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Abstract

This paper offers new evidence on agglomeration economies by examining the link between total factor productivity (TFP) and employment density in Italy. We investigate whether and how the TFP-density nexus contributes to explaining a relevant share of the marked productivity gap between the northern and the southern Italian regions. We estimate TFP for a large sample of manufacturing firms and then aggregate it at the level of local labour market areas (LLMAs). We tackle the endogeneity issues stemming from the presence of omitted covariates and reverse causation with an innovative set of diagnostic tests and an instrumental variable approach that relies on geological and historical data. Our estimate of the TFP elasticity to the spatial concentration of economic activities is about 0.045, a magnitude comparable to those measured for other developed countries. We also show that no significant heterogeneity emerges in the intensity of agglomeration economies across the country and that the positive TFP difference in favour of the firms located in the North is not due to the tougher competition taking place in those areas.

Keywords: agglomeration economies, regional disparities, selection effects, density, total factor productivity
JEL codes: R12, R23

1. Introduction

The concentration of workers, companies, or institutions in specific areas may generate productivity advantages for the firms located within those borders. Extensive theoretical and empirical literature has investigated this nexus, showing that the total factor productivity (TFP) of firms increases with the density of economic activities in the local markets. In this paper, we contribute to the existing literature in three ways.

First, we provide a novel picture of the spatial distribution of TFP in Italy. To address this issue, *i*) we measure firm-level productivity by resorting to a rich dataset that includes a large sample of Italian manufacturing companies observed from 1995 to 2019; and *ii*) we aggregate TFP for all local labour market areas (LLMAs).

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Second, we provide a point estimate of the TFP elasticity to an indicator of local economic density for the Italian private sector. This makes it possible to compare the Italian case with related exercises carried out for other countries. We are fully aware that the empirical investigation of the TFP elasticity is plagued with endogeneity issues, which we address by resorting to instrumental variable (IV) regressions. For this purpose, we use a rich collection of geological and historical predictors and discuss several identification problems that could affect our estimations, seldom tackled in other contributions.

Finally, armed with this evidence, we investigate whether agglomeration economies can contribute to explaining the traditional productivity gap between the firms located in the northern and southern Italian regions. Even though numerous studies have mentioned agglomeration as one of the potential explanations for the inefficiency of southern firms in Italy, we are not aware of any work directly addressing a similar topic in the way it is done here.

We report that the lower spatial concentration of economic activity in the southern LLMAs is a relevant determinant of the lower productivity of the firms in the South compared to those in the North. Further, there is no evidence that returns to density are lower in southern areas. We also implement a non-parametric methodology to discriminate between classes of determinants (other than agglomeration effects) that are believed to reasonably affect the distribution of firm efficiency. This technique allows us to reject the hypothesis that part of the North-South disparities in terms of productivity is determined by localised selection mechanisms and not by different levels of density.

The remainder of the paper is organised as follows. Section 2 gives a brief review of the existing literature dealing with theoretical and empirical issues of agglomeration economies. Section 3 is a short preview of the results. Section 4 describes the variables and controls. Section 5 outlines the econometric strategy and provides a discussion on the contribution of agglomeration economies to the differences in productivity between the northern and southern Italian regions. Section 6 examines alternative explanations for the results and the possibility that selection mechanisms may have determined the relationship between density and TFP. The paper ends with some concluding remarks in Section 7.

2. Literature review on agglomeration economies

Population and economic activities are not evenly distributed in space. The most evident reasons for explaining this evidence since the early stages of economic development are both the physical endowment and the morphology of territories, the so-called *first-nature* advantages: climate, raw resources, and accessibility. Though *agglomeration* (i.e., spikes of density of firms, workers, and people) can be a byproduct of a multitude of location choices aimed at capturing the localised benefits of first-nature characteristics, natural factors account for just a fraction of the observed spatial differences in levels of density.[1] Various

[1] Ellison and Glaeser (1999) attribute roughly one-fifth of the observed industry spatial concentration to a small set of natural advantages. Henderson et al. (2018) show that the effects of specific first-nature

strands of the literature argue that agglomeration allows economic agents to "*economise on local trade costs, spread information and ideas more easily, diversify the range of products produced, and access larger pools of workers and jobs*" (Henderson et al., 2021). These benefits are available, to a large extent, independently from the geographic features of the territories where they are generated.

The share of agglomeration that cannot be explained by the exogenous space heterogeneity is the focus of two different streams of research: the *urban economics* (UE) and the *new economic geography* (NEG) approaches (Combes et al., 2005). Both strands of literature model possible mechanisms for the endogenous emergence of density.

In NEG models (e.g., Fujita et al., 1999), increasing returns at the firm level, imperfect competition, and trade costs might lead to spatial concentration at the equilibrium. In agglomerated areas, some pecuniary advantage (e.g., higher wages, land values, and rents) can emerge, but agglomeration *per se* does not grant any productivity advantage.

In the tradition of UE, starting from the seminal work of Henderson (1974), however, the observed agglomeration at the equilibrium is associated with the advantages that density brings forth directly, determined by pure positive externalities. The Marshallian idea that denser local markets produce positive externalities and make incumbent firms more efficient can be derived from several models.[2] Duranton and Puga (2004) proposed the now-standard classification of agglomeration economies consisting of the triad of *matching*, *sharing*, and *learning* mechanisms.[3] In this literature, agglomeration (and density) is just a channel through which economic activities generate and benefit from *localised* externalities. In that sense, agglomeration is then an *intermediate* determinant of productivity, and its effectiveness could vary with the intensity of the available externalities.

Ciccone and Hall (1996) pioneered a flourishing modern wave of empirical research aimed at measuring the benefits of agglomeration. They have moved from the tradition of studies on *city* or *industry size* as determinants of productivity (e.g., Sveikauskas, 1975; Segal, 1976; Henderson, 1986) to the detection of increasing returns in a local (i.e., relative to a well-defined geographical area but external to the boundaries of single firms) production function, where the *density of firms* or *workers* is (sort of) an input. Various survey papers (in particular, Rosenthal and Strange, 2004; Melo et al., 2009; Combes and Gobillon, 2015;

characteristics on the density of economic activities explain approximately half of the worldwide variation of density and more than one-third of the within-country variations. For the Italian case, Accetturo and Mocetti (2019) analyse the role of geography and history in explaining the distribution of the population across space and its evolution over time.

[2] Agglomeration externalities arise due to the indivisibility in the provision of certain goods or facilities, the specialisation of labour forces, and the production, diffusion (thanks to face-to-face communications), and accumulation of ideas.

