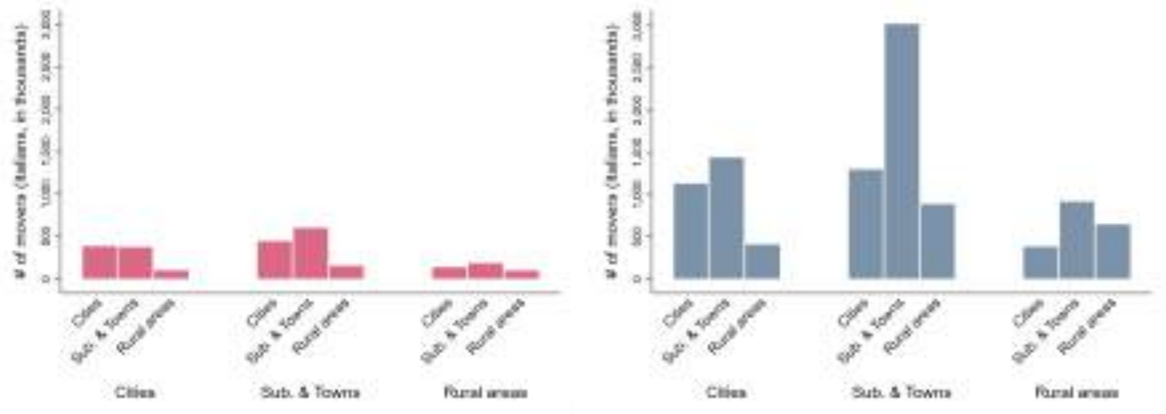
tertiary-educated individuals, and around 10% were not experiencing any inflow of high skill individuals in 2012. Nonetheless, the number of destination municipalities involved in high skill movements has grown, rising from around 90% in 2012 to nearly 94% in 2022, suggesting that over the past decade, more than 300 municipalities have become new destinations for tertiary educated movers.[6]

Additionally, Figure 4 provides a descriptive overview of the total number of bilateral moves by origin–destination urbanisation type, divided into high skill and low skill individuals. For high skill movers (Panel a), the most common flows are between suburbs, followed by suburbs to cities and cities to cities. This suggests that more urbanised and intermediate urban areas are key nodes for high skill internal mobility. Flows involving rural areas as either the origin or the destination are substantially less frequent. Similarly, low skill mobility (Panel b) is more frequent and more skewed towards town-to-town and town-to-city flows. Moves originating from rural areas are more common among low skill individuals than among their high skill counterparts, particularly when the destination is a town.

Another aspect that we consider in our empirical analysis is that internal mobility in Italy has historically originated to a significant extent from Southern Italy and the islands (collectively referred to as the Mezzogiorno) (Etzo, 2011, Piras, 2017). Using information available from ADELE, between 2012 and 2022 there were approximately 1.27 million

[6]Figure A-1 in the Appendix presents the distribution of the average share of skill-specific inflows and outflows. Interestingly, while low skill flows involve mainly the same NUTS 1 macro regions both in terms of inflows and outflows. In contrast, high skill flows exhibit a clearer geographical pattern: outflows predominantly originate from the South and Insular regions, while inflows of high skill movers are concentrated in the Northeast and Northwest macro regions.

Figure 4: Internal mobility by skill level and origin degree of urbanisation



(a) High skill

(b) Low skill

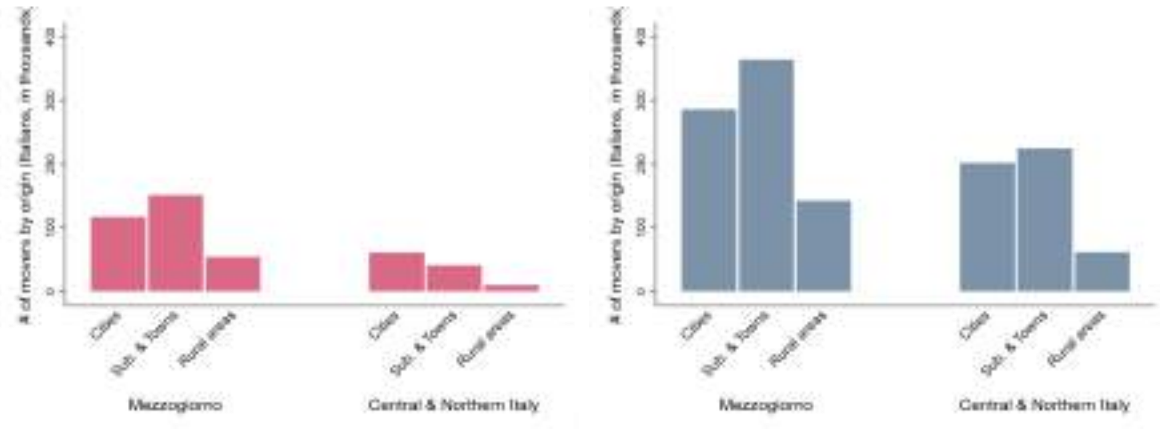
Notes: Authors' elaborations based on ADELE data. The figures illustrate the total number of high skill (Panel a) and low skill (Panel b) movers by degree of urbanisation of origin and destination.

transfers from the Mezzogiorno to the Center-North Italy, compared to approximately 675 thousand migrations in the opposite direction. These dynamics are part of a well-established historical trend, widely documented in the literature (Piras and Melis, 2007, Pugliese, 2002, SVIMEZ, 2015). Pugliese (2002) reported that between 1951 and 1975, approximately 3.71 million people moved from the Mezzogiorno to the Center-North Italy, while 1.36 million moved in the opposite direction. Piras and Melis (2007) updated the analysis for the period 1971-2002, recording 3.88 million migrations from the Mezzogiorno to the Center-North, compared to 2.34 million movements in the opposite direction. In the following period, between 2001 and 2014, approximately 1.67 million people left the southern regions to move to the center-north, while less than one million moved in the opposite direction (SVIMEZ, 2015). The phenomenon is even more pronounced when considering university graduates. In the period 2012-2022, approximately 321 thousand Italian graduates left the Mezzogiorno to move to the Center-North, while just over 111 thousand made the reverse migration.

Figure 5 illustrates the distribution of internal movers by skill level and origin characteristics, specifically macro-area (Mezzogiorno vs. Central and Northern Italy) and degree of urbanisation (Urban, Suburban and Rural areas). For each macro-area, we report the number of individuals moving to the other macro-area, i.e. from the Mezzogiorno to the Centre-North and vice versa. The figure confirms that the volume of movers is significantly higher for both high- and low skill individuals when the origin is the Mezzogiorno. Suburban areas and cities are the main sources of migration, with the former generally being the most common origin for both skilled and unskilled workers.

Finally, Figure 6 delves into the destination municipality's characteristics by skill group before (a) and after (b) the COVID-19 pandemic. Specifically, it shows the distribution

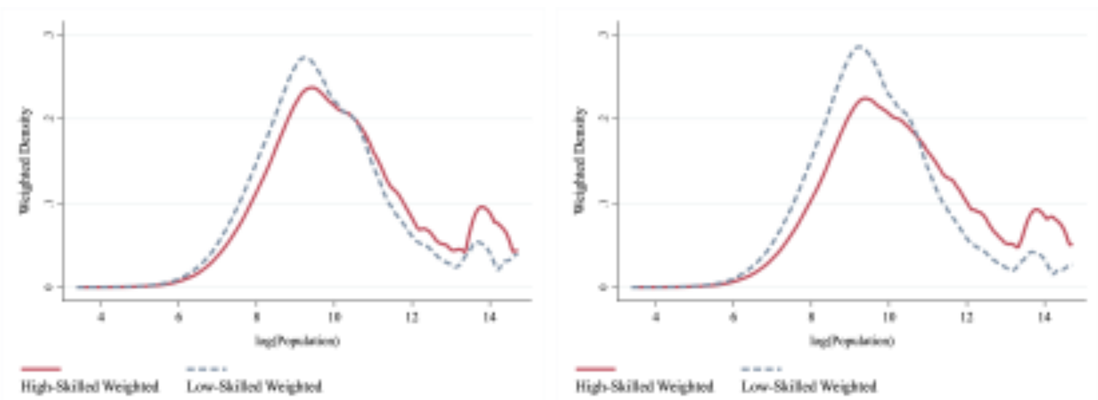
Figure 5: Internal mobility between macro-areas, by skill level and origin degree of urbanisation



(a) High skill (b) Low skill

Notes: Authors' elaborations based on ADELE data. shows the total number of highly skilled (Panel a) and low skill (Panel b) individuals who moved between macro-areas between 2012 and 2022. The data is disaggregated by the origin area (Mezzogiorno vs. Central and Northern Italy) and the degree of urbanisation of the origin municipality. For each macro-area, only flows to the other macro-area are included.

Figure 6: Mobility by population size of destination municipalities, before and after COVID-19



(a) Before (b) After

Notes: Authors' elaboration based on ADELE data. The figures show the kernel-densities of the (log) population of the destination municipalities, weighted by the inflow of high skill (red, solid line) and low skill (blue, dashed line) individuals. Panel (a) shows the densities for the period before the COVID-19 pandemic. In Panel (b), densities are shown for the period after the outbreak of the COVID-19 pandemic.

of municipalities by population, weighted by the average inflow of low- and high skill residents. Both distributions reveal a bimodal pattern, with peaks for both skill groups centered around mid-sized towns (averaging 40,000 inhabitants) and large metropolitan areas. However, metropolitan areas attract proportionally more tertiary-educated than low-educated movers. Comparing distributions before and after the 2020 pandemic, low skill movers increasingly concentrated in mid-sized towns, while high skill movers shifted toward larger metropolitan areas.

2.2 The Drivers of Internal Mobility

As we will clarify in the theoretical framework in Section 3.1, individuals' mobility choices can be described as a function of the potential gains across alternative destinations. Therefore, we collect data on economic and non-economic conditions of the universe of Italian municipalities to proxy the attractiveness of each potential destination choice. This approach follows the framework proposed by Diamond (2016), who distinguishes between economic and non-economic drivers of internal mobility.

Economic – We focus on income per capita at the municipal level as proxy to capture the main economic driver.[7] The Ministry of Economy and Finance (MEF) provides data on income per capita at the municipal level annually, based on information from Personal Income Tax returns (IRPEF). The data include total declared income, categorized into employment, self-employment, pensions and other types of taxable income, in relation to the number of taxpayers in each municipality.[8]

In Table 1, we present summary statistics of income per capita across the Italian municipalities in our sample. When municipalities are distinguished according to their degree of urbanisation, some differences emerge. Urban areas have the highest mean income per capita, suggesting that these areas tend to be more economically prosperous. Suburban areas follow closely behind, reflecting their economic ties and proximity to urban centres. In contrast, rural areas have the lowest mean income per capita. This consistent socioeconomic gradient implies that less urbanised regions generally have lower average incomes and potentially fewer economic opportunities than Italy's more dynamic urban and peri-urban areas.

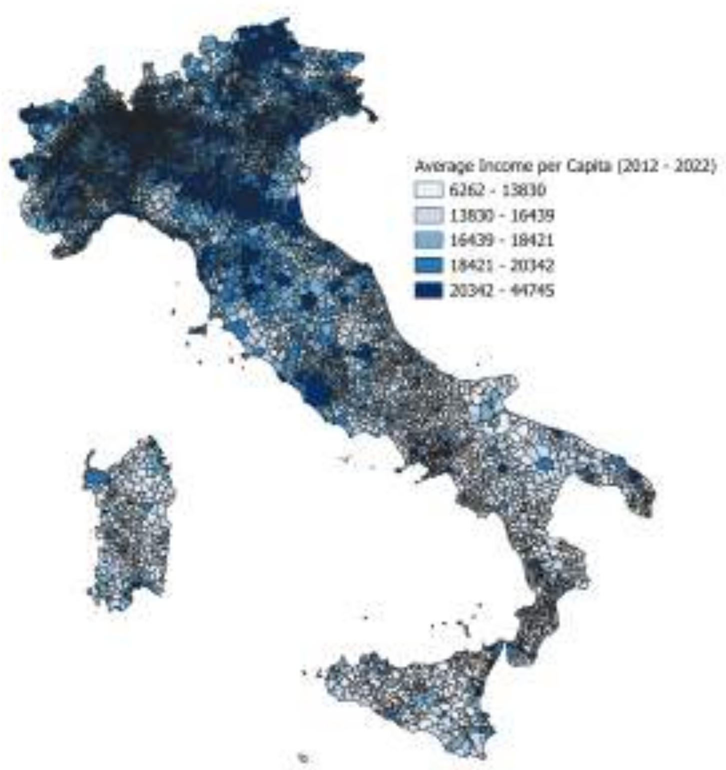
Figure 7 shows the spatial distribution of the average income per capita, over the period 2012–2022, at municipal level and reveals a rather stark North–South divide, with municipalities in Northern and Central Italy consistently having higher income levels than those in the South and Islands.

In addition, Figure 8 illustrates the evolution of average income per capita over time according to the two dimensions, which will be relevant for our empirical analysis: NUTS-1 macro-regions (Panel a) and groups of municipalities according to their degree of ur-

[7] In the international migration literature, GDP per capita has been used as a proxy (e.g., Grogger and Hanson, 2011, Beine et al., 2016).

[8] Over the full sample of observations, we have 0.83% of missing values. In handling these gaps, we apply the following approach: (i) when feasible, we replace missing observations with estimates based on the trend of values present in other years; (ii) if unavailable, we approximate income per capita by averaging values from neighboring municipalities.

Figure 7: Average Income per Capita (2012-2022)



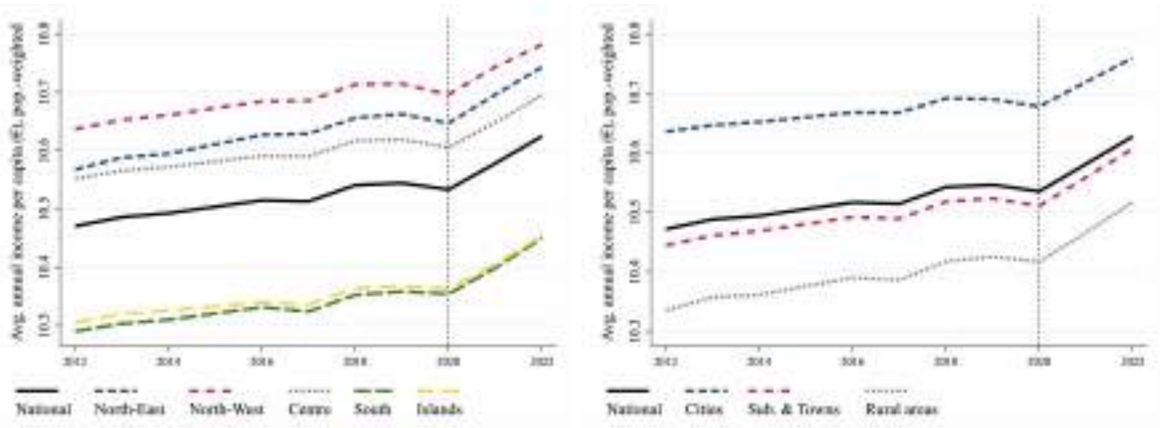
Notes: Authors' calculations based on MEF data. The figure illustrates the distribution of average values of income per capita for the period 2012-2022 over the entire Italian territory.

banisation (Panel b).[9] When examining the NUTS1 classification, although all areas experienced an average positive trend over the decade, the regional rankings remained stable. The North-West and North-East consistently led, while the South and the Islands lagged behind. When municipalities are grouped according to their degree of urbanisation, the pattern highlights heterogeneity across the different groups, with urban areas showing average income levels well above the national average, as well as compared to less urbanised areas.[10]

[9]We will use this information in order to construct the origin-destination nest, to capture the degree of sustitutability across destination municipalities with similar characteristics (Beine et al., 2025). NUTS 1 macro regions are defined as follows: Northeast (Emilia-Romagna, Friuli-Venezia Giulia, Trentino-Alto Adige, Veneto), Northwest (Liguria, Lombardia, Piemonte, Valle d'Aosta), Centre (Toscana, Umbria, Marche, Lazio), South (Abruzzo, Molise, Campagnia, Basilicata, Puglia, Calabria), and Islands (Sicilia, Sardegna).

