Agglomeration, Segregation and Imperial Origins*

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Abstract

What explains the dramatic differences in earnings across locations? We employ an employer-employee-linked dataset from Italy covering the entire workforce to estimate firm-worker (AKM) and location-worker effects, aggregated within each location. We also augment those specifications with cumulated years of experience in firms or locations to estimate human capital accumulation. The elasticity of location premia to density is smaller than in other settings, and other locational characteristics, such as segregation in schools or the workplace and intergenerational mobility, are more strongly correlated with earnings and earnings growth. Our place-based estimates are validated when we focus on movers forced to relocate after the L'Aquila Earthquake. Using a regression discontinuity design, we find that the historic border between House of Savoy-ruled Piedmont and the Hapsburg Empire significantly affected current earnings and historical proxies of urban density. The channels of persistence appear to be linked to the significant impact of the Hapsburg Empire on industrialization and urbanization: the administrative and civil service reforms undertaken at the time have plausibly fostered the scaling of cities.

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1. Introduction

What determines whether wages increase with the size of an agglomeration (Moretti, 2010b, Moretti (2010a), Combes et al. (2008)) or other location characteristics? Do higher urban wages reflect unobserved ability or the accumulation of skills over time, as in Glaeser and Mare (2001) and De La Roca and Puga (2017)? Are these benefits eroded by the segregation of communities and workplaces, as models of learning in cities suggest (Glaeser (1999)), and as found by Barza et al. (2024) for Brazil and Dillon et al. (2025) in the U.S.? We answer those questions by estimating worker-learning premia and cumulative experience within firms or locations: we then aggregate them across locations (see Card et al. (2025)) and leverage on arguably exogenous sources of variation, either form natural disasters or from historical colonization, to provide convergence evidence of causal identification for the relation between density and segregation, on the one side, and location earnings premia, on the other.

Italy provides a particularly compelling case for studying the link between location and earnings, because it has an extraordinarily rich urban past that offers abundant, hyper-local variation in historic infrastructure and institutions. In this paper, we use Italian administrative social security data that cover the country's entire workforce[1] and employ two-way fixed effects (firm-worker and location-worker) specifications to investigate the role of locational characteristics in the wage premium. We also estimate the impact of years of exposure to places or firms. We estimate the empirical links between earnings and earnings growth and density, indices of segregation in schools and the workplace, and intergenerational mobility. Our analysis also relies on two sources of arguably exogenous variation – relocation after the 2009 Aquila earthquake, which should limit the extent of self-selection, and the historic border between the Hapsburg Empire and the domains of the House of Savoy, which unveils the deep roots of current local institutions.

We find that while density retains a significant role in boosting earnings and earnings growth, agglomeration effects appear weaker than in other settings. Segregation in schools or the workplace significantly depresses earnings and earnings growth, perhaps because isolation reduces the extent

1 We use the time sample 2010-2023. The largest sample we used for the two-way fixed effects contains roughly 88 millions year-workers observations.

of knowledge spillovers and other network externalities. These results remain true when we focus on a sample of workers who relocated from an earthquake zone. We also find that the earning premium jumps at the Hapsburg border and document significant historical differences in urbanization and industrialization between the Hapsburg Empire and the nearby House of Savoy region.

The Social Security data set contains information on the universe of workers in Italy, including their biographies and information on the firms they worked in. We employ both firm-worker and location-worker fixed effects specifications to estimate five core regressions. These specifications differ depending on whether they include firm or city fixed effects and whether they allow different firms or cities to have different age-earning profiles. We start with the now classic Abowd et al. (1999), or AKM, the worker-firm fixed effects method. As in Card et al. (2025), we then compute the location-specific earnings premium as the employment-weighted average firm effect for the firms in that place. This average reflects the characteristics of the local industrial composition or the learning channels within the company. We therefore compare it to the one we estimated under a location-worker specification, which captures broader learning channels and their link to local institutions.

We then augment both sets of specifications with workers' prior experience in certain locations or in large firms (which we refer to as dynamic models).[2] These experience terms capture the learning and human-capital accumulation associated with exposure to specific places or to large, productivity-enhancing employers. Subsequently, we relate location-average earnings, or location-averages of firm and worker effects, to locational attributes, including population density, our proxy for agglomeration externalities.[3], segregation in schools[4] or at workplace[5] and an index of intergenerational mobility.[6] We expect density to propel the learning externalities, and isolation indices are expected to curb them.

Our estimate of the location-earning premium's elasticity is smaller than those from recent

2 We compute experience as the cumulative number of years in each location or in the largest cities.
3 We construct this following De La Roca and Puga (2017).
4 We measure segregation in schools using the indexes developed by Agasisti and Falzetti (2017).
5 We measure this either with the index constructed by Dillon et al. (2025) or with the index proposed by Song et al. (2018). The second is constructed using the firm fixed effects estimated within AKM; therefore, we use it primarily to estimate the elasticities for the AKM earnings premia, and their components.
6 The index is from Acciari et al. (2022).

literature: for instance, De La Roca and Puga (2017) finds a value of 0.024 for Spain. We find a value of 0.011 when using the same specification and a value of 0.013 when we estimate the location premium by averaging AKM firm effects. We find that segregation and mobility are significantly and negatively correlated with the location earning premium. High levels of segregation and low levels of upward mobility are also associated with a smaller link between earnings and density. Segregation in schools explains roughly 20-25% of the variance, and segregation in schools can explain 30%-50% of the variance, depending on the specifications. Intergenerational mobility, too, is robustly correlated with earnings and earnings growth, although this is perhaps less surprising, since mobility measures are also constructed using the same earnings data that we use.

We provide variance decompositions of the location-average of the firms' fixed effects, estimated via AKM, across industries and worker skill types. We find, for instance, that industrial composition explains more than 50% of the variation in firms' fixed effects. Furthermore, the elasticity of the location-average worker effect with respect to the density is more than 2.5 times larger for college-educated workers than for non-college-educated workers. Skills and density appear to be complements in Italy, as have been found elsewhere.

In the specifications that include components for exposure to location or firms, the elasticity of the earnings with respect to the density is even lower. The magnitudes of the elasticities with respect to the segregation measures also decline.[7] However, the overall message remains: isolation measures have an extraordinary, and so far unknown, adverse effect on location-based earning components.[8] These results may therefore shed light on why cities of similar density, such as Milan and Naples (or Pittsburgh and Detroit) have very different earnings trajectories.

Next, we delve deeper into our analysis and ask whether our results may be driven by endogenous mobility, rather than predetermined local characteristics, and whether the segregation measures result from institutions inherited from the past.

Our results may reflect the selection of more skilled workers in more integrated or dense metropoli-

7 In this case, segregation in schools explains a share of the variance between 15% and 36%, whereas segregation in the workplace and upward mobility explain again the largest share of the variance, between 30% and 50%.

8 As examples, the returns to density are roughly 7 times larger in high mobility than low mobility places. A 1 standard deviation increase in segregation in the workplace implies a 1.01% loss in earnings.

tan areas. If moves after a natural disaster are more likely to be random, focusing on people who relocate after an earthquake should cause the estimated place-related coefficients to attenuate. We reestimate all of our core specifications using a sample of workers who moved after the 2009 earthquake that hit the city of L'Aquila.[9] We provide several falsification tests that corroborate the hypothesis that those movers were arguably exogenous. The estimated elasticities are essentially unchanged. We validate the estimates obtained when using all movers and we find that the difference with those obtained using only the sample of exogenous movers is not statistically significant.

Omitted place-based characteristics pose a second challenge to interpret the effects of agglomeration or segregation. If a place is naturally more productive, then it will attract more people, leading to a misleading relationship between density and productivity. To address this, we focus on an inherited institutional environment, which should have little impact on productivity today. Using a regression discontinuity design (Dell et al. (2018)), we find a significant jump in the estimated earning premia[10] at the 19th-century border between the Hapsburg Empire and the lands of Piedmont belonging to the House of Savoy. We also find at the same border a significant jump in historical population density,[11] and in several industrialization indices[12]. Furthermore, historical trends for indices of urbanization and industrialization appear to grow much faster than in the nearby Savoy region. To validate our estimates, we verify that geographical variables are balanced across regions on both sides of the border and they are. Furthermore, the border discontinuity persists even after controlling for regional fixed effects and distance from large cities.

We conclude by describing two major sets of reforms that encouraged urbanization and proto-industrialization. The first was the administrative reform initiated by Maria Theresa and Joseph I, which included the professionalization of the civil service and the expansion of access to the

9 In the aftermath of the disaster, the entire historical center of L'Aquila was classified as a "red zone," rendering it uninhabitable. These circumstances arguably generate quasi-experimental variation, as relocation decisions made under such extreme conditions are unlikely to be driven by the same factors that govern migration choices in regular times.

10 Earning premia used as dependent variable the regression discontinuity are estimated with worker-location or worker-firm fixed effects specifications at municipal level. Point estimates for the location premia range from 3.2% to 2.6% in the baseline specification, from 2.9% to 2.1% when controlling for distance from large cities, and from 2.8% to 3.3% when adding regional fixed effects.

11 We gather data on city size from Bairoch and Goertz (1986), and Malanima (2005) and data on population in each 1 km^2 grid from Eurostat (GISCO).

12 We take the historical data on this from Ciccarelli and Fenoaltea (2013).

education system. Historians claim that by broadening access to the civil service across all social strata and reducing uncertainty in the administrative process, these reforms fostered meritocracy, improved education, and enhanced urbanization. A second set of trade reforms focused on trade, including the removal of internal tariffs and the creation of a customs union. The Hapsburg Empire, burdened by high debts, had a compelling need to exploit Northern Italy's trade connectivity to boost production and, in turn, revenues. Those extractive motives, in turn, seem to have had unintended consequences of promoting industrialization.

Literature Review. Our paper follows the literature on measuring the dynamic effects of urban location on wages, as in Glaeser and Mare (2001) and De La Roca and Puga (2017). A recent paper by Barza et al. (2024) applies the De La Roca and Puga (2017) methodology to Brazilian data and focuses on workplace integration. While that literature estimates the dynamic impact of place, without examining the effect of the firm, we also estimate firm-worker fixed effects as in Abowd et al. (1999) and compute the location premia by averaging the fixed effects in each location (see Card et al. (2025)). Our paper also relates to the large literature on the role of agglomeration externalities (see Glaeser et al. (1992), Moretti (2004), Moretti (2010b) or Moretti among others). Relatively to this literature our paper leverages sources of arguably exogenous variation, either form natural disasters or from historical colonization, to provide convergence evidence of causal identification of the relation between density and segregation, on the one side, and location earnings premia, on the other.

Our estimates of the learning elasticities, within firms or locations, relate to a literature that examines how shocks induce firms to restructure so as to optimize workers' learning (see Jarosch et al. (2021)). Our focus on learning within firms and our measures of segregation as proxies for learning, relate our paper to the literature on learning from peers (see Ammermueller and Pischke (2009), Angrist and Lang (2004)) or the literature on the role of firms' heterogeneity for earnings (see Card et al. (2013)).

Our work using the L'Aquila earthquake follows in the literature that relies on natural disasters to identify the impact of relocation: Deryugina et al. (2020) exploit quasi-experimental evidence

from Hurricane Katrina to its effects on health; Sprung-Keyser and Porter (2023) exploit exogenous variation from the same disaster to disentangle childhood experience from learning at work (see Dell et al. (2014) for a recent overview of the methods. See Baker et al. (2024) for an application to growth).

Finally, our Hapsburg design is based on the methodology developed and applied by Dell et al. (2018). Overall, our evidence on the role of the Hapsburg colonization relates to the literature on the persistent effects of institutional change (a non-comprehensive list includes: Acemoglu et al. (2001), Nunn (2009a), Nunn (2009b), Michalopoulos and Papaioannou (2013), Spolaore and Wacziarg (2014), Spolaore and Wacziarg (2014), Spolaore and Wacziarg (2016), Bandiera et al. (2019) and Desmet et al. (2025).) or the literature that explains "long divergences" across regions based on historical political-religious bargains (see Bénabou et al. (2022)). See Abramitzky (2015) or Cantoni and Yuchtman (2021) for an overview of the methods and goals. Some of this literature also examines the role of the Hapsburg Empire in current economic institutions in Europe (Becker et al. (2016) and Cainelli et al. (2023)).

2. Methodology

Our empirical strategy builds on several econometric approaches designed to identify, including in a causal sense, the determinants of the location premium.

First, we estimate wage equations using either firm-worker effects specifications, commonly employed in labor economics (see Abowd et al. (1999)), or location-worker effects specifications, which are standard in urban economics (see Glaeser and Mare (2001); Barza et al. (2024)). The firm-worker specifications included worker and firm fixed effects, but not location fixed effects. In the location-worker specification, we allow worker and place-based fixed effects, but not firm-fixed effects. In all cases, the dependent variable is a Mincerian residual obtained by regressing observed wages on time fixed effects and a polynomial in age. In the worker–firm specification, the location premium for each province is constructed as the average of the firm fixed effects, where each firm is weighted by its number of employees. In both the firm-worker and location-worker specifications,

the workforce component for each location is defined as the average of the worker fixed effects. Comparing these two approaches allows us to separate the role of firms and industrial composition from that of local agglomeration externalities.

We use "static" to describe specifications without interactions between the firm, or place effects, and experience, and "dynamic" to describe the specifications with such interactions. We measure experience as the number of years spent in each location or firm, focusing on their size (as in De La Roca and Puga (2017)). We also examine the relationship between the estimated location premia and population density, indices of school and workplace segregation, and intergenerational mobility. We see these estimates as tests for the existence of static and dynamic agglomeration effects, and we test whether interactions between skilled and unskilled workers are important for earnings and earnings growth.

Finally, we provide quasi-experimental evidence on the relation with density and segregation by estimating our two-way fixed-effects specifications on a sample of movers who left L'Aquila following a major earthquake. These out-migration flows may be less likely to reflect unobserved worker attributes than less constrained choices. Lastly, we examine the historical roots of the location premium with a spatial regression discontinuity design along the lines of Dell (2010). We find a significant discontinuity at the Hapsburg-Savoie border established in 1815 by the Congress of Vienna, both in population density and in location premium.

2.1. The Data

Our primary data source is an employer-employee linked dataset for Italy, gathered from the archives of the *Istituto Nazionale della Previdenza Sociale* (INPS), the Italian national institute of social security. The data set covers the universe of all Italians working in the private sector. The data can only be accessed on-site and upon passing a peer-reviewed selection process through the VisitINPS program. The dataset provides records of detailed individual-level sociodemographic characteristics and income information for each worker, including their address, dating back to 1974. We can reconstruct a workers' complete employment history, and hence measure the exposure of a worker to

particular cities or firms. We use annual data and focus our analysis on the male population during 2010-2023, the years for which we have the data needed to compute the segregation measures. More details on the variables, definitions, and the datasets' construction are in Appendix A.

We matched our primary INPS dataset with several other data sources. We measure isolation in schools using the indices of skill segregation from Agasisti and Falzetti (2017). To proxy occupational segregation, we rely on two alternative indices. The first is by Dillon et al. (2025) and is the probability that a randomly chosen non-college worker shares a workplace with another non-college worker. The second is from Song et al. (2018) and measures task concentration within firms, constructed from the fixed effects estimated using AKM. We use the measures of intergenerational mobility described by Acciari et al. (2022). Again, the details are in Appendix. A.

The sample we use to estimate the two-way fixed effects around the earthquake in L'Aquila in 2009 includes individuals who were working at L'Aquila in 2008 and moved out in 2009 or in 2010, from one of the 107 municipalities in the area of the earthquake epicenter. Roughly 4199 individuals moved out of that area.

To implement our regression discontinuity design, we use data on historical borders (shapefile, level) from an archival or published source, data on weather variables at the grid level for the period 1950–1974 from Cornes et al. (2018), and data on elevation and slope at the grid level from Tarquini et al. (2012). For urbanization, we use historical data on city size for the period 1000–1861 from Bairoch and Goertz (1986), and from Malanima (2005). For industrialization, we use indices for the period 1821–1911 from Ciccarelli and Weisdorf (2019).

2.1.1. Firm and Worker Effects Specification.

The baseline specification is the two-way fixed effects wage regression a' la Abowd et al. (1999):

$$y_{it} = \alpha_i + \delta_{f(i,t)} + \beta X_{it} + \epsilon_{it} \tag{1}$$

where α_i denotes the worker fixed effects, $f(i,t)$ is an index function that identifies the establishment f at which worker i is employed at time t, δ_f represents the establishment fixed effects, and $X_{i,t}$ is

a vector of control variables. We use the term *establishment* to indicate a firm–province pair, since a given firm may operate across multiple provinces, and our interest lies in estimating province-level wage premia. Consequently, all fixed effects are specified and estimated at the establishment level. For ease of exposition, however, we refer to these as *firm fixed effects*; and in what follows, the terms *establishment fixed effects* and *firm fixed effects* are used interchangeably.

As in De La Roca and Puga (2017), the Abowd et al. (1999) model can be estimated either on raw earnings or on the residuals from a Mincer-type earnings regression. Our baseline specification uses residuals obtained from regressing log earnings on time effects and a polynomial in age, estimated on the largest connected set of the worker–establishment mobility network, which covers more than 99% of our sample.

Average Location Premia across Workers and Firms. We compute the average earnings premium across firms in province c as:

$$\psi_c \equiv \frac{\sum_{c(f)=c} N_f \delta_f}{\sum_{c(f)=c} N_f} \tag{2}$$

where $c(f)$ is an index function giving the province of the establishment f and N_f is the number of person-year observations in our estimation sample for that establishment. These represent the gains or losses in pay associated with a move from the average establishment in one location to the average establishment in another. Next, we average equation (1) across workers in each location unit:

$$\bar{y}_c = \bar{\alpha}_c + \psi_c + \bar{X}_c\beta \tag{3}$$

where $\overline{\alpha}_c$ is the mean of workers' fixed effects in each locality and summarizes the average skill of the workforce, ψ_c is the location premium, and $\overline{X}_c\beta$ is a coefficient-weighted average of the time-varying effects.

Decompositions of Location Premia across Education and Industries. Human capital

and industrial composition are likely to affect the location premia. We assess the role of human capital by averaging equation (1) for each education group separately:

$$\bar{y}_{ce} = \bar{\alpha}_{ce} + \psi_{ce} + \bar{X}_{ce}\beta. \tag{4}$$

$e = H, L$ denotes the education group and $\psi_{ce} = \frac{\sum_{c(f)=c} N_{fe}\delta_f}{\sum_{c(f)=c} N_{fe}}$, where N_{fe} represents the number of workers of education group e at firm f.

To analyze the contribution of sectoral composition, we aggregate the firm-specific effects f within locality c across sectors j as:

$$\psi_{cj} = \frac{\sum_{cj(f)=(cj)} N_f \delta_f}{\sum_{cj(f)=(cj)} N_f}. \tag{5}$$

This index can be decomposed into location- and sector-specific components according to:

$$\psi_{cj} = \theta_c + \mu_j + \epsilon_{cj}. \tag{6}$$

This decomposition allows us to quantify the extent to which province-by-industry earnings premia are attributable to location-specific effects, industry-specific effects, and their interaction term.