[3] Of course, the dark side of agglomeration is the emergence of negative externalities (i.e., congestion effects) that explain the observed upper bounds for density. As Duranton and Puga (2004) put it (p. 2065), "*we can regard cities as the outcome of a trade-off between agglomeration economies or localised aggregate increasing returns and the costs of urban congestion*".

Ahlfeldt and Pietrostefani, 2019) illustrate the methods and motivations for detecting and measuring the underlying phenomena.

As for the way the effects of agglomeration economies are measured, factor productivity, wages, and sometimes employment are usually considered. These variables can then be obtained from regional (or urban) aggregate data or firm-level information. Combes and Gobillon (2015) maintain that (p. 302) "*it is worth studying the effects*" of agglomeration on TFP rather than on wages "*since it is a direct measure of productivity*" and that its use (p. 283) "*avoids making any assumption about the relationship between the local monopsony power*" of firms on labour "*and agglomeration economies*".

The main challenge in the more recent literature is to sort out the direct causal relationship from agglomeration to productivity of input factors from the relations where agglomeration is the effect (and not the cause) or the by-product of productivity.

This spurious correlation between agglomeration and productivity emerges first, and most evidently, as the effect due to the availability of natural advantages that concentrate firms and workers in specific places, thus leading to better local outcomes. However, a positive relationship between productivity and density is also observed in two other cases: *i*) since tougher competition is associated with market density and size, agglomerated markets develop stronger selection effects whereby denser areas show higher levels of productivity (Melitz and Ottaviano, 2008); and *ii*) sorting effects emerge if workers and firms that are intrinsically more productive prefer agglomerated areas – either because they benefit more from proximity or because denser locations turn out to have better institutions, higher amounts of amenities, *et cetera* – and, in this case, more productive individuals will be over-represented in agglomerated places (Combes et al., 2012; De la Roca and Puga, 2017; Gaubert, 2018).[4]

As witnessed by various meta-analyses and surveys, the empirical strategies for measuring pure agglomeration economies are rather differentiated, and, in particular, do not often address endogeneity, selection, and sorting simultaneously, resulting in somehow upward-biased estimates.[5]

In general, the available evidence confirms that the elasticity of productivity to the spatial concentration of economic activities is significantly positive, even if estimates fluctuate greatly in magnitude.[6] The seminal paper that estimated increasing returns to density, taking endogeneity into account, is Ciccone and Hall (1996). They explained differences in labour productivity across the US states with elasticity to density of about 0.06. Henderson

[4] Note that while pure agglomeration economies can arise even in a homogeneous space and among homogeneous individuals, the sources of spurious correlation illustrated above when agglomeration is not a determinant of productivity need some form of heterogeneity (i.e., non-homogeneity of space, firms, and workers).

[5] Section 5.3 provides a more detailed discussion on this point.

[6] The evidence provided in the literature is always an assessment of the *net* agglomeration effects, what scholars can observe is the portion of positive effects that are not offset by the negative ones (e.g., congestion).

(2003) in the US, Cingano and Schivardi (2004) in Italy, Graham (2009) in the UK are the first to exploit a measure of TFP based on firm-level data. The subsequent research in this stream of literature offers more sophisticated estimates of productivity and tries to better tackle possible endogeneity biases. In particular, Combes et al. (2010), regress wages and TFP (estimated at the firm level with the technique proposed by Olley and Pakes, then aggregated at the local scale) on density for the French case, addressing both reverse causation and sorting of workers. They report a proper elasticity of wages and TFP to density at 0.02 and 0.04, respectively. All that said, the usual point estimates for the elasticity are in the range of 0.02 to 0.09 (Rosenthal and Strange, 2004; Melo et al., 2009; Combes, 2011; Ahlfeldt and Pietrostefani, 2019; Donovan et al., 2024), proving to be strongly dependent on the industry, time, country, and the spatial structure assumed.

3. A preview of the main findings

In this section, we provide a preview of our results using the lens of economic geography and, in particular, that of the extant literature on agglomeration economies. The following sections will then present a more in-depth analysis as well as the motivations behind this evidence. Here, we summarise the main findings to help the reader grasp them beyond the technicalities that will be addressed later.

As for the spatial scale of our empirical analysis, we divide Italy into the 611 local labour market areas (LLMAs) defined by Italian National Institute of Statistics (ISTAT) for 2011. These functional units are built by aggregating all the 8,092 Italian municipalities based on their spatial contiguity and self-containment of daily commuting flows to work. They constitute the ideal reference grid for the study of agglomeration economies since most of the externalities mentioned by the theory are likely to occur at the level of the local labour market, an area that can be effectively represented by the LLMA definition.[7]

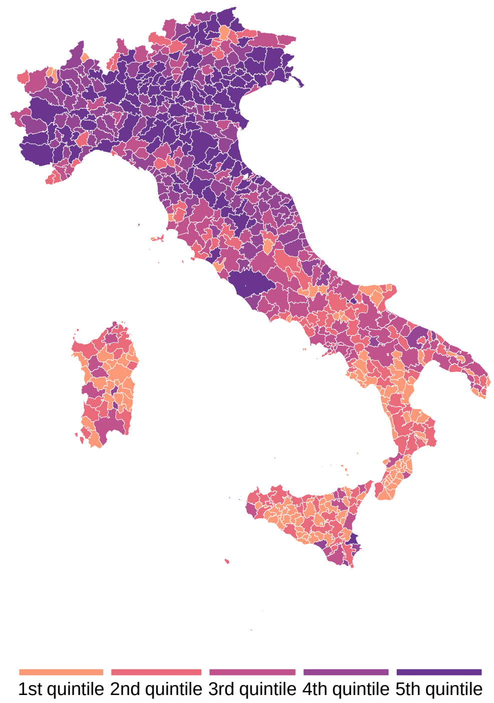
The central question being investigated in this work is the link between productivity and density of the economic activities; for this aim, we compute for each LLMA *i*) an indicator of TFP in the manufacturing sector that is netted out for the effects of sectoral composition and *ii*) a measure of density that relies on the total number of employees per surface unit.[8]

The two Figures 1a and 1b represent the spatial distribution of productivity and density. Both variables are characterised by a clear north-south gradient; the two choropleth maps reveal a high degree of overlap for the above-mentioned patterns. In other words, the less productive LLMAs in the South also display a lower employment density than those in the North.