[10]We use the Degree of Urbanisation (DEGURBA) classification, developed by Eurostat, to classify municipalities according to their level of urbanisation. This system categorises each local administrative unit (LAU) across EU member states as either cities, suburbs and towns or rural. Specifically, this classification uses a harmonised methodology involving 1 km^2 population grid cells, and categorises municipalities according to the proportion of their population living in high-density grid cells. Each municipality is therefore assigned to one of the following groups: (i) Urban areas (densely populated

Figure 8: Income per capita time trends by NUTS 1 regions and degree of urbanisation



(a) NUTS 1 regions (b) Degree of Urbanisation

Notes: Authors' elaborations based on MEF data. The figures illustrates the time trends for average annual income per capita, weighted by population. Panel (a) shows the national average trend (solid black line) and the trends for NUTS1 regions: North-East (dashed blue), North-West (dash-dotted red), Centre (short dashed grey), South (long dashed green) and Islands (long dash-dotted yellow). Panel (b) shows the trends for the national average (solid black line) and for different urbanisation classes: Urban areas (dashed blue), suburban areas (dash-dotted red) and rural areas (short-dashed grey). The vertical line indicates 2020, the year of the outbreak of COVID-19.

Besides income differences, housing market conditions are a key driver of internal economic mobility (Olney and Thompson, 2024, Diamond, 2016). While our primary analysis focuses on income per capita as the main economic driver, in Appendix A.2 we discuss the role of housing market, showing the spatial distribution (Figure A-2) and time trends (Figure A-3 and Figure A-4) in purchase and rental prices across Italian municipalities. Furthermore, Figure A-5 in the Appendix provides insight into the correlation between average income levels and housing market prices. While there is a positive correlation between average annual income per capita and both purchase and rental prices, some municipalities display relatively higher housing prices than would be expected based on average income levels, echoing findings from prior studies (Gallin, 2006).

Non-economic – The literature has shown that local services and quality of life also play a crucial role in migration choices between alternative destinations, making some cities more attractive to potential residents (Florida, 2002, Chen and Rosenthal, 2008, Diamond, 2016).[11] Many of these services depend on factors exogenous to the model under

areas where at least 50% of the population lives lives in urban centers), (ii) Suburban areas (areas of intermediate density where less than 50% of the population lives in an urban centre and at least 50% of the population lives in an urban cluster), (iii) Rural areas (areas with a low population density where more than 50% of the population lives in rural areas).

[11]From an econometric point of view, failing to control for amenities in a regression of migration decisions may introduce a correlation between the error term and the economic variable, leading to

Table 2: Summary Statistics of Amenity Variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Artistic and entertainment activities per 1,000 residents	104,096	0.278	0.504	0.000	5.650
Sports activities per 1,000 residents	104,096	0.421	0.895	0.000	12.346
Eating and drinking activities per 1,000 residents	104,096	5.618	4.688	0.000	56.995
Accessibility index: railway	104,096	11.446	22.373	0.001	227.937
Bank branches per 1,000 residents	104,096	0.428	0.474	0.000	4.348
Hospital beds per 1,000 residents	104,096	0.926	5.124	0.000	87.599
Court cases for common crimes per 1,000 residents	104,096	3.078	1.476	0.320	11.087
Court cases for minor crimes per 1,000 residents	104,096	18.465	6.052	5.576	45.664
Cars below Euro 4 standard (share)	104,096	0.450	0.149	0.019	0.821
Recycling rate	104,096	0.547	0.233	0.000	0.933
Education sector employment per 1,000 workers	104,096	4.230	12.763	0.000	209.498
Average Invalsi test score	104,096	62.169	8.546	7.018	94.118
Unemployment rate	104,096	0.100	0.051	0.004	0.392
High-tech sector specialization	104,096	0.017	0.037	0.000	0.473
Big business density per 1,000 residents	104,096	0.024	0.094	0.000	1.220

Notes: Authors' elaborations. All variables were winsorized at the 99.9th percentiles to reduce the influence of extreme outliers. See Table B-2 in online Appendix for detailed description of amenity data and their data sources.

consideration, while others are endogenously adapted to the characteristics of the resident population (Diamond, 2016). To capture the presence of services and quality of life at the local level, we adopt the approach proposed by Diamond (2016), which employs a two-stage Principal Component Analysis (PCA) to construct a synthetic amenities index. This index is designed to reflect the diversity and availability of services within each municipality. In the first stage, we apply PCA to 15 local-level variables—closely aligned with those used in the original study—and extract the first six principal components.[12] Table 2 reports summary statistics for these variables, while Table B-2 in the Online Appendix provides measurement details. The resulting factors, presented in Table 3, include retail, services, crime, environment, education, and jobs, and represent the main dimensions of local amenities.

The retail index reflects the presence of recreational and artistic activities at the municipal level, such as restaurants, bars, cinemas and theaters, capturing the economic and social vibrancy of an area and the availability of leisure opportunities for residents. Similarly, the service index assigns positive weights to the railway network, the number of bank branches and hospital beds, capturing both physical infrastructure and access to essential services for residents.[13] The crime index assigns positive and equal weights to both common and minor crimes, capturing crime in a broader sense. The environment

biased estimates (Selod and Shilpi, 2021).

[12]The dataset by Amaddeo et al. (2024) offers an extensive coverage of variables at the municipal and NUTS-3 levels for Italy.

[13]Unlike the amenities index constructed by Diamond (2016), we chose to include additional services beyond public transportation.

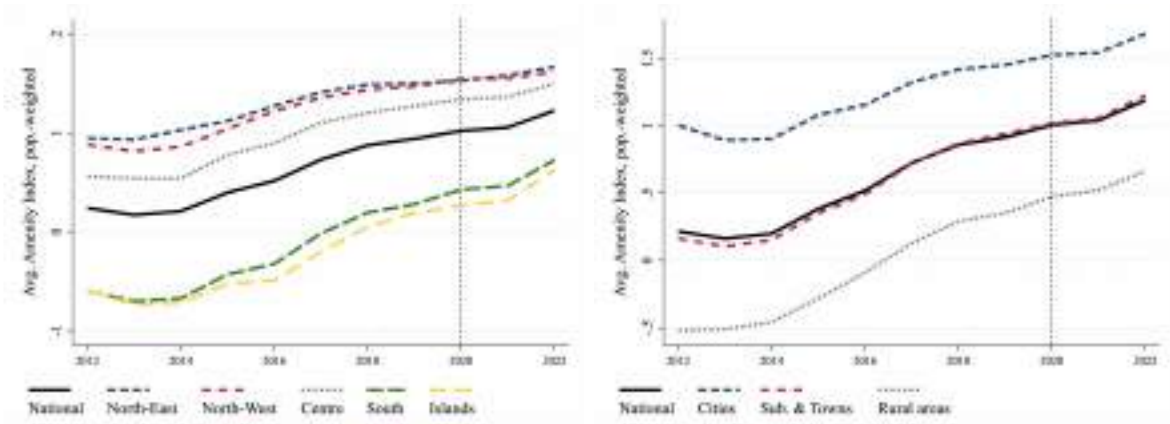
Table 3: Principle Component Analysis for Amenity Indices

	Loading	**Unexplained variance**
Panel A. Retail index		
Artistic and entertainment activities per 1,000 residents	0.318	0.872
Sports activities per 1,000 residents	0.698	0.379
Eating and drinking activities per 1,000 residents	0.642	0.476
Panel B. Service index		
Accessibility index: Railway	0.594	0.593
Bank branches per 1,000 residents	0.450	0.766
Hospital beds per 1,000 residents	0.667	0.487
Panel C. Crime index		
Court cases for common crimes per 1,000 residents	0.707	0.190
Court cases for minor crimes per 1,000 residents	0.707	0.190
Panel D. Environment index		
Recycling rate	0.707	0.223
Cars below Euro 4 standard	-0.707	0.223
Panel E. Education index		
Education sector employment per 1,000 workers	0.707	0.490
Average Invalsi test score	0.707	0.490
Panel F. Job index		
Unemployment rate	-0.550	0.627
High-tech sector specialization	0.580	0.584
Big business density per 1,000 residents	0.601	0.553
Panel G. Overall amenity index		
Retail index	0.191	0.920
Service index	0.404	0.653
Crime index	-0.418	0.627
Environment index	0.537	0.387
Education index	0.305	0.802
Job index	0.492	0.485

Notes: Authors' elaborations. All amenity data are transformed using the inverse hyperbolic sine (arcsinh) function. See Table B-2 in online Appendix for detailed description of amenity data and their data sources. Panels A–F report weights used in each subindex construction. Panel G reports loadings on each subindex to create overall amenity index.

index, on the other hand, assigns positive weights to the percentage of recycled waste and negative weights to the percentage of vehicles that do not comply with Euro 4 standards. The education index assigns positive weights to both the number of people employed in the education sector and the average test scores in Italian from the National Institute for the Evaluation of the Education System (INVALSI), reflecting the importance of human capital and educational outcomes. Finally, the job index assigns positive weights to both specialization in the high-tech sector and the presence of large enterprises, as indicators of a dynamic and attractive labour market. In particular, the presence of high-tech

Figure 9: Amenity index time trends by NUTS 1 regions and degree of urbanisation



(a) NUTS 1 regions

(b) Degree of Urbanisation

Notes: Authors' elaborations. The figures illustrates the time trends for the average level of the PCA-derived amenity index. Panel (a) shows the national average trend (solid black line) and the trends for NUTS1 regions: North-East (dashed blue), North-West (dash-dotted red), Centre (short dashed grey), South (long dashed green) and Islands (long dash-dotted yellow). Panel (b) shows the trends for the national average (solid black line) and for different urbanisation classes: Urban areas (dashed blue), suburban areas (dash-dotted red) and rural areas (short-dashed grey). The vertical line indicates 2020, the year of the outbreak of COVID-19.

firms suggests the availability of more skilled and challenging job opportunities, while, as expected, the unemployment rate receives a negative weight.

Once the first six factors have been obtained, we proceed to the second stage, where these category indices are combined into an overall index, extracted through a second PCA. The validity of the index is supported by the sign of the coefficients, as all categories display positive weights except for the crime index. Following Diamond (2016), we therefore assume that a one-dimensional index can effectively represent the set of services that relates with skill-specific mobility choices.

Table 1 provides insights into the variation of the amenity index across all municipalities. This index clearly shows variations in urbanisation levels across municipalities. Urban areas have the highest mean amenity index (0.8368), suggesting that cities generally have many features that enhance quality of life. Suburban areas have an average amenity index that is lower than that of urban areas (0.5403), which is consistent with their intermediate position in the urbanisation hierarchy. In contrast, rural areas display a negative mean Amenity Index (-0.1860), indicating a relative scarcity or lower quality of amenities in these less densely populated regions. These patterns suggest that the availability and quality of amenities vary according to the level of urbanisation and could significantly influence residential mobility choices.

Furthermore, as with income per capita, we descriptively analyze the dynamics of the Amenity index using the same nests that we will adopt in the empirical analysis. Figure

9 illustrates the evolution of the municipality-level index across NUTS1 macro-regions and urbanization groups. In Panel (a), a substantial ad persistent North-South divide is evident with municipalities in the Nort-East and North-West consistently exhibiting the highest average amenity levels, followed by those in the Centre. In contrast, the South and Islands lag behind. While all areas show an upward trend over the period 2012-2022, the gap between macro-regions remains consistent. The national average (black line) increases steadily, suggesting a general improvement in levels.[14] Panel (b) shows consistent patterns across urbanization classes: urban areas have the highest average amenity levels, followed by suburban and then rural areas. Although rural areas start from a lower base, they show steady improvement over time, narrowing the gap—though the overall ranking remains unchanged. The COVID-19 pandemic in 2020 does not appear to cause any noticeable shift in amenity trends, either nationally or across urbanization classes.

3 Empirical Framework

In Section 3.1, we introduce the benchmark theoretical model that describes individuals' mobility choices. After discussing the assumptions and challenges involved in modeling such behavior, Section 3.2 outlines the empirical strategy and estimation techniques used to estimate the relevant parameters.

3.1 Theoretical framework

We follow the literature on optimal location choices (Jia et al., 2023) by adopting the Random Utility Maximization (RUM) framework to describe individual discrete location-choice problems (Beine et al., 2016, Bertoli et al., 2020, Beine et al., 2025).[15] A representative individual n's decision to change her residence, and to which alternative municipality, depends on the available set of potential residential locations j ($j = 0, 1, \ldots, J$). The current municipality of residence is included in the choice set (i.e., the option to stay) and is indexed as 0, with 1 to J representing potential new municipalities of residence. We aim to describe the probability that individual n selects destination j, given the available set of choices C_n: $P_n(j \mid C_n)$. Initially, we assume that the set of location choices (i.e., internal mobility across Italian municipalities) is identical for all individuals, so $C_n = C$ for any individual n. This assumption will be relaxed later.

The RUM model suggests that individuals seek to maximize their utility across all potential destination choices. The utility gained by individual n from selecting destination

[14] Figure A-7 in the Online Appendix provides a spatial representation of the average amenity index across Italian municipalities.

[15] An alternative way to model migration choices is through a spatial equilibrium model of local market aggregates, where agents respond to disequilibrium conditions, such as persistent wage gaps across locations (Jia et al., 2023). While this approach is useful for estimating the presence of barriers and frictions to migration, it comes with the cost of relying on a series of general equilibrium assumptions.

j as a residence is denoted by U_{jn}, which can be additively decomposed into a deterministic and observable component V_{jn}, and a stochastic and unobserved component ϵ_{jn}:

$$U_{jn} = V_{jn} + \epsilon_{jn}. \tag{1}$$

The deterministic component describes all the observable municipality-specific characteristics that drives the mobility choice of the individual n (Beine et al., 2025). We can characterize the deterministic component of equation (1) as follows:

$$V_{jn} = \Gamma \mathbf{X_{jn}} + \theta_{k(j)}. \tag{2}$$

Equation (2) represents the utility gain for individual n when moving to destination $j = 0, \ldots, J$ generated by municipality observable characteristics. The vector $\mathbf{X_{jn}}$ includes the characteristics of municipality j that determine its attractiveness. In our study, we consider municipality-specific attractiveness factors such as average income per capita and an amemities index (Diamond, 2016). Additionally, we account for dyadic factors between destination j and individual n's current municipality of residence, such as geographical distance. The vector of parameters Γ captures the influence of destination-specific characteristics on the probability of choosing municipality j as a residence. The vector $\theta_{k(j)}$ represents nest-specific parameters, capturing the average attractiveness of municipalities that share similar relative appeal for individual n (Bertoli and Fernández-Huertas Moraga, 2015).

Defining the stochastic component of the RUM has been one of the major challenges in discrete choice models related to migration (Bertoli and Fernández-Huertas Moraga, 2013, Beine et al., 2016). For tractability, many studies assume that the parameter ϵ_{jn} is independent and identically distributed across destinations. Moreover, it is often assumed to follow a Type 1 Extreme Value Distribution (EVD), which satisfies the assumptions of a traditional logit model (McFadden, 1973). This assumption implies that individuals evaluate all potential destinations (including their current residence) equally, so any unexpected shock in one destination would equally affect the likelihood of migrating to other destinations. However, this assumption is rarely validated across various applications of discrete choice models (Train, 2009), particularly in the context of migration choices (Bertoli and Fernández-Huertas Moraga, 2013, Beine et al., 2025). Individuals typically evaluate their current residence and alternative destinations differently (Ortega and Peri, 2013). Furthermore, some potential destinations share characteristics that group them in the eyes of the agent when facing migration decisions (Bertoli and Fernández-Huertas Moraga, 2013).

We follow the more general approach proposed by Beine et al. (2025), which accommodates more complex patterns among the error terms. By adopting a Multivariate Extreme Value model, compatible with the RUM framework, the choice set C of potential destinations is partitioned into K overlapping sets ($k = 1, \ldots, K$). This approach introduces correlation among similar destination alternatives, making the model more flexible. While the determination of these sets, or nests, is an empirical question (further discussed in the next section), the correlation is captured by incorporating the nest-specific parameters $\theta_{k(j)}$ into the deterministic component.