Finally, to assess how much of the variation in average provincial pay effects can be attributed to industry composition and to province–industry specific pay premia, we apply an Oaxaca (1973) decomposition:

$$\psi_c = k + \sum_j \overline{s}_j(\psi_{cj} - \overline{\psi}_j) - \sum_j (s_{cj} - \overline{s}_j)\overline{\psi}_j + \sum_j (s_{cj} - \overline{s}_j)(\psi_{cj} - \overline{\psi}_j) \tag{7}$$

where w_c is the share of national employment in location c, s_{cj} and $\overline{s}_j$ are the shares of employment in industry j in location c and in the nation, respectively, and $\overline{\psi}_j \equiv \sum_c w_c \psi_{cj}$ is the national average wage premium for industry j. The term $k \equiv \sum_j \overline{s}_j \overline{\psi}_j$ represents the average industry premium earned by workers in a representative location with national-average industry shares, and is constant between locations.

2.1.2. Location and Worker Effects Specification

We also estimate wage equations using the location fixed effects, which are more common in urban economics. The baseline from Glaeser and Mare (2001) included worker and location fixed effects:

$$y_{it} = \alpha_i + \psi_{c(i,t)} + \beta X_{it} + \epsilon_{it}, \tag{8}$$

This specification explicitly controls for workers' tenure and labor market experience. In this framework, location-specific wage premia are identified using province fixed effects, whereas the workforce component is computed as the mean of worker fixed effects within each province.

2.2. Learning through Exposure to to Locations and Firms

It is typically hard to disentangle the role of location, or firms, onto earnings from that of selection. We progressively adopt several empirical strategies to do that start with a dynamic design, inspired by De La Roca and Puga (2017) and later used also in other strands of the literature (see Chetty and Hendren (2018) for role of location on inter-generational mobility). The design exploits variation in exposure to cities to identify the two: by comparing similar workers who have spent different amount of time in the same location, one exploits variation in exposure to place that is plausibly exogenous to long-term outcomes. This specification implicitly exploits also variations in the moves, as it compares workers with similar characteristics who move to the same province (or city) destination at different times. A novel aspect of our design is that we employ this design both in the worker-firm and in the worker-location specifications and we consider alternatively the impact for years of exposures to locations or firms. The two also identify the different role of positive complementarities, or spillovers, stemming from firms or locations.

Extending the Abowd et al. (1999) specification with experience in location or firms. In the spirit of De La Roca and Puga (2017), we augment the specification by adding a term that captures the experience workers have accumulated in each location or in firms of different size categories. This dynamic component reflects the human-capital accumulation associated with the

time a worker has already spent, up to period t, in specific provinces or in firms belonging to the size classes, which we define below. The extended specification is:

$$y_{it} = \alpha_i + \delta_{f(i,t)} + \sum_{\kappa=1}^{K} \gamma_\kappa \, e_{\kappa(i,t)} + \beta X_{it} + \epsilon_{it} \tag{9}$$

where all variables are defined as in 1, K is the number of locations in which the worker lived, $e_{\kappa(i,t)}$ is the cumulative experience that worker i has acquired in province κ up to time t.

We then define the human capital accumulation premium in province c as:

$$\phi_c \equiv \gamma_c \, \bar{e}_c,$$

where $\bar{e}_c$ is the average number of years of experience in province c. Analogously, we compute the human capital accumulation premium in each province c as follows:

$$\phi_c \equiv \frac{\sum_{\kappa=1}^{K} N_{\kappa c} \gamma_\kappa \, \bar{e}_\kappa}{N_c},$$

where $N_{\kappa c}$ is the number of person-year observations in firm category κ and province c, N_c is the total number of person-year observations in province c, and $\bar{e}_\kappa$ is the average number of years of experience in firms of category κ across the whole sample.

In the baseline specification, firm size is measured by total employment, and firms are partitioned into three size classes: the 90th–94th percentiles, the 95th–99th percentiles, and the top 1st percentile of the national firm-size distribution. Firms below the 95th percentile are excluded from this classification, as we directly control for workers' total labor market experience.

Extending the worker-location specification with exposure to location and firms. As we did for the Abowd et al. (1999) we can extend also the worker-location specifications to include years of exposure to location or firms. Formally, the specification in equation 8 can be extended to include a dynamic component that captures experience accumulated within a given province or within large firms.

Note that the past literature (De La Roca and Puga (2017)) has instead cumulated years of experience by grouping and ranking locations based on location-size categories. We also estimate this alternative specification, as it allows us to compare our results with those reported in previous literature. Hence, we will present results for the worker-location specification augmented with years of exposure tom large cities, with years of exposure to any location and with years of exposure to firms.

2.3. Covariates of the Location Earning Premia

Next, we investigate the impact of a set of provincial characteristics on average earnings, on the fixed effect components (worker, firms and locations) and on the estimates for the impact of exposure. For the covariates we employ population density as a proxy for agglomeration externalities, and segregation, conceptualized as a mechanism that may impair knowledge diffusion and learning spillovers. We construct measures of both school and workplace segregation, and additionally employ an index of intergenerational mobility. Following Card et al. (2025), we estimate the following empirical specification:

$$y_c = \mu + \gamma Z_c + \nu_c, \tag{10}$$

where Z_c denotes the vector of provincial characteristics. The aggregate effect of Z_c can be decomposed into the contributions that operate through the composition of the workforce, the location-specific earnings premium and the human-capital accumulation premium, when the latter is included in the specification.

Density. Following De La Roca and Puga (2017), we measure the size of each urban area as the average number of people living within a given distance of the average person in that area. Specifically, we computed this measure for radii of 5 km and 10 km using a 1 km resolution population grid (2021 census, Eurostat GISCO). For each 1×1 km cell in the urban area, we draw a circle of radius around the cell (encompassing both locations within and outside the urban area), count the total population within that circle, and then average these counts across all cells in the urban area, weighted by each cell's population. This procedure yields the number of people

within 5 km or 10 km of the average person in the urban area. In Appendix Figure 11, we map the population measure for the 5-km radius.

Segregation at school. We use the OECD's Economic, Social and Cultural Status Index (ESCS), which combines information on parental education and occupation with household possessions, standardized to have a mean of zero and a standard deviation of one. To measure socioeconomic sorting, we use the INVALSI segregation index, which captures the between-class variance of the Economic, Social and Cultural Status Index (ESCS) within each school. Formally, the school-level index reads as follows:

$$ESCS_Var_Within_k = \frac{1}{N_k} \sum_j (ESCS_{jk} - \overline{ESCS}_k)^2, \tag{11}$$

where N_k is the number of students in school k, $ESCS_{jk}$ is the average ESCS of class j in school k, and $\overline{ESCS}_k$ is the average ESCS of school k. The school-level index is then averaged at the provincial level. Higher values indicate greater segregation, with students from similar socioeconomic backgrounds concentrated in the same classes; lower values indicate more heterogeneous class composition. In Appendix Figure 12, we map the aggregated segregation index at the provincial level.

Segregation in Mobility. Our measures of intergenerational mobility were computed for the Italian provinces by Acciari et al. (2022). Across various specifications, we employ three measures: (i) the mean rank of children whose parents are below the median of their own national income distribution; (ii) the probability of rising from the lowest to the highest quintile of the income distribution; and (iii) the slope of the relationship between the average rank of the child and the average rank of the parents in their respective national distributions. In Appendix Figure 13, we map the mean rank of children whose parents are below the median of their own national income distribution. For the baseline second-stage specifications, we employ the mean rank. In some specifications designed to unpack the elasticity of the initial and medium-term premia, we employ all three indices.

Segregation at workplace. We used two alternative indices of segregation in the workplace, as one is preferable to the other depending on the second-stage specifications. The first is taken from Dillon et al. (2025) and is the probability that a randomly chosen non-college worker shares a workplace with another non-college-educated worker. This measure encompasses both educational segregation and workplace isolation, and, as such, is a more general concept of network externalities; as such, it is well suited for computing the elasticities of the location-earnings estimated with the dynamic DP. The second measure we employ is the share of the total variance in worker fixed effect (estimated through Abowd et al. (1999)) within a province c that is attributable to differences between firms (see also Song et al. (2018)):

$$\text{Segregation score}_c = \frac{\text{sd}_{f:\, c(f)=c}\left(\overline{\alpha}^{\,f}\right)}{\text{sd}_{i:\, c(i)=c}\left(\alpha_i\right)} \tag{12}$$

where $\bar{\alpha}^f$ is the firm average of the worker fixed effects. A higher index value indicates that workers with different abilities are more isolated across firms, reducing the scope of interactions, peer effects, and knowledge spillovers within local labor markets. This measure is well-suited for computing elasticities of location-earnings premia estimated via specifications that include a firm effect or a within-firm experience component.

2.4. Quasi-Experimental Evidence: Movers from an Earthquake Area.

The additively separable specifications, which are part of our main econometric strategy, implicitly assume that identification occurs through exogenous movers across firms (for the worker-firm specification) and across locations (for the location-worker fixed effect specification). Moves are, however, likely endogenous and consequently, firm- and location-fixed effects may also reflect aspects of self-selection.

We assess the importance of this self-selection with a sample of movers who left L'Aquila after a 2009 earthquake.[13] Those moves are less likely to be driven by unobserved shifts in worker

13 The earthquake was large and hence caused a lot of distress: its magnitude was 6.3 on the Richter scale. The entire historical center of L'Aquila, a typical area of aggregation, has been declared a red zone, making it unsuitable for building and residing.

productivity than standard moves. Our sample for this specification includes individuals who were working at L'Aquila in 2008 and moved out of one of the 107 municipalities in the area of the earthquake epicenter in 2009 or 2010. The sample includes roughly 4199 individuals. Another aspect that supports the case for quasi-experimental evidence is that out-migrants in this episode spread sparsely, almost randomly, across different cities in the North and in the South.

2.5. Historical Origins: Spatial Regression Discontinuity

To gain further insights on the causal determinants of the relation that we uncovered, we use a spatial discontinuity design along the lines of Dell (2010); Dell et al. (2018). Italy has experienced in various parts a variety of colonizations that marked the historical borders of regions with different customs and institutions. We focus on the border in Northern Italy between the Hapsburg and Savoy lands established in 1815 by the Congress of Vienna. Interestingly we have entertained the possibilities that other historical borders, within the peninsula, may have a persistent effect, but only the Hapsburg border showed significant jump in the earnings. This historical discontinuity, which divided the Hapsburg domains from the Savoyard lands, introduced variation in institutional and social structures that may have had an enduring impact on density, productivity, and upward mobility. Formally, the econometric specification reads as follows:

$$\psi_c = \alpha + \gamma\, Hapsburg_c + f\big(\text{geographic location}_c\big) + \sum_{i=1}^{n} seg_c^i + \varepsilon_c, \tag{13}$$

where ψ_c is either the location earning premium of municipality c, or other outcome variables (namely population size and another index of agglomeration taken from Eurostat) which we interpret as mediators of the historical transmission of institutions, $Hapsburg_c$ equals 1 if municipality c lay within the Hapsburg-ruled territories of the 1815 boundary (and 0 otherwise), $f(\text{geographic location}_c)$ is the RD polynomial in location, and seg_c^i are fixed effects of a 25 km segment (equal to 1 if municipality c is closest to segment i). The segment fixed effect is added to ensure that the units being compared are not only close to the threshold in terms of the forcing variable, but also similar in terms of other unobserved characteristics. In our main specification, $f(\text{geographic location}_c)$ is a

second-degree polynomial in latitude and longitude. We use a 40 km bandwidth, but also look at an 80 km bandwidth to test robustness. In regression discontinuity design a polynomial of the running variable (location) is added to model the relationship between that variable and the outcome on both sides of the cutoff. This allows us to flexibly control for potential non-linear trends, reducing the biases in estimating the treatment effects. The polynomial acts as a control for underlying, smooth trends in the data that could be confounded with the treatment. We choose a second order polynomial within a small bandwith of the location also based on recent econometric practice (see Gelman and Imbens (2019)), that argues that higher order polynomial can cause noise.

To understand the channels of persistence, we proceed as follows. First, we estimate the regression discontinuity design using earnings as the dependent variable and its fixed effects components, estimated with worker-firm and worker-location fixed effects specifications. This informs us on whether this historical border has a persistent effect on earnings variation, which is actually largest between the North and the South. Second, to understand the origin of this variation, we re-estimate the regression discontinuity, but using as a dependent variable a historical proxy for urban density.[14] At last, we examine a set of other indicators for urbanization and industrialization and examine whether their patterns differ significantly at the border between the Hapsburg and the Savoy region.

3. Results: Elasticity of the Location Premia

We now turn to the results on the links between earnings premia, and their fixed effect components, on one side and density, segregation, and upward mobility on the other.

3.1. Elasticities for the Firm-Worker and Location-Worker Static Specifications

We begin by examining the elasticities of the premia obtained from the static specifications with respect to population density, segregation, and mobility, using the complete set of estimates from

14 Data are from Malanima (2005) or Bairoch and Goertz (1986).

both the worker–firm and worker–location models. The three sets of variables considered, density or segregation measures, capture the extent of learning that can happen within firms or within locations: density can potentially foster it, and segregation may dampen it. Together, they are more likely to account for variation, which may explain why locations, or urban areas, of equal density may exhibit very different earning premia. To provide a first assessment of the channels through which learning propagates, we use as dependent variables the earnings components we gathered across all specifications; hence, we aggregate at the firm or worker level, add location or city fixed effects, and include cumulative exposure to firms or locations. The summary results are reported in Table 1.

The first panel of Table 1 reports the estimated elasticities with respect to density of average log earnings, y (column 1), the worker-fixed effect component (columns 2 and 4), and the location premium (columns 3 and 5) for the firm–worker (henceforth AKM static) and location–worker (henceforth DP static) specifications. In the first column, we find an elasticity of earnings with respect to density of .039, which is approximately equal to the sum of the AKM static worker-fixed effect component of .023 and the AKM firm-fixed effect component of 0.013. Taken literally, these results indicate that two-thirds of the density premium is associated with more productive workers and one-third with more productive firms. The fact that workers appear to be more productive in denser areas could reflect the selection of better workers into those areas or more learning in those areas, either at school or on the job.

In columns (4) and (5), we find that in the DP static specification, the elasticity of the worker fixed effects with respect to density is .028, and the elasticity of the location fixed effects with respect to density is .011. This suggests that more than two-thirds of the place-effect is associated with better workers in Italy. Our estimate of .011 is about one-half of the 0.024 reported by De La Roca and Puga (2017) for Spain. Density accounts for about 15-19% of the variation in the place-average worker fixed effect but only 8% of the variation in the location fixed effects, which is also less than the 14% reported by De La Roca and Puga (2017). The first panel of Figure 1 shows the positive association between the DP location fixed effects and density.

In the second panel of Table 1, we examine the rank-to-rank slope (RRS), a measure of intergenerational mobility that indicates lower social mobility for higher values, and its interaction with density. All covariates that enter interactions have mean zero, so the coefficients on the main effects can be interpreted as the average effects of these variables. The coefficient on density is essentially unchanged in the second and third panels of the table, relative to the comparable regressions in the first panel.

Accordingly, at the mean level of population density (-1.502), a one-standard-deviation increase in the rank-to-rank slope (SD = 0.028) is associated with a 4.2 percent decrease in average earnings (column 1). The estimated interaction coefficient (-0.739) captures the extent to which the earnings elasticity with respect to population density varies with RRS. A one standard deviation increase in RRS above its mean (-0.739) is associated with a 0.021 decrease in the elasticity of earnings with respect to density, which means that the connection between density and earnings has dropped by more than one-half.

The province at the 10th percentile of the RRS distribution (RRS = 0.032 below the mean) has an estimated elasticity of earnings with respect to density of 0.062. A province at the 90th percentile of upper mobility has a value of RSS 0.208 above the mean, and consequently, the implied elasticity decreases to 0.011.[15]. Hence, the estimated elasticity of earnings with respect to density is approximately six times larger in high-mobility provinces than in low-mobility provinces.

Upward mobility is associated with higher earnings, and the interaction between density and earnings is stronger in all five columns. The second panel of Figure 1 graphs the positive association between the DP location fixed effects and upward mobility. Interpreting these coefficients is difficult because upward mobility itself is a function of earnings. Nonetheless, these results suggest that density is associated with higher earnings in places with relatively high levels of upward mobility, but with lower earnings in places with relatively low levels of upward mobility.

The third panel examines socioeconomic segregation in schools and its interaction with population density. Because density is mean-centered and school segregation is standardized, the coefficient on density (0.034) can be interpreted as the earnings elasticity for a province with average school

15 The number is obtained from: $0.038 - 0.739 \times 0.037 = 0.011$.

segregation. The interaction term (−0.021) implies that an increase in segregation is associated with a 0.021, or approximately two-thirds of the decline, in the earnings elasticity with respect to density. The third and fourth panels of Figure 2 show that segregation in school is also associated with lower mean scores and a greater variance of test scores. In a province in the 10th percentile of segregation, which has a segregation value 1.04 below the mean, the estimated density effect is 0.056. In a province in the 90th percentile of the segregation distribution, the segregation value is 1.04 above the mean, and the density effect decreases to 0.012. The relationship between earnings and density is five times as large in low-segregation provinces as in high-segregation provinces.

In columns (2) and (3), we see that much of the school segregation effect appears to work through the average firm fixed effect. This result may reflect the choice of more productive firms to locate in places with more integrated and apparently better schools, or the presence of better entrepreneurs in such places. The magnitude of the interaction between density and segregation is approximately the same for the fixed effect of the average firm and the fixed effect of the average worker. Columns (4) and (5) show that school segregation is more strongly associated with location-fixed effects than with worker-fixed effects. The interaction between density and segregation is much larger for the location effect than for the average worker effect.

The fourth panel examines the magnitude of earnings segregation across firms within provinces, which we measure as the share of variance in worker fixed effects attributable to sorting across firms (Song et al. (2018)). In the first column, we estimate coefficients indicating that at the mean level of population density, a one-standard-deviation increase in firm-level segregation (SD = 0.031, Mean= -1.431) is associated with a 4.4 percent reduction in earnings. In this case, the interaction coefficient (−0.180) is not statistically significant. Although firm segregation is negatively associated with average earnings, it appears to have only a modest influence on the returns to density. The interaction between firm-level segregation and density is not significant in any of the other four specifications.

In specifications (2) and (3), we find that our segregation measure has a somewhat stronger negative effect on the average firm effect than on the average worker effect. We have trouble

interpreting these specifications because the firm-segregation measure is itself based on average-worker effects in quite similar regressions. In columns (4) and (5), we find that worker segregation is also associated with lower location fixed effects and lower average worker fixed effects. The estimated coefficient is about twice as large in the location-fixed effect regression, suggesting that places with more productive firms also have more integrated firms. It is instructive to compare the economic magnitudes of the segregation indices. In terms of quantitative implications, a 1 percent increase in firm segregation reduces the location earnings premium by 0.99 percent - roughly 12 times the effect of school segregation (-0.08%) and 4 times the effect of upward mobility (-0.26%). This evidence suggests that workplace sorting by ability is the most consequential form of segregation for location earnings premia.[16]

3.2. A Decomposition and Further Correlations

A large part of the location premium is due to the concentration of skilled workers or productive industrial activities in specific places. Examining the relative roles of those elements is also informative about the channels of variations in earnings premia. To this purpose, we provide several decompositions of the AKM fixed effects across industries and workers' skill types.