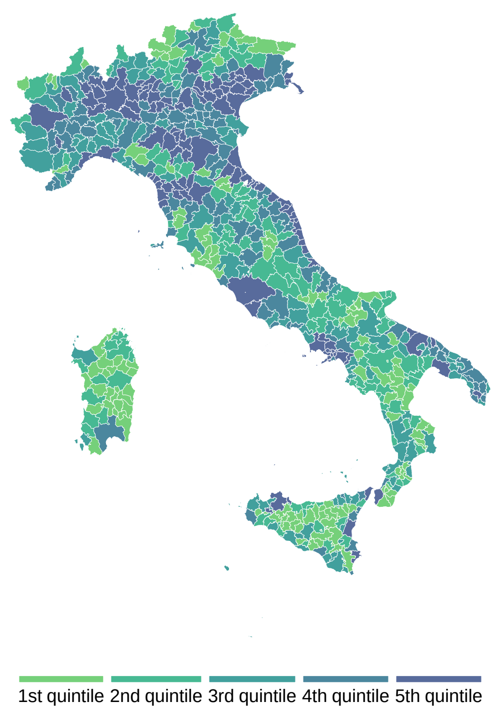
[7] Note that such a spatial partition is generated every ten years, since the data needed in this respect comes from the census of population and economic activities carried out by ISTAT at the beginning of each decade. Although this mapping has undergone some evolution over time (the number of LLMAs has decreased slightly from 1981 onwards), it also exhibits a certain degree of stability, justifying its use as the reference year in a structural analysis.

[8] The detailed definition of these variables is reported in the following Sections 4.1 and 4.2.

Figure 1: Spatial distribution of productivity (a) and employment density (b) by LLMA



(a) Choropleth map of the (logarithm of the) employment-weighted total factor productivity net of sector effects



(b) Choropleth map of the (logarithm of the) employment density

Figure 2 is a simple correlation plot between (the logarithm of) the density measure at the level of LLMAs and (the logarithm of) our TFP indicator. The chart points to a positive relationship between the concentration of economic activity and the productivity that may be consistent with the existence of agglomeration economies.[9]

Figure 2 distinguishes LLMAs belonging to the North from those located in the South.[10,11] Southern labour markets are mostly found in the third quadrant of the plane (i.e., that of the units exhibiting jointly a lower TFP and density). Such evidence would hint that LLMAs in the South are less productive in part because they feature a low density of workers. The disproportionate presence of blue-coloured observations below the regression line in the scatter plot highlights the presence of substantial localisation effects that should be further investigated. According to the tenets of the urban economics literature surveyed

[9] Two quite well-known examples of successful agglomeration stories in Italy include the case of the major Italian firms in northern cities, in particular within the so-called *industrial triangle* (i.e., Turin, Milan, and Genoa), and the case of the industrial districts. The former has been considered as one of the main drivers of the industrial take-off of the Italian economy during the first half of the twentieth century. As for industrial districts, these consist of the spatial concentration of small-sized firms mostly located in non-urbanised areas of North-west, North-east, and Centre macro-areas displaying a strong specialisation into specific industrial activities that imply a huge accumulation of local competencies in the production of a particular good. They were defined as a socio-territorial entity characterised by the active presence of both a community of people and a population of firms in a naturally and historically bounded area (Becattini, 1990). Due to the externalities generated within the local network, incumbent firms were able to obtain substantial productivity benefits that are fully consistent with the agglomeration economies described in Section 2. For previous contributions measuring the local productivity advantages associated with industrial districts, see Signorini (1994) and Signorini (2000). Di Giacinto et al. (2014) compare the productivity of urban areas and industrial districts in Italy and find that the advantages of the latter have been declining over time while those of the former have remained stable.

[10] In our classification, the North includes three of the five geographical breakdowns (i.e., North-west, North-east, and Centre) at the first level of the nomenclature of territorial units for statistics (NUTS) for Italy, whereas our South includes the remaining two (i.e., South and Islands). Figure C.1 in the Appendix offers a representation of the territorial reference grid in Italy and depicts the LLMAs belonging to the northern and southern regions according to our definition. The South hosts 281 labour markets, whereas 330 are in the North, respectively 46.0% and 54.0%. The southern regions together cover 40.9% of the national territory. If the surfaces of LLMAs were represented as circles, those located in the South would have, on average, a radius of 11.0 kilometres compared to 12.4 kilometres for those in the North. Summing up these pieces of evidence, it turns out that southern LLMAs are more fragmented and smaller than northern ones.

[11] In 2001, the North-west and North-east accounted for 45.0% of the Italian population and 40.1% of the overall surface. Their population and employment densities were 211.5 inhabitants and 75.3 workers per square kilometre, respectively. In the same year, 19.1% of the national population was resident in the Centre, which represents 19.0% of the overall surface. Its population and employment densities were 189.8 inhabitants and 55.7 workers per square kilometre, respectively. The South and Islands accounted for 36.0% of the population and 40.9% of the overall surface. Their population and employment densities were 165.8 inhabitants and 27.5 workers per square kilometre, respectively. In the following Section 5.2, we provide some robustness checks by showing how the main results change with different aggregations of the Italian geographical breakdowns (i.e., merging the Centre with the South and Islands or treating it separately). In general, results support our initial choice of including the Centre into the North, as the former displays structural characteristics that are more similar to those of the northern LLMAs.

in Section 2, the fact that employees are sparser in the southern LLMAs would weaken the formation of those positive externalities associated with agglomerated areas. Productivity differences could become important to explain the backwardness of the South in terms of other indicators, such as GDP per capita or additional welfare measures.

Figure 2: Scatterplot, regression line, and confidence interval of productivity against density