Finally, we assumed that the maximization problem presented in equation (1) is identical for all individual n. However, individuals may respond differently to the characteristics of potential destinations j based on their own characteristics. Specifically, migration choices vary across skill groups (Grogger and Hanson, 2011, Beine et al., 2011). Highly educated individuals, compared to those with less education, are more attracted to amenities and tend to move to high-productivity localities (De la Roca, 2017, Clemens and Mendola, 2024). Less educated individuals, on the other hand, may face different monetary and psychological constraints, which influence their migration decisions (Mani et al., 2013, Lichand and Mani, 2020). Moreover, migration choices may be influenced by other factors linked to the municipality of residence specific characteristics. Individuals living in urban areas hold distinctive preferences compared to those in rural areas (Beckett, 2016, Henshell, 2024, Moriconi et al., 2025), due to the exposure of a more diverse environment and, on average, more economically vibrant (Glaeser et al., 2001, Duranton and Puga, 2004, Glaeser, 2011). Additionally, they may have different expectations based on the information available to them (Bertoli et al., 2020). Finally, the relevant mobility response to the COVID-19 pandemic may have been different depending by the available choice set shaped by individuals' education and municipality of residence (Kotsubo and Nakaya, 2023, Rowe et al., 2023).

Therefore, by defining that agent n can has an educational attainment s which can be either college educated (H) or less than college educated (L), and coming from a municipality m, which can be urban (U), suburban (S) or rural (R) we recast the maximization problem as follows:

$$U_{jn}^{sm} = V_{jn}^{sm} + \epsilon_{jn}^{sm}. \tag{3}$$

Our empirical approach will thus allow for heterogeneous responses across the education and place of residence gradient, both in the deterministic and stochastic components of the maximization problem.

3.2 Empirical Strategy

We follow the literature to set up the empirical counterpart of the RUM described in the previous section. This paper aligns with studies that focus on aggregate bilateral flows rather than variations in population stocks (Ortega and Peri, 2013, Bertoli and Fernández-Huertas Moraga, 2013, Guichard and Machado, 2024). This feature of our data, presented in Section 2, helps minimize potential measurement errors caused by other factors affecting local populations, such as births or deaths (Beine et al., 2016). Defining $Y_{i,j,t}^{sm}$ as the skill-specific (s) and/or urbanization at origin (m) bilateral flow from municipality i to j in year t, we describe it as follows:

$$Y_{i,j,t}^{sm} = \mathbf{F^{sm}}\left(\mathbf{X}_{i,t}, \mathbf{Z}_{j,t}, d_{i,j}\right). \tag{4}$$

The bilateral flows of Italian citizens across municipalities are modeled as a function of origin-specific ($\mathbf{X}_{i,t}$) and destination-specific ($\mathbf{Z}_{j,t}$) characteristics, as well as the distance between municipalities ($d_{i,j}$). The vectors of municipal characteristics capture factors that influence the attractiveness of municipalities. To represent the economic dimension, we consider per capita income before taxes, while for the quality-of-life dimension, we use an amenity index constructed through a two-level principal component analysis (Diamond, 2016). To exclude commuting patterns, we exclude bilateral migration corridors with a distance of less than 70 km (Biagi et al., 2011, De la Roca, 2017). For example, in the case of Italy's largest city, Rome, many people work in the capital but live in neighboring municipalities, where the quality of life may be higher and the cost of living lower.

The functional form $\mathbf{F^{sm}}$ depends on the nature of the variable of interest, $Y^{sm}_{i,j,t}$. Since 97.60% of the bilateral municipal corridors have no residential flows, estimating a linear model using OLS would result in biased and inconsistent estimates. Therefore, we use the Poisson pseudo-maximum likelihood (PPML) estimator (Silva and Tenreyro, 2006), which has been widely applied in gravity models due to its robustness in handling a large number of zeroes, various heteroskedasticity patterns, and rounding errors in the dependent variable (Silva et al., 2015, Yotov, 2024).[16] Consequently, we estimate the skill-specific general model, as presented in equation (4), as follows:

$$\begin{aligned} Y^{sm}_{i,j,t} = \; & \exp[\alpha^{sm} + \beta^{sm}_0(Z_{j,t}) + \beta^{sm}_1(Z_{j,t}) \times \eta^{Covid}_t + \lambda^{sm}_t(d_{i,j}) \\ & + \theta^{sm}_j + \theta^{sm}_{i,t} + \theta^{sm}_{i,k(j)} + \epsilon^{sm}_{i,j,t}]. \end{aligned} \tag{5}$$

Using PPML helps avoid biases inherent in the structure of the data. However, as noted by Beine et al. (2016), this choice comes with certain trade-offs. Estimating the gravity model with bilateral flows and a PPML estimator requires the inclusion of origin-year dummies ($\theta^{sm}_{i,t}$) to control for origin-specific unobserved factors, such as the number of potential migrants (Bertoli and Fernández-Huertas Moraga, 2013). The downside is that these dummies absorb all the variability from the origin-specific factors ($\mathbf{X}_{i,t}$) introduced in equation (4), preventing us from separately estimating the partial correlation between origin-specific characteristics and bilateral migration flows. Destination-specific variables are lagged by one year to account for the time required for migration decisions to respond to changing conditions (Olney and Thompson, 2024). Additionally, our vector of control variables is transformed using the inverse hyperbolic sine function (arcsinh), which resembles a logarithmic transformation but is defined at zero and for negative values (Bellemare and Wichman, 2020), as in the case of the amenity index. Consequently, the estimated coefficients $\hat{\beta}^{sm}$ and $\hat{\lambda}^{sm}_t$ in our model can be interpreted as elasticities, in line with the interpretation of log-transformed variables. Notably, we estimate a yearly-specific parameter for distance to capture the evolution of transportation networks and technology (Feyrer, 2019).

[16] Alternatively, negative binomial estimator is often employed to address overdispersion (e.g., Basile et al., 2021, 2023). Nevertheless, Blackburn (2015) demonstrate that, in panel data applications, the Poisson-like estimator remains the most robust choice in presence of count-data, specifically PPML, which is well-designed to overcome overdispersion.

In addition, while empirical evidence indicates that the COVID-19 pandemic affected both international and internal mobility (e.g., Peri and Zaiour, 2023, Rowe et al., 2023), there is less evidence on its implications for skill-specific flows and the differential effects on various economic and non-economic drivers of individuals' mobility choices. To further our understanding of the consequences of COVID-19 and to uncover potential new post-pandemic mobility patterns, we include the parameter η_t^{Covid}. This parameter is a dummy variable that takes the value of one from 2020 onwards.[17] Consequently, the parameter $\hat{\beta}_1^{sm}$ captures the estimated partial correlation of various economic and non-economic factors on the skill-specific internal mobility of Italian citizens during and after the COVID-19 pandemic. Finally, we account for time-invariant destination characteristics by including destination fixed effects (θ_j^{sm}). We cluster the standard errors at origin-destination level (Abadie et al., 2023).

As discussed in the previous section, one of the main empirical challenges in this context is the potential cross-sectional correlation in the error term ($\epsilon_{i,j,t}^{sm}$), which could bias the estimation of the coefficients of interest. To address it and restore cross-sectional independence in our observations, we include origin-nest dummies ($\theta_{i,k(j)}^{sm}$), which capture common variation across subsets of destinations (Bertoli and Fernández-Huertas Moraga, 2015). While this approach reduces variability for identification, it effectively accounts for unobserved common components across destinations (Pesaran, 2006).[18] The decision regarding the optimal set of nests is an empirical one, involving a trade-off (Beine et al., 2025). While having multiple nests allows for capturing most of the common unobserved variation, the inclusion of too many nests may absorb all the variability in the outcome.

We propose the following two sets of overlapping nests, to capture complementarities across destinations. First, we include five nests based on broad administrative regions (NUTS 1), under the assumption that municipalities within the same macro-region may share similar characteristics. Second, we create nests based on municipality degree of urbanisation. Following Eurostat classification (DEGURBA), we define three grades of nests based on the degree of urbanisation: cities; suburbs and towns; and rural areas. This nesting structure distinguishes municipalities along an urban-suburban-rural continuum, capturing differences in settlement patterns and population density. It reflects the idea that potential movers are more likely to consider areas with similar spatial and infrastructural characteristics as substitutes.

In a later step of the analysis, we introduce two dimensions of heterogeneity, distinguishing between the direction of flows and the impact of cost of living. Specifically,

[17] The first confirmed case of COVID-19 in Italy was reported on February 20, 2020 (Remuzzi and Remuzzi, 2020).

[18] Although residual cross-sectional dependence is a potential concern, it is not feasible, in our setting, to formally test for it using the cross-sectional dependence statistic proposed by Pesaran (2021). The dyadic structure of the data, encompassing more than 8,000 municipalities across a decade, yields more than 70 million corridors per year, making the computation of pairwise residual correlations unfeasible. For this reason, the analysis relies on a nesting structure of fixed effects, as discussed above, in order to account for unobserved common factors that affect multiple destinations.

considering that internal mobility in Italy has historically originated, to a significant extent, from the Mezzogiorno to the Centre-North (Etzo, 2011, Piras, 2017), we evaluate the model in both directions. In other words, excluding movements within the same macro-areas, we analyze flows from the Mezzogiorno to the Centre-North and, vice versa, from the Centre-North to the Mezzogiorno. Regarding the heterogeneity related to cost of living, we construct an indicator that approximates the relative cost in the province of destination as follows:

$$\text{Cost of Living}_{jt} = \frac{\text{Price of rent per m}^2_{jt}}{\text{Income per capita}_{jt}} \tag{6}$$

where j represents the destination municipality and t the reference year. Again, we distinguish two sample. The first takes into account only destinations belonging to the top decile of the index distribution, indicative of municipalities with the highest living cost, while the second refers to the remaining set of municipalities.[19]

4 Results

Table 4 presents our baseline results, over the more than 700 millions bilateral migration corridors observed across Italian municipalities, and exploiting the potential heterogeneous effects driven by movers' education and place of residence.

The estimated parameters from equation (5), based on the full sample of Italian movers, are presented in column (1). Since origin-year specific factors are absorbed by the inclusion of origin-year fixed effects, the coefficients capture the partial correlation between changes in bilateral migration flows and destination-specific, time-varying factors.

Four main empirical findings emerge. First, and unsurprisingly, income per capita at the destination acts as a pull factor for internal mobility: a 1% increase in destination income per capita is associated with a 0.9% increase in migration flows. Both the sign and magnitude of this coefficient are consistent with the existing literature.[20] Second, regarding amenities, we find a small and negative partial correlation during the pre-COVID-19 period: a 1% increase in the amenities index is associated with a 0.05% decrease in migration flows. The magnitude of this partial correlation is substantially lower than the one associated to income per capita. Notably, Diamond (2016) also reports a negative coefficient between her amenities index and the migration choices of Black individuals and immigrants across U.S. cities. This suggests that the relationship between amenities and mobility is likely shaped by individual preferences and contextual factors. Third, and in line with Peri and Zaiour (2023) for the U.S., the post-COVID-19 period appears to have altered the role of destination-specific push and pull factors, as indicated by the sta-

[19] Figure A-6 shows that the average cost of living of municipalities in the top decile of the distribution is 25% higher compared to the previous decile, while the average increase across deciles is around 10%.

[20] For example, in the US, Olney and Thompson (2024) finds that a 1% increase in per capita wages increases internal mobility flows across community zones by 0.77%.

tistically significant interaction terms. While the partial correlation between income per capita and internal mobility remains positive, it is approximately 5% smaller in the post-COVID-19 period. Conversely, the partial correlation remains with amenities remains negative, although its magnitude is reduced by nearly 70% in the post-COVID-19 years. Overall, these findings suggest that in the aftermath of the pandemic, purely economic factors have become slightly less influential. Lastly, in line with the literature estimating gravity model associated to migration choices (e.g., Bertoli and Fernández-Huertas Moraga, 2013, Beine et al., 2016), geographical distance, as a proxy of mobility cost, acts as push factor.

Columns (2) and (3) present results for the full sample of Italian municipalities, exploiting heterogeneity along the education gradient. The estimates reveal that low skill movers are more influenced by economic factors than their high skill counterparts: a 1% increase in income per capita at the destination is associated with a 1.13% increase in mobility among low skill individuals, compared to only 0.42% among high skill ones. Conversely, high skill movers are more responsive to amenities than low skill individuals. This pattern is consistent with evidence from the U.S., where Diamond (2016) finds that economic factors primarily influence low skill mobility, while non-economic factors, such as amenities, are more relevant for college-educated movers. Furthermore, columns (2) and (3) show that, in the post-COVID-19 period, amenities act as pull factors for both skill groups. This suggests that, in the aftermath of the pandemic, non-economic factors have begun to play a more prominent role in shaping the internal mobility decisions of Italians.

Finally, columns (4) to (6) exploit heterogeneity by place of residence. These results present PPML estimates from our benchmark equation (5) on three subsamples of municipalities classified as urban (column 4), suburban (column 5), and rural (column 6), according to Eurostat's degree of urbanization. Differences in the estimated parameters across these origin-based subsamples would reveal variation in mobility preferences depending on the urbanization level of the municipality of origin. The findings show that destination-specific economic factors are positively associated with internal mobility choices, with larger coefficients for movers originating from rural areas than for those from suburban or urban municipalities. This suggests a negative relationship between the degree of urbanization at origin and the importance of economic drivers at destination in shaping mobility decisions. In contrast, we find that individuals from urban areas are more responsive to amenities than those from suburban or rural origins. This indicates that urban residents are more influenced by non-economic factors in their mobility choices, compared to individuals from less urbanized areas.

Our set of evidence highlights as empirical regularity that both the education and the place of residence matters to shape individuals mobility preferences. On the education side, low skill movers are more sensitive to economic factors and less to non-economic factors than high skill movers. Concerning the place of residence, individuals from rural areas are more responsive then individuals living in urban areas to income per capita at

Table 4: Regression results: Baseline estimates

	Total			From Urban	From Suburban	From Rural
	(1) ITA	(2) LS	(3) HS	(4) ITA	(5) ITA	(6) ITA
Income	0.902***	1.133***	0.423***	0.694***	0.968***	1.204***
	(0.045)	(0.049)	(0.074)	(0.079)	(0.062)	(0.095)
Income COVID	-0.049***	-0.270***	-0.078**	-0.022	-0.066***	-0.076**
	(0.014)	(0.018)	(0.032)	(0.024)	(0.021)	(0.033)
Amenity	-0.049***	-0.014**	-0.094***	-0.070***	-0.044***	-0.015
	(0.005)	(0.005)	(0.007)	(0.008)	(0.006)	(0.009)
Amenity COVID	0.033***	0.022***	0.102***	0.016**	0.046**	0.018**
	(0.004)	(0.004)	(0.007)	(0.007)	(0.006)	(0.009)
Distance_{2012}	-1.611***	-1.599***	-1.659***	-1.485***	-1.569***	-1.884***
	(0.010)	(0.009)	(0.013)	(0.019)	(0.009)	(0.015)
Distance_{2013}	-1.584***	-1.568***	-1.641***	-1.451***	-1.547***	-1.858***
	(0.009)	(0.009)	(0.013)	(0.018)	(0.009)	(0.015)
Distance_{2014}	-1.599***	-1.588***	-1.632***	-1.447***	-1.576***	-1.880***
	(0.009)	(0.009)	(0.012)	(0.017)	(0.008)	(0.014)
Distance_{2015}	-1.607***	-1.598***	-1.631***	-1.444***	-1.593***	-1.884***
	(0.009)	(0.009)	(0.012)	(0.017)	(0.008)	(0.014)
Distance_{2016}	-1.602***	-1.594***	-1.619***	-1.422***	-1.588***	-1.922***
	(0.009)	(0.009)	(0.012)	(0.017)	(0.008)	(0.014)
Distance_{2017}	-1.600***	-1.595***	-1.607***	-1.419***	-1.593***	-1.907***
	(0.009)	(0.009)	(0.012)	(0.017)	(0.008)	(0.014)
Distance_{2018}	-1.587***	-1.578***	-1.604***	-1.402***	-1.577***	-1.907***
	(0.009)	(0.009)	(0.012)	(0.018)	(0.009)	(0.013)
Distance_{2019}	-1.564***	-1.552***	-1.598***	-1.368***	-1.567***	-1.875***
	(0.009)	(0.008)	(0.012)	(0.018)	(0.008)	(0.012)
Distance_{2020}	-1.591***	-1.583***	-1.626***	-1.409***	-1.591***	-1.879***
	(0.009)	(0.008)	(0.012)	(0.018)	(0.008)	(0.013)
Distance_{2021}	-1.611***	-1.602***	-1.648***	-1.430***	-1.607***	-1.907***
	(0.009)	(0.008)	(0.013)	(0.018)	(0.008)	(0.013)
Distance_{2022}	-1.604***	-1.598***	-1.638***	-1.419***	-1.599***	-1.912***
	(0.009)	(0.009)	(0.013)	(0.018)	(0.008)	(0.012)
Cons	-0.286	-2.763***	4.782***	2.686***	-1.742***	-3.954***
	(0.480)	(0.534)	(0.783)	(0.854)	(0.663)	(1.022)
Origin-time FE	Yes	Yes	Yes	Yes	Yes	Yes
Destination FE	Yes	Yes	Yes	Yes	Yes	Yes
$\textit{Origin-Destination}^{Urb}$ FE	Yes	Yes	Yes	Yes	Yes	Yes
$\textit{Origin-Destination}^{N1}$ FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	702,579,012	702,579,012	702,579,012	22,422,913	231,228,091	448,928,008
Pseudo-R^2	0.536	0.485	0.568	0.638	0.422	0.362