The upper part of Table 2 shows the variance decomposition of mean log earnings across places using the AKM-estimates. Columns (1) and (2) show the results for the entire sample. The first column shows that the standard deviation of the average worker effects is larger than that of the average firm effects, yet these two place-level averages are quite highly correlated. As discussed above, this correlation could reflect the selection of better firms into places with better workers or the fact that places with better workers start better firms. The second column shows that a slightly larger share of the variance is associated with the worker effects than with firm effects. The

16 Since the coefficients are semi-elasticities, to make effects comparable, we convert them into elasticities by multiplying each coefficient by its mean value. To express it per unit of the index, for school segregation we divide the semi-elasticity by the standard deviation (-0.024 / 2.225 = -0.011), and compute the elasticity at the mean (-0.011 × 7.816 = -0.084). For firm segregation and RRS: -1.431 × 0.689 = -0.986 and -1.502 × 0.171 = -0.257.

correlation between worker and firm effects accounts for the largest share of the total variance. The relative magnitudes are comparable to those uncovered in previous literature using this method.[17]

In Columns (3) and (4) (upper part of Table 2), we focus on workers without a college degree. For these, the share of the variance explained by firm fixed effects is larger than the share of the variance explained by worker fixed effects, which reflects the fact that while the variance of average worker effects is significantly smaller for non-college workers, the variance of average firm effects is not. This suggests that a significant advantage for less educated workers of being located in higher-wage areas stems from access to more productive firms. The interaction between the firm and worker fixed effects is also quite crucial for these workers.

Furthermore, columns (5) and (6) show results for workers with a college degree. In this case, the variation of average worker fixed effects is much larger than for the whole sample. Consequently, worker fixed effects explain 32.4 percent of the variation in locational earnings. Average firm effects for college-educated workers also exhibit a somewhat larger variation, although they explain only 15.4 percent of the total sample. The correlation between the two effects remains sizable.

The bottom part of Table 2 shows the elasticity of the worker and firm components of the premium with respect to log density for college and non-college educated workers. The elasticity of wages with respect to density is almost three times larger for college-educated than for non-college-educated workers (.073 vs .026). The elasticity of the average worker fixed effect is more than three times larger for the college-educated than for the non-college-educated workers (.043 vs. .014). The elasticity of average firm effects is also substantially higher for the college-educated. Density also explains a larger share of the earnings variance for college-educated workers (R^2 of 0.27 and 0.20) than for non-college-educated workers (R^2 of 0.10 and 0.04). These results continue to suggest a complementarity between density and education (see Glaeser and Resseger (2010).)

Industrial composition. In Table 3 we examine the role of industrial composition in explaining province-industry fixed effects. Those are defined as the sum of firm fixed effects with any given province (c) and two digit industry (j) or $\psi_{cj} = \frac{\sum_{cj(f)=(cj)} N_f \delta_f}{\sum_{cj(f)=(cj)} N_f}$. We regress this quantity on the

17 Given the large sample size, due to both the cross-sectional and the time series dimension, the connected set of our regressions is very large and close to 99%.

province, θ_c and the industry, μ_j fixed effects. Column (1) of the table shows that province fixed effects can explain only 5% of the variance in firm fixed effects. Column (2) shows that industry effects alone (column 2) explain roughly 53% of the variance.[18] Adding both the province and the industry effects (column 3) increases R^2 slightly, to 0.59.[19]

Columns (4) and (5) look at the correlation between the size of the province-industry cluster and the average firm fixed effects in that cluster. The estimates in column (4) show that as the share of provincial employment in the industry increases by one percentage point, the log of earnings in that industry increases by .01 log points, which is essentially the same amount. The estimates in column (5) show that the elasticity of earnings with respect to employment is .018, indicating also a strong relationship. These results suggest that industries locate in places that enhance their productivity, or that agglomerating forces make industries more productive as they increase in scale.

Table 4 presents a Oaxaca (1973) decomposition (as per (7) of the location average of firm fixed effects. We divide the variance into components and their covariances. The first component, which we label the *average earnings premium*, captures differences in average pay levels across provinces, after adjusting for industry composition. It measures the wage gain (or loss) that a typical worker would experience if moving between provinces, while remaining in the same industry. This component accounts for 80% of the variance. The second component, which we label *composition*, reflects differences based on industry shares and national wage patterns. Provinces with a higher concentration of employment in high-wage industries have a higher premium through this channel. This term explains 5.3% of the variance. Lastly, the *interaction effect* captures the correlation between local industry shares and local industry-specific wage premia. It is positive when industries, that are more concentrated locally, also pay higher local wage premia, in line with what we just documented. This component explains 4.9% of the variance. The most important *covariance term* is between the earnings premium and the composition effect (13%), reflecting the fact that provinces with a high earnings premium also tend to have a more favorable industry mix.

18 The importance of industry is not incompatible with the fact that the worker component of the AKM is larger than the firm component, as industrial composition can also affect the pool of workers.

19 To this purpose, we augment the specification with the share or the log share of provincial employment (see estimates in Columns (4) and (5)). In both cases, the coefficients are positive and highly significant, but the overall variance explained remains the same.

3.3. Estimating Dynamic Effects of Exposure to Firm and Place

We now turn to the results for the elasticities of the earnings premia obtained under the dynamic specifications presented in section 3.3. The earning premia here include the average of the Mincer, the estimated fixed effects and the estimated coefficient for the impact of the years of exposure to location and firms. As mentioned before, we use the estimates obtained under the AKM (firm-worker) and the DP (city-worker) specifications, allowing differential experience effects across places or firms. The number of years spent in a location or a firm will enable us to identify the differential impact on two workers, who are otherwise identical and who moved into that location (or firm) for similar reasons. We then examine the links across places between earnings growth, the estimated fixed and the estimated coefficients for years of exposure to firms and locations (which we define the exposure components since now on) in each of those specifications on the one with side with density, segregation, and mobility on the other.

Note that our baseline estimates obtain the location exposure components from specifications (worker-firm or location firm) that cumulate the number of years in each location-province. We use those estimates to compute the elasticities with respect to density and segregation. However, the exposure component in De La Roca and Puga (2017) is obtained by cumulating the number of years spent in large cities. For comparison with past literature, we present the estimates of the exposure component, and the related elasticities, for this case as well.

Elasticities for AKM Location-Earnings and Fixed Effects, Augmented with Experience in Location or Large Firms. Table 8 presents elasticities to density, mobility, and segregation for location earnings averages and location-averaged of firm and worker fixed effects estimated with AKM augmented with exposure to location or to the large firms. Again, the main message remains. The effect of density is positive and significant, whereas those of segregation measures and mobility are negative and significant. The magnitudes of the coefficients are now somewhat smaller, than those in the equivalent regressions in the absence of the experience terms. The covariates, however, account for a larger share of the variance due to the inclusion of experience at the location or firm level in the first stage.

We now delve more deeply into the quantitative implications of the coefficients for each covariate. In what follows, we also comment on the comparison between the elasticities of the location-earnings under AKM and DP.

Panel A (Density). The first panel shows results on density and wage growth. The estimates shown in columns (1)-(3) show the elasticities for the place-level earnings growth effects. The estimates in columns (4)-(6) show the elasticities for the firm-level earnings growth effects. Columns (1) and (2) provide estimates of the elasticities, with respect to the covariates, of ($\bar{\alpha}_c$, ψ_c). Those estimates are comparable to those in columns (2) and (3) of Table 1. The average worker fixed-effect elasticity with respect to density has shrunk by more than one-half with respect to the static specification (from 0.023 in Table 1, column 2, to 0.009 in Table 8, column 2), while the average firm effect remains largely unchanged at 0.013.

We estimate a density coefficient of 0.01 for the learning effect. This coefficient implies that moving from the least to the most dense province (a 3.84 log-point difference) raises ϕ_c by 0.038 log points.[20]

When we estimate returns to experience in large firms, we observe less attenuation in the relationship between the average worker effect and density. The average firm-fixed effect remains unchanged.

Panel B (Intergenerational mobility). In the second panel, we add the interactions with upward mobility. In the first specification, RRS reduces both the level of wage growth and the connection between density and wage growth.

The elasticity of the location-average firms' effect, estimated from AKM with location-exposure, with respect to RRS is -0.317. This coefficient implies that at the mean density, a 1 SD increase in RRS (0.028) reduces ϕ_c by 0.009 log points.[21] We also include an interaction term between density and mobility. The estimated coefficient for the interaction term is also negative and significant (-0.230); therefore, low mobility reduces the benefits that density provides in terms of experience accumulation. At mean RRS, moving from the least to the most dense province raises ϕ_c by 0.042

20 The number is obtained from: $0.010 \times 3.84 = 0.038$, which is equivalent to 3.87% higher earnings ($e^{0.038} - 1 = 0.0387$).

21 The number is obtained from: $-0.317 \times 0.028 = -0.009$.

log points.[22] In high-mobility provinces (10th percentile, RRS = 0.139, centered = −0.032), the density coefficient rises to 0.018, so the same move increases ϕ_c by 0.070 log points.[23] In low-mobility provinces (90th percentile, RRS = 0.208, centered = +0.037), the density coefficient falls to 0.0025, so the same move raises ϕ_c by only 0.010 log points.[24] The returns to density on the accumulation of experience are thus roughly 7 times larger in high-mobility than in low-mobility provinces.

Under AKM with firm experience, effects are much smaller: a 1 SD increase in RRS reduces ϕ_c by only 0.0005 log points ($-0.019 \times 0.028 = -0.0005$), equivalent to 0.05% lower earnings, and the interaction is not significant. In comparison, under DP with firm experience (estimates shown in table 7), a 1 SD increase in RRS reduces ϕ_c by 0.0017 log points ($-0.060 \times 0.028 = -0.0017$), equivalent to 0.17% lower earnings, and the interaction is not significant.

Hence, the inter-generational mobility index is more associated with institutions, within locations, that affect the opportunities to climb the ladder. Hence, it is more likely to be associated with places', than with firms' fixed effects.

Panel C (School segregation). Under the worker-firm specification (AKM) augmented with cumulated years of experience in each province, the coefficient on school segregation is −0.004: a 1 standard deviation increase reduces ϕ_c by 0.004 log points; the interaction term is not significant. Moreover, under the AKM specification augmented with cumulative experience in the firm, the direct effect is negligible (−0.000), although the interaction is marginally significant. In comparison, when the earnings are estimated with the worker-location (DP) specification augmented with experience in the firm (estimates shown in table 7), a 1 standard deviation increase in school segregation reduces ϕ_c by 0.001 log points, and the interaction is marginally significant.

To summarize, school segregation does not play a large and significant role for the static fixed effects, but we will see that it plays a more significant role for the coefficients capturing the exposure or learning in locations and firms, which we discuss below.

22 The number is obtained from: $0.011 \times 3.84 = 0.042$.

23 The quantification for the density coefficient is done as follows: $0.011 - 0.230 \times (-0.032) = 0.018$. This implies that the same move increases ϕ_c by 0.070 log points and this is obtained as follows: $0.018 \times 3.84 = 0.070$.

24 Once again the quantification for the density coefficient is obtained as follows: $0.011 - 0.230 \times 0.037 = 0.0025$. This implies that the same move raises ϕ_c by only 0.010 log points, which is obtained from: $0.0025 \times 3.84 = 0.010$.

Panel D (Firm segregation). The last panel shows the elasticities with respect to segregation within the firm. Using earnings estimate with AKM with cumulated experience in provinces, the coefficient on firm segregation is -0.331: a 1 standard deviation increase (0.031) reduces ϕ_c by 0.010 log points, equivalent to 1.01% lower earnings. Instead, using the earnings from AKM with firm experience, a 1 standard deviation increase in firm segregation reduces ϕ_c by 0.0004 log points, equivalent to 0.04% reduction in earnings. In comparison, under DP with firm experience (estimates shown in table 7), a 1 standard deviation increase in firm segregation reduces ϕ_c by 0.0012 log points, equivalent to 0.12% lower earnings. In all those cases, the interaction is not significant.

Overall, the experience premium from provincial exposure is far more sensitive to local barriers — low mobility and segregation — than the premium from within-firm experience.

Experience in Large Cities. Table 5 follows the dynamic specification used in De La Roca and Puga (2017) exactly and estimates a return to working in large cities. Column (1) reports the full set of coefficients. In that column, we show a strong effect of experience in the densest city (Milan), but a negative effect in the next two densest areas (Rome and Naples). Column (2) reports the elasticity of the initial premium with respect to density, which essentially means the relationship between the city fixed effects and density. This coefficient of 0.011 is modest relative to the literature. Even more surprisingly, column (3) shows the elasticity of the medium-premium (the initial premium plus the average years of local experience) with respect to density and it is .01. This shows a much weaker relationship between wage growth and urban density than in either Spain or Brazil. One reason this medium-term coefficient is so small is that the wage growth gradient is negative in some particularly large cities, including Naples and Rome. In column (4), we remove cities in the categories that experience a negative earnings growth coefficient from the sample (Naples, Rome, Caserta, Palermo, Como, Varese, and Prato). The coefficient rises to better align with results from Spain and Brazil. It is particularly interesting that Naples, which was a political capital until 1860, and Rome, which has been an on-and-off political capital for 2700 years, have negative experience effects. Table 6 shows the relationship between the initial and medium-term coefficients and upward mobility and educational segregation at the workplace. In this case, we employ the index proposed by Dillon et al. (2025), which is the probability that a randomly chosen non-college worker shares a workplace with

another non-college worker. The measure is well-suited to this case, as it encompasses both skill concentration and workplace isolation, thereby capturing a general concept of network externalities. In this table, we use the whole sample of cities and essentially just reuse the dependent variables seen in columns (2) and (3) of table 5. In the top panel, we look at upward mobility. The first column shows a coefficient on density of .01, roughly in line with the one observed in column (2) of table 5. The coefficient on mobility (RSS) is high and in line with the numbers already uncovered in table 1. The second column shows a tiny coefficient on density, as in column (3) of table 5. The coefficient on RRS increases in magnitude to -.5104. An increase in one standard deviation in RRS (.028) is associated with a decline in the initial wage premium of .012 (log points) and a decline in the medium wage premium of .014. Despite being significant, these coefficients are small.

The bottom panel examines the connection between educational segregation in the workplace and the initial and medium-term coefficients. Both estimated coefficients are statistically significant,[25] and their magnitudes are larger than the ones on density. One possibility is that big cities generate benefits by housing large firms, and workers find it easier to acquire knowledge in denser places. To examine this hypothesis, the next paragraphs examine elasticities of the earnings premia estimated using DP specifications, augmented with experience in firms, and AKM specifications, featuring firm-worker fixed effects, which we augment with experience in locations and firms. Since those specifications unpack the earnings parts related to firms, we also extend our definitions of segregation by distinguishing segregation in schools (taken from Agasisti and Falzetti (2017)) and at the workplace (taken from Song et al. (2018)).[26]

Elasticities for Location-Earnings Estimated with DP Augmented with Exposure to All Location or to Large Firms. We now examine the elasticities of the location and worker effects and the returns to experience in all location or in large firms, estimated with the DP specifications, with respect to all our covariates and their interactions. Results are shown in table 7, the left block shows the elasticities when the dependent variables come from the specification with

25 The negative and significant correlation persists with alternative measures of workplace segregation, such as the measure of education dissimilarity by Dillon et al. (2025), which measures the share of workers who would need to change establishments to equalize distributions.

26 Note that the segregation measure by Song et al. (2018) is computed by using the firms fixed effects estimated in AKM.

exposure to large firms and the right block when they come the specification with exposure to large firms.

To measure the exposure to firms, we split the distribution of firms into 3 bins, which are defined as those at the top 99%, which has an average of 126.763 employees, those in the range 95% to 99% (which has a mean of 21.860 employees) and those in the range 90% to 94% (which has a mean of 9.6). With these estimates, we calculate an average worker effect, a location effect, and the average growth rate in a city by multiplying the estimated growth rate times the number of workers in firms of that size in the city.

Starting with the case of exposure to firms (left block), the first row shows that the elasticity of worker fixed effects with respect to density is .024, which is slightly smaller than the estimate shown in the fourth column of the first row of Table 1. The elasticity of the location effect with respect to density is .01, which is also comparable to the effect in the Table 1. The coefficient of earnings growth on density is 0.002, which implies that the same move raises ϕ_c by 0.008 log points, equivalent to 0.80% higher earnings.

The second panel examines the correlation between upward mobility on the one hand and worker and location effects or the effects of learning in the firm on the other hand. As before, upward mobility is strongly negatively correlated with both the average-worker effect and the location effect. Low mobility (high RSS) is also negatively associated with growth. The interaction between density and RRS is negative and statistically significant for the worker component, but not for the location effect or the experience premium, indicating that limited mobility attenuates agglomeration benefits primarily by limiting worker sorting.

The bottom two panels show the elasticities with respect to segregation in schools and within the firm. In all cases, the direct impact of segregation is negative. In some specifications, there is also a negative interaction between segregation and density, meaning that the positive effects of urban size are limited when people from different groups don't share interests. These panels also show that places with more segregation are less likely to have the types of firms that typically engender wage growth.

Next, moving to the case with exposure to all locations (right block of table 7): in this case the elasticity of the average worker and firms effects to density are lower than in the case with exposure to firms, while the elasticity of the exposure term is larger. This is intuitive as the exposure to locations is more likely to capture the local agglomeration externalities. The same ranking in the magnitude is true for the elasticities to the inter-generational mobility index: the earnings generated from the exposure to a place are higher when equality of opportunity is higher. Less intuitive is the ranking in the magnitude that we observe for the elasticities to the firm segregation index: once again the location exposure estimate has the higher elasticity with respect to this measure of segregation. This is likely to signal once again that firm or industrial composition is an important determinant of the geographical variation in earnings.

Next, we discuss and quantify the elasticities of the learning premium. When earnings are estimated with the worker-location specification, augmented with location experience (columns 4–6), the elasticity to firm segregation is -36.7%, the elasticity to RRS is -9.6%, and that to school segregation is -2.4%.[27] Hence, the concentration of workers' skills within firms appears to matter the most. This is compatible with theories of learning among workers' teams within firms, such as Jarosch et al. (2021).

The elasticities are smaller when we use earnings estimated with the worker-location specification augmented with cumulative experience in large firms (columns 1–3): elasticity to firm segregation is -0.028 (-2.8%), the one to RRS is -0.010 (-1.0%), and the elasticity to school segregation is -0.004 (-0.4%). This seems to suggest that large establishments partially insulate skill accumulation from local barriers.

The ranking—firm segregation > mobility barriers > school segregation holds across specifications, confirming that workplace sorting by ability is the most binding constraint on urban learning dynamics.

27 The elasticity to firm segregation is given by: $-0.533 \times 0.689 = -0.367$ (-36.7%), the one to RRS is given by $-0.560 \times 0.171 = -0.096$ (-9.6%), and the elasticity to school segregation is given by: $[-0.007/2.225] \times 7.816 = -0.024$ (-2.4%).