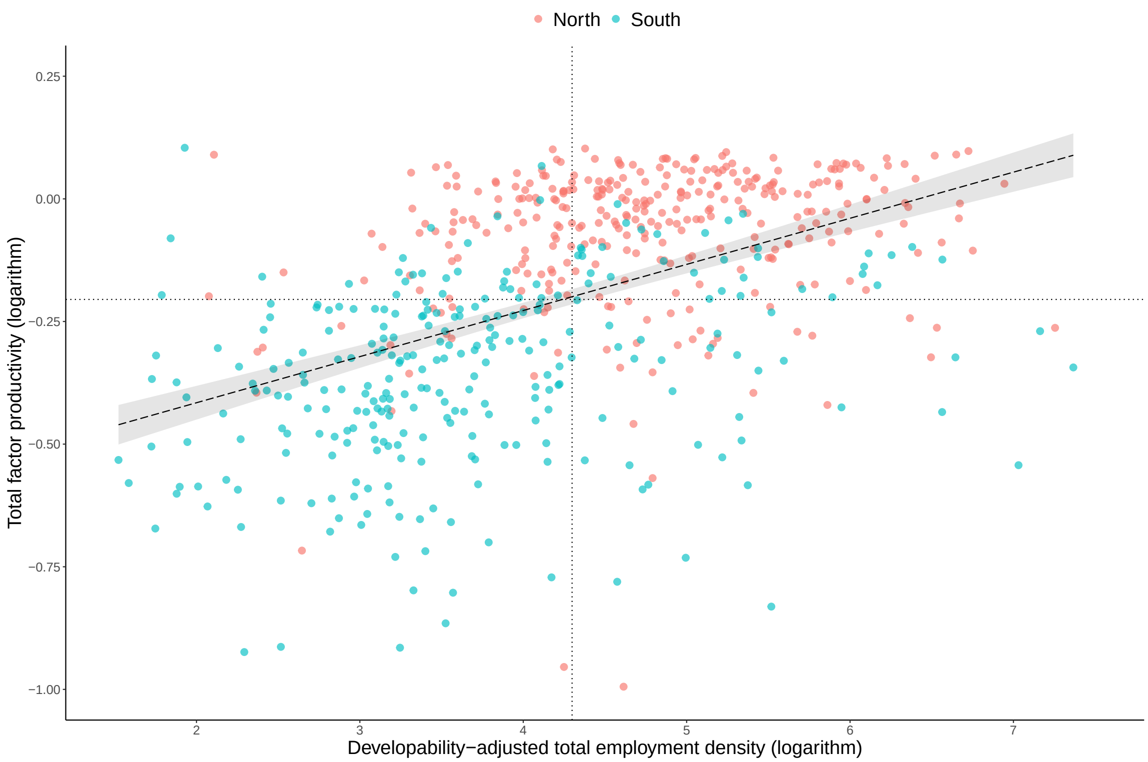


Table 1 provides a detailed comparison of the distribution of productivity and density in the two macro-areas. The LLMAs in the South display lower productivity compared to those in the North: the average and median TFP of the southern geographical units are 25.1% and 26.9% lower than those of the northern ones, respectively. Similar gaps are confirmed across the other percentiles of the productivity distribution. The LLMAs in the South also exhibit a lower density. The spatial units in northern and southern macro-areas host, on average, 200.8 and 103.9 employees (the corresponding median values are 114.9 and 33.3) per square kilometre, respectively.

The issue of the North-South disparities in Italy has been explored from several perspectives. Coming to the papers dealing with the North-South differences in productivity, a stream of literature used aggregate data to conclude that, even limiting the analysis from the end of WWII onwards, firms in southern regions displayed much lower TFP levels (e.g., Mauro and Podrecca, 1994; Aiello and Scoppa, 2000; Di Liberto et al., 2008; Felice, 2019).[12] As for

[12] For other works comparing the North-South divide in Italy with the West-East one in Germany, see

Table 1: Differences in total factor productivity and employment density by macro-area

Total factor productivity	**Mean**	**5th centile**	**25th centile**	**50th centile**	**75th centile**	**95th centile**
North	0.944	0.732	0.885	0.972	1.030	1.084
South	0.707	0.496	0.615	0.711	0.799	0.907
Difference	-0.237***	-0.236***	-0.270***	-0.261***	-0.231***	-0.177***
	(0.010)	(0.027)	(0.017)	(0.013)	(0.012)	(0.016)
Employment density	**Mean**	**5th centile**	**25th centile**	**50th centile**	**75th centile**	**95th centile**
North	200.806	27.699	66.097	114.857	225.760	581.965
South	103.946	7.465	19.762	33.338	68.165	382.858
Difference	-96.860***	-20.234***	-46.335***	-81.523***	-157.595***	-199.107
	(23.806)	(3.358)	(3.958)	(7.675)	(22.536)	(144.238)

We test differences in employment-weighted total factor productivity net of sector effects and employment density across LLMAs in each macro-area by regressing the two variables on the South dummy and the constant term. We use ordinary least-squares and quantile regressions for mean and percentile differences. We report standard errors robust to heteroskedasticity in parentheses. Stars from one to three indicate statistical significance at 10%, 5%, and 1% levels, respectively.

the catching-up of the South, evidence is mixed.[13] Whatever the initial causes that might explain why southern regions were not a favourable environment for the concentration of firms and workers, the agglomeration processes could have supported a dynamic effect that self-feeds such differentials of density. In Toniolo (2013), the interested reader can find a summary of the long-standing debate between historians and economists concerning the causes that explain the relative backwardness of the South and its persistence over time.[14] In recent years, different studies have used firm-level data to quantify the magnitude of the North-South productivity gap in Italy (Calligaris et al., 2016; Locatelli et al., 2019; Rungi and Biancalani, 2019). This information allows to control for input compositional differences and broadens the scope of the analysis to include topics such as market selection and misallocation.[15] All these papers confirm that southern firms are much less efficient than northern ones, even when the differential is measured with microdata. Di Giacinto et al. (2014) estimate the productivity gap in the South with a large sample of companies observed in the years from 1995 to 2006 and taking into account several factors (e.g., the degree of urbanisation, the presence of industrial districts).

All in all, factors like corruption and criminality, the quality of local interactions, the lower

Boltho et al. (1997, 2018) and Boeri et al. (2020).

[13] Despite some consensus on the fact that there was a convergence in TFP levels until the Seventies, mainly due to direct and indirect public intervention and capital accumulation, yet there is much more uncertainty about what happened thereafter.

[14] Felice (2018) summarised the aforementioned explanations of the North-South divide into those related to geographical, social capital, and cultural factors, the exploitation of southern regions by the northern ones, and differences in the socio-institutional devices. The author empirically discusses the relative merits of those alternative explanations concluding that the differences between the formal and informal institutions in the North and the South were the main driver of the underdevelopment of the latter.

[15] Dealing with the issue of misallocation is beyond our current goals. We discuss selection models in Section 6.

propensity to cooperate and the lack of social capital, weak institutions and infrastructures, a highly sloped congestion cost curve might have coexisted with density in explaining the marked North-South TFP gap. In any case, we emphasise that whenever these alternative explanations predicted a pattern where southern LLMAs were less agglomerated than northern ones, they could be made compatible with the arguments based on agglomeration economies that will be discussed in the following pages.

4. Data

In what follows, we describe all the variables used in the econometric analysis and provide specific methodological details on how the indicators of productivity, agglomeration, and first-nature advantages were constructed.