Notes: Authors' elaborations. The dependent variable in columns 1, 4, 5 and 6 is the bilateral flow of Italian citizens between municipalities; in column 2 the bilateral flow of low skill Italian citizens; in column 3 the bilateral flow of high skill Italian citizens. Columns 1, 2 and 3 include the entire sample of Italian municipalities. Columns 4, 5 and 6 exploit heterogeneity with respect to the municipality of origin level of urbanisation, using three subsamples classified as urban (column 4), suburban (column 5) and rural (column 6) municipalities, considering all types of destination municipalities. In all estimates, migration corridors between municipalities with a distance of less than 70 km are excluded to preclude commuting patterns. Income and amenity variables related to the destination municipality are expressed in *arcsinh* form and lagged by one year. Robust standard errors, corrected for clustering at the origin-destination level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

destination, while the opposite is true concerning amenities. Nonetheless, at this stage, it is hard to disentangle education from the place of residence, knowing that highly educated individuals tend to sort into urban areas (De la Roca, 2017). Is it the place of residence that is the main factor shaping individuals preferences towards residential choices? Or is

Table 5: Regression Results: Origin and Education specific estimates

	From Urban		From Suburban		From Rural	
	(1) LS	(2) HS	(3) LS	(4) HS	(5) LS	(6) HS
Income	0.929***	0.302**	1.205***	0.409***	1.362***	0.894***
	(0.089)	(0.121)	(0.073)	(0.103)	(0.107)	(0.167)
Income COVID	-0.203***	-0.194***	-0.312***	-0.014	-0.311***	0.108**
	(0.008)	(0.053)	(0.025)	(0.032)	(0.040)	(0.053)
Amenity	-0.041***	-0.081***	-0.004	-0.116***	0.026**	-0.104***
	(0.008)	(0.011)	(0.006)	(0.010)	(0.010)	(0.016)
Amenity COVID	-0.001	0.088***	0.039***	0.121***	0.027**	0.138***
	(0.007)	(0.011)	(0.006)	(0.009)	(0.011)	(0.016)
Travel-Distance (year-specific)	Yes	Yes	Yes	Yes	Yes	Yes
Origin-time FE	Yes	Yes	Yes	Yes	Yes	Yes
Destination FE	Yes	Yes	Yes	Yes	Yes	Yes
Origin-Destination^{Urb} FE	Yes	Yes	Yes	Yes	Yes	Yes
Origin-Destination^{N1} FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	22,422,913	22,422,913	231,228,091	231,228,091	448,928,008	448,928,008
Pseudo-R^2	0.581	0.658	0.374	0.470	0.327	0.388

Notes: Authors' elaboration. The dependent variable is the bilateral flow of Italian citizens between municipalities, disaggregated by level of education. The estimates exploit heterogeneity with respect to the municipality of origin level of urbanisation, using three subsamples classified as urban (columns 1 and 2), suburban (columns 3 and 4) and rural (columns 5 and 6) municipalities, considering all types of destination municipalities. In all estimates, migration corridors between municipalities with a distance of less than 70 km are excluded to preclude commuting patterns. Income and amenity variables related to the destination municipality are expressed as *arcsinh* and lagged by one year. Estimates with year-specific distance-related parameters are given in Table B-5 in online appendix. Robust standard errors, corrected for clustering at origin-destination level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

education?

To provide novel empirical evidence on this issue, Table 5 reports results from our benchmark regression, estimated separately by subsample based on the degree of urbanization of the origin municipality and the skill level of movers. Specifically, columns (1)–(2) refer to movers from urban areas, columns (3)–(4) to those from suburban areas, and columns (5)–(6) to movers from rural areas. Within each pair, the first column reports estimates for low skill individuals, while the second focuses on high skill ones. The number of observations and the time span of our dataset allows us to perform a subsample analysis, without being concerned by the potential fluctuations of the estimates due to the small number of observations within each subsample.

Regarding the influence of economic factors, Table 5 shows that, across all origin-specific subsamples, low skill movers are more responsive to changes in income per capita at the destination than high skill movers. However, the magnitude of these effects is stronger for individuals originating from rural areas compared to those from urban areas. For instance, a 1% increase in income per capita is associated with a 0.92% increase in low skill movers and a 0.30% increase in high skill movers from urban areas, whereas it corresponds to a 1.36% and 0.89% increase, respectively, for low- and high skill movers from rural areas. The positive effect of destination income per capita diminishes during the COVID-19 period across all groups, with the exclusion of highly educated movers from rural areas, for whom the effect become stronger. Overall, these findings confirm that the education gradient observed in the baseline analysis holds across different origin types. However, the degree of urbanization at the origin appears to enhance the skill-specific responsiveness to economic factors.

Concerning the role of amenities, the results indicate that high skill movers are generally more responsive to changes in destination amenities than low skill movers across all subsamples. However, the urban gradient observed in Table 4 is less evident when focusing specifically on high skill individuals: their responsiveness to amenities is actually greater when originating from suburban or rural areas than from urban ones. This suggests that the urban-rural gradient highlighted in Table 4 may be driven more by the concentration of highly educated individuals in urban areas than by intrinsic urban-rural differences in preferences. Similarly, low skill individuals display relatively consistent responsiveness to amenities across origin types, particularly in the post-pandemic period.

While the role of amenities is positive or near zero in the post-pandemic period, the negative relationship between mobility flows and our Amenity index, particularly for highly educated migrants and low-skill movers from urban areas, may appear surprising. To understand this pattern, Table B-6 disaggregates the Amenity index into its six subcomponents, as presented in Table 3. Two main findings emerge. First, the diminished attractiveness to highly educated individuals in the pre-pandemic period is primarily driven by the environmental component of our index, which also accounts for the largest share of variance in the aggregate measure. While this component captures waste management quality and the prevalence of low-emission vehicles, it implicitly reflects the costs of environmental policies that are often passed on through local taxes. In the Italian context, green policies have faced considerable resistance from local populations (Colantone et al., 2024), who may perceive them as regressive (Douenne and Fabre, 2022). Second, these policy costs appear to negatively influence the location choices of low-skill movers from urban areas, who have direct experience with such expenses. Moreover, low-skill urban movers show greater attraction to municipalities with lower provision of public services, likely reflecting preferences for areas with lower housing costs.

Overall, our analysis of residential changes across Italian municipalities from 2012 to 2022 shows that both educational attainment and place of residence are important factors shaping individuals' mobility decisions. The evidence indicates that the empirical patterns associated with the education gradient are relatively stable across the urban–rural divide. However, urban–rural preferences appear to be strongly mediated by individuals' educational levels, particularly in relation to the role of amenities. These findings suggest that educational attainment is a more robust and consistent determinant of residential mobility than the urban–rural classification alone.

4.1 Heterogeneity by Broad Areas of Origin

As highlighted in Section 3.2, certain internal migration corridors within Italy are more intensively used than others. Historically and in recent decades, a substantial share of internal mobility has involved migration from the southern regions (i.e., the Mezzogiorno) to the Centre-North (Etzo, 2011, Piras, 2017). The persistent economic disparities between northern and southern regions, discussed in Section 2.2, likely contribute to this pattern, as predicted by the canonical RUM model. To substantiate such statement, Table 6 shows the potential heterogeneity across the two main internal mobility channels: Panel A focuses on the primary corridor—movements from the South to the Centre-North, while Panel B considers the secondary flow, from the Center-North to the South.

The influence of economic and non-economic factors on mobility from the South to the Center-North largely mirrors the dynamics described in the previous section. Low-educated movers are more likely to relocate to municipalities with higher income per capita, while highly educated movers appear less responsive to economic push factors. As a result, municipalities in the Centre-North experiencing stronger income growth are more likely to have attracted a larger share of low-educated individuals through internal migration. Consistent with earlier findings, the pull effect of income growth diminishes in the post-pandemic period. With respect to amenities, highly educated movers are more sensitive to changes in destination amenities than low skill movers, both before and after the pandemic. Overall, these results suggest that along Italy's main internal migratory corridor, low-educated individuals are more strongly influenced by economic factors, while highly educated movers respond more to non-economic drivers such as amenities.

However, Panel B indicates that the same patterns do not necessarily apply to the reverse corridor—from the Centre-North to the South. First, high skill movers are, on average, more likely than low skill ones to relocate to southern municipalities experiencing economic growth. For example, a 1% increase in income per capita in a typical southern municipality is associated with a 2.6% increase in high skill inflows from rural areas (rising to 3.6% in the post-pandemic period), compared to just 0.99% for low skill movers. Notably, the influence of economic factors appears to have strengthened in the aftermath of the pandemic. Second, in contrast to the South-to-North pattern, low skill movers from the Centre-North exhibit slightly greater sensitivity to amenities than high skill movers. For instance, considering flows from suburban areas, a 1% increase in the amenities index is associated with a 0.09% rise in low skill mobility, compared to a 0.07% increase among high skill individuals.

Overall, these results highlight that the relative importance of economic and non-economic factors in shaping skill-specific mobility choices among Italians aligns with findings from the existing literature (e.g., Diamond, 2016), particularly when focusing on the South-to-North migratory corridor—i.e., movements from regions with lower economic and amenity levels to more prosperous areas. However, Table 6 shows that these patterns do not necessarily hold for North-to-South migration flows, where individuals move from regions with higher economic and non-economic conditions to comparatively poorer and less amenity-rich areas. This result may be explained by the fact that this type of migratory choice can be explained by other less tangible motives, such as family ties, return migration and lifestyle preferences, which are more individual-specific and less easily cap-

Table 6: Regression results: Subsample by Main Area of Origin

Panel A: From Mezzogiorno

	From Urban		From Suburban		From Rural	
	(1) LS	(2) HS	(3) LS	(4) HS	(5) LS	(6) HS
Income	1.515***	0.188	1.756***	-0.021	1.683***	0.480
	(0.172)	(0.236)	(0.144)	(0.195)	(0.216)	(0.317)
Income COVID	-0.272***	-0.006	-0.448***	-0.167***	-0.343***	-0.031
	(0.065)	(0.088)	(0.050)	(0.057)	(0.077)	(0.093)
Amenity	-0.001	-0.143***	0.043**	-0.151***	0.064***	-0.094***
	(0.017)	(0.026)	(0.013)	(0.027)	(0.020)	(0.033)
Amenity COVID	-0.024	0.196***	-0.013	0.219***	-0.041*	0.200***
	(0.020)	(0.030)	(0.016)	(0.023)	(0.025)	(0.037)
Travel-Distance (year-specific)	Yes	Yes	Yes	Yes	Yes	Yes
Origin-time FE	Yes	Yes	Yes	Yes	Yes	Yes
Destination FE	Yes	Yes	Yes	Yes	Yes	Yes
Origin-Destination^{Urb} FE	Yes	Yes	Yes	Yes	Yes	Yes
Origin-Destination^{N1} FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,525,515	6,525,515	44,267,327	44,267,327	101,989,690	101,989,690
Pseudo-R^2	0.587	0.688	0.405	0.530	0.338	0.406

Panel B: From Central and Northern Italy

	From Urban		From Suburban		From Rural	
	(1) LS	(2) HS	(3) LS	(4) HS	(5) LS	(6) HS
Income	0.172	-0.091	0.629***	1.622***	0.990***	2.604***
	(0.174)	(0.317)	(0.172)	(0.322)	(0.321)	(0.647)
Income COVID	-0.104	0.308***	-0.078	0.749***	0.200	1.064***
	(0.067)	(0.095)	(0.066)	(0.117)	(0.127)	(0.247)
Amenity	0.065***	-0.008	0.095***	0.069**	0.122***	0.044
	(0.015)	(0.026)	(0.015)	(0.027)	(0.028)	(0.054)
Amenity COVID	-0.007	0.072**	-0.019	-0.018	0.014	0.083
	(0.014)	(0.026)	(0.013)	(0.023)	(0.026)	(0.119)
Travel-Distance (year-specific)	Yes	Yes	Yes	Yes	Yes	Yes
Origin-time FE	Yes	Yes	Yes	Yes	Yes	Yes
Destination FE	Yes	Yes	Yes	Yes	Yes	Yes
Origin-Destination^{Urb} FE	Yes	Yes	Yes	Yes	Yes	Yes
Origin-Destination^{N1} FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,101,870	4,101,870	53,110,168	53,110,168	95,570,494	95,570,494
Pseudo-R^2	0.523	0.528	0.264	0.228	0.187	0.148

Notes: Authors' elaboration. The dependent variable is the bilateral flow of Italian citizens between municipalities, disaggregated by level of education. The estimates exploit heterogeneity with respect to the level of urbanization of the municipality of origin and the direction of the shift between macroareas (Mezzogiorno and North Central). In Panel A we consider three subsamples of origin municipalities classified as urban (columns 1 and 2), suburban (columns 3 and 4) and rural (columns 5 and 6), limited to outflows from the Mezzogiorno to North-Central Italy, considering all types of destination municipalities. In parallel, outflows from the North-Central to the Mezzogiorno are analyzed in Panel B, with the same breakdown by level of urbanization of the municipality of origin. In all estimates, migration corridors between municipalities with a distance of less than 70 km are excluded to preclude commuting patterns. Income and Amenity variables related to the destination municipality are expressed in *arcsinh* form and lagged by one year. Estimates with distance-related year-specific parameters are shown in Table B-7 and Table B-8 in appendix. Robust standard errors, corrected for clustering at the origin-destination level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

tured by standard economic and non-economic measures. In support of this hypothesis, De la Roca (2017) document that around 30% of native Spanish migrants internally move a second time within five years, and that 67% of these second moves involve a return to their place of origin.

4.2 Heterogeneity by Cost of Living

While our analysis has accounted for both economic and non-economic factors influencing residential choices, it has so far not explicitly considered the cost of living—particularly housing costs—which can play a central role in shaping mobility decisions. As the literature suggested, moving to a new location requires moving to a new house (Jia et al., 2023), therefore the dynamics of the housing market at the potential destination location can influence residential choices (e.g., Dohmen, 2005, Chung, 2015, Bloze and Skak, 2016, Botsch and Morris, 2021).[21] Given the strong correlation between income per capita and housing prices at the destination level shown in Figure A-5, we assess the potential influence of the cost of living on the determinants of the skill-specific mobility decisions of Italian movers by conducting a subsample analysis. Specifically, we divide destination municipalities into two groups: high-cost municipalities (i.e., municipalities in the top decile of our cost-of-living index, defined in equation (6)) and all others.[22] The results are presented in Table 7, with Panel A showing estimates for high-cost municipalities and Panel B reporting estimates for the rest of the sample.