3.4. Results from Quasi-Experimental Evidence: Movers from Earthquake Area

The estimates for the worker fixed effects in additive separable specifications may capture self-selection, as moves across locations or firms may reflect shocks to unobserved human capital. If moves after a natural disaster are less likely to reflect unobserved forces, then selection biases will be attenuated in specifications that use only such workers. We focus on a sample of movers forced out of a red zone following the 2009 earthquake in the city of L'Aquila and its vicinity.

We start by presenting a series of validation test that can reassure us that there is no consistent bias in the sample of movers that we consider here and that their migration flows is sparsely allocated across the rest of the peninsula. Next, we present the results of the second stage, namely the regression of the DP earning components (fixed effects and estimated exposure effect) on the density and segregation indeces. Note that we cannot estimate the AKM earning residuals, or the worker and firm fixed effects, for this case since the sample of movers out of L'Aquila does allow us to reach the minimum size for the connected set needed to guarantee identification in AKM.[28]

Falsification Tests. We now present a series of falsification tests that support the hypothesis that the movers from the Earthquake areas were indeed exogenously forced out of their regions.

No Bias in Movers. First, we verify that the earthquake shock affected a population that, prior to the event, was observationally similar to individuals residing in non-affected municipalities within the same provinces. In other words, we test whether exposure status is orthogonal to pre-determined characteristics. The estimation sample includes all individuals residing in provinces at $t = -1$ where at least one municipality was declared earthquake-affected, independently of subsequent mobility. We then estimate the following cross-sectional specification:

$$X_{i,-1} = \lambda_{p(o(i))} + \delta \, Exposure_{o(i)} + u_i. \tag{14}$$

The dependent variable $X_{i,-1}$ captures a predetermined individual characteristic measured before

28 In AKM estimates the firm fixed effect is identified by the set of movers across firms. The connected set if the set of firms connected through those movers. To guarantee identification the connected set should be significant large.

the earthquake. $Exposure_{o(i)}$ equals one if individual i resided, at $t = -1$, in a municipality officially classified as earthquake-affected. $\lambda_{p(o(i))}$ denote province fixed effects, with $p(o(i))$ identifying the province of the origin municipality. The coefficient δ measures whether baseline characteristics differ systematically between exposed and non-exposed municipalities within the same province. Results are reported in Table 9. Standard errors are clustered at the province-of-origin level. For college education, we estimate a logit model. The table shows no significant and systematic relationship between the individual characteristics and the exposure to the earthquake.

Abnormal Migration Flows. Next, we wish to establish whether indeed the earthquake had induced more migration flows than normal: this would make the circumstances and the migration flows qualify as abnormal. To this purpose, we estimate the causal effect of the earthquake on migration outflows using a municipality-level difference-in-differences design. The unit of observation is municipality m in year t, observed annually from 2007 to 2015. Let Y_{mt} denote the out-migration rate from municipality m in year t. We classify the units in the sample as treated or control as follows. We define $Treated_m = 1$ if municipality m was officially classified as earthquake-affected. We also define the following additional variables: $Post_t = 1$ for $t \geq 2009$,μ_m are the municipality fixed effects, λ_t are year fixed effects. The control group consists of municipalities located in the same provinces as the affected municipalities but not directly classified as earthquake-affected. We therefore compare treated municipalities to other municipalities within the same earthquake provinces. We then estimate:

$$Y_{mt} = \mu_m + \lambda_t + \beta \left(Treated_m \times Post_t\right) + \varepsilon_{mt}. \tag{15}$$

The coefficient β captures the differential change in out-migration after 2009 in earthquake-affected municipalities relative to other municipalities in the same provinces. A positive and statistically significant β indicates abnormal out-migration from treated municipalities following the shock.

Standard errors are clustered at the province level. To assess the dynamic response and test for pre-existing trends, we estimate as an event-study specification:

$$Y_{mt} = \mu_m + \lambda_t + \sum_{k \neq -1} \beta_k \left(Treated_m \times \mathbf{1}\{t - 2009 = k\} \right) + \varepsilon_{mt}, \tag{16}$$

where k indexes years relative to the earthquake, and $k = -1$ (year 2008) is omitted as the reference category. The coefficients β_k trace the evolution of out-migration in treated municipalities relative to control municipalities before and after the earthquake. The absence of significant pre-2009 coefficients supports the parallel trends assumption. The post-2009 coefficients capture the abnormal increase in out-migration induced by the shock. Standard errors are clustered at the province level throughout. Figure 3 plots the estimated β_k coefficients and their confidence intervals.

Sparseness in Destination. Third, if movers were to cluster in specific areas after the move, the random-assignment assumption would be invalid. To see if this is the case, we examine whether displaced individuals sort systematically across destination provinces according to pre-existing economic characteristics. The unit of observation is the destination province. For each province, we calculate the total number of earthquake-displaced workers observed there between 2009 and 2015. Specifically, we first identify workers who resided in an earthquake-affected municipality in 2008 and subsequently moved to a different municipality after the earthquake. We then count, for each year between 2009 and 2015, how many of these displaced workers are observed residing in each destination province. The dependent variable, therefore, measures the total number of mover-year observations in a given province over the period 2009–2015. We then estimate the following cross-sectional specification:

$$M_p = \alpha + \beta Z_p + \varepsilon_p, \tag{17}$$

where M_p denotes the total number of displaced mover-year observations in province p between 2009 and 2015. The independent variables capture pre-earthquake economic characteristics of the destination province. In particular, we consider: (i) average log earnings, (ii) the total number

of workers (as a proxy for province size), and (iii) the total number of college-educated residents. For provinces that include earthquake-affected municipalities, these characteristics are computed excluding the affected municipalities, so that destination attributes are not mechanically influenced by the shock itself. Standard errors are clustered by a binary indicator distinguishing provinces with at least one earthquake-affected municipality from those without. Results, which are reported in table 10, show no significant relation of the move with the characteristics considered.

Migration Probability and Ex-Ante Demographics. At last, and in the same vein as the previous test, we examine whether the probability of changing municipality after the earthquake varies systematically with individual characteristics among workers initially exposed to the shock. The estimation sample includes all individuals residing in earthquake-affected municipalities at $t = -1$. We use annual data from 2007 to 2015. Let $Move_{it} = \mathbf{1}\{c(i,t) \neq c(i,t-1)\}$, denote an indicator equal to one if individual i changes municipality between $t-1$ and t. To study heterogeneous mobility responses, we estimate a set of linear probability models of the form:

$$Move_{it} = \lambda_t + \beta \left(Post_t \times X_i \right) + u_{it}, \tag{18}$$

where λ_t are year fixed effects and X_i is, in turn, (i) lagged log earnings, (ii) age (measured in years), and (iii) an indicator for college education. The coefficient β captures whether post-earthquake mobility differs systematically with X_i. The results are reported in Table 11. In Column (1), the coefficient on $Post_t \times \log w_{i,-1}$ is 0.0080 (s.e. 0.0060), indicating no statistically significant differential mobility response by earnings. In Column (2), the coefficient on $Post_t \times Age_{i,-1}$ is -0.0009 (s.e. 0.0003), implying that older individuals were significantly less likely to move after the earthquake; a 10-year age difference corresponds to a 0.9 percentage point lower mobility probability. In Column (3), the coefficient on $Post_t \times College_i$ is 0.0191 (s.e. 0.0111), implying that college-educated individuals experienced a 1.9 percentage point higher probability of moving after the earthquake relative to non-college individuals. Overall, the evidence suggests that younger and more educated individuals were more likely to relocate following the shock, but these effects are small in magnitude. Standard errors are clustered at the municipality-of-origin level.

Results: Relation between Earnings and Segregation for Exogenous Movers. Tables 12 and 13 present the results of the estimation for the second stage, using the residual earnings and the fixed effects of the DP specifications both the static and the dynamic one (with exposure to each location). The elasticities in tables 12 and 13 are therefore comparable to those of the DP specifications presented in table 1 and 5.

The elasticities of the location premia to density are still positive, and the ones with respect to segregation and mobility measures are negative and even larger than in the full sample. The coefficients are essentially equivalent to or larger than the corresponding coefficients in tables 1 and 5. This supports the view that selection is not driving our results.

Validation of the Baseline Results. We can now leverage the evidence uncovered with the exogenous movers and the fact that it appears to align with the evidence uncovered in the full sample, and validate the estimates of the second. Specifically, we can compare regression results based on movers from L'Aquila with those from the full sample of workers' locations, using the same time sample. We begin by constructing a sample of workers who moved from municipalities in the earthquake-affected area to provinces outside the affected area. Movers are defined as individuals who changed provinces in 2009 or 2010, and in both samples, we restrict attention to workers employed in 2008. For this group of earthquake out-migrants, we estimate destination wage premia using the following two-way fixed effects specification:

$$w_{it} = \alpha_i + \psi_{c(i,t)} + \varepsilon_{it} \tag{19}$$

where w_{it} denotes wages, α_i are worker fixed effects, and $\psi_{c(i,t)}$ are province (location) fixed effects. This delivers a set of estimated destination effects for the earthquake movers. As a benchmark, we construct a comparison group of "ordinary" movers, defined as workers who changed provinces in 2009–2010 between provinces outside the earthquake-affected area, again restricting to those employed in 2008. Estimating equation (3) on this sample yields a corresponding set of destination fixed effects. To assess the role of selection in our baseline location effects, we regress the fixed effects estimated among the earthquake movers on those estimated among the ordinary movers.

The regression is weighted by the number of earthquake movers to each destination province. The estimated coefficient is 0.93 (s.e. = 0.0026). Figure 4 reports the corresponding scatter plot. A coefficient close to 1 indicates that the two sets of location effects are closely aligned, suggesting that selection bias in the baseline fixed effects is limited.

4. Discontinuity at Imperial Borders

The exogenous variation in movers we obtained from the earthquake analysis allowed us to support a causal relation between workplace and earnings premia. Italy also has a very rich history, with several colonizers occupying various parts of the peninsula. Those historical events may have shaped institutional developments across regions, and this, in turn, may have consequences for the geographical variation we observe today in the earning premia. The goal, once again, is to explain why cities or regions with similar densities may have very different earnings premia.

To understand the role of historical factors for the variation in earning premia, we estimate the regression discontinuity design in 13 focusing on the Hapsburg historical borders. While we did explore the role of other borders, we found this one to be the only one exhibiting a significant impact nowadays. The unification of the Italian peninsula only occurred in 1870, and before 1866, the Habsburgs controlled the Kingdom of Lombardy-Venetia. The Habsburgs' control imposed a set of norms, institutions, and cultural attitudes that endure and may still have an effect today. In the regression discontinuity design, we use the historical Habsburg-Savoy border in Northern Italy, established by the Congress of Vienna in 1815.

To uncover the channels of persistence, we proceed in two steps. First, we estimate the regression discontinuity using the earnings premia as the dependent variable and employ worker-firm or worker-location specifications. Second, we re-estimate the same specification using a proxy for historical urbanization as the dependent variable, based on city size data from Malanima (2005) or Bairoch and Goertz (1986). We then complement this evidence by examining patterns in various indices of industrialization and urbanization and comparing them between the Habsburg-dominated region and the nearby Savoy region.

Identification Concerns. Three main identification concerns may arise from the design described above: here we explain how we address them. The first, is that the historical borders may coincide with certain geographical areas, whose characteristics may explain the discontinuity we observe. Below, we exclude this possibility by running balance tests on geographical characteristics.

Second, it is possible that results on the wage premia are driven not by historical differences between the regions at the border, but by the concentration of cities in each of the region. To address this, we control for both region fixed effects and distance from cities.

At last, and as discussed earlier, it is possible that city density, both historically and now, is associated with higher productivity, as more productive places attract more people. However, this association is excluded by two facts. First, the Hapsburg were not the only colonizers in Italy. Other like the Bourbons Empire had settled in the South, which at the time was one of the most prosperous regions precisely due to geographical factors. However, we find no significant relation between wage premia and other historical colonization borders. Second, and as argued earlier Italy includes cities of similar density, but very different productivity: see for instance Milan and Naples. This fact excludes the association a priori.

Historical Border and Geographical Bakance. We use as a reference the 1815 border established at the time of the Vienna Congress, classifying as "Savoy" the continental part of the Kingdom of Sardinia (excluding the island of Sardinia) -namely, the mainland territories of Piedmont, the Duchy of Savoy and Liguria - and as "Hapsburg" the domains under Austrian control: the Duchy of Milan, the Republic of Venice, the Grand Duchy of Tuscany and other territories under direct Hapsburg influence. Figure 5 displays the reconstructed 1815 border. The regions west of the boundary are classified as "Savoy" and those east as "Hapsburg". These 19th century borders seem likely to be more important than earlier borders between the two polities.

As mentioned above, a potential concern is that our estimates on the border confound other geographical differences between the former Hapsburg and Savoy region. Figures 6 and 7 display elevation, slope, temperature, and precipitation within an 80 km band centered on the historical boundary. There are no apparent discontinuities at the border for any of these variables. To

formalize this comparison, we estimate a spatial regression discontinuity design within ±40 km of the border, treating each geographic characteristic as the dependent variable. Formally, the specification is as in equation 13, which includes fixed effects for 25 km segments. Standard errors are clustered at the segment level. The results, reported in Table 14, show that the differences across the border are small and statistically insignificant for all variables except the slope, which is slightly lower on the Hapsburg side. These findings show little systematic geographic difference at the historical divide.

Location Wage Premia at the Border with Savoy. Figure 9 illustrates the spatial distribution of the estimated municipal wage premia on either side of the historical border. We then implement the spatial regression discontinuity design, shown in equation 13, using as a dependent variable the municipality-level wage premia, estimated using either the static worker-firm or the worker-location specification. Within a ±40 km bandwidth around the historical border, we compare the average location premium on the Hapsburg versus Savoy side, including 25 km segment fixed effects and clustering standard errors at the segment level.

The results for the worker-location specification are reported in Table 15 and those for the worker-firm specifications are reported in Table 16. For this second case we also report the regression using as dependent variable the worker and firms components. In all cases the columns show the results under alternative set of controls, geared at addressing various potential concerns with confounders coming from modern institutions.

A first potential concern with our identification strategy is that much of the historic Hapsburg-Savoy border overlaps with current regional boundaries. If so, the estimated discontinuity might capture the effect of modern regional institutions rather than the legacy of historical ones. To address this issue, we adopt two complementary strategies. The first is to include in the regression regional fixed effects. In this case, the comparison is between municipalities within the same present-day region, but opposite sides of the historical border. Second, we also control for a second-degree polynomial in latitude and longitude, as in our baseline specifications. Furthermore, we repeat the estimates by adding controls for the distance from Milan and Turin. This allows us to exclude

the possibility that the significant discontinuity at the border is due to the proximity of the areas in question to two large and productive cities. Finally, we also report estimates over a sample restricted to Lombardy: this too helps us to exclude that results are driven by the current regional borders between Lombardy and Piemonte.[29]

In all cases, and with both worker-location and worker-firm specifications, the coefficients are positive, significant (either at 1% or 5%) and their magnitudes are economically meaningful.

Urbanization and Industrialization Patterns Before and After. To complete the assessment of the channels of persistence, we now examine how historical variables about urbanization and industrialization developed within the Hapsburg Empire. First, we provide suggestive evidence on differences in indeces of urbanization and industrialization between the Hapsburg and the nearby Savoy region. Second, we re-estimate our regression discontinuity using as dependent variable an historical measure of city size.

First, figure 10 shows simple trends of industrialization indices, share of manufacturing, and employment from 1871 to 1910 with data from Ciccarelli and Fenoaltea (2013). All indicators increased more in the Hapsburg region than in the Savoy. Employment shows a convergence in the latter part of the sample, but is largely above before 1900. On the other hand, we see no significant differences in other variables (also shown in figure 10, such as education, height, or infant mortality. On the other hand, we observe significant gender differences in literacy rates. Overall, this suggests the absence of underlying unobserved variables that drive our results.

Next, we examine the role of the Hapsburg border in shaping current population density, a measure of agglomeration externalities. We draw on two distinct sources of pre-unification data on urbanization, both measured at the municipality level. The first is from Bairoch and Goertz (1986) and reports the total population living in cities for benchmark years between 1500 and 1861. The second comes from Malanima (2005) and provides an alternative measure of the urban population over a similar period.

We estimate the same spatial regression discontinuity design as in the previous subsection, at the municipality level, comparing urban populations on the Hapsburg and Savoy sides of the border

29 Due to the smaller sample size, we use a first-degree polynomial in latitude and longitude.

across several benchmark years. The results, reported in the upper and middle part of Table 17, indicate that there were no statistically significant differences at 5% in urbanization before 1715, independently of whether we use the Bairoch and Goertz (1986) (upper part of the table) or Malanima (2005) (lower part of the table) data. In contrast, from the early nineteenth century onward, municipalities in the Hapsburg area had significantly larger urban populations. This pattern suggests no preexisting differences predating our period of interest.

We then turn to current population patterns, using 2021 census data from the Eurostat GISCO population grid at the 1 km^2 level. The bottom part of Table 17 reports spatial regression discontinuity estimates for the total population per cell (in logs), as well as the number of people living within a radius of 5 km and 10 km (in logs). The estimated coefficients for the density measures on the Hapsburg border are significant at 5%. The magnitudes are between 40% and 45%, hence large. To quantify the agglomeration elasticities we can compute the ratio between the discontinuity of the wage premia and the one of the log density. Across all estimates the range for this ratio is between 0.078 and 0.05. The spatial distribution of these measures is visualized in Figure 8, which confirms that the Hapsburg area is now more densely populated.

The patterns of urbanization and industrialization serve as mediators of the enduring effects of institutions, but reforms and economic incentives of the Hapsburg Empire may have shaped them. We therefore conclude with an account of two of the most significant sets of reforms undertaken during the Hapsburg Empire, which may explain the patterns we observed.

The Civil Service. In 1748, amid increasing rivalry with the rising Prussian state, the Hapsburg monarchy recognized the need to reform its antiquated administrative system and reduce the burden of debt. These developments paved the way for a series of reforms undertaken by Maria Theresa, which began in 1749 and ended in 1780, at the end of her reign, and were led by her chancellors, Friedrich Wilhelm von Haugwitz and, later, Wenzel Anton Kaunitz. The most significant and enduring of those reforms took place between 1763 and 1780. The overarching goal of the reform was in line with the enlightened theories of the time, which supported a strong, secular, centralized

state that improved the well-being of its people and reduced the influence of the feudal estates and the Catholic Church.[30]

The focus of the reforms was on internal administration, and the aim was to make bureaucracy more efficient. The administration was centralized, rules were harmonized, and census and central statistics were introduced. Altogether, those reforms reduced uncertainty in exchanges and helped limit the power of local lobbies and feudal power. Special rights and privileges, such as the exemption of the nobility and the Church from taxes, were abolished. Those reforms led to greater meritocracy and may explain the enduring attitudes toward mobility, which in turn account for the location-earning premium.

Alongside the reform of the administration came the professionalization of the civil service: middle-class professionals increasingly replaced the aristocratic functionaries, based on the principles of national equality. This change also fostered meritocracy, the rise of the middle class and increased the value attached to education, given that an examination became a necessary condition for entering professional occupations and civil servant roles.[31] Becker et al. (2016) further argue that the Hapsburg administrative system had left a legacy of high trust in institutions, a key element for a well-functioning economy. Like the Hapsburg, the Savoy reign had taken some steps to reduce the privileges of the nobility and the Church, particularly with the introduction in 1730 of the land registry, which equalized taxation. However, more significant privileges remained in Savoy, such as tax exemptions for those with chivalric honors, such as the Supreme Order of the Most Holy Annunciation, judicial privileges (Privilegium de non appellando), and hereditary status. These practices limited the development of meritocracy.