4.1. Productivity

We estimate firm-level TFP for a large sample of Italian manufacturing companies observed in the years from 1995 to 2019. Our starting panel includes 264,166 unique firms extracted from the archives of Cerved and Centrale dei Bilanci, which correspond to an average of about 94,683 companies per year. Such a figure is substantially larger than the samples used in previous empirical analyses of firm-level productivity for the manufacturing sectors in Italy (see, in particular, Locatelli et al., 2019).[16] Since each company is observed for roughly 9 years, the sample size varies over time.[17] We collect data on value-added, labour cost, capital stock, value of intermediate goods, geographic location (i.e., the municipality), and economic activity.[18] We derive the number of employees, distinguished in white and blue collars, from the *National Institute for Social Security* (INPS) database.[19]

Productivity measures are obtained by estimating the residuals of the predicted outcomes with a multi-factor Cobb-Douglas production function. We compute our TFP indicator using the procedure developed by Wooldridge (2009), which implements a general method

[16] Locatelli et al. (2019) estimate the geographical differences in productivity among Italian macro-areas with a sample of 188,124 manufacturing firms, corresponding to an average of 74,975 companies per year.

[17] Note that more than a third of all the companies (i.e., 37.4%) are observed for at least 10 years and 5.5% for the entire reporting period. Cerved handles and distributes firm-level data extracted from the repositories of the Italian Chambers of Commerce. The factors causing the exit (entry) of companies from its database, and consequently from (into) the sample, are not disclosed. Reasonably (see also what is discussed in Section 6), most of the exits (entries) of the firms from (into) our sample are due to actual bankruptcies (start-ups), but we cannot exclude other reasons, such as misreporting of data.

[18] The classification of manufacturing industries is obtained by aggregating 19 sectors of the two-digit ATECO system into 10 categories (see Table C.5 in the Appendix) to ensure that a sufficient number of observations is associated with each cell. We exclude some economic activities from our sample: firms operating in the coke and refined oil sectors are disregarded because their performance is closely tied to commodity prices; pharmaceutical firms are also omitted because their trends are heavily affected by the budget policies for public health expenditure. We also remove from the sample the residual category (i.e., *Other manufacturing activities*) because it is generally not very relevant, and the corresponding data cannot be easily interpreted.

[19] We have merged the two repositories by firm code.

of moments (GMM) approach to reduce the effects of unobserved productivity (Rovigatti and Mollisi, 2018). Since we do not have data on physical quantities, firm output is proxied through value-added. All monetary variables are deflated.[20] This procedure does not take into account differences in prices across geographic locations owing to different demand elasticity or supply concentration. This means that our empirical measure of TFP is also determined by the factors that affect the prices of local companies. Note, however, that all our firms belong to the manufacturing sector, and, therefore, their reference market is expected to be mainly non-local.[21] TFP estimations are carried out separately for each of the 10 manufacturing industries defined in Footnote 18 and Table C.5 in Appendix.[22]

The second step of the empirical strategy consists of getting an aggregate measure of TFP at the LLMA level. Knowing the municipality where each firm i is located, we are able to place those companies within our mapping system based on the LLMA definition.[23] On that ground, we first compute the following quantity:

$$TFP_{r,s,t} = \sum_{i \in (r,s)} \frac{L_{i,t}}{L_{r,s,t}} TFP_{i,t} \tag{1}$$

which is a weighted average of firm-level productivity where the weights are defined by the share of employment associated with company i over the total of the area ($r = 1, \dots, 611$), sector ($s = 1, \dots, 10$), and year ($t = 1995, \dots, 2019$). Through this averaging, we assign more importance to large firms in the TFP computation.[24] Following Combes et al. (2010), as a further step in the aggregation procedure, we estimate a weighted least squares (WLS) regression:[25]

$$TFP_{r,s,t} = \delta_s + \varphi_{r,s,t} \tag{2}$$

[20] We deflate all the variables from the archives of Cerved and Centrale dei Bilanci (i.e., value-added, net revenues, cost of labour, and tangible fixed assets) using the Eurostat sector-specific deflator of the value-added with a base year equal to 2010.

[21] Jacob and Mion (2024) demonstrate, using a large sample of manufacturing firms, that differences in prices explain a large fraction of the revenue-productivity advantage of denser areas in France, suggesting that less productive regions could be more disadvantaged in terms of their competitiveness than for lower technical efficiency.

[22] Further details are illustrated in Appendix A.

[23] A major drawback of the dataset is that it does not distinguish mono-plant companies from multi-establishment ones. The latter are considered in our sample as single observations because we allocate each firm to the municipality in which its headquarters are located. While this limitation does not affect the TFP aggregation process in the case of small businesses, it could be problematic for large corporations with production facilities located in many LLMAs. However, the incidence of multi-unit enterprises should be relatively lower in our empirical setting of the Italian manufacturing sector.

[24] We compute this variable as a weighted average, alternatively using the employment, the wages, or the value-added as weights. Our preferred weighting scheme is the former and can also be interpreted as a measure of the productivity of the aggregated production function of the area r and the sector s, assuming constant returns to scale (see Appendix B). Combes et al. (2010) adopt the same definition.

[25] Weights are given by the number of firms in each LLMA and sector.

where the parameter δ_s represents industry fixed effects. We define $TFP_{r,t}$ as the arithmetic average of estimated residuals of Eq. (2) by geographical area and year. This measure allows us to eliminate all the differences in terms of sectoral composition that characterise local markets and make productivity comparable. $TFP_{r,t}$ is further averaged over time, thus obtaining the TFP_r variable. This choice is motivated by our interest in long-term effects of agglomeration economies without emphasising short-term variations in productivity. The averaging process should also help reduce the impact of measurement errors.[26]

4.2. Agglomeration

The main independent variable in our models, the concentration of economic activity, has been variously defined according to the extant literature as the number or spatial density of workers or firms. Accordingly, we test several alternative definitions for this regressor.[27] The key predictor in the baseline specifications, however, is the (logarithm of the) number of workers, L_r, divided by the surface of the spatial unit, S_r.

The numerator includes the employees of all sectors characterising the local economy in 2001.[28] The decision to include workers from industries not considered in our TFP analysis (in particular, those operating in the services, excluding the public administration) is aimed at capturing their possible contribution to the generation and transmission of agglomeration externalities.

Our preferred denominator is a normalised measure of surface that correctly assumes that human presence (and, in particular, economic activities) cannot deploy on water bodies and very rough terrain. For this purpose, we collect high-resolution data on each LLMA and compute a *net* area by excluding *undevelopable* land pixels, such as those located within major lakes[29] or having a slope greater than 15%[30] (Saiz, 2010, and Harari, 2020).[31]

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[26] To reassure the reader that the aggregation of TFP over the entire period from 1995 to 2019 does not conceal a relevant dynamic of productivity measures, we computed the corresponding annual time series on a national scale and for the northern and southern macro-areas. These variables exhibit a regular upward trend. Moreover, since our agglomeration measures are based on 2001 data, the TFP values as of 2001 appear to be representative of the average for the period. With the aim of showing that our temporal aggregation does not affect our main results, in Appendix D, we propose several robustness exercises that divide the overall time span under consideration into two sub-periods covering the years from 1995 to 2008 and from 2009 to 2019.