By firstly focusing on the estimates associated to average income per capita across high cost municipalities (Panel A) and the other (Panel B), three main findings emerge. First, the empirical regularity identified earlier along the education gradient remains largely stable: low skill movers are more responsive to economic factors at the destination than high skill movers. The only exception is represented by highly educated individuals from rural areas moving to high-cost municipalities, which tend to have an higher response to economic factors than low skill ones. Second, the magnitude of the estimated partial correlations between income and mobility is substantially larger for high-cost municipalities (Panel A) than for the rest of the sample (Panel B). This result is consistent with the notion that residing in high-cost areas requires above-average income levels, thereby strengthening the relationship between income and mobility flows. Third, while the COVID-19 pandemic dampened the positive correlation between income and mobility toward high-cost municipalities—as reflected by a negative and significant interaction term—this pattern does not hold for the rest of the sample. In fact, in non–high-cost destinations, economic factors become increasingly relevant for high skill movers from suburban and rural areas during the post-pandemic period.

Turning to the estimates associated with amenities across the two subsamples, the results reveal a pattern broadly consistent with that observed for economic factors. As for our benchmark results shown in Table 5, high skill movers are more responsive to

[21] In the Italian setting, Mocetti and Porello (2009) highlights how higher housing costs can reduce real income, thereby reducing the relative attractiveness of certain destinations.

[22] Figure A-6 supports this classification: municipalities in the top decile exhibit a cost of living that is, on average, 25% higher than those in the ninth decile, whereas the average increase across other deciles is approximately 10%.

Table 7: Regression results: By cost of living

Panel A: High cost

	From Urban		From Suburban		From Rural	
	(1) LS	(2) HS	(3) LS	(4) HS	(5) LS	(6) HS
Income	1.784***	0.899***	1.824***	1.073***	1.369***	1.506***
	(0.203)	(0.208)	(0.141)	(0.171)	(0.208)	(0.309)
Income COVID	-0.330***	-0.405***	-0.472***	-0.344***	-0.577***	-0.209**
	(0.049)	(0.075)	(0.049)	(0.053)	(0.074)	(0.087)
Amenity	-0.052***	-0.094***	0.025*	-0.113***	0.048**	-0.149***
	(0.015)	(0.024)	(0.015)	(0.021)	(0.023)	(0.036)
Amenity COVID	-0.033	0.184***	0.006	0.296***	-0.002	0.232***
	(0.018)	(0.033)	(0.018)	(0.026)	(0.028)	(0.014)
Travel-Distance (year-specific)	Yes	Yes	Yes	Yes	Yes	Yes
Origin-time FE	Yes	Yes	Yes	Yes	Yes	Yes
Destination FE	Yes	Yes	Yes	Yes	Yes	Yes
Origin-Destination^{Urb} FE	Yes	Yes	Yes	Yes	Yes	Yes
Origin-Destination^{N1} FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,045,472	2,045,472	21,125,815	21,125,815	41,056,950	41,056,950
Pseudo-R^2	0.730	0.804	0.530	0.625	0.463	0.507

Panel B: Other

	From Urban		From Suburban		From Rural	
	(1) LS	(2) HS	(3) LS	(4) HS	(5) LS	(6) HS
Income	0.593***	-0.094	1.013***	-0.130	1.200***	0.301
	(0.098)	(0.156)	(0.089)	(0.145)	(0.135)	(0.223)
Income COVID	0.002	0.009	-0.103***	0.211***	-0.011	0.468***
	(0.036)	(0.050)	(0.031)	(0.048)	(0.050)	(0.079)
Amenity	-0.033***	-0.041***	-0.015**	-0.086***	-0.008	-0.097***
	(0.008)	(0.013)	(0.008)	(0.012)	(0.012)	(0.020)
Amenity COVID	-0.019**	0.046***	0.026***	0.078***	0.012	0.097***
	(0.008)	(0.021)	(0.007)	(0.009)	(0.011)	(0.012)
Travel-Distance (year-specific)	Yes	Yes	Yes	Yes	Yes	Yes
Origin-time FE	Yes	Yes	Yes	Yes	Yes	Yes
Destination FE	Yes	Yes	Yes	Yes	Yes	Yes
Origin-Destination^{Urb} FE	Yes	Yes	Yes	Yes	Yes	Yes
Origin-Destination^{N1} FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,377,441	20,377,441	210,102,276	210,102,276	407,871,058	407,871,058
Pseudo-R^2	0.501	0.523	0.297	0.330	0.249	0.268

Notes: Authors' elaboration. The dependent variable is the bilateral flow of Italian citizens between municipalities, disaggregated by level of education. The estimates exploit heterogeneity with respect to the level of urbanisation of the municipality of origin and the cost of living at destination. The cost of living is computed as the ratio between rent cost per square meter and income per capita. Panel A presents results for three sub-samples of origin municipalities, classified as urban (columns 1 and 2), suburban (columns 3 and 4), and rural (columns 5 and 6). The analysis is restricted to outflows directed toward municipalities belonging to the top decile in the cost of living distribution, i.e., those with the highest cost of living. In parallel, outflows to municipalities belonging to the remaining deciles by cost of living are analysed in panel B, with the same breakdown by level of urbanisation as the municipality of origin. In all estimates, migration corridors between municipalities with a distance of less than 70 km are excluded to avoid capturing commuting movements. Income and Amenity variables related to the destination municipality are expressed in *arcsinh* form and lagged by one year. Estimates with year-specific distance-related parameters are given in Table B-9 and Table B-10 in the Appendix. Robust standard errors, corrected for clustering at origin-destination level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

amenities at the destination than low skill movers. Moreover, the estimated coefficients are substantially larger for those relocating to high-cost municipalities. Consistent with previous results, the positive correlation between amenities and high skill mobility is particularly strong and statistically significant in the post-pandemic period, suggesting an increasing role of non-economic factors in shaping residential preferences among more educated individuals.

Overall, the provided set of evidence reveals that our skill-specific results presented in Table 5 are reinforced once focusing on municipalities characterized by high cost of living.

5 Conclusions

While internal migration trends is declining across many developed countries (Alvarez et al., 2021, Jia et al., 2023), this paper provides a novel stylized facts and analysis of internal migration patterns across Italian municipalities over the 2012–2022 period, with a particular focus on the interaction between education and the urban–rural divide in shaping residential choices. In the Italian context aggregate flows appear relatively stable, especially among low skill individuals. Nonetheless, we document a modest increase in mobility among the college-educated, driven largely by moves within regions and from suburban or Southern areas.

Relying on granular registry data and employing an empirical strategy grounded in a Random Utility Model, our estimates on the determinants of internal mobility shows the presence of a persistent and robust education gradient in internal migration decisions: low skill individuals are more responsive to economic incentives at destination, whereas high skill individuals are more influenced by non-economic factors, such as local amenities. Importantly, the urban–rural context at origin municipality further enhanced these patterns: economic drivers are especially salient for low skill movers from rural areas rather than urban ones, as well as non-economic factors among high skill ones.

Finally, the paper provides evidence of a milt shift in mobility determinants following the COVID-19 pandemic (Peri and Zaiour, 2023). We find a weakening role of economic factors and a growing salience of amenities and lifestyle-related considerations in post-pandemic location choices. These shifts suggest that structural changes in preferences — potentially related to hybrid work, lifestyle revaluation, or health concerns — may have long-lasting implications for internal mobility patterns and the spatial distribution of human capital. Our findings highlights the relevance of municipal-level dynamics and heterogeneity in migration drivers, particularly in the design of regional and urban policies aimed at retaining talent and reducing spatial disparities.

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Shaped by Urban-Rural Divide and Skill: the Drivers of Internal Mobility in Italy

Angela Bergantino, Antonello Clemente, Stefano Iandolo, and Riccardo Turati

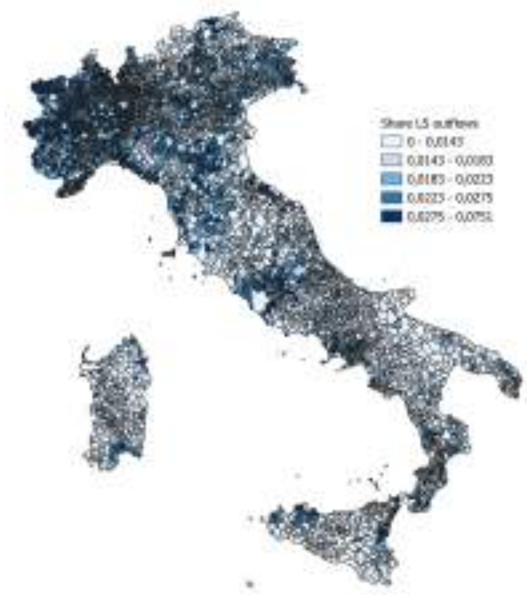
Appendix – For Online Publication

A Additional Stylized Facts

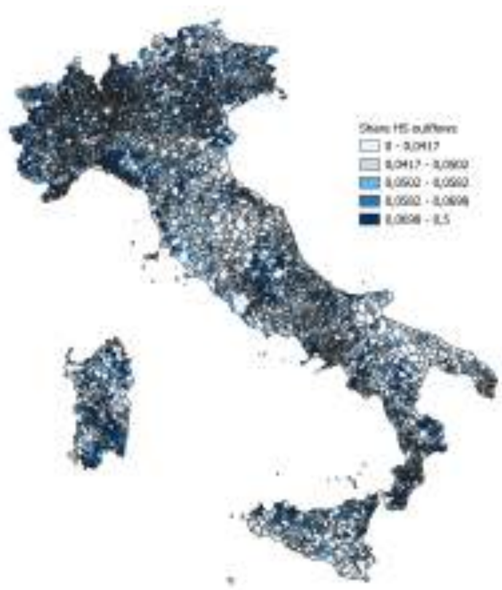
A.1 Skill-Specific Internal Mobility

Figure A-1 presents the spatial distribution of municipalities of origin and destination. Specifically, Figures A-1(a) and A-1(b) show the average skill-specific share of individuals that moved out from their municipality of origin, while Figures A-1(c) and A-1(d) present the average share of individuals that registered in new municipalities. Therefore, these figures present the average skill-specific outflows and inflows, adjusted by the origin and destination skill-specific population. By comparing inflows and outflows by skill-groups, two main findings appear. First, low skill inflows and outflows largely involve the same set of municipalities, with flows highly concentrated in Central Italy and the Northeast and Northwest, while being less prominent in the South and Insular regions. Second, tertiary-educated flows show a more distinct sorting pattern: high skill outflows are concentrated in the South and Insular regions, while inflows are predominantly in the Northeast and Northwest. These findings corroborate the importance of analyzing mobility flows by skill-groups.

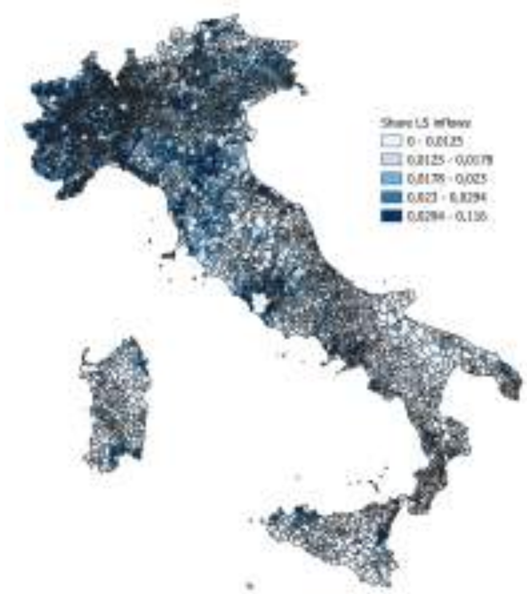
Figure A-1: Average Share skill-specific flows (2012-2022)



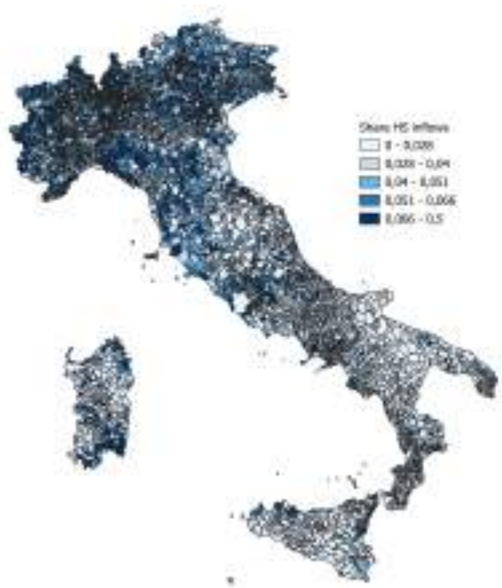
(a) Outflow LS



(b) Outflow HS



(c) Inflow LS



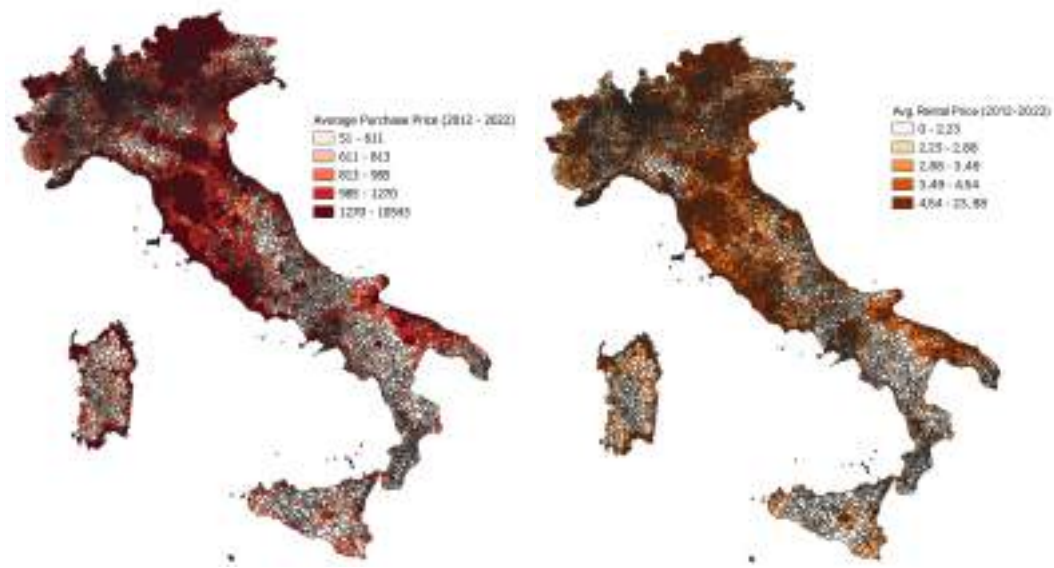
(d) Inflow HS

Notes: Authors' calculations based on ISTAT data. The figures illustrate the distribution of average share of skill-specific cancellations (a, b) and registrations (c, d) over the skill-specific population of destination municipality and origin municipality, respectively.

A.2 Housing Market

Housing market conditions are a key component of the broader set of location-specific attributes that influence decisions about internal mobility. Recent evidence (e.g., Olney and Thompson, 2024) shows how housing constraints and price differences can affect mobility in different ways, influencing the direction and intensity of migration. In Italy, where regional disparities in housing affordability and availability are still significant, it is useful to understand the role of housing in order to fully grasp the sorting patterns observed in skill-specific internal migration (OECD, 2023). In this regard, Mocetti and Porello (2009) highlights how higher housing costs can reduce real income, thereby reducing the relative attractiveness of certain destinations.

Figure A-2: Average Purchase and Rental Prices (2012-2022)



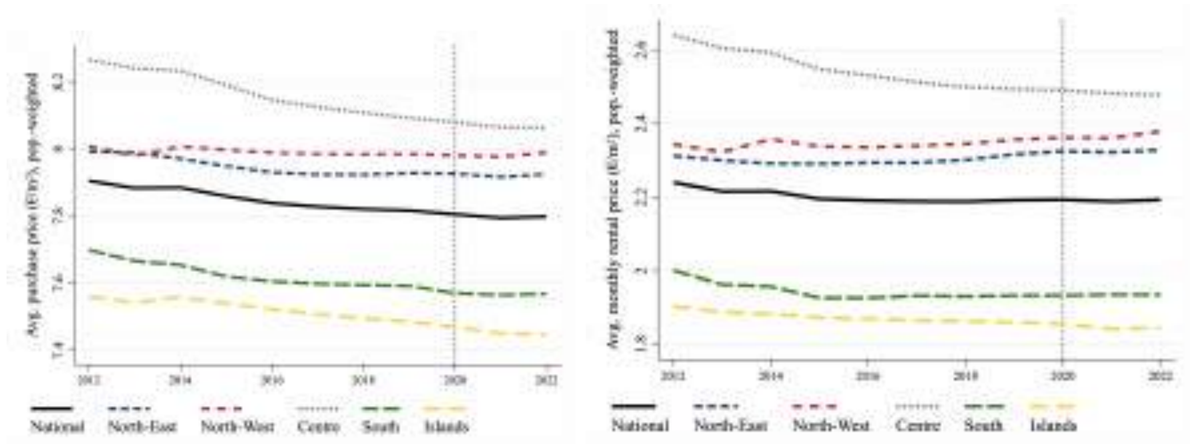
(a) Purchase price

(b) Rental price

Notes: Authors' calculations based on OMI data. The figures illustrate the distribution of average purchase price per square meter (Panel a), and monthly rental price per square meter (Panel b) for the period 2012-2022 over the entire Italian territory.