Overall, the move toward more efficient administration seems to have helped the scale-up of urbanization. The professionalization of civil servants, along with reforms to the education system, increased the likelihood of learning. Both allowed cities to scale up and fostered urbanization. Higher levels of urbanization, in turn, propelled the role of agglomeration externalities.

30 Taxes were increased mostly on the nobility. To prevent the exploitation of peasants, Kaunitz created land registries, standardized feudal obligations, increased mechanization, and launched programs to abolish serfdom.

31 Less definitive evidence concerns the development of the public education system. In comparison, in the nearby region ruled by the Savoy House, compulsory education was introduced later. .

Economic Forces: Trade Connectivity and Unintended Consequences of Exploitation. The Hapsburg Empire was militarly engaged on many fronts and, as a result it was highly indebted. Later on, public investments further fueled waves of over-borrowing (see Flandreau (2003)). The need to cover borrowing costs was also a powerful incentive for economic reforms. First, the increase of taxation also for the nobility was part of the efforts to fix the public finances and indirectly fostered meritocracy. Second, the extractive motives induced the Monarchy to exploit trade connectivity in the region (see Cafagna (1989)). The goal of creating a custom union, to be used to their advantage, led to major trade reforms. Those include the formation of the unified customs union in 1850, the removal of tariffs in 1852 and 1854, and the commercial Treaty with the German Zollverein (see Huertas (1977)). Several authors have argued that the acceleration of industrialization was more pronounced in the last part of the reign between 1841 and 1857 (see Huertas (1977) or Schiffer (2009)).

Taken together, the evidence on industrialization and urbanization supports the interpretation that the Hapsburg institutional legacy persisted through its interaction with urban and economic dynamics.

5. Conclusions

Using administrative data for the Italy's entire workforce and several two-way fixed-effects methodologies, we find that the location-earnings premium exhibits substantial heterogeneity across regions, leading to substantial geographical inequalities. Motivated by this finding, we seek determinants of the location premium beyond the classical measures of agglomeration externalities and find that segregation, as well as mobility measures, help explain this variation, acting as propellant (or a restrainer) of knowledge diffusion. We seek quasi-experimental and causal evidence of those links through two econometric designs, one exploiting arguably exogenous migrations of workers due to disasters, and the other testing for the enduring effects of historical events. First, we find robust evidence across several specifications that density increases earnings in each location and segregation or impediments to intergenerational mobility depress them. Those results also hold when tested on

a sample of movers out of an earthquake area, which reduces the role of the self-selection of workers. Furthermore, we find a significant discontinuity in the location premium at the historical border between the Hapsburg and Savoy reigns, driven by differences in urbanization and industrialization. The rise of the latter was likely triggered by two of the most significant reforms undertaken under Maria Theresa, namely the professionalization of the civil service and a set of trade reforms aimed at creating one of the first customs unions on European soil.

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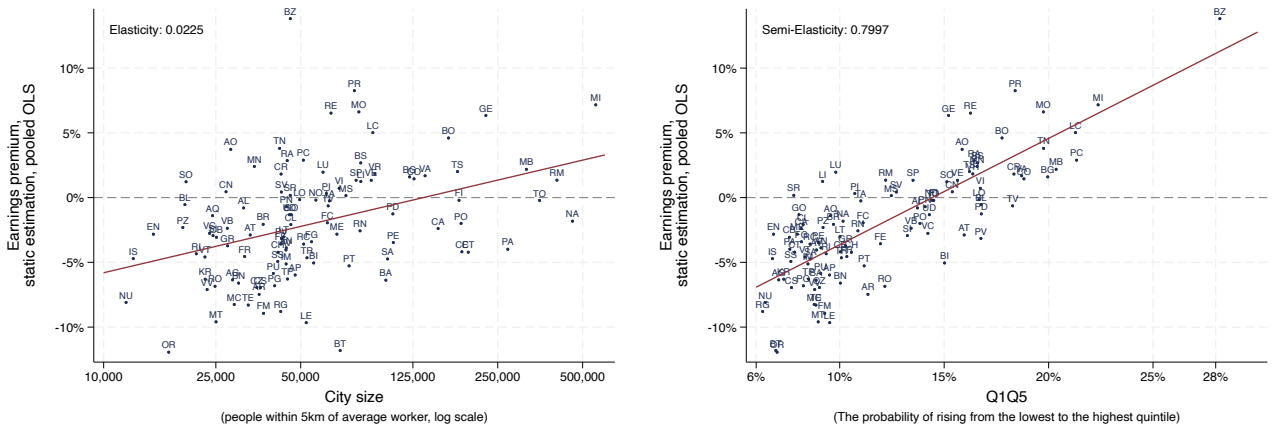


Figure 1: Location Premia against the density and inter-generational mobility index. The city premia is obtained from the two-way location-worker fixed effects regression for our time sample period 2010-2023. Density is the average number of people living within a given distance of the average person in that area. Intergenerational mobility index is the probability of rising from the lowest to the highest quintile.

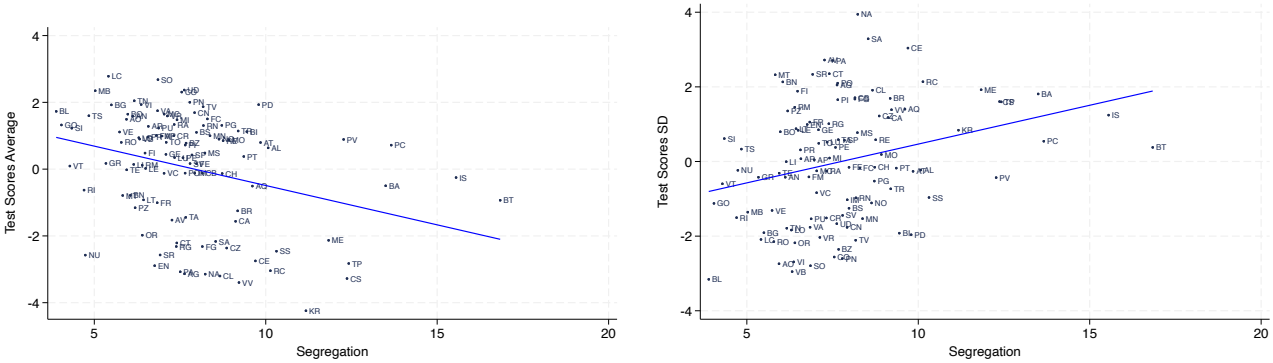


Figure 2: Relation between segregation in school, as measured by Agasisti and Falzetti (2017) and the mean and standard deviation of tests scores from PISA data.

Table 1: Elasticities of Static Location Earnings Premia to Density, Segregation and Mobility.

		AKM Static		DP Static	
	y	$\bar{\alpha}_c$	ψ_c	$\bar{\alpha}_c$	ψ_c
Log Density	0.039***	0.023***	0.013***	0.028***	0.011***
	(0.010)	(0.006)	(0.005)	(0.008)	(0.003)
Observations	107	107	107	107	107
R^2	0.15	0.19	0.08	0.15	0.08
Log Density	0.038***	0.023***	0.013***	0.027***	0.010***
	(0.008)	(0.004)	(0.004)	(0.006)	(0.003)
Rank-to-Rank	-1.502***	-0.867***	-0.596***	-1.046***	-0.446***
	(0.169)	(0.083)	(0.102)	(0.124)	(0.077)
Rank-to-Rank × Density	-0.739***	-0.422***	-0.285**	-0.611***	-0.103
	(0.235)	(0.111)	(0.134)	(0.173)	(0.091)
Observations	106	106	106	106	106
R^2	0.45	0.53	0.29	0.45	0.26
Log Density	0.034***	0.021***	0.011**	0.024***	0.010***
	(0.010)	(0.005)	(0.004)	(0.008)	(0.003)
School Segregation	-0.024***	-0.015***	-0.009***	-0.018***	-0.006***
	(0.006)	(0.003)	(0.003)	(0.004)	(0.002)
School Segregation × Density	-0.021***	-0.010***	-0.009**	-0.017***	-0.003
	(0.006)	(0.003)	(0.004)	(0.004)	(0.003)
Observations	107	107	107	107	107
R^2	0.25	0.30	0.14	0.26	0.12
Log Density	0.033***	0.020***	0.010**	0.023***	0.008***
	(0.009)	(0.005)	(0.004)	(0.007)	(0.003)
Firm Segregation	-1.431***	-0.789***	-0.595***	-0.982***	-0.430***
	(0.197)	(0.109)	(0.099)	(0.159)	(0.069)
Firm Segregation × Density	-0.180	-0.179	-0.018	-0.210	0.015
	(0.329)	(0.167)	(0.163)	(0.238)	(0.114)
Observations	107	107	107	107	107
R^2	0.46	0.51	0.31	0.43	0.29

Notes: Entries are elasticities of the wage residuals and the location-averages of the worker, firm and location effects, estimated with the static two-way specifications (firm-worker effects a' la Abowd et al. (1999) or location-worker effects a' la De La Roca and Puga (2017)) with respect to city density, segregation in schools (measured as in Agasisti and Falzetti (2017)), segregation within firms (this is the share of the total variance in AKM worker fixed effect within a province c that is attributable to differences between firms; see Song et al. (2018)) or upward mobility (measured as in Acciari et al. (2022)). Each specification also includes the interaction between density and each of the other measures. Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2: AKM Variance Decomposition and Relation of AKM Effects to Density and Segregation

	All		Non-college-educated		College-educated	
	(1) Std. Dev. or Correlation	(2) Variance Share	(3) Std. Dev. or Correlation	(4) Variance Share	(5) Std. Dev. or Correlation	(6) Var. Share
Mean earnings, $\overline{y}$	0.079	—	0.069	—	0.114	—
Worker effects, $\overline{\alpha}_c$	0.043	0.288	0.034	0.248	0.066	0.324
Firm effects, ψ_c	0.037	0.223	0.036	0.271	0.045	0.154
$Corr(\overline{\alpha}_c, \Psi_c)$	0.817	0.415	0.782	0.406	0.888	0.397

	(1) y	(2) $\overline{\alpha}_c$	(3) ψ_c	(4) $\overline{y}$	(5) $\overline{\alpha}_c$	(6) ψ_c
Log density	0.0391***	0.0232***	0.0133***	0.0325***	0.0196***	0.0105**
	(0.0101)	(0.0056)	(0.0045)	(0.0092)	(0.0051)	(0.0041)
Log segregation				-0.977***	-0.534***	-0.409***
				(0.128)	(0.0706)	(0.0669)
R^2	0.15	0.18	0.07	0.44	0.49	0.30
Obs.	107	107	107	107	107	107

	Non-college-educated Workers			College-educated Workers		
	(1) y	(2) $\overline{\alpha}_c$	(3) ψ_c	(4) $\overline{y}$	(5) $\overline{\alpha}_c$	(6) ψ_c
Log density	0.026***	0.014***	0.010**	0.073***	0.043***	0.026***
	(0.009)	(0.004)	(0.004)	(0.014)	(0.008)	(0.005)
R^2	0.08	0.10	0.04	0.25	0.27	0.20
Observations	107	107	107	107	107	107

Notes: The upper part of the table reports the variance decomposition of the mean log earnings (residualized with respect to age and calendar time effects), computed with equation (1). Columns (1)–(2) report estimates for the *All sample*, estimating $\bar{y}_c = \bar{\alpha}_c + \psi_c + \bar{X}_c\beta$. Columns (3)–(4) and (5)–(6) use province–education cells (c, e), with $e \in \{\text{Non-college-educated}, \text{College-educated}\}$, estimating $\bar{y}_{ce} = \bar{\alpha}_{ce} + \psi_{ce} + \bar{X}_{ce}\beta$. Odd columns report either the standard deviation across provinces or the correlation. Even columns report the corresponding variance shares implied by the decomposition. Mid part of the table shows estimates of the elasticities for the wage premium obtained averaging equation (1) across workers and time periods: $\overline{y}_c = \overline{\alpha}_c + \psi_c + \bar{X}_c\beta$. Columns (1) and (4) report the regression coefficients of $\overline{y}_c$, columns (2) and (5) of $\overline{\alpha}_c$, and columns (3) and (6) of ψ_c on the log city density and the (log) ability segregation. Bottom part of the table shows elasticities for the wage premium obtained by averaging equation (1) across college (columns (1)-(3)) and non-college (columns (4)-(6)) educated workers and across time periods. In each panel, the first column reports the regression coefficients of $\overline{y}_{ce}$, the second of $\overline{\alpha}_{ce}$, and the third of ψ_{ce} on log city size. Coefficients are reported with robust standard errors in parenthesis. ***, **, and * indicate significance at the 1, 5, and 10% levels.

Table 3: Linear Regression Models for Estimated Province-Industry Effects

	(1)	(2)	(3)	(4)	(5)
Share of Province Emp. in Industry				1.088***	
				(0.0896)	
Log Share of Province Emp. in Industry					0.0188***
					(0.00106)
Province FE	YES	NO	YES	YES	YES
Industry FE	NO	YES	YES	YES	YES
R^2	0.05	0.53	0.59	0.59	0.60
Observations	8610	8610	8610	8610	8610

Notes: Regression of estimated province-by-2-digit-industry effects on province indicators (column 1), industry indicators (column 2), and province and industry indicators (columns 3-5). Regression specification reads as follows: $\psi_{cj} = \theta_c + \mu_j + \epsilon_{cj}$. Models in columns 4-5 augment the specification with the share (or log share) of province employment in the industry. Coefficients are reported with robust standard errors in parenthesis. ***, **, and * indicate significance at the 1, 5, and 10% levels.

Table 4: Decomposition of Variance of Average Province Earnings Premium

	Std. Dev. or Correlation	Variance Share
Average Industry-Province Premium	0.037	—
Variance components		
Average Earnings Premium	0.033	0.800
Composition Effect	0.009	0.053
Interaction Effect	0.008	0.049
Covariance components		
Earnings Premium & Composition Effect	0.312	0.129
Earnings Premium & Interaction Effect	-0.072	-0.028
Composition Effect & Interaction Effect	-0.018	-0.002

Notes: Table shows the Oaxaca decomposition of the city premium estimated with the specification of equation (1): $\psi_c = k + \sum_j \overline{s}_j(\psi_{cj} - \overline{\psi}_j) - \sum_j(s_{cj} - \overline{s}_j)\overline{\psi}_j + \sum_j(s_{cj} - \overline{s}_j)(\psi_{cj} - \overline{\psi}_j)$. The decomposition uses 2-digit industries. The first columns reports either the standard deviation across provinces or the correlation. The second column reports the corresponding variance shares implied by the decomposition.

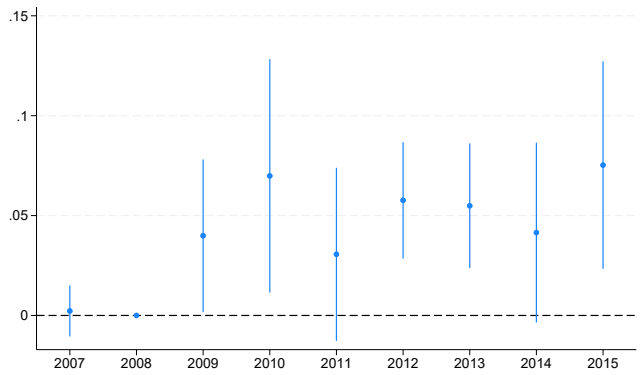


Figure 3: Dynamic effects of the earthquake on out-migration.

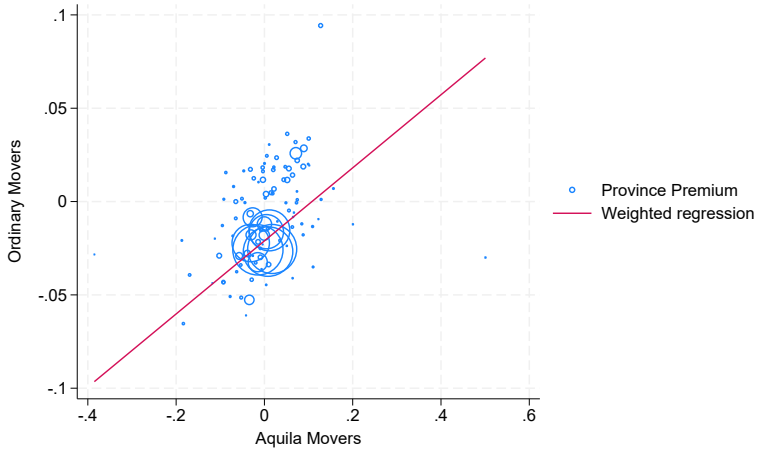


Figure 4: Selection Bias in Location Fixed Effects. The figure presents a scatter plot of destination wage premia estimated among workers who moved out of municipalities in the earthquake-affected area (horizontal axis) against destination wage premia estimated among ordinary movers between non-affected provinces (vertical axis). Each point represents a destination province. The fitted line corresponds to a weighted regression, where the weights are the number of earthquake movers to each destination province.