[27] We report some pieces of evidence associated with the comparison of various spatial concentration measures in Appendix D.

[28] Data are obtained from the industry and service census of ISTAT.

[29] Spatial information on European water bodies comes from the river and catchment database (De Jager and Vogt, 2010; Vogt et al., 2007).

[30] We employ a digital elevation model (DEM) of the entire Italian territory having a cell size grid of 100 square meters to compute a slope map (Tarquini et al., 2007).

[31] It should be noted that *gross* density measurements obviously dilute the presence of human proximity in mountainous areas and where the biggest lakes are located. The northern territories of Italy are home to the largest flat area in the country (i.e., the Po Valley), the main water basins, and the highest mountain range (i.e., the Alps). However, in many southern LLMAs, the terrain is often very rugged, although at

4.3. First-nature advantages

To estimate the intensity of agglomeration economies in Italy, we also consider a set of geographical variables that control for the main exogenous determinants of productivity and that we can reasonably regard as measures of *first-nature advantages*.

We first compute an indicator of *spatial connectedness*, defined as the share of developable surface, i.e., the surface of the entire LLMA excluding water bodies or territories with a slope greater than 15%. As discussed in Section 4.2, the developable area is the part of the territory that is able to host economic activities in general (see Harari, 2020). For a given level of density, a place where the distribution of economic activity is less connected (e.g., interrupted by a mountain range) will spread agglomeration externalities to a lesser extent. In this sense, *ceteris paribus*, we expect a higher TFP in labour markets where the share of developable surface is larger.

Second, we also calculate a measure of the distance to the nearest (relevant) freshwater body. This variable is defined as the minimum distance of the centroid of the LLMA to the nearest point of major lakes and rivers. The relevance of proximity to coastal areas and navigable rivers for lowering transport costs (i.e., the accessibility) along with increased opportunities for gains from trade, is discussed in Mellinger and Gallup (2000). Similarly, Henderson et al. (2018) show that being near the natural harbours, lakes, and navigable rivers is associated with more density and development. Consequently, higher productivity is expected for areas where this distance is lower.

Finally, we use a variable that measures the water endowment of the LLMA, operationalized as the length of all river segments (main or secondary) flowing within its territory and normalised by the corresponding surface. A rich water endowment can be considered as an economic input for many productive activities, not only for the primary sector. A'Hearn and Venables (2013) and Missiaia (2016) discuss the importance of water endowment in stimulating the industrial take-off of northern Italy after the reunification of the country. Therefore, higher values of river density are expected to be associated with higher TFP.

The specification of our models will also include a number of geographical dummies that identify LLMAs *i*) with coastal access, *ii*) located along the national borders, or *iii*) located on *minor* islands (i.e., excluding the large islands of Sicily and Sardinia).

Altogether, this set of geographic controls appears to be parsimonious but still relevant in capturing the large morphological differences of the Italian territory. Alternative controls we have tested are all highly correlated with our set of covariates.[32] As will be illustrated below, our set of first-nature variables and geographical controls – together with the density measure – explains a large share of the spatial variation in productivity.

lower altitudes. Overall, normalising with net areas significantly changes the density measures in both the North and South compared to normalising with total surfaces.

[32] For instance, the mean altitude of the LLMA is (strongly and) inversely correlated with the share of developable surface and takes on the highest values for areas located along the national borders.

Table 2 reports the summary descriptives of all the variables illustrated in this section, whereas Table C.2 in the Appendix provides the correlation matrix.[33]

Table 2: Descriptive statistics of the main variables

Regressands	**Count**	**Mean**	**Median**	**SD**	**Min**	**Max**
Total factor productivity	611	0.835	0.847	0.173	0.184	1.110
Regressors on agglomeration	**Count**	**Mean**	**Median**	**SD**	**Min**	**Max**
Employment density	611	156.260	69.831	299.255	4.585	3,324.195
Controls on first-nature advantages	**Count**	**Mean**	**Median**	**SD**	**Min**	**Max**
Share of developable surface	611	0.455	0.398	0.308	0.020	1.000
Distance to the nearest freshwater body	611	0.303	0.162	0.374	0.000	1.971
River density	611	0.066	0.067	0.046	0.000	0.252
Coastal dummy	611	0.385	0.000	0.487	0.000	1.000
Island dummy	611	0.010	0.000	0.099	0.000	1.000
Border dummy	611	0.070	0.000	0.256	0.000	1.000

Total factor productivity has been estimated with the procedure described by Wooldridge (2009) and weighted (in logarithms) using the share of the firm employment with respect to the total by LLMA, sector, and reference year. Agglomeration is measured via the employment density (in 2001) adjusted to account for the developable surface of each LLMA. The distance to the nearest freshwater body is expressed in hundreds of kilometres. A coastal LLMA includes at least one municipality that is either contiguous to the sea or has more than half of its surface within 10 km of the coastline.

5. The estimation of agglomeration economies in Italy

5.1. Baseline models

We employ the following econometric specification to estimate the elasticity of total factor productivity with respect to the spatial concentration of economic activity:

$$TFP_r = \eta \log\left(\frac{L_r}{S_r}\right) + X_r\mathit{\Gamma} + \varepsilon_r \tag{3}$$

Our regressand measures the average TFP for each LLMA, whereas the main covariate, L_r/S_r, is the employment density (in logarithms).[34] We also include a vector of geographic controls, X_r, that proxy *first-nature advantages* to account for some of the key exogenous determinants of productivity.

Table 3 shows the results for the OLS regression of Eq. (3) with standard errors clustered at the level of regions. All the coefficients are significantly different from zero and take on the expected sign. In general, the estimates are rather stable.

[33] Table C.1 in the Appendix reports the descriptive statistics of the variables for the northern and southern LLMAs.

[34] The η parameter is the elasticity of productivity to density. Provided that η is correctly estimated, we will be able to answer questions such as the impact on local TFP resulting from shifts in the L_r/S_r ratio.