We gather municipal level data on local housing prices from the Real Estate Market Observatory Quotation Database (BDQ OMI). This dataset is constructed by the Italian Fiscal Authority and it is based on purchasing and rental contracts. It provides, for each delimited territorial area on a semi-annual basis, a minimum and maximum range relating to purchasing market values and monthly rents per unit area, classified by property type, state of maintenance and preservation. We compute average *purchase price* and *rental price* per square meter, calculated as the average of the minimum and maximum values, related to houses and flats with residential use. In the event of missing values, we applied the same approach previously described for income per capita. These variables are used

Figure A-3: Purchase and Rental prices time trends by NUTS 1 regions



(a) Purchase price (b) Rental price

Notes: Authors' elaborations based on OMI data. The figures illustrate the time trends for average purchase price per square metre (Panel a), and average monthly rent per square metre (Panel b), weighted by population. The trends are shown for the national average (solid black line) and, on the scale of NUTS1 regions, for the North-East (dashed blue), North-West (dash-dotted red), Centre (short dashed grey), South (long dashed green) and Islands (long dash-dotted yellow). The vertical line indicates 2020, the year of the outbreak of COVID-19.

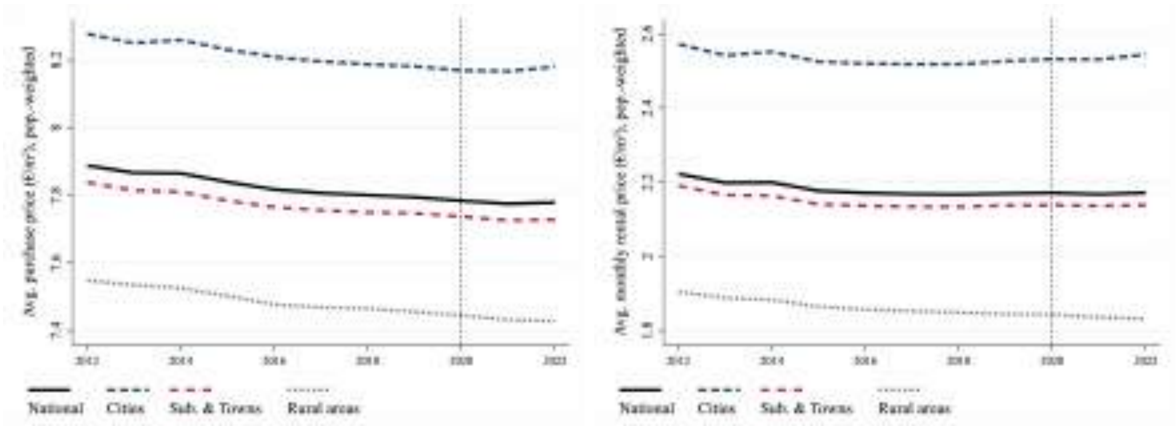
as proxy of the municipality-specific housing market prices.

In Figure A-2 we show the spatial distribution of average housing prices, for both purchase and rent, across Italian municipalities from 2012 to 2022. Panel (a) shows that average purchase prices tend to be higher in municipalities located in the North and Centre of the country. However, some coastal areas in the South and Islands also exhibit relatively high purchase prices per square meter. A similar spatial distribution is evident in rental prices, as shown in Panel (b).

Figure A-3 complements this evidence, illustrating the evolution of average housing prices over time, disaggregated by NUTS-1 macro-regions. While national averages show no clear trend over the decade, significant regional variation emerges. Notably, purchase and rental prices both declined substantially in the Centre, while the North-West experienced a mild but steady increase. It is notable that the impact of the pandemic on housing price trends appears to be limited.

To further explore heterogeneity, Figure A-4 provides a more detailed analysis of heterogeneity by breaking down time trends according to the degree of urbanisation of the municipality, distinguishing between cities, suburbs, and rural areas. Housing prices (for purchase and rent) are consistently higher in cities than in suburbs and rural areas, relative to the national average. Moreover, housing prices exhibit some variation. Purchase prices are slightly decreasing over time on a national average, with prices exhibiting mild upward trends in cities (especially in recent years), and declining in suburbs and rural areas. The trend in rental prices is comparable across cities and less urbanised areas, with cities

Figure A-4: Purchase and Rental prices time trends by Degree of Urbanisation



(a) Purchase price

(b) Rental price

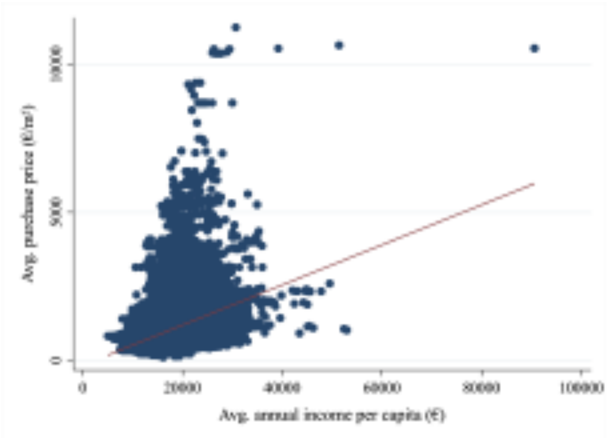
Notes: Authors' elaborations based on OMI data. The figures illustrate the time trends for average population-weighted purchase price per square metre (Panel a), and average population-weighted monthly rent per square metre (Panel b). Trends are shown for the national average (solid black line) and for municipalities grouped by their degree of urbanisation, categorised as *Urban areas* (dashed blue), *Suburban areas* (dash-dotted red), *Rural areas* (dotted gray). The vertical line indicates 2020, the year of the outbreak of COVID-19.

displaying higher prices and witnessing a modest increase in recent years, whereas trends in less urbanised areas have remained more stable. These patterns suggest that levels differ substantially according to degree of urbanisation and that the underlying dynamics diverge to some extent.

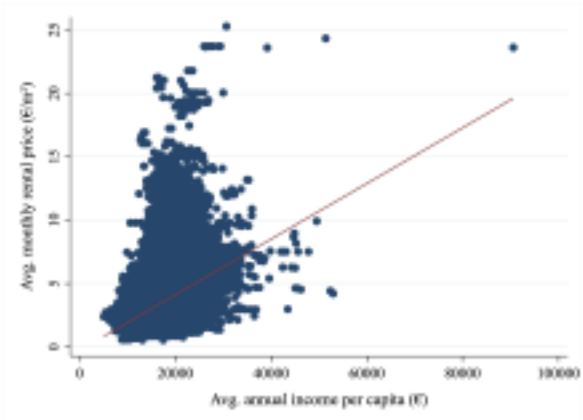
Figure A-5 illustrates the correlation between the primary economic driver in our analysis, average income, and housing market prices. Although a positive correlation observed between average annual income per capita and both purchase and rental prices, certain municipalities exhibit housing prices that are comparatively higher with respect to their average income levels, thereby echoing the findings of earlier studies (Gallin, 2006).

Finally, Figure A-6 displays the distribution of the average cost-of-living index, as constructed in equation (6). Notably, the figure reveals that municipalities in the top decile exhibit a substantially higher cost of living compared to the rest of the distribution, effectively identifying them as a distinct group. These municipalities stand out as outliers relative to the broader population, justifying their treatment as a separate subsample in the analysis.

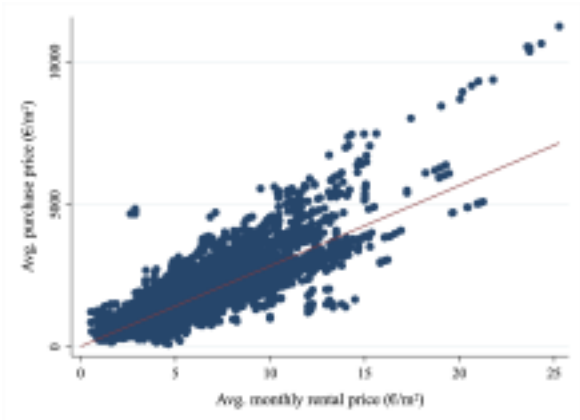
Figure A-5: Correlations between economic variables



(a) Income and Purchase



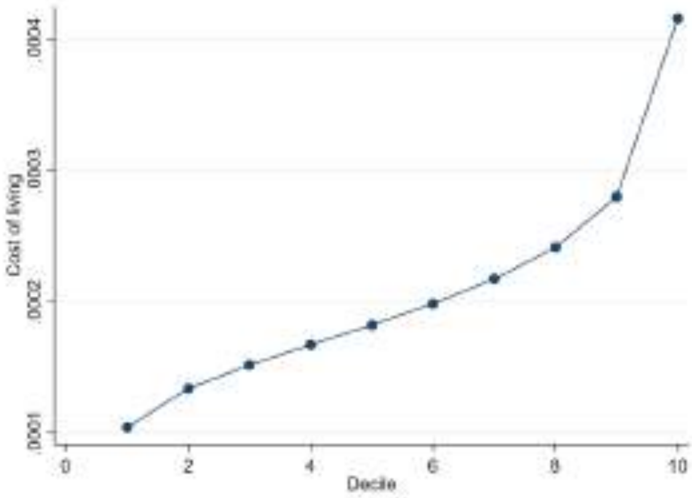
(b) Income and Rental



(c) Purchase and Rental

Notes: Authors' elaborations based on MEF and OMI data. The figures plot the correlation between the average purchase price and the average annual income per capita (Panel a), between the average annual income per capita and the average monthly rental price (Panel b), and between the average monthly rental price and the average purchase price (Panel c).

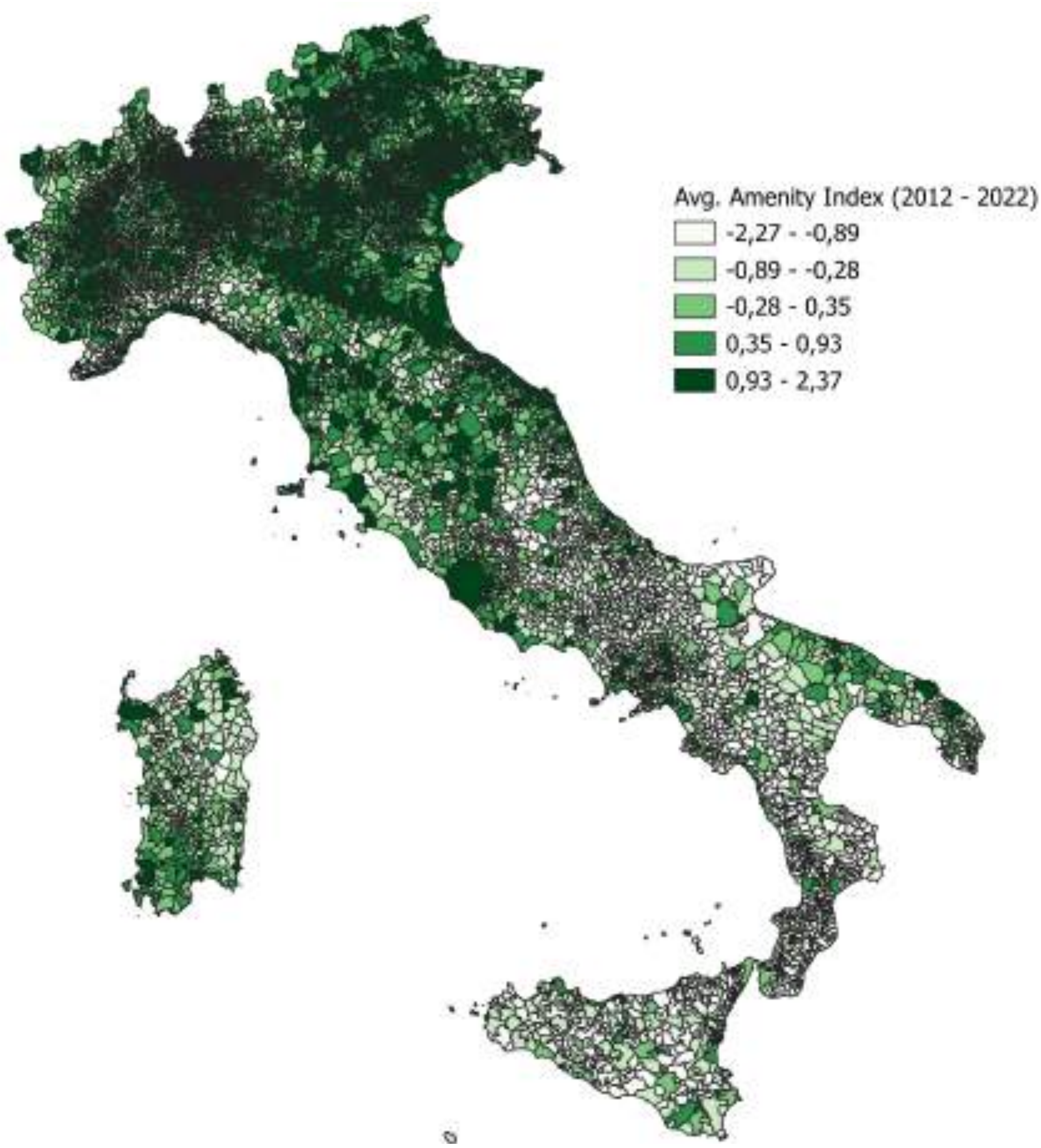
Figure A-6: Cost of living decile distribution



Notes: Authors' calculations based on data from MEF and Istat. The figure shows the decile distribution of the average cost of living, computed as the ratio of rent cost per square meter to per capita income.

A.3 Amenity index

Figure A-7: Average Amenity Index (2012-2022)



(a) Amenity index

Notes: Authors' calculations. The figures illustrate the distribution of amenity index for the period 2012-2022 over the entire Italian territory.

B Additional Data

B.1 Descriptive data

Table B-1: Variable Descriptions and Sources

Variable	Source	Notes
Migration flow	Elementary Data Analysis Laboratory (ADELE) 2012–2022	Matrices of bilateral mobility flows of Italians between Italian municipalities, distinguishing between those with a tertiary qualification (high skill) and those with a high school diploma or less (low skill).
Income per capita	Italian National Statistics Institute (ISTAT) 2011-2022	For missing values, we apply the following approach: (i) when possible, we replace missing observations with estimates based on trends in values in other years; (ii) if not available, we approximate per capita income by averaging the values of neighboring municipalities.
Purchase price and rental price	Real Estate Market Observatory Quotation Database (BDQ OMI) 2011 - 2022	We compute average purchase price and rental price per square meter, calculated as the average of the minimum and maximum values, related to houses and flats with residential use. In the event of missing values, we applied the same approach previously described for income per capita.
Population	Statistics Institute (ISTAT) 2012-2022	We use ISTAT annual data on the resident population as of 1 January. Starting in 2019, the data are based on the permanent population census, while data for previous years have been reconstructed on the basis of intercensal estimates.
Bilateral distance between municipalities	Italian National Statistics Institute (ISTAT) 2021	The analysis was conducted using GIS (Geographic Information System) tools. In the presence of missing values, the distance to a neighboring municipality was used as a reference.
Degree of Urbanization	Statistical Office of the European Communities (EUROSTAT)	DEGURBA classifies areas into three main categories: Urban, Suburban and Rural, based on population density and size.
NUTS-1 Italian macro regions	Italian National Statistics Institute (ISTAT)	In the presence of missing values, the level was considered to be the neighboring municipality.