Table 5: Estimation of the worker-city dynamic model with exposure to large cities

	(1)	(2)	(3)	(4)
Log density		0.011***	0.0100	0.0212***
		(0.0028)	(0.0070)	(0.0064)
Experience 1st most-dense city	0.0152***			
	(0.0002)			
Experience 2nd to 3rd most-dense city	- 0.0011***			
	(0.0002)			
Experience 4th to 5th most-dense city	0.0100***			
	(0.0003)			
Experience 6th to 10th most-dense city	-0.0042***			
	(0.0003)			
Experience	0.0342***			
	(0.0001)			
Experience^2	-0.0005***			
	(0.0000)			
Experience 1st most-dense city × now in	-0.0004*			
10th biggest city	(0.0002)			
Experience 1st most-dense city × experience × now in	0.0000**			
10th biggest city	(0.0000)			
Experience 2nd to 3rd most-dense city × now in	-0.0031***			
10th biggest city	(0.0002)			
Experience 2nd to 3rd most-dense city × experience	0.0001***			
× now in 10th most-dense city	(0.0000)			
Experience 4th to 5th most-dense city × now in	-0.0041***			
10th biggest city	(0.0003)			
Experience 4th to 5th most-dense city × experience	0.0001**			
× now in 10th most-dense city	(0.0000)			
Experience 6th to 10th most-dense city × now in	-0.0035***			
10th biggest city	(0.0003)			
Experience 6th to 10th most-dense city × experience	0.0002***			
× now in 10th most-dense city	(0.0000)			
Experience outside 10th most-dense city × now in	0.0016***			
10th most-dense city	(0.0002)			
Firm tenure	0.0078***			
	(0.0003)			
Firm tenure^2	-0.0002***			
	(0.0000)			
Observations	88,183,678	107	107	101
R^2	0.77	0.09	0.05	0.18

Notes: The specification in column (1) is $y_{it} = \alpha_i + \psi_{c(i,t)} + \sum_{\kappa=1}^{C} \gamma_{\kappa c(i,t)} e_{\kappa(i,t)} + \beta X_{it} + \epsilon_{it}$ *and include year indicators. Column (2) reports the elasticity of the location earnings premium with respect to density and estimated by regressing the city fixed effects from column (1) on log density. Column (3)-(4) shows the elasticity of the medium-premium (the initial premium plus the average years of local experience) with respect to density. In column (4) the elasticity is estimated removing from the sample the provinces with a negative learning (Naples, Rome, Caserta, Palermo, Como, Varese, and Prato) Coefficients are reported with robust standard errors in parenthesis, which are clustered by worker in columns (1). ***, **, and * indicate significance at the 1, 5, and 10% levels. Worker values of experience and tenure are calculated on the basis of actual days worked and expressed in years.*

Table 6: Elasticities of DP with Exposure to Large Cities with respect to Density, Segregation and Inter-generational Mobility across Horizons

	Initial premium, ψ_c	**Medium-term premium, $\psi_c + \phi_c$**
Rank-rank slope	-0.4527***	-0.5104***
	(0.0771)	(0.0896)
Log density	0.0103***	0.0090
	(0.0025)	(0.0067)
Observations	106	106
R^2	0.27	0.20
	Initial premium, ψ_c	**Medium-term premium, $\psi_c + \phi_c$**
Workplace Segregation by Schooling	-0.5178***	-0.9098***
	(0.0985)	(0.1801)
Log density	0.0050*	-0.0007
	(0.0029)	(0.0050)
Observations	107	107
R^2	0.21	0.32

Notes: The dependent variable in columns (1)-(3) is the initial premium estimated by the specification $y_{it} = \alpha_i + \psi_{c(i,t)} + \sum_{\kappa=1}^{C} \gamma_{\kappa c(i,t)} e_{\kappa(i,t)} + \beta X_{it} + \epsilon_{it}$*, which includes year indicators and controls for tenure and overall experience (entered as second-degree polynomials). The dependent variable in columns (4)-(6) is instead the medium-premium (the initial premium plus the average years of local experience) of the same specification of columns (1)-(3). rank-to-rank slope is the slope of the relationship between the average rank of the child and average rank of the parents in their respective national distributions. The measure is from Acciari et al. (2022). Educational segregation at the workplace is measured as the probability that a randomly chosen non-college worker shares a workplace with another non-college worker. The measure is from Dillon et al. (2025). Coefficients are reported with robust standard errors in parenthesis. ***, **, and * indicate significance at the 1, 5, and 10% levels.*

Table 7: Elasticities of Location Earnings Premia to Density, Segregation and Intergenerational Mobility - DP with Exposure to Firms or Locations.

	DP - Exp Firms			DP - Exp Locations		
	$\bar{\alpha}_c$	ψ_c	ϕ_c	$\bar{\alpha}_c$	ψ_c	ϕ_c
Log Density	0.024***	0.010***	0.002***	0.009**	0.009***	0.012**
	(0.007)	(0.003)	(0.000)	(0.004)	(0.003)	(0.005)
Observations	107	107	107	107	107	107
R^2	0.17	0.08	0.17	0.08	0.08	0.12
Log Density	0.024***	0.009***	0.002***	0.014***	0.007***	0.013***
	(0.006)	(0.003)	(0.000)	(0.004)	(0.003)	(0.003)
Rank-to-Rank	-0.778***	-0.392***	-0.060***	-0.069	-0.398***	-0.560***
	(0.103)	(0.076)	(0.007)	(0.071)	(0.075)	(0.072)
Rank-to-Rank × Density	-0.565***	-0.098	-0.005	-0.212***	-0.081	-0.309***
	(0.145)	(0.089)	(0.009)	(0.103)	(0.070)	(0.082)
Observations	106	106	106	106	106	106
R^2	0.43	0.23	0.42	0.28	0.24	0.50
Log Density	0.021***	0.009***	0.002***	0.007*	0.009***	0.009
	(0.006)	(0.003)	(0.000)	(0.003)	(0.003)	(0.006)
School Segregation	-0.015***	-0.006***	-0.001***	-0.005***	-0.005**	-0.007***
	(0.003)	(0.002)	(0.000)	(0.002)	(0.002)	(0.003)
School Segregation × Density	-0.015***	-0.003	-0.001*	-0.010***	-0.003	-0.006
	(0.003)	(0.003)	(0.000)	(0.003)	(0.003)	(0.005)
Observations	107	107	107	107	107	107
R^2	0.28	0.11	0.23	0.18	0.11	0.18
Log Density	0.021***	0.008***	0.002***	0.014***	0.006*	0.011**
	(0.006)	(0.003)	(0.000)	(0.005)	(0.003)	(0.005)
Firm Segregation	-0.769***	-0.392***	-0.040***	-0.110	-0.401***	-0.533***
	(0.129)	(0.067)	(0.010)	(0.091)	(0.067)	(0.076)
Firm Segregation × Density	-0.205	0.020	0.004	0.015	0.094	-0.079
	(0.199)	(0.108)	(0.015)	(0.142)	(0.120)	(0.155)
Observations	107	107	107	107	107	107
R^2	0.43	0.27	0.31	0.25	0.24	0.40

Notes: Entries are elasticities of the location-averages of worker-effects (α_c), location (ψ_c) fixed effect, as well as the learning premium (ϕ_c), estimated with De La Roca and Puga (2017), augmented with exposure in large firms, with respect to city density, segregation in schools (measured as in Agasisti and Falzetti (2017)), segregation within firms (this is the share of the total variance in AKM worker fixed effect within a province c that is attributable to differences between firms; see Song et al. (2018)) or upward mobility (measured as in Acciari et al. (2022)). Each specification includes the interaction between density and each of the other measures. Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Table 8: Elasticities of Location Earnings Premia to Density, Segregation and Mobility - AKM Exposure to Location or Firms.

	AKM - Exp Location			AKM - Exp Firms		
	$\bar{\alpha}_c$	ψ_c	ϕ_c	$\bar{\alpha}_c$	ψ_c	ϕ_c
Log Density	0.009***	0.013***	0.010***	0.021***	0.013***	0.0004***
	(0.002)	(0.004)	(0.003)	(0.005)	(0.004)	(0.0001)
Observations	107	107	107	107	107	107
R^2	0.19	0.08	0.18	0.24	0.08	0.13
Log Density	0.012***	0.013***	0.011***	0.0211***	0.0130***	0.0004***
	(0.003)	(0.004)	(0.002)	(0.004)	(0.004)	(0.0001)
Rank-to-Rank	-0.199***	-0.553***	-0.317***	-0.583***	-0.560***	-0.019***
	(0.039)	(0.104)	(0.052)	(0.065)	(0.098)	(0.002)
Rank-to-Rank × Density	-0.098	-0.303**	-0.230***	-0.381***	-0.281**	-0.002
	(0.065)	(0.116)	(0.059)	(0.090)	(0.131)	(0.003)
Observations	106	106	106	106	106	106
R^2	0.43	0.33	0.48	0.51	0.28	0.43
Density	0.008***	0.011**	0.008**	0.019***	0.011**	0.0004***
	(0.002)	(0.004)	(0.004)	(0.004)	(0.004)	(0.0001)
School Segregation	-0.006***	-0.008***	-0.004**	-0.012***	-0.008***	-0.0002**
	(0.001)	(0.003)	(0.002)	(0.002)	(0.003)	(0.0001)
School Segregation × Density	-0.004**	-0.009**	-0.004	-0.009***	-0.010**	-0.0002*
	(0.002)	(0.004)	(0.003)	(0.002)	(0.004)	(0.0001)
Observations	107	107	107	107	107	107
R^2	0.31	0.15	0.23	0.36	0.15	0.18
Log Density	0.011***	0.011*	0.010***	0.019***	0.011***	0.0004***
	(0.003)	(0.006)	(0.004)	(0.004)	(0.004)	(0.0001)
Firm Segregation	-0.182***	-0.574***	-0.331***	-0.574***	-0.569***	-0.012***
	(0.053)	(0.097)	(0.053)	(0.083)	(0.096)	(0.003)
Firm Segregation × Density	0.043	0.022	-0.049	-0.165	-0.017	0.002
	(0.092)	(0.185)	(0.105)	(0.137)	(0.159)	(0.004)
Observations	107	107	107	107	107	107
R^2	0.40	0.29	0.41	0.51	0.32	0.29

Notes: Entries are elasticities of the average log earnings (y), location-averages of the worker (α) and firm (ψ_c) effects, as well as the learning premium (ϕ_c), estimated with Abowd et al. (1999), augmented with years of experience in locations or in firms, with respect to city density, segregation in schools (measured as in Agasisti and Falzetti (2017)), segregation within firms (this is the share of the total variance in AKM worker fixed effect within a province c that is attributable to differences between firms; see Song et al. (2018)) or upward mobility (measured as in Acciari et al. (2022)). Each specification also includes the interaction between density and each of the other measures. Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Table 9: Systematic Exposure Earthquake.

	(1)	(2)	(3)
	age	log earnings	College
treated	0.3283*	0.0345*	0.1775
	(0.1953)	(0.0192)	(0.1397)
R-square	0.00	0.01	
Obs	249,540	249,540	249,540

Notes: The estimates below are from the specification $X_{i,-1} = \lambda_{p(o(i))} + \delta\, Exposure_{o(i)} + u_i$, where $X_{i,-1}$ captures a predetermined individual characteristic measured before the earthquake. $Exposure_{o(i)}$ equals one if individual i resided, at $t = -1$, in a municipality officially classified as earthquake-affected. Standard errors are clustered at the municipality-of-origin level. $^{*}p < 0.10$, $^{***}p < 0.01$.

Table 10: Destination-Province Characteristics and Migrant Inflows.

	(1)	(2)	(3)
log earnings	2.7171		
	(4.1435)		
# workers		0.0008	
		(0.0005)	
# college educated worker			0.0008
			(0.0005)
R-squared	0.02	0.07	0.07
Obs	107	107	107

Notes: The table shows estimates from the specification $M_p = \alpha + \beta Z_p + \varepsilon_p,$, where M_p denotes the total number of displaced mover-year observations in province p between 2009 and 2015. The independent variables capture pre-earthquake economic characteristics of the destination province. Standard errors are clustered at the municipality-of-origin level. $^{*}p < 0.10$, $^{***}p < 0.01$.

Table 11: Heterogeneous Mobility Responses Among Exposed Workers.

	(1)	(2)	(3)
	Move	Move	Move
Post × log earnings (t=-1)	0.0080		
	(0.0060)		
Post × Age (t=-1)		-0.0009***	
		(0.0003)	
Post × College			0.0191*
			(0.0111)
Year FE	Yes	Yes	Yes
Observations	542,844	542,844	542,844
R-squared	0.010	0.011	0.010

Notes: The dependent variable is an indicator equal to one if the individual changes municipality between $t-1$ and t. The sample includes individuals residing in earthquake-affected municipalities at $t=-1$. Each column reports a separate regression including year fixed effects (also individual fixed effects for earnings). Age is measured in years. Standard errors are clustered at the municipality-of-origin level. $^{*}p<0.10$, $^{***}p<0.01$.

Table 12: L'Aquila Earthquake Movers - Static Earnings Specification with Location-Worker Effects

	L'Aquila Earthquake Movers		
	y	$\bar{\alpha}_c$	ψ_c
Log Density	0.066***	0.034**	0.020**
	(0.024)	(0.016)	(0.0081)
Observations	107	107	107
R-squared	0.09	0.04	0.05
Log Density	0.066***	0.041**	0.017**
	(0.022)	(0.015)	(0.007)
Rank-to-Rank	-2.399***	-0.943**	-1.080***
	(0.529)	(0.501)	(0.200)
Rank-to-Rank × Density	-0.192	-0.425	-0.097
	(0.661)	(0.549)	(0.214)
Observations	106	106	106
R-squared	0.24	0.11	0.24
Log Density	0.059**	0.032*	0.017**
	(0.022)	(0.016)	(0.007)
School Segregation	-0.042***	-0.018*	-0.021***
	(0.013)	(0.011)	(0.005)
School Segregation × Density	-0.025	-0.008	-0.012**
	(0.023)	(0.006)	(0.14)
Observations	107	107	107
R-squared	0.14	0.06	0.14
Log Density	0.053**	0.027	0.016**
	(0.023)	(0.016)	(0.007)
Firm Segregation	-2.532***	-1.397***	-0.854***
	(0.495)	(0.382)	(0.191)
Firm Segregation × Density	0.374	0.112	0.064
	(0.873)	(0.559)	(0.191)
Observations	107	107	107
R^2	0.29	0.15	0.19

Notes: Sample includes workers displaced by the 2009 L'Aquila earthquake. Entries are elasticities of average log earnings (y), location-averages of worker fixed effects ($\bar{\alpha}_c$), static location premium (ψ_c) estimated with the static location-worker effects specification from De La Roca and Puga (2017), with respect to city density, segregation in schools (measured as in Agasisti and Falzetti (2017)), segregation within firms (this is the share of the total variance in AKM worker fixed effect within a province c that is attributable to differences between firms; see Song et al. (2018)) or upward mobility (measured as in Acciari et al. (2022)). Each specification includes the interaction between density and each of the other measures. Regressions for $\psi_c + \phi_c$ and ϕ_c are weighted by inverse standard errors. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 13: L'Aquila Earthquake Movers - with Exposure to Location

	L'Aquila Earthquake Movers - With Exposure to Locations				
	y	$\bar{\alpha}_c$	ψ_c	$\psi_c + \phi_c$	ϕ_c
Log Density	0.065**	0.016	0.015**	0.119***	0.047***
	(0.028)	(0.019)	(0.007)	(0.037)	(0.011)
Observations	107	107	107	107	107
R-squared	0.06	0.01	0.03	0.08	0.10
Log Density	0.081***	0.037***	0.008	0.058***	0.049***
	(0.023)	(0.011)	(0.006)	(0.014)	(0.010)
Rank-to-Rank	-1.468**	-0.277	-0.472**	-1.419***	-0.947**
	(0.603)	(0.476)	(0.202)	(0.422)	(0.387)
Rank-to-Rank × Density	-2.412***	-1.627***	-0.354	-0.590	-0.236
	(0.704)	(0.444)	(0.242)	(0.453)	(0.324)
Observations	106	106	106	106	106
R-squared	0.27	0.15	0.10	0.18	0.13
Log Density	0.057**	0.011	0.012*	0.048***	0.046***
	(0.028)	(0.019)	(0.006)	(0.015)	(0.011)
School Segregation	-0.052***	-0.014	-0.026***	-0.023*	-0.009
	(0.015)	(0.014)	(0.005)	(0.012)	(0.010)
School Segregation × Density	-0.032	-0.020	-0.009*	-0.014	-0.001
	(0.027)	(0.020)	(0.005)	(0.016)	(0.012)
Observations	107	107	107	107	107
R-squared	0.11	0.02	0.15	0.13	0.10
Log Density	0.069**	0.030	0.006	0.051***	0.045***
	(0.034)	(0.018)	(0.007)	(0.016)	(0.011)
Firm Segregation	-2.089***	-1.157***	-0.555***	-1.201**	-0.647
	(0.647)	(0.418)	(0.146)	(0.487)	(0.467)
Firm Segregation × Density	-0.101	-0.437	0.162	0.531	0.369
	(1.186)	(0.638)	(0.242)	(0.625)	(0.456)
Observations	107	107	107	107	107
R^2	0.25	0.14	0.13	0.18	0.12

Notes: Sample includes workers displaced by the 2009 L'Aquila earthquake. Entries are elasticities of average log earnings (y), location-averages of worker fixed effects ($\bar{\alpha}_c$), location premium (ψ_c), and the dynamic components, namely the medium-term premium ($\psi_c + \phi_c$), and experience premium (ϕ_c) estimated with De La Roca and Puga (2017), augmented with years of experience in the firms, with respect to city density, segregation in schools (measured as in Agasisti and Falzetti (2017)), segregation within firms (this is the share of the total variance in AKM worker fixed effect within a province c that is attributable to differences between firms; see Song et al. (2018)) or upward mobility (measured as in Acciari et al. (2022)). Each specification also includes the interaction between density and each of the other measures. Regressions for $\psi_c + \phi_c$ and ϕ_c are weighted by inverse standard errors. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 14: Geographic balance at the historical Hapsburg–Savoy border

	(1) Elevation	(2) Temperature	(3) Precipitation
Hapsburg	-44.85	0.301	-0.0441
	(29.77)	(0.193)	(0.0678)
Observations	23224	23040	23040
Clusters	15	15	15
Mean	474.34	11.43	3.12

Notes: Each column reports the coefficient on the Hapsburg indicator from a spatial regression discontinuity estimated within ±40 km of the 1815 border, using 25 km segment fixed effects. The dependent variables are: *Elevation*, the mean height (m) of each 1 km cell; *Slope*, the average local gradient to neighboring cells (degrees); *Temperature*, mean annual temperature (°C) for 1950–1973; and *Precipitation*, mean annual precipitation (mm) for 1950–1973. Temperature and precipitation are from the E-OBS daily gridded dataset (0.1° × 0.1°), based on in-situ observations. Elevation and slope are computed from the TINITALY/1.1 digital elevation model (10 m resolution), aggregated to a 1 km grid. Coefficients are reported with robust standard errors in parenthesis, which are clustered by segment fixed effect. ***, **, and * indicate significance at the 1, 5, and 10% levels.

Table 15: Regression of location earning premium, estimated with De La Roca and Puga (2017) worker-location specification onto the historical Hapsburg empire border.

	(1)	(2)	(3)	(4)	(5)	(6)
Hapsburg	0.0261**	0.0210**	0.0282***	0.0327**	0.0479***	0.0419***
	(0.00900)	(0.00836)	(0.00827)	(0.0114)	(0.0169)	(0.0146)
Dist. from MI and TO	NO	YES	YES	YES	NO	NO
REG_FE	NO	NO	YES	YES	NO	NO
Only Lombardy	NO	NO	NO	NO	YES	YES
Poly	2	2	2	2	1	1
Observations	2117	2117	2117	2117	623	623

Notes: Each column reports estimates from a spatial regression discontinuity within ±80 km of the 1815 Hapsburg–Savoy border, with 25 km segment fixed effects. The dependent variables are the municipal earning premium estimated with static location-effect specifications. Controls include distance from large cities, namely Milan and Torino, regional fixed effects. Estimates are also done restricting the sample to Lombardy. Coefficients are reported with robust standard errors in parenthesis, which are clustered by segment fixed effect. ***, **, and * indicate significance at the 1, 5, and 10% levels.

Table 16: Regression of location earning premium, estimated with Abowd et al. (1999) worker-firm specification onto the historical Hapsburg empire border.