Table 3: Baseline models

Model	(1)	(2)	(3)	(4)
Employment density (logarithm)	0.092***	0.114***		0.110***
	(0.016)	(0.016)		(0.007)
Share of developable surface		0.302***	0.194***	0.297***
		(0.065)	(0.051)	(0.039)
Distance to the nearest freshwater body			-0.242***	-0.149***
			(0.034)	(0.025)
River density			0.621**	0.636***
			(0.221)	(0.158)
Coastal, border, and minor island dummies	No	No	Yes	Yes
Constant	-0.600***	-0.832***	-0.250***	-0.774***
	(0.077)	(0.095)	(0.051)	(0.051)
Observations	611	611	611	611
Adjusted R-squared	0.221	0.370	0.303	0.563

The dependent variable is the (logarithm of the) employment-weighted total factor productivity net of sector effects. The main regressor is the (logarithm of the) developability-adjusted employment density. A control for the share of developable surface is added in Model (2), whereas Models (3) and (4) contain additional first-nature covariates on the distance to the nearest freshwater body (in hundreds of kilometres), the river density as well as coastal, border, and minor island dummies. All specifications include the constant term. Standard errors robust to heteroskedasticity and intra-cluster correlation at the level of regions are reported in parentheses. Stars from one to three indicate statistical significance at 10%, 5%, and 1% levels, respectively.

The parameter of the employment density is positive throughout all the specifications. Its magnitude is approximately equal to 0.09 in the univariate Model (1) and then increases to around 0.11 in the other multivariate specifications. Overall, we confirm the existence of positive effects originating from the local concentration of economic activity in Italy. An elasticity of 0.11 implies that doubling the employment density would also increase the productivity of incumbent firms by about 8%.[35] This elasticity is above the range of those estimated in the extant literature for other developed countries. However, it is not easy to make a proper comparison due to the sharp differences between methodologies, data, and years examined (Melo et al., 2009). Moreover, our definition of density is different from the ones normally employed in similar analyses since we normalise the number of workers by a *net* surface measure (i.e., corrected by the share of developable territory).

For the Italian case, Di Giacinto et al. (2014) estimated that the productivity advantage of urban areas (i.e., LLMAs with more than 200,000 inhabitants) is approximately 0.11, using data comparable to ours. Cingano and Schivardi (2004), were among the first to measure agglomeration economies using firm-level productivity data. Although focused on TFP dynamics, they reported (p. 735) that the elasticity of TFP with respect to the logarithm of local manufacturing employment was equal to 0.07.

The effects of first-nature controls are also stable and highly significant. More connected LLMAs with a higher share of developable surface (these local markets are mainly located in the flat territories of the Po Valley) are associated with higher productivity. The same applies to more accessible (i.e., closer to large water bodies) and more freshwater-endowed

[35] Note that when agglomeration doubles, total factor productivity increases by $2^{\eta} - 1$ times.

areas. Note that these results are confirmed when excluding (or including) density from the specifications, as is evident when comparing Models (3) and (4).

To complement the previous findings and shed more light on the relative importance of the variables considered in our econometric models, Table C.3 in the Appendix provides a Shapley decomposition of the explained variance based on the OLS regressions in Table 3.[36] In the most complete specification of Model (4), the employment density explains 43.1% of the variation in TFP across the LLMAs, whereas the joint contribution of three first-nature controls amounts to 48.6%. The residual share (i.e., less than 9%) is attributed to the set of geographical dummies.

5.2. The productivity gap

Our baseline specifications account for much of the spatial heterogeneity of TFP in Italy, attributing it to the different concentration of economic activity and to local first-nature advantages. In what follows, we investigate whether the lack of agglomeration in the South might explain the traditional productivity differentials between firms in the northern and southern regions of Italy (as conjectured in Section 3).

Agglomeration economies can be a relevant factor in explaining such a productivity gap provided that two conditions hold: *i*) there are substantial and persistent imbalances in the agglomeration rates between the North and the South of the country; *ii*) these differences translate into positive TFP differentials in favour of the more agglomerated northern areas because of the positive externalities generated via the concentration of firms and workers in specific local markets.

To go deeper into the empirical analysis, we enrich previous models by introducing into the specification a South dummy for the LLMAs located in the southern Italian regions. This simple setup enables us to obtain a very parsimonious representation of all the other factors that, apart from density and first-nature controls, affect the TFP differences across LLMAs, and compare the relative magnitudes of the different forces at work.

As a further enrichment of the analysis, we also interact density in the baseline model with the South dummy to test whether differences in terms of the intensity of the agglomerations economies might play a role in explaining southern backwardness. Moreover, we check the robustness of our results to alternative definitions of the territories included in the North and the South of the country.

We report the results in Table 4. All specifications include the set of first-nature controls, whose estimated parameters are fairly stable.

[36] The Shapley value (1953) was introduced to measure the real power among players in a cooperative game theory context. Based on this concept, Shorrocks (2013) proposed a general procedure that assigns to individual predictors their joint multivariate impact on the regressand. The method relies on successively eliminating covariates from the specification to calculate their marginal effect, and the result is an additive, symmetrical decomposition of the contribution associated with each variable in a regression model.

Table 4: Models with spatial controls and interactions

Model	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Employment density (logarithm)		0.080∗∗∗	0.078∗∗∗	0.097∗∗∗	0.078∗∗∗
		(0.007)	(0.008)	(0.011)	(0.012)
South dummy	-0.262∗∗∗	-0.160∗∗∗	-0.179∗∗∗		
	(0.028)	(0.022)	(0.045)		
South dummy × Employment density (logarithm)			0.005		
			(0.012)		
Centre-south dummy				-0.074∗	-0.189∗∗∗
				(0.040)	(0.062)
Centre-south dummy × Employment density (logarithm)					0.024
					(0.016)
Share of developable surface	0.186∗∗∗	0.265∗∗∗	0.264∗∗∗	0.272∗∗∗	0.262∗∗∗
	(0.033)	(0.033)	(0.034)	(0.038)	(0.041)
Distance to the nearest freshwater body	-0.108∗∗∗	-0.092∗∗∗	-0.092∗∗∗	-0.138∗∗∗	-0.135∗∗∗
	(0.032)	(0.024)	(0.023)	(0.029)	(0.029)
River density	0.337∗	0.458∗∗∗	0.458∗∗∗	0.541∗∗∗	0.533∗∗∗
	(0.161)	(0.137)	(0.137)	(0.170)	(0.166)
Coastal, border, and minor island dummies	Yes	Yes	Yes	Yes	Yes
Constant	-0.159∗∗∗	-0.576∗∗∗	-0.564∗∗∗	-0.662∗∗∗	-0.564∗∗∗
	(0.024)	(0.045)	(0.052)	(0.068)	(0.079)
Observations	611	611	611	611	611
Adjusted R-squared	0.519	0.625	0.624	0.576	0.577