Table B-2: Amenity Index Variable Descriptions and Sources

Variable	Source	Notes
Artistic, cultural, and sports facilities per 1,000 residents	Italian National Statistics Institute (ISTAT) 2012-2022	Ateco codes R90, R91 and R93. For the absent year, we consider the value of the nearest year.
Accessibility index: Railway	Italian National Statistics Institute (ISTAT) 2021	Railway stations with active passenger service. In the case of missing value, the values of a neighboring municipality were considered.
Bank branches per 1,000 residents	Italian National Statistics Institute (ISTAT) 2015-2022	For the absent year, we consider the value of the nearest year.
Healthcare beds per 1000 residents	Italian National Statistics Institute (ISTAT) 2014-2021	For the absent year, we consider the value of the nearest year.
Court cases for common and minor crimes per 1,000 residents	Italian Ministry of Justice: Directorate-General for Statistics and Organizational Analysis (Dg-Stat) 2011-2022	Data from 140 courts. Cases are counted based on the 'registration date' within the reference period. The formula used is: (number of cases / total population in the court area) * 1,000.
Recycling rate	Italian National Institute for Environmental Protection and Research (ISPRA) 2011-2022	For missing values, we use an average of the values of the neighboring municipalities.
Cars below Euro 4 standard	Italian National Statistics Institute (ISTAT) 2011-2022	Passenger cars on the road with emission standards below Euro 4 class by municipality (Incidence on total passenger cars).
Education sector employment per 1,000 workers	Italian National Statistics Institute (ISTAT) 2012-2022	Ateco codes P85. For the absent year, we consider the value of the nearest year.
Average Invalsi test score	National Institute for the Evaluation of the Education System, Statistical Service (INVALSI) 2012-2022	For missing values, we apply the following approach: (i) when possible, we replace missing observations with estimates based on trends in values in other years; (ii) if not available, we approximate by averaging the values of neighboring municipalities.
Unemployment rate	Italian National Statistics Institute (ISTAT) 2011-2022	Data on the unemployment rate are provided by ISTAT at the level of Local Labour Market Areas (LLMAs), which are sub-regional units designed to reflect self-contained commuting zones in which most people live and work. This level of geographic detail provides an accurate representation of local labour market conditions, taking commuting patterns and job accessibility into account.
High-tech sector specialization	Italian National Statistics Institute (ISTAT) 2014-2022	For the absent year, we consider the value of the nearest year.
Big business density per 1,000 residents	Italian National Statistics Institute (ISTAT) 2012-2022	The formula used is: (Number of large firms (more than 250 employees) / total population) * 1,000

Table B-3: Summary statistics by macro-area

Panel A: Mezzogiorno					
Variable	Obs	Mean	Std. Dev.	Min	Max
Total	152,782,532	0.0073	0.3725	0	1210
High Skill	152,782,532	0.0021	0.1632	0	369
Low Skill	152,782,532	0.0052	0.2376	0	876
Income pc	152,782,532	10.2073	0.1575	9.7135	10.9768
Amenity index	152,782,532	-0.7570	0.8059	-2.4471	2.1231
Number of municipalities	2,562				
Panel B: Central and Northern Italy					
Variable	Obs	Mean	Std. Dev.	Min	Max
Total	152,782,532	0.0039	0.1658	0	319
High Skill	152,782,532	0.0007	0.0508	0	115
Low Skill	152,782,532	0.0032	0.1300	0	254
Income pc	152,782,532	10.5317	0.1600	9.7135	11.0910
Amenity index	152,782,532	0.4838	0.8790	-2.0622	2.5798
Number of municipalities	5,640				

Notes: Authors' elaborations. The table reports the number of observations, means, standard deviations, minimum, and maximum values for each variable across macro-areas. Mezzogiorno includes the NUTS 1 areas of the Islands and Southern Italy, while Central and Northern Italy includes the NUTS 1 regions of the Centre, North-East, and North-West. The count of municipalities includes all municipalities that existed at any time between 2012 and 2022. Income per capita values are winsorized at the 0.1st and 99.9th percentiles to reduce the influence of extreme outliers. The reported means for income per capita and the amenity index refer to the municipalities of origin and are expressed using the inverse hyperbolic sine (arcsinh) transformation.

Table B-4: Summary statistics by cost of living

Panel A: High cost of living					
Variable	Obs	Mean	Std. Dev.	Min	Max
Total	64,228,237	0.0454	2.0410	0	1971
High Skill	64,228,237	0.0113	0.5793	0	945
Low Skill	64,228,237	0.0341	1.5855	0	1794
Income pc	64,228,237	10.4409	0.2202	9.7135	11.0910
Amenity index	64,228,237	0.3717	0.9655	-2.0184	2.3177
Rent cost (per m^2)	64,228,237	-2.6272	0.3083	-3.4569	-1.7191
Number of municipalities	841				
Panel B: Rest of sample					
Variable	Obs	Mean	Std. Dev.	Min	Max
Total	638,350,775	0.0151	0.7938	0	1411
High Skill	638,350,775	0.0027	0.1563	0	314
Low Skill	638,350,775	0.0124	0.6636	0	1232
Income pc	638,350,775	10.4265	0.2193	9.7135	11.0910
Amenity index	638,350,775	0.0569	1.0348	-2.4471	2.5798
Rent cost (per m^2)	638,350,775	-1.8145	0.3560	-3.0081	-0.9163
Number of municipalities	7,361				

Notes: Authors' elaborations. The table reports the number of observations, means, standard deviations, minimum, and maximum values for each variable across high cost of living areas (Panel A) and the rest of the sample (Panel B). The cost of living is computed as the ratio of rent cost per m^2 to income per capita. The count of municipalities includes all municipalities that existed at time point between 2012 and 2022. Income per capita and rent cost values are winsorized at the 0.1st and 99.9th percentiles to reduce the influence of extreme outliers. The reported means for income per capita, rent cost, and the amenity index refer to the municipalities of destination and are expressed using the inverse hyperbolic sine (arcsinh) transformation.

B.2 Additional Results

Table B-5: Full regression results: Origin and Education specific estimates

	From Urban		From Suburban		From Rural	
	(1) LS	(2) HS	(3) LS	(4) HS	(5) LS	(6) HS
Income	0.929***	0.302**	1.205***	0.409***	1.362***	0.894***
	(0.089)	(0.121)	(0.073)	(0.103)	(0.107)	(0.167)
Income COVID	-0.203***	-0.194***	-0.312***	-0.014	-0.311***	0.108**
	(0.008)	(0.053)	(0.025)	(0.032)	(0.040)	(0.053)
Amenity	-0.041***	-0.081***	-0.004	-0.116***	0.026**	-0.104***
	(0.008)	(0.011)	(0.006)	(0.010)	(0.010)	(0.016)
Amenity COVID	-0.001	0.088***	0.039***	0.121***	0.027**	0.138***
	(0.007)	(0.011)	(0.006)	(0.009)	(0.011)	(0.016)
$Distance_{2012}$	-1.478***	-1.516***	-1.547***	-1.654***	-1.865***	-1.973***
	(0.018)	(0.023)	(0.009)	(0.013)	(0.016)	(0.019)
$Distance_{2013}$	-1.439***	-1.496***	-1.521***	-1.644***	-1.837***	-1.940***
	(0.017)	(0.022)	(0.009)	(0.012)	(0.017)	(0.019)
$Distance_{2014}$	-1.439***	-1.472***	-1.555***	-1.642***	-1.864***	-1.940***
	(0.017)	(0.021)	(0.009)	(0.012)	(0.015)	(0.019)
$Distance_{2015}$	-1.437***	-1.470***	-1.577***	-1.637***	-1.864***	-1.951***
	(0.018)	(0.021)	(0.009)	(0.012)	(0.015)	(0.019)
$Distance_{2016}$	-1.409***	-1.451***	-1.573***	-1.622***	-1.909***	-1.967***
	(0.017)	(0.022)	(0.009)	(0.011)	(0.015)	(0.018)
$Distance_{2017}$	-1.411***	-1.435***	-1.580***	-1.620***	-1.898***	-1.935***
	(0.018)	(0.021)	(0.008)	(0.011)	(0.015)	(0.018)
$Distance_{2018}$	-1.392***	-1.428***	-1.560***	-1.621***	-1.897***	-1.937***
	(0.018)	(0.021)	(0.008)	(0.012)	(0.014)	(0.018)
$Distance_{2019}$	-1.362***	-1.382***	-1.543***	-1.644***	-1.849***	-1.973***
	(0.018)	(0.022)	(0.008)	(0.011)	(0.013)	(0.016)
$Distance_{2020}$	-1.409***	-1.569***	-1.570***	-1.685***	-1.854***	-2.013***
	(0.018)	(0.021)	(0.009)	(0.011)	(0.014)	(0.017)
$Distance_{2021}$	-1.439***	-1.431***	-1.580***	-1.717***	-1.883***	-2.040***
	(0.017)	(0.022)	(0.008)	(0.011)	(0.014)	(0.017)
$Distance_{2022}$	-1.427***	-1.423***	-1.578***	-1.694***	-1.889***	-2.033***
	(0.018)	(0.021)	(0.772)	(1.195)	(0.014)	(0.016)
Cons	0.084	7.064***	-4.247***	4.102***	-5.559***	-1.103
	(0.987)	(1.333)	(0.772)	(1.195)	(1.143)	(1.794)
Origin-time FE	Yes	Yes	Yes	Yes	Yes	Yes
Destination FE	Yes	Yes	Yes	Yes	Yes	Yes
Origin-Destination^{Urb} FE	Yes	Yes	Yes	Yes	Yes	Yes
Origin-Destination^{N1} FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	22,422,913	22,422,913	231,228,091	231,228,091	448,928,008	448,928,008
Pseudo-R^2	0.581	0.658	0.374	0.470	0.327	0.388

Notes: Authors' elaboration. The dependent variable is the bilateral flow of Italian citizens between municipalities, disaggregated by level of education. The estimates exploit heterogeneity with respect to the municipality of origin level of urbanisation, using three subsamples classified as urban (columns 1 and 2), suburban (columns 3 and 4) and rural (columns 5 and 6) municipalities, considering all types of destination municipalities. In all estimates, migration corridors between municipalities with a distance of less than 70 km are excluded to preclude commuting patterns. Income and amenity variables related to the destination municipality are expressed as *arcsinh* and lagged by one year. Robust standard errors, corrected for clustering at origin-destination level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table B-6: Regression results: Amenities Indices

	From Urban		From Suburban		From Rural	
	(1) LS	(2) HS	(3) LS	(4) HS	(5) LS	(6) HS
Income	0.656***	0.469***	0.888***	0.548***	1.081***	0.900***
	(0.086)	(0.117)	(0.071)	(0.106)	(0.108)	(0.170)
Income COVID	-0.113***	-0.100**	-0.225***	0.014	-0.219***	0.154**
	(0.033)	(0.049)	(0.027)	(0.039)	(0.042)	(0.063)
Retail	-0.001	0.047***	-0.021***	0.055***	-0.014	0.064***
	(0.006)	(0.010)	(0.006)	(0.009)	(0.008)	(0.014)
Service	-0.023***	-0.001	-0.024***	0.007	-0.016	-0.007
	(0.008)	(0.012)	(0.007)	(0.009)	(0.010)	(0.016)
Crime	0.008**	0.002	0.011***	0.018***	0.015***	0.028***
	(0.004)	(0.005)	(0.003)	(0.004)	(0.008)	(0.007)
Environment	-0.038***	-0.021**	0.094***	-0.033***	-0.001	-0.017
	(0.005)	(0.009)	(0.005)	(0.008)	(0.008)	(0.012)
Education	-0.007	-0.027***	0.008**	0.002	0.009	-0.004
	(0.005)	(0.001)	(0.004)	(0.006)	(0.006)	(0.011)
Job	0.053***	-0.003	0.035***	-0.017**	0.023***	-0.027*
	(0.007)	(0.010)	(0.006)	(0.009)	(0.009)	(0.014)
Retail COVID	0.015***	0.002	0.020***	0.004	-0.017**	0.009
	(0.003)	(0.006)	(0.003)	(0.005)	(0.006)	(0.020)
Service COVID	-0.015***	0.041***	-0.012***	0.041***	-0.011***	0.041***
	(0.003)	(0.004)	(0.003)	(0.004)	(0.004)	(0.006)
Crime COVID	-0.001	-0.052***	0.001	-0.041***	0.008	-0.022***
	(0.004)	(0.006)	(0.004)	(0.005)	(0.006)	(0.008)
Environment COVID	0.081***	-0.070***	0.096***	-0.031***	0.111***	0.014
	(0.006)	(0.009)	(0.005)	(0.007)	(0.008)	(0.011)
Education COVID	-0.015***	0.036***	-0.013**	0.029***	-0.023***	-0.001
	(0.005)	(0.008)	(0.005)	(0.008)	(0.008)	(0.013)
Job COVID	-0.036***	-0.001	-0.021***	0.024***	-0.034***	0.024***
	(0.005)	(0.007)	(0.004)	(0.006)	(0.009)	(0.009)
Travel-Distance (year-specific)	Yes	Yes	Yes	Yes	Yes	Yes
Origin-time FE	Yes	Yes	Yes	Yes	Yes	Yes
Destination FE	Yes	Yes	Yes	Yes	Yes	Yes
Origin-Destination^{Urb} FE	Yes	Yes	Yes	Yes	Yes	Yes
Origin-Destination^{N1} FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	22,422,913	22,422,913	231,228,091	231,228,091	448,928,008	448,928,008
Pseudo-R^2	0.581	0.658	0.374	0.470	0.327	0.388

Notes: Authors' elaboration. The dependent variable is the bilateral flow of Italian citizens between municipalities, disaggregated by level of education. The estimates exploit heterogeneity with respect to the municipality of origin level of urbanisation, using three subsamples classified as urban (columns 1 and 2), suburban (columns 3 and 4) and rural (columns 5 and 6) municipalities, considering all types of destination municipalities. In all estimates, migration corridors between municipalities with a distance of less than 70 km are excluded to preclude commuting patterns. Income and amenities variables related to the destination municipality are expressed as *arcsinh* and lagged by one year. Robust standard errors, corrected for clustering at origin-destination level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table B-7: Full regression results: Subsample by area of origin Mezzogiorno

	From Urban		From Suburban		From Rural	
	(1) LS	(2) HS	(3) LS	(4) HS	(5) LS	(6) HS
Income	1.515***	0.188	1.756***	-0.021	1.683***	0.480
	(0.172)	(0.236)	(0.144)	(0.195)	(0.216)	(0.317)
Income COVID	-0.272***	-0.006	-0.448***	-0.167***	-0.343***	-0.031
	(0.065)	(0.088)	(0.050)	(0.057)	(0.077)	(0.093)
Amenity	-0.001	-0.143***	0.043**	-0.151***	0.064***	-0.094***
	(0.017)	(0.026)	(0.013)	(0.027)	(0.020)	(0.033)
Amenity COVID	-0.024	0.196***	-0.013	0.219***	-0.041*	0.200***
	(0.020)	(0.030)	(0.016)	(0.023)	(0.025)	(0.037)
Distance_{2012}	-1.297***	-1.561***	-1.589***	-1.942***	-2.064***	-2.181***
	(0.075)	(0.070)	(0.038)	(0.048)	(0.048)	(0.065)
Distance_{2013}	-1.171***	-1.530***	-1.448***	-1.915***	-1.957***	-2.081***
	(0.078)	(0.073)	(0.041)	(0.049)	(0.049)	(0.067)
Distance_{2014}	-1.193***	-1.311***	-1.520***	-1.707***	-1.991***	-1.857***
	(0.069)	(0.085)	(0.038)	(0.051)	(0.050)	(0.069)
Distance_{2015}	-1.150***	-1.220***	-1.494***	-1.579***	-1.963***	-1.773***
	(0.074)	(0.089)	(0.039)	(0.053)	(0.050)	(0.071)
Distance_{2016}	-1.094***	-1.189***	-1.525***	-1.505***	-2.037***	-1.795***
	(0.072)	(0.094)	(0.039)	(0.052)	(0.050)	(0.068)
Distance_{2017}	-1.091***	-1.059	-1.522***	-1.433***	-2.003***	-1.634***
	(0.072)	(0.085)	(0.039)	(0.052)	(0.050)	(0.068)
Distance_{2018}	-0.917***	1.064***	-1.304***	-1.384***	-1.804***	-1.735***
	(0.077)	(0.088)	(0.039)	(0.053)	(0.050)	(0.068)
Distance_{2019}	-0.772***	-1.193***	-1.180***	-1.584***	-1.631***	-1.838***
	(0.089)	(0.076)	(0.042)	(0.047)	(0.052)	(0.063)
Distance_{2020}	-0.837***	-1.375***	-1.189***	-1.693***	-1.652***	-1.886***
	(0.083)	(0.071)	(0.042)	(0.048)	(0.053)	(0.065)
Distance_{2021}	-0.918***	-1.408***	-1.239***	-1.853***	-1.735***	-1.954***
	(0.086)	(0.076)	(0.042)	(0.047)	(0.053)	(0.062)
Distance_{2022}	-0.907***	-1.471***	-1.225***	-1.823***	-1.705***	-1.956***
	(0.082)	(0.069)	(0.039)	(0.046)	(0.051)	(0.062)
Cons	-7.961***	8.108***	-9.541***	11.627***	-7.238***	5.199
	(1.957)	(2.647)	(1.561)	(2.135)	(2.318)	(3.447)
Origin-time FE	Yes	Yes	Yes	Yes	Yes	Yes
Destination FE	Yes	Yes	Yes	Yes	Yes	Yes
$\textit{Origin-Destination}^{Urb}$ FE	Yes	Yes	Yes	Yes	Yes	Yes
$\textit{Origin-Destination}^{N1}$ FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,525,515	6,525,515	44,267,327	44,267,327	101,989,690	101,989,690
Pseudo-R^2	0.587	0.688	0.405	0.530	0.338	0.406