	(1)	(2)	(3)	(4)	(5)	(6)
	y	y	α	α	ψ	ψ
Habsburgic	0.0580***	0.0649***	0.0398***	0.0421***	0.0174***	0.0228***
	(0.00931)	(0.0192)	(0.00700)	(0.0126)	(0.00390)	(0.00710)
Dist. from MI and TO	NO	NO	NO	NO	NO	NO
Poly	2	2	2	2	2	2
REG_FE	NO	YES	NO	YES	NO	YES
Obs	2254	2254	2253	2253	2253	2253
Mean	4.44	4.44	-0.02	-0.02	-0.00	-0.00

	(1)	(2)	(3)	(4)	(5)	(6)
	y	y	α	α	ψ	ψ
Habsburgic	0.0410***	0.0432**	0.0285***	0.0278**	0.0136***	0.0172*
	(0.00841)	(0.0196)	(0.00744)	(0.0123)	(0.00482)	(0.00924)
Dist. from MI and TO	YES	YES	YES	YES	YES	YES
Poly	2	2	2	2	2	2
REG_FE	NO	YES	NO	YES	NO	YES
Obs	2254	2254	2253	2253	2253	2253
Mean	4.44	4.44	-0.02	-0.02	-0.00	-0.00

Notes: Each column reports estimates from a spatial regression discontinuity within ±80 km of the 1815 Hapsburg–Savoy border, with 25 km segment fixed effects. The dependent variables are the municipal earning premium estimated with worker-firm fixed effects specifications. Controls include distance from large cities, namely Milan and Torino, regional fixed effects. Estimates are also done restricting the sample to Lombardy. Coefficients are reported with robust standard errors in parenthesis, which are clustered by segment fixed effect. ***, **, and * indicate significance at the 1, 5, and 10% levels.

Table 17: Regression discontinuity with population size from Bairoch or Malanima data or from Eurostat

Year	1600	1700	1750	1800	1861
Hapsburg	0.309	0.306	0.371*	0.371*	0.559*
	(0.192)	(0.181)	(0.203)	(0.200)	(0.303)
Segment FE	YES	YES	YES	YES	YES
Obs.	2256	2255	2257	2265	2264
Mean	0.23	0.23	0.26	0.32	0.41

	1500	1600	1700	1800	1861
Hapsburg	0.189	0.294	0.315*	0.349*	0.639*
	(0.134)	(0.179)	(0.170)	(0.175)	(0.300)
Segment FE	YES	YES	YES	YES	YES
Obs.	2267	2267	2267	2267	2267
Mean	0.20	0.24	0.22	0.29	0.46

	Population	Density 5km	Density 10km
Hapsburg	0.330	0.410**	0.453***
	(0.206)	(0.153)	(0.126)
Obs	15467	23208	23226
Clusters	15	15	15
Mean	4	9	11

Notes: Each column in the upper and middle parts of the table reports estimates from a spatial regression discontinuity within ±80 km of the 1815 Hapsburg–Savoy border, with segment fixed effects. The dependent variable is the total population living in cities. The upper part of the table uses data reported by Bairoch and Goertz (1986), the lower part of the table uses data reported by Malanima (2005). The bottom part of the table reports estimates from a spatial regression discontinuity within ±40 km of the 1815 Hapsburg–Savoy border, including 25 km segment fixed effects. The dependent variables are: *Population*, the total population in each 1 km^2 grid cell (2021 census, Eurostat GISCO); *Density 5km*, the number of people living within a 5 km radius of the cell; and *Density 10km*, the number of people living within a 10 km radius of the cell. Coefficients are reported with robust standard errors in parenthesis, which are clustered by segment fixed effect. ***, **, and * indicate significance at the 1, 5, and 10% levels.

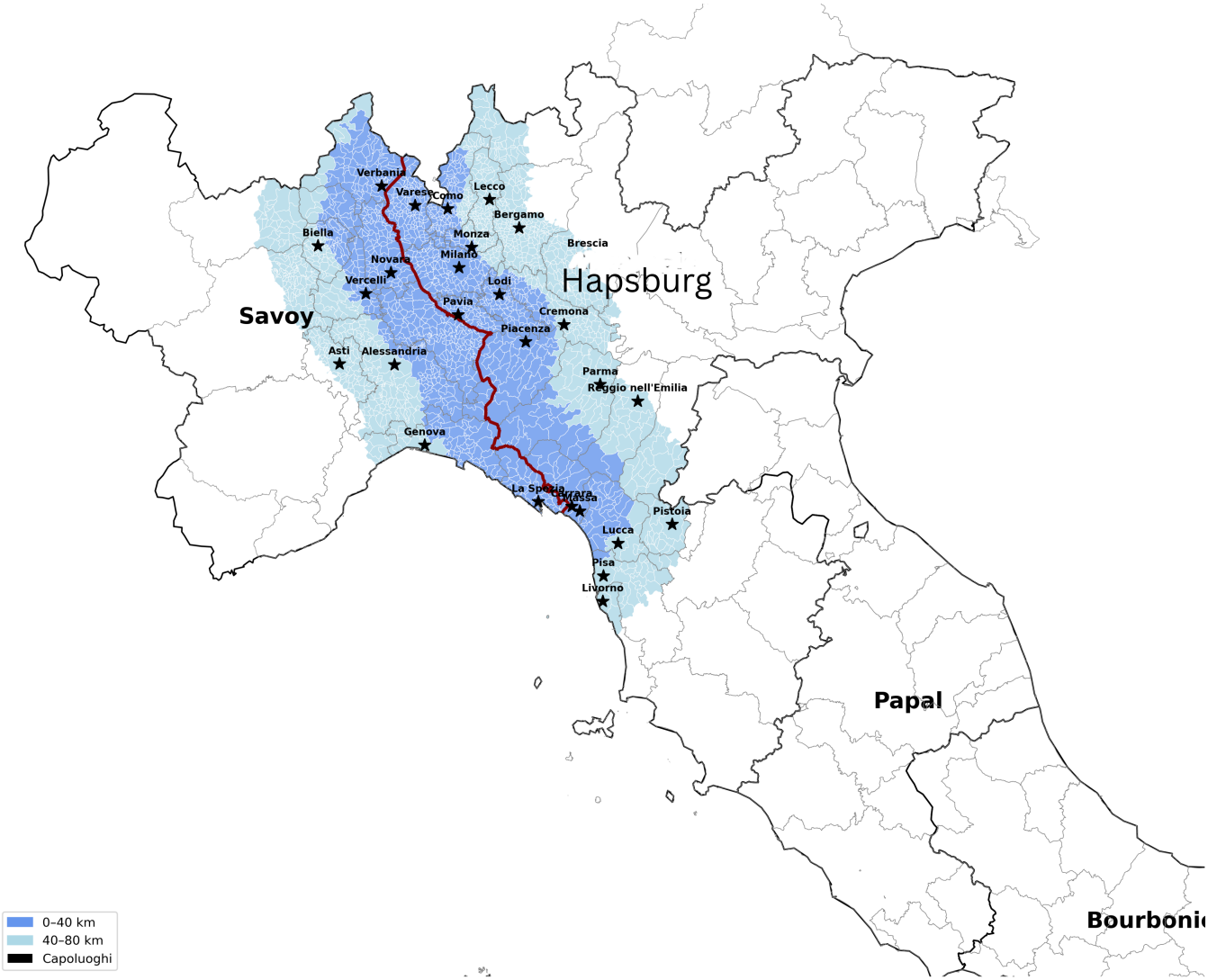


Figure 5: The 1815 border between the continental part of the Kingdom of Sardinia (mainland Savoy) and the Hapsburg domains, as used in our analysis. The historical border is shown in red. The dark blue area represents locations within approximately 40 km from the border, while the light blue area extends this range to within 80 km on both sides of the border.

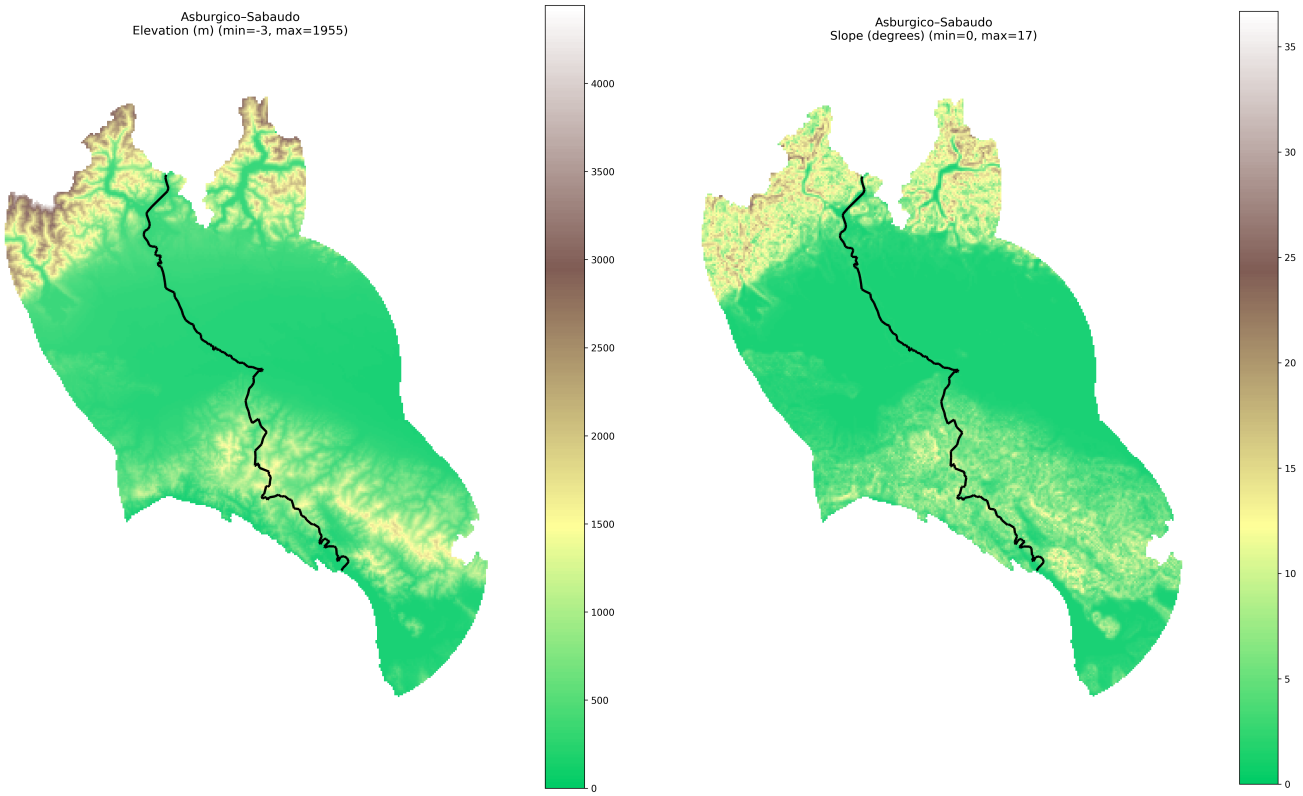


Figure 6: Elevation and slope in the 80 km area around the 1815 Hapsburg–Savoy border. Panel (a) shows mean elevation (m) in each 1 km grid cell. Panel (b) shows the mean slope (degrees) in each grid cell, calculated from the maximum variation in elevation with adjacent cells.

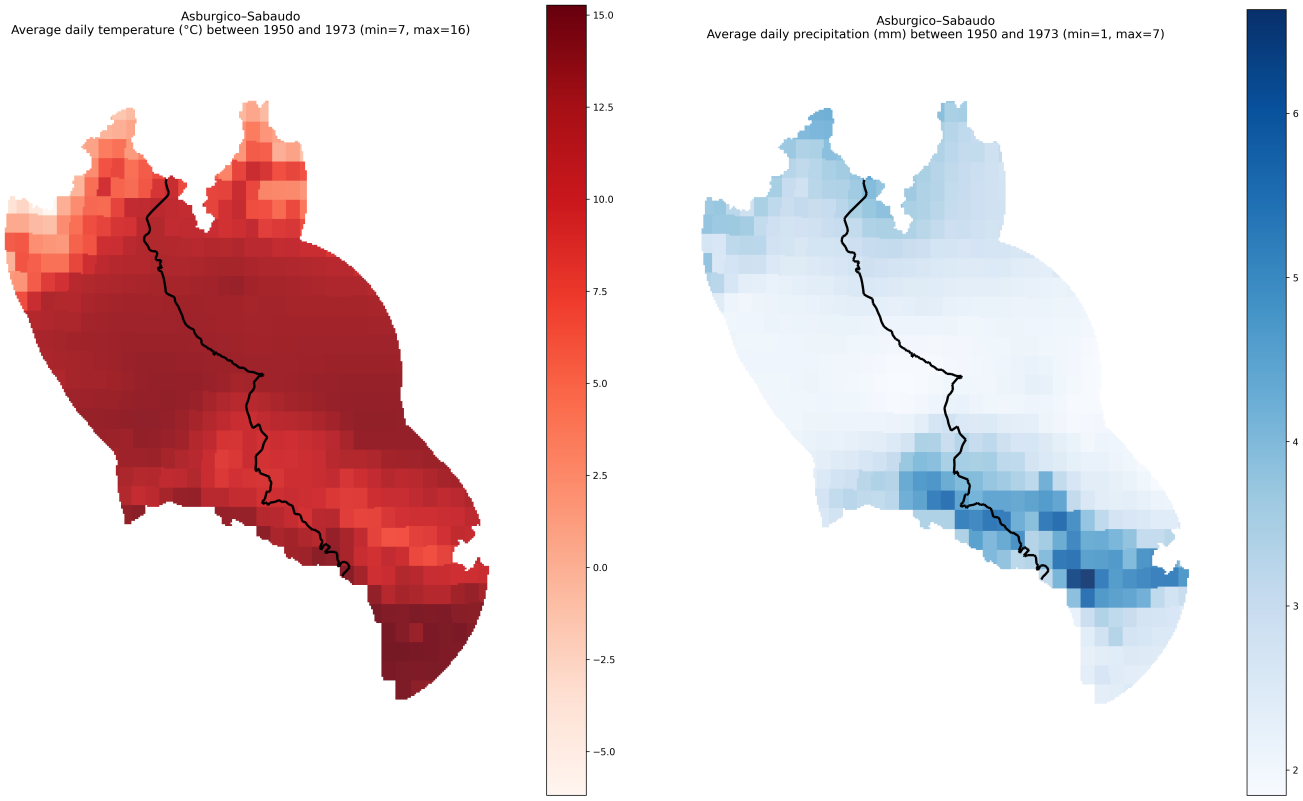


Figure 7: Temperature and precipitation in the 80 km area around the 1815 Hapsburg–Savoy border. Panel (a) shows the mean annual temperature (°C) for the period 1950–1973. Panel (b) shows the mean annual precipitation (mm) for the same period.

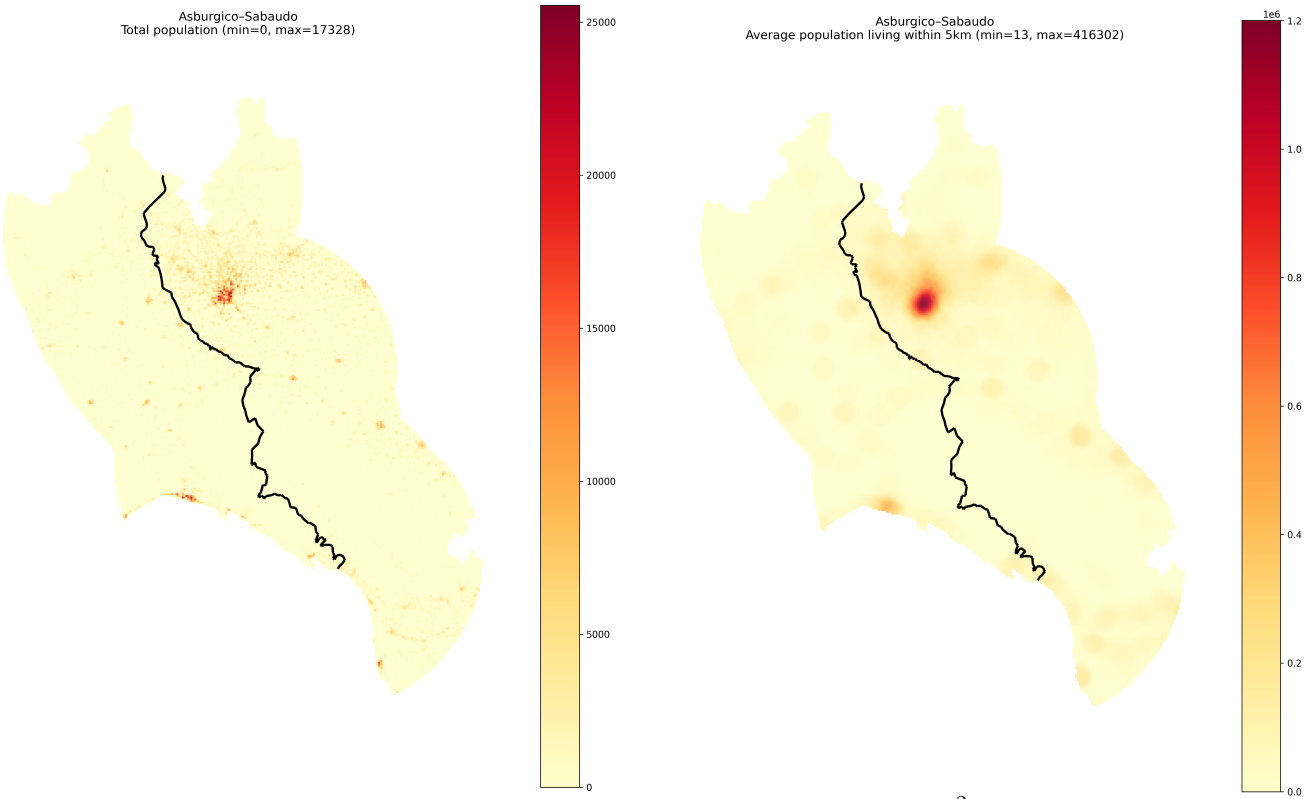


Figure 8: Current population and population density at the 1 km^2 grid level within an 80 km band around the 1815 Hapsburg–Savoy border. Panel (a) shows the total population in each grid cell (2021 census, Eurostat GISCO). Panel (b) shows the average number of people living within a 5 km radius of each cell.

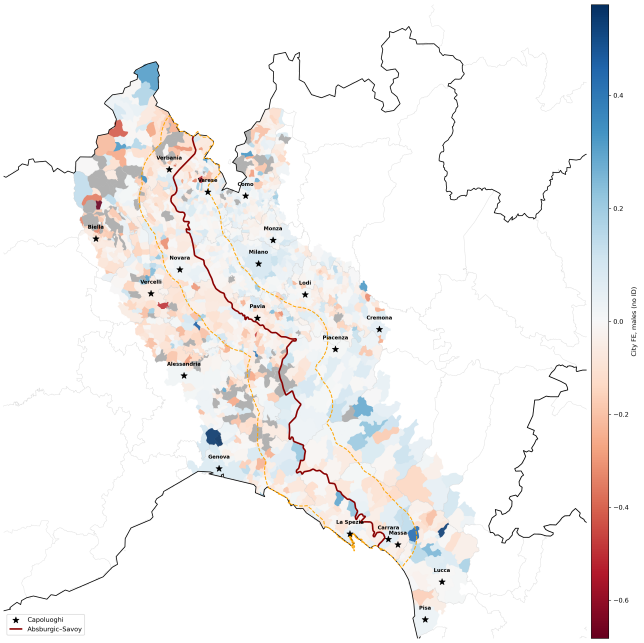


Figure 9: The figure reports municipality fixed effects estimated without worker fixed effects. The historical border is shown in red.

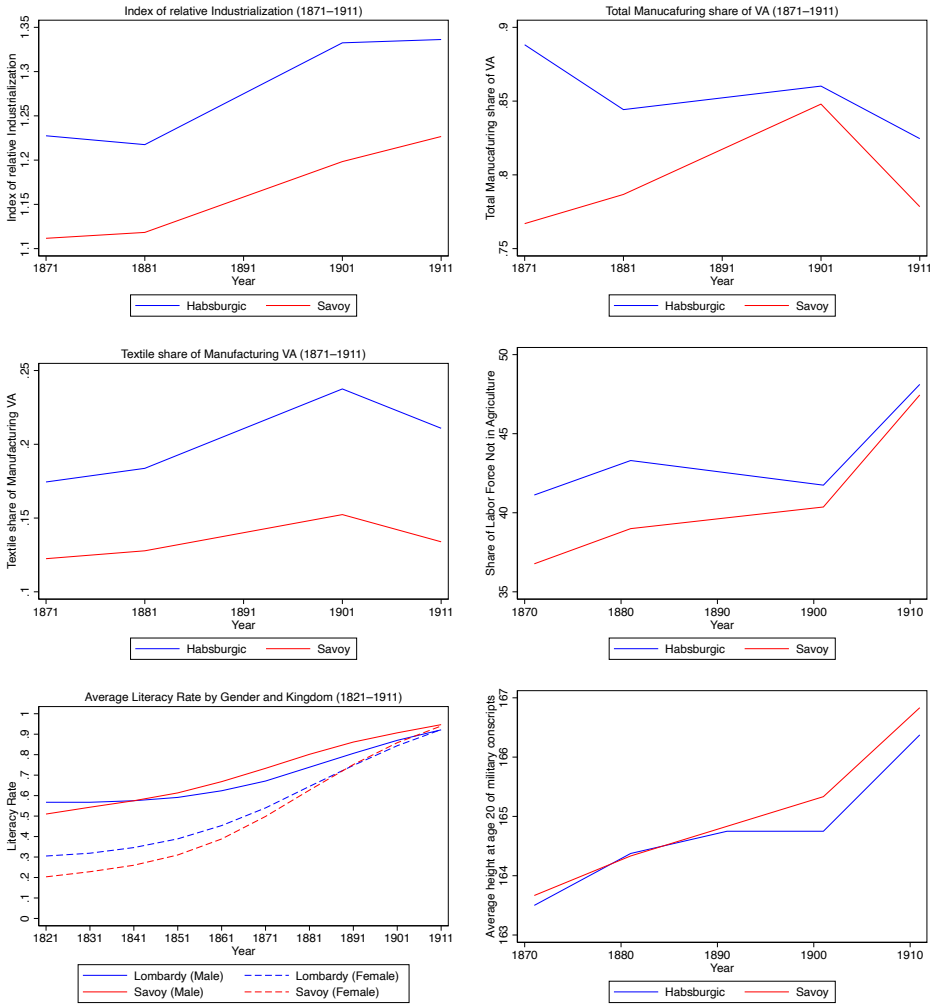


Figure 10: Indices of relative industrialization (1871–1911) and other demographic variables. The plots show indices of relative industrialization, of population share outside agriculture and share of textile in manufacturing in Lombardy and Savoy over the period 1871-1911. Data are from Ciccarelli and Fenoaltea (2013).

A. Data

A.1. INPS Samples

Our analysis draws on data from the Istituto Nazionale della Previdenza Sociale (INPS), which contains social security-based earnings records for all people employed in Italy at any time between 1974 and 2023. The INPS data provide information on annual job spells, including start and end dates, the number of days worked, and the total yearly wage compensation. In addition, the data set includes the gender of each worker and various geographic indicators that identify the location of the employer.

We employ annual wage records for workers in the non-farm private sector covering the period 1974–2023. For each worker and year, we identify a single job by selecting the employment spell with the longest duration and retain information on wages, number of days worked, municipality and province of employment, and the type of contract (part-time or full-time). These job-level data are merged with personal records to include the worker's date of birth and sex, and with firm records to add information on the sector of activity and other firm-level characteristics.

Starting in 2010, the data also contain occupation (ISCO codes) and education as reported by firms to INPS when a worker's job position changes. When multiple occupation reports are available for the same worker and year, we retain the most recent ISCO code. Education is treated as time-invariant; in cases where multiple education levels are reported for the same worker over time, we retain the highest level attained.

Annual labor earnings are expressed in euros per day of full-time equivalent work. We calculate this measure by dividing the total amount received ("importo") by the number of days worked, adjusting for part-time jobs according to the percentage of a full-time schedule actually worked. Earnings are then expressed in 2015 euros.

We use the full 1974–2023 panel to reconstruct complete employment histories, but the analysis sample is restricted to male workers born after 1954 who are aged 18-64 at some point during

2010–2023 and for whom both occupation and education information is observed. The birth year cut-off is imposed to ensure that the entire working history of each individual is observed.

We also exclude individuals who report a daily wage below 5 real euros, who have zero days worked, or who lack education information. We then eliminate all observations from establishment-year with only one worker as well as workers who are observed for only a single year[32]. We further drop all observations for which we do not observe the municipality, province, or sector of the firm. Finally, we restrict the data to the largest connected set, which represents 99% of the selected sample.

A.2. Additional data

- **Intergenerational mobility (provincial level)** – Measures of intergenerational mobility at the provincial level. *Source:* Acciari, Paolo, Alberto Polo, and Giovanni L. Violante (2022), *And Yet It Moves: Intergenerational Mobility in Italy*, *American Economic Journal: Applied Economics*, 14(3): 118–163. Open access dataset available at: https://doi.org/10.1257/app.20210151.
- **INVALSI test scores (provincial level, 2012/13–2023/24)** – Aggregated results of the INVALSI standardized tests, including average percentage scores (cheating-corrected), WLE ability estimates, socio-economic background indicators (ESCS), standard deviations, distribution of students across competence levels, percentage reaching learning targets, and participation rates. *Source:* Open Data INVALSI. Available at: https://serviziostatistico.invalsi.it/invalsi_ss_data/punteggi-e-percentuale-di-studenti-nei-livelli-di-competenza-per-ripartizioni-territoriali-e-caratteristiche-di-contesto/.
- **City size (historical, city level, 1000–1861)** – Historical data on the population of Italian cities, used to compute urbanisation rates and population thresholds at different points in time (1000, 1300, 1800, 1861). *Source:* Malanima, Paolo (2005), *Urbanization and the Italian economy during the last millennium*, *European Review of Economic History*, 9(1): 97–132.
- **City size (historical, city level, 800–1850)** – Historical data on the population of European

32 For the purposes of the analysis, we define an establishment as a firm–province pair, since the same firm may operate in different provinces and we are interested in estimating city wage premia.

cities, including Italy, used to analyze urbanization trends between 800 and 1850. *Source:* Bairoch, Paul and Gary Goertz (1986), *Factors of urbanization in the nineteenth century developed countries: a descriptive and econometric analysis*, *Urban Studies*, 23: 285–305.

- **Literacy rates (provincial level, 1821–1911)** – Adult literacy rates by gender at the provincial level reconstructed at 1911 borders using census sources and back-projection methods. *Source:* Ciccarelli, Carlo and Jacob Weisdorf (2019), *Pioneering into the Past: Regional Literacy Developments in Italy before Italy*, *European Review of Economic History*, 23(3): 329–364.
- **Weather variables (grid level, 1950–1974)** – Mean temperature (°C) and precipitation (mm) derived from the 0.1° × 0.1° daily gridded E-OBS dataset, which is based on in-situ meteorological observations. *Source:* Cornes, Richard C., Gerard van der Schrier, Erich J. M. van den Besselaar, and Philip D. Jones (2018), *An Ensemble Version of the E-OBS Temperature and Precipitation Data Sets*, *Journal of Geophysical Research: Atmospheres*, 123(17): 9391–9409. Dataset available at: https://www.ecad.eu/download/ensembles/ensembles.php.
- **Elevation and slope (grid level)** – Mean height (m) and average local gradient of each 1 km cell relative to its neighboring cells. Both variables are derived from the TINITALY/1.1 digital elevation model (10 m resolution), aggregated to a 1 km grid; slope is computed by the authors based on the same DEM. *Source:* Tarquini, Simone, Isola, Iacopo, Favalli, Massimiliano, Battistini, Alessandro, and Nannipieri, Lorenzo (2012), *Release of a 10-m-resolution DEM for the entire Italian territory: Version 2.0 of the TINITALY/01 DEM*, *Italian Journal of Geosciences*, 131(1): 3–20. Dataset available at: http://tinitaly.pi.ingv.it/.
- **Historical Borders (shapefile, level)** – *Definition:* historical boundaries used to define regions in the empirical analysis. *Source:* archival or published source (author, year, publisher).

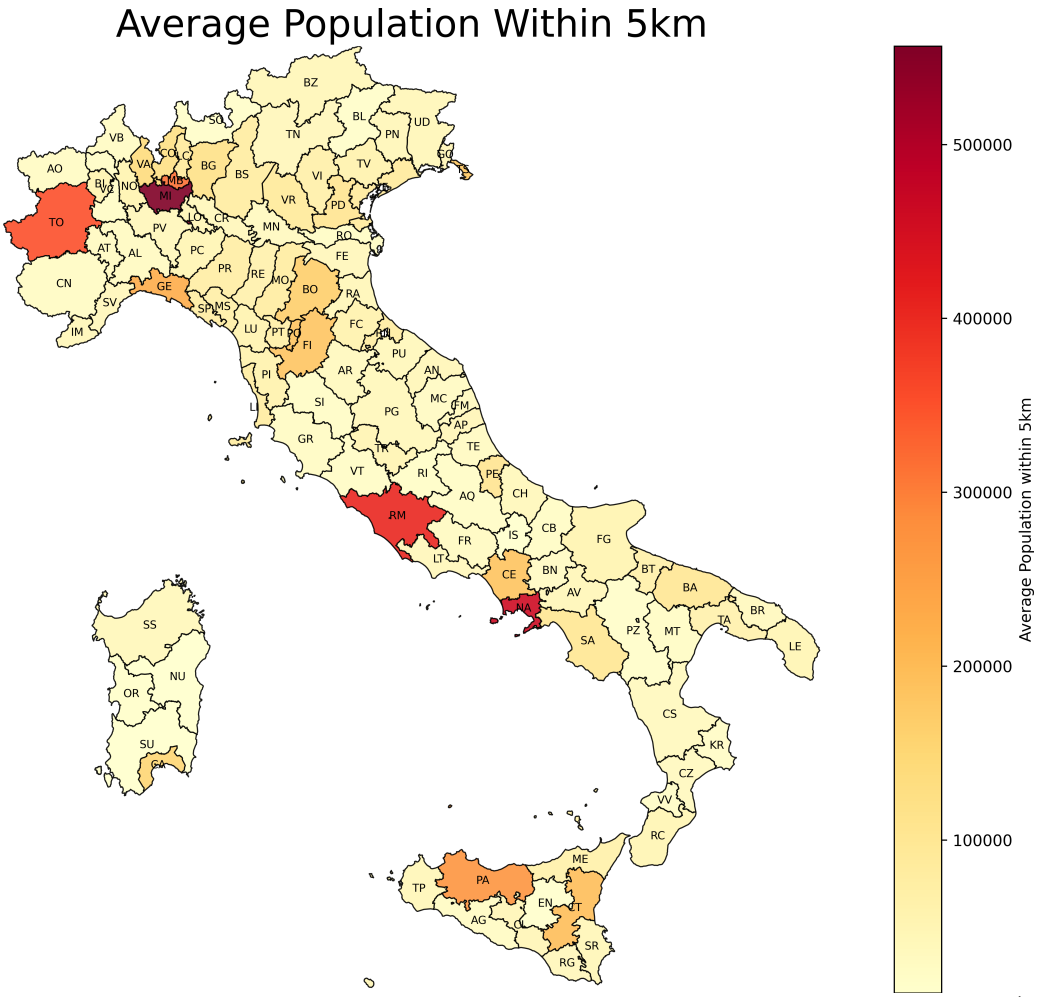


Figure 11: The map shows the average population within 5 km of each province (log scale).

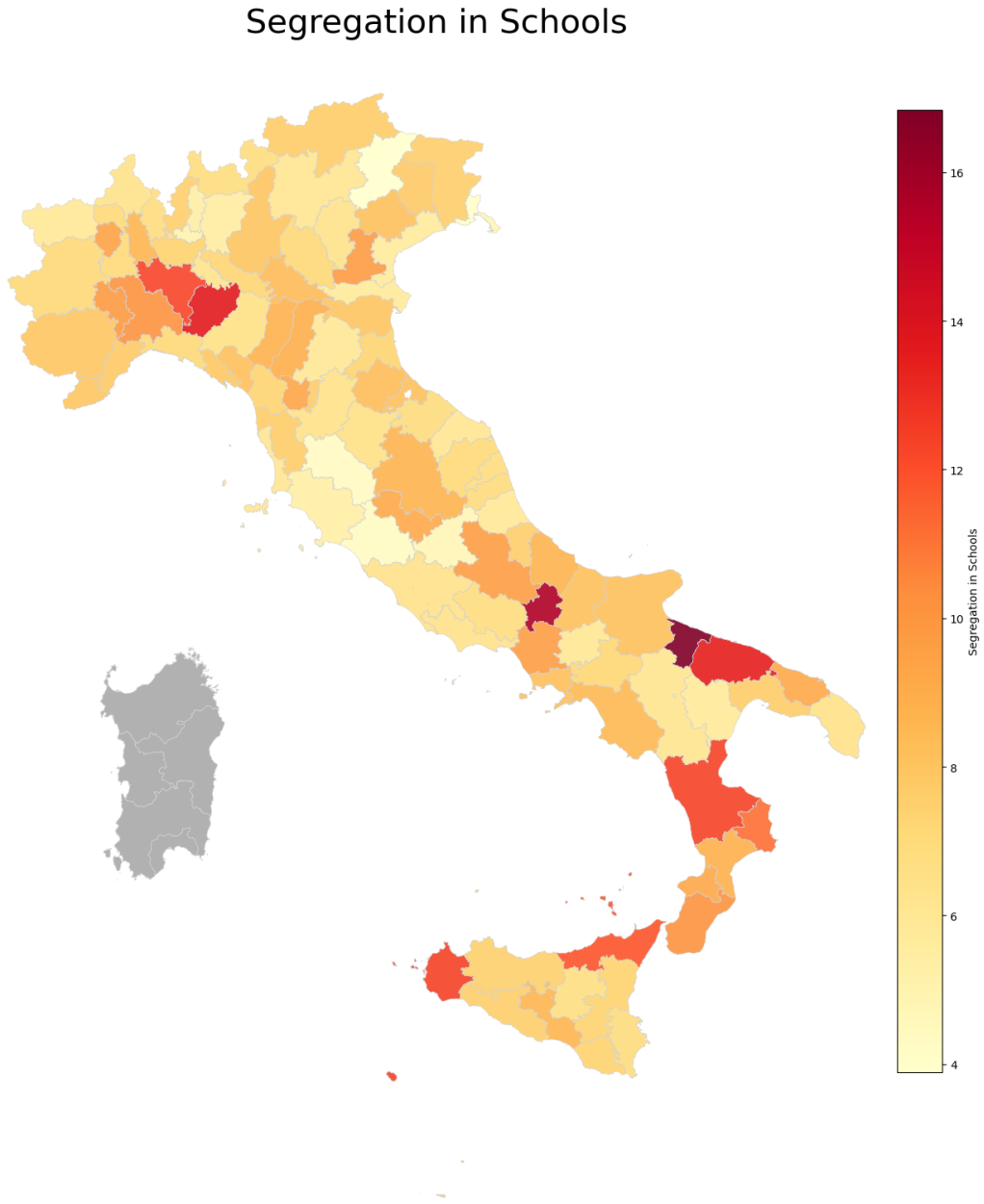


Figure 12: The map shows the school segregation index. Red colors is higher intensity.

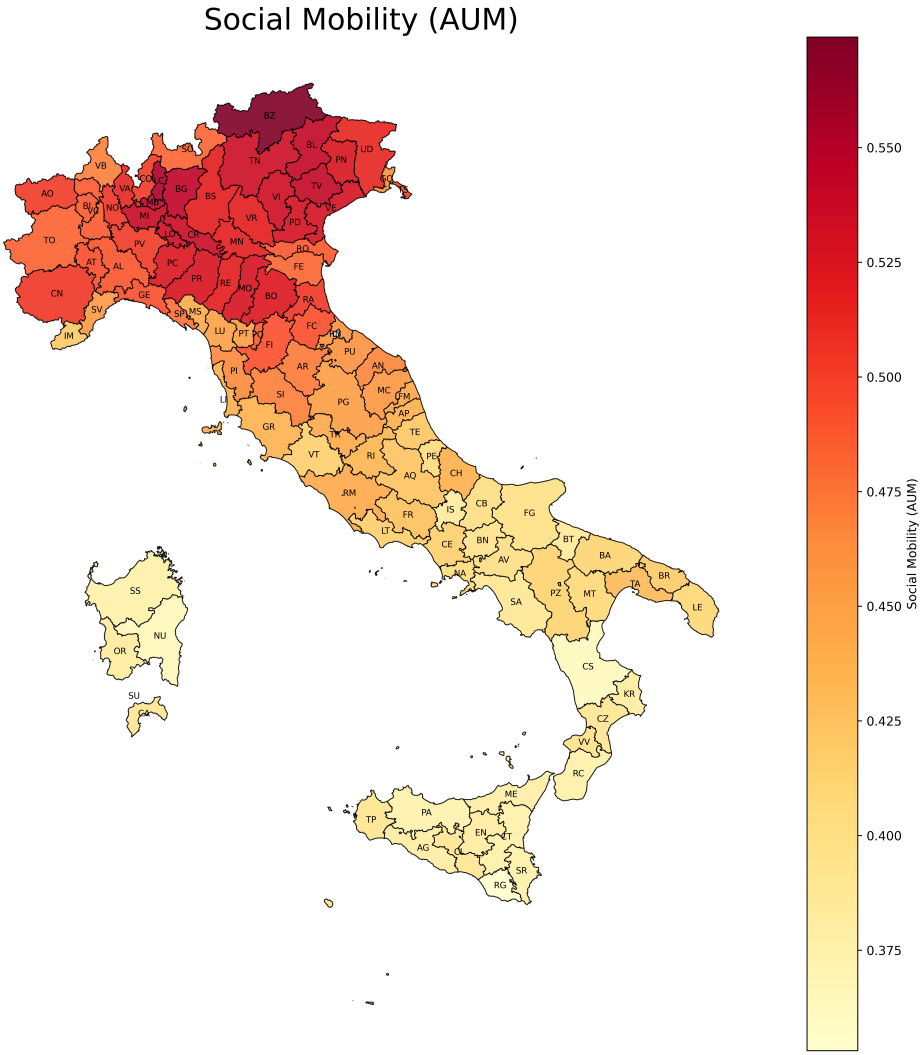


Figure 13: The map shows the intensity of the absolute upward mobility index computed by Acciari et al. (2022). Red colors is higher intensity.