Notes: Authors' elaboration. The dependent variable is the bilateral flow of Italian citizens between municipalities, disaggregated by level of education. The estimates exploit heterogeneity with respect to the level of urbanization of the municipality of origin and the direction of the shift between macroareas (Mezzogiorno and North Central). We consider three subsamples of origin municipalities classified as urban (columns 1 and 2), suburban (columns 3 and 4) and rural (columns 5 and 6), limited to outflows from the Mezzogiorno to North-Central Italy, considering all types of destination municipalities. In all estimates, migration corridors between municipalities with a distance of less than 70 km are excluded to preclude commuting patterns. Income and Amenity variables related to the destination municipality are expressed in *arcsinh* form and lagged by one year. Robust standard errors, corrected for clustering at the origin-destination level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table B-8: Full regression results: Subsample by area of origin Central and Northern Italy

	From Urban		From Suburban		From Rural	
	(1) LS	(2) HS	(3) LS	(4) HS	(5) LS	(6) HS
Income	0.172	-0.091	0.629***	1.622***	0.990***	2.604***
	(0.174)	(0.317)	(0.172)	(0.322)	(0.321)	(0.647)
Income COVID	-0.104	0.309***	-0.078	0.749***	0.200	1.064***
	(0.067)	(0.095)	(0.066)	(0.117)	(0.127)	(0.247)
Amenity	0.065***	-0.008	0.095***	0.069**	0.122***	0.044
	(0.015)	(0.026)	(0.015)	(0.027)	(0.028)	(0.054)
Amenity COVID	-0.007	0.072***	-0.019	-0.018	0.014	0.083
	(0.014)	(0.026)	(0.013)	(0.023)	(0.026)	(0.119)
$Distance_{2012}$	-1.614***	-1.260***	-1.731***	-1.557***	-1.928***	-1.401***
	(0.079)	(0.089)	(0.037)	(0.063)	(0.069)	(0.127)
$Distance_{2013}$	-1.649***	-1.278***	-1.707***	-1.593***	-1.999***	-1.693***
	(0.079)	(0.088)	(0.038)	(0.061)	(0.069)	(0.127)
$Distance_{2014}$	-1.647***	-1.336***	-1.793***	-1.690***	-1.955***	-1.620***
	(0.080)	(0.084)	(0.039)	(0.061)	(0.070)	(0.123)
$Distance_{2015}$	-1.603***	-1.340***	-1.810***	-1.652***	-1.974***	-1.671***
	(0.078)	(0.084)	(0.039)	(0.059)	(0.072)	(0.123)
$Distance_{2016}$	-1.653***	-1.354***	-1.793***	-1.693***	-2.029***	-1.816***
	(0.079)	(0.082)	(0.039)	(0.061)	(0.073)	(0.126)
$Distance_{2017}$	-1.651***	-1.277***	-1.786***	-1.677***	-2.040***	-1.809***
	(0.079)	(0.078)	(0.038)	(0.061)	(0.071)	(0.124)
$Distance_{2018}$	-1.645***	-1.363***	-1.852***	-1.752***	-1.988***	-1.781***
	(0.080)	(0.080)	(0.039)	(0.060)	(0.074)	(0.119)
$Distance_{2019}$	-1.673***	-1.338***	-1.823***	-1.758***	-2.018***	-1.967***
	(0.079)	(0.078)	(0.038)	(0.060)	(0.071)	(0.131)
$Distance_{2020}$	-1.674***	-1.256***	-1.774***	-1.697***	-1.950***	-1.582***
	(0.080)	(0.074)	(0.039)	(0.060)	(0.073)	(0.128)
$Distance_{2021}$	-1.707***	-1.247***	-1.843***	-1.654***	-1.936***	-1.772***
	(0.079)	(0.077)	(0.039)	(0.059)	(0.076)	(0.125)
$Distance_{2022}$	-1.669***	-1.243***	-1.785***	-1.731***	-1.994***	-1.817***
	(0.083)	(0.078)	(0.039)	(0.063)	(0.066)	(0.127)
Cons	10.052***	8.028**	3.238*	-11.592***	-1.105	-22.738***
	(1.926)	(3.332)	(1.838)	(3.460)	(3.398)	(6.876)
Origin-time FE	Yes	Yes	Yes	Yes	Yes	Yes
Destination FE	Yes	Yes	Yes	Yes	Yes	Yes
Origin-Destination^{Urb} FE	Yes	Yes	Yes	Yes	Yes	Yes
Origin-Destination^{N1} FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,101,870	4,101,870	53,110,168	53,110,168	95,570,494	95,570,494
Pseudo-R^2	0.523	0.528	0.264	0.228	0.187	0.148

Notes: Authors' elaboration. The dependent variable is the bilateral flow of Italian citizens between municipalities, disaggregated by level of education. The estimates exploit heterogeneity with respect to the level of urbanization of the municipality of origin and the direction of the shift between macroareas (Mezzogiorno and North Central). We consider three subsamples of origin municipalities classified as urban (columns 1 and 2), suburban (columns 3 and 4) and rural (columns 5 and 6), limited to outflows from North-Central Italy to the Mezzogiorno, considering all types of destination municipalities. In all estimates, migration corridors between municipalities with a distance of less than 70 km are excluded to preclude commuting patterns. Income and Amenity variables related to the destination municipality are expressed in *arcsinh* form and lagged by one year. Robust standard errors, corrected for clustering at the origin-destination level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table B-9: Full regression results: By high cost of living

	From Urban		From Suburban		From Rural	
	(1) LS	(2) HS	(3) LS	(4) HS	(5) LS	(6) HS
Income	1.784***	0.899***	1.824***	1.073***	1.369***	1.506***
	(0.203)	(0.208)	(0.141)	(0.171)	(0.208)	(0.309)
Income COVID	-0.330***	-0.405***	-0.472***	-0.344***	-0.577***	-0.209**
	(0.049)	(0.075)	(0.049)	(0.053)	(0.074)	(0.087)
Amenity	-0.052***	-0.094***	0.025*	-0.113***	0.048**	-0.149***
	(0.015)	(0.024)	(0.015)	(0.021)	(0.023)	(0.036)
Amenity COVID	-0.033	0.184***	0.006	0.296***	-0.002	0.232***
	(0.018)	(0.033)	(0.018)	(0.026)	(0.028)	(0.014)
Distance_{2012}	-1.227***	-1.247***	-1.435***	-1.574***	-1.777***	-1.906***
	(0.015)	(0.047)	(0.015)	(0.023)	(0.025)	(0.033)
Distance_{2013}	-1.131***	-1.187***	-1.388***	-1.534***	-1.765***	-1.838***
	(0.016)	(0.048)	(0.017)	(0.023)	(0.026)	(0.034)
Distance_{2014}	-1.121***	-1.159***	-1.396***	-1.501***	-1.742***	-1.788***
	(0.017)	(0.040)	(0.016)	(0.022)	(0.026)	(0.036)
Distance_{2015}	-1.133***	-1.172***	-1.417***	-1.494***	-1.741***	-1.823***
	(0.017)	(0.042)	(0.017)	(0.024)	(0.027)	(0.036)
Distance_{2016}	-1.115***	-1.146***	-1.431***	-1.451***	-1.788***	-1.774***
	(0.018)	(0.043)	(0.017)	(0.022)	(0.026)	(0.035)
Distance_{2017}	-1.133***	-1.120***	-1.450***	-1.430***	-1.735***	-1.742***
	(0.045)	(0.043)	(0.017)	(0.024)	(0.026)	(0.038)
Distance_{2018}	-1.030***	-1.145***	-1.391***	-1.467***	-1.713***	-1.778***
	(0.046)	(0.045)	(0.017)	(0.025)	(0.026)	(0.037)
Distance_{2019}	-1.061***	-1.073***	-1.361***	-1.489***	-1.717***	-1.797***
	(0.045)	(0.045)	(0.018)	(0.022)	(0.026)	(0.031)
Distance_{2020}	-1.086***	-1.141***	-1.410***	-1.535***	-1.715***	-1.798***
	(0.041)	(0.044)	(0.018)	(0.023)	(0.025)	(0.033)
Distance_{2021}	-1.127***	-1.161***	-1.429***	-1.601***	-1.757***	-1.905***
	(0.044)	(0.055)	(0.018)	(0.023)	(0.026)	(0.033)
Distance_{2022}	-1.104***	-1.146***	-1.445***	-1.550***	-1.729***	-1.821***
	(0.060)	(0.060)	(0.019)	(0.021)	(0.027)	(0.037)
Cons	-9.351***	1.284	-10.086***	-0.897	-4.269	-5.509
	(2.245)	(2.257)	(1.505)	(1.853)	(2.207)	(3.359)
Origin-time FE	Yes	Yes	Yes	Yes	Yes	Yes
Destination FE	Yes	Yes	Yes	Yes	Yes	Yes
Origin-Destination^{Urb} FE	Yes	Yes	Yes	Yes	Yes	Yes
Origin-Destination^{N1} FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,045,472	2,045,472	21,125,815	21,125,815	41,056,950	41,056,950
Pseudo-R^2	0.730	0.804	0.530	0.625	0.463	0.507

Notes: Authors' elaboration. The dependent variable is the bilateral flow of Italian citizens between municipalities, disaggregated by level of education. The estimates exploit heterogeneity with respect to the level of urbanisation of the municipality of origin and the cost of living at destination. The cost of living is computed as the ratio between rent cost per square meter and income per capita. The table presents results for three sub-samples of origin municipalities, classified as urban (columns 1 and 2), suburban (columns 3 and 4), and rural (columns 5 and 6). The analysis is restricted to outflows directed toward municipalities belonging to the top decile in the cost of living distribution, i.e., those with the highest cost of living. In all estimates, migration corridors between municipalities with a distance of less than 70 km are excluded to avoid capturing commuting movements. Income and Amenity variables related to the destination municipality are expressed in *arcsinh* form and lagged by one year. Robust standard errors, corrected for clustering at origin-destination level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table B-10: Full regression Results: By low and medium cost of living

	From Urban		From Suburban		From Rural	
	(1) LS	(2) HS	(3) LS	(4) HS	(5) LS	(6) HS
Income	0.593***	-0.094	1.013***	-0.130	1.200***	0.301
	(0.098)	(0.156)	(0.089)	(0.145)	(0.135)	(0.223)
Income COVID	0.002	0.009	-0.103***	0.211***	-0.011	0.468***
	(0.036)	(0.050)	(0.031)	(0.048)	(0.050)	(0.079)
Amenity	-0.033***	-0.041***	-0.015**	-0.086***	-0.008	-0.097***
	(0.008)	(0.013)	(0.008)	(0.012)	(0.012)	(0.020)
Amenity COVID	-0.019**	0.046***	0.026***	0.078***	0.012	0.097***
	(0.008)	(0.021)	(0.007)	(0.009)	(0.011)	(0.012)
Distance_{2012}	-1.640***	-1.681***	-1.598***	-1.684***	-1.873***	-2.001***
	(0.015)	(0.019)	(0.011)	(0.015)	(0.022)	(0.024)
Distance_{2013}	-1.622***	-1.685***	-1.585***	-1.697***	-1.861***	-1.980***
	(0.015)	(0.019)	(0.011)	(0.015)	(0.022)	(0.022)
Distance_{2014}	-1.624***	-1.652***	-1.628***	-1.705***	-1.902***	-2.015***
	(0.015)	(0.019)	(0.011)	(0.014)	(0.020)	(0.029)
Distance_{2015}	-1.614***	-1.639***	-1.650***	-1.700***	-1.920***	-2.013***
	(0.015)	(0.019)	(0.011)	(0.013)	(0.020)	(0.022)
Distance_{2016}	-1.584***	-1.624***	-1.641***	-1.694***	-1.957***	-2.047***
	(0.016)	(0.019)	(0.011)	(0.013)	(0.020)	(0.021)
Distance_{2017}	-1.577***	-1.598***	-1.643***	-1.694***	-1.953***	-2.004***
	(0.015)	(0.019)	(0.011)	(0.013)	(0.019)	(0.021)
Distance_{2018}	-1.535***	-1.583***	-1.634***	-1.682***	-1.960***	-2.005***
	(0.015)	(0.019)	(0.010)	(0.013)	(0.018)	(0.021)
Distance_{2019}	-1.584***	-1.560***	-1.618***	-1.695***	-1.903***	-2.049***
	(0.015)	(0.018)	(0.010)	(0.013)	(0.017)	(0.019)
Distance_{2020}	-1.605***	-1.565***	-1.637***	-1.749***	-1.911***	-2.109***
	(0.015)	(0.019)	(0.010)	(0.013)	(0.018)	(0.020)
Distance_{2021}	-1.600***	-1.573***	-1.646***	-1.773***	-1.931***	-2.108***
	(0.015)	(0.019)	(0.010)	(0.013)	(0.018)	(0.020)
Distance_{2022}	-1.600***	-1.577***	-1.645***	-1.758***	-1.955***	-2.122***
	(0.016)	(0.018)	(0.010)	(0.012)	(0.017)	(0.019)
Cons	3.565***	10.189***	-2.916***	8.026***	-4.914***	3.259
	(1.046)	(1.662)	(0.952)	(1.550)	(1.446)	(2.389)
Origin-time FE	Yes	Yes	Yes	Yes	Yes	Yes
Destination FE	Yes	Yes	Yes	Yes	Yes	Yes
$\textit{Origin-Destination}^{Urb}$ FE	Yes	Yes	Yes	Yes	Yes	Yes
$\textit{Origin-Destination}^{N1}$ FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,377,441	20,377,441	210,102,276	210,102,276	407,871,058	407,871,058
Pseudo-R^2	0.501	0.523	0.297	0.330	0.249	0.268

Notes: Authors' elaboration. The dependent variable is the bilateral flow of Italian citizens between municipalities, disaggregated by level of education. The estimates exploit heterogeneity with respect to the level of urbanisation of the municipality of origin and the cost of living at destination. The cost of living is computed as the ratio between rent cost per square meter and income per capita. The table presents results for three sub-samples of origin municipalities, classified as urban (columns 1 and 2), suburban (columns 3 and 4), and rural (columns 5 and 6). The analysis is restricted to outflows directed toward municipalities belonging to the first nine deciles of the cost of living distribution, excluding those with the highest cost of living. In all estimates, migration corridors between municipalities with a distance of less than 70 km are excluded to avoid capturing commuting movements. Income and Amenity variables related to the destination municipality are expressed in *arcsinh* form and lagged by one year. Robust standard errors, corrected for clustering at origin-destination level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.