The dependent variable is the (logarithm of the) employment-weighted total factor productivity net of sector effects. The main regressor is the (logarithm of the) developability-adjusted employment density. All specifications include the constant term, controls for the share of developable surface, the distance to the nearest freshwater body (in hundreds of kilometres), and the river density as well as coastal, border, and minor island dummies. Model (5) has been estimated without the (logarithm of the) employment density whereas Models (6), (7), (8), and (9) include the South or the Centre-south dummies. The interaction terms between the South or the Centre-south indicator variables and the (logarithm of the) employment density are contained in Models (7) and (9). Standard errors robust to heteroskedasticity and intra-cluster correlation at the level of regions are reported in parentheses. Stars from one to three indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Model (5) replaces the density variable with the South dummy. Its estimated parameter is negative, significant, and equal to -0.26. Once the effect of the first-nature controls has been partialled out, the North-South productivity gap is captured by the coefficient of the South indicator variable. Model (6) includes both the density variable and the South dummy into the same econometric specification: the magnitudes of the two parameters are lower than those obtained in Models (4) and (5), but they remain highly significant. Specifically, the estimated value of the elasticity is now equal to 0.08 and basically picks up TFP variability *within* the northern and southern macro-areas, due to the differences in agglomeration between LLMAs, controlling for first-nature advantages. The estimated parameter for the South dummy drops to -0.16.

In Model (7), we then introduce the possibility to have different density elasticities for the two northern and southern regions. In the TFP-density plane, this would be equivalent to having two different regression lines for each macro-area with distinct intercepts and slopes. The evidence indicates that interaction terms are never significant, i.e., we detect no heterogeneity in the elasticity of productivity with respect to the density of economic activity. Finally, in Models (8) and (9), we change the macro-area definitions by attributing the Centre to the southern regions instead of the northern ones (see again Footnote 11).[37]

5.3. Instrumental variable estimation

Despite the rich set of controls introduced in our last OLS specification, we cannot rule out that additional endogeneity problems might affect the results. To tackle this problem, we resort to an IV estimation.

As usual, the variables that are suitable to play the role of instruments have to be correlated, conditional on the other exogenous regressors in the model, with the endogenous variables (i.e., the relevance condition) and uncorrelated with the error term in the main equation (i.e., the exogeneity condition). The latter requirement implies that each instrument must affect the regressand in the main specification only through its impact on the endogenous variable (i.e., the exclusion restriction). While it is relatively straightforward to check for the validity of the instruments, it is cumbersome to assess their exogeneity.

The endogeneity of our main regressor originates from the fact that once cities are created, typically where first-nature advantages favour human settlements, they usually display a strong morphological persistence through time. In this sense, the past population density was high in places featuring high land fertility or located in a central position with respect to the territory. Moreover, while fertile soil was crucial for agricultural productivity, it is unlikely to have any relevance for the TFP of manufacturing companies nowadays. This orthogonality condition might not hold in the presence of other long-term factors that could have driven population density and productivity in recent times. For instance, *accessibility* (affected by the position of each LLMA relative to natural communication ways) might have induced agglomeration in areas located at the intersection of strategically relevant communication routes but could still be an important factor in determining transportation costs for manufacturing firms.

All this considered, we follow the extant literature (see Ciccone and Hall, 1996 and Combes et al., 2010) and resort to a set of historical, geographical, and geological instruments. First, a measure of the density of major Roman roads, as proposed by De Benedictis et al. (2023),[38] appropriately controls for historical accessibility, thus circumventing potential criticism. For similar reasons, we also introduced a purely geographic centrality indicator, based on (log of) the sum of the inverse physical distance from all other LLMAs (Head and Mayer, 2006, use this indicator to instrument market potential). A third group of variables consists of indicators that capture several characteristics of the geological composition of the soil (e.g., the presence of an impermeable layer, the mineralogical profile, the available water capacity). Again, the correlation between these measures is very high. Our favourite instrument of this group is the profile differentiation of the terrain. In a similar vein,

[37] In unreported evidence, we find that the Centre is not significantly different from the North, hence supporting our initial choice.

[38] Spatial data on the network of Roman roads has been derived from the *Barrington Atlas* and made available via the *Digital Atlas of Roman and Medieval Civilization*. We thank the authors for providing us with this information at the level of each LLMA.

we included other variables on the risk of an LLMA being exposed to earthquakes and floods.[39] Finally, the list of possible instruments is completed by the historical population density.[40,41,42]

The results of IV regressions are in Table 5. The diagnostic tests clearly indicate that we can reject the null hypothesis of exogeneity for our density variable and, hence, that it is the case to move to an IV approach. Both the partial coefficient of determination in the first stage and the F statistic on the null hypothesis of simultaneous irrelevance of all the instruments point to the fact that our instrumental variables are strongly correlated with the employment density (i.e., they are relevant). As for the exogeneity condition, the over-identification test is passed.

In Model (11), the TFP shifter, represented by the South dummy, gauges the productivity gap with a coefficient of -0.20 for the firms located in the southern regions. Hence, all the above-mentioned factors contribute to lower TFP in the South beyond what is predicted by the differences in terms of density and first-nature advantages. The estimated parameter for employment density is 0.05, which is positive and significant and well below the value obtained with OLS models. The magnitude of the latter estimate is consistent with the values found in most empirical studies on agglomeration externalities. This result indicates that our preceding OLS estimates might be affected by some degree of endogeneity and, in particular, that they are biased upward. The upward bias implies that our variable of interest may be positively correlated with the error term. Model (12), finally, has the same structure as Model (11) but uses the additional lagged population instrument. While aware of the possible endogeneity concerns for this variable, the last specification provides results fully in line with those obtained with a set of surely exogenous instruments.

5.4. Additional empirical checks for endogeneity

To further check whether the results based on Eq. (3) are robust to omitted variables bias, we resort to the bounding analysis developed by Oster (2019) that, in turn, adapted the method of Altonji et al. (2005).[43] To convey the intuition underlying this approach,

[39] Raster information (the size of a pixel is equal to 1 square kilometre) on all the geological instruments was obtained from the *European Soil Database* (Panagos et al., 2012). Municipality-level indicators on hydro-geological and seismic risks are provided by the *Italian Institute for Environmental Protection and Research* (Trigila et al., 2021).

[40] Despite having observations that date back to 1861, we selected 1921 as the reference point for our historical instrument because most of the territorial changes that have altered the national borders and the number of municipalities occurred before that year.

[41] Although widely employed in the extant literature (e.g., Koh et al., 2013), the use of an instrument based on the (relatively recent) past population density could raise endogeneity concerns. We, therefore, consider the results obtained when employing this variable as a complementary source of evidence.

[42] Table C.4 in the Appendix reports the descriptive statistics of the instruments.

[43] The bounding approach proposed by Altonji et al. (2005) focuses on the sensitivity of the coefficients of the relevant variable in models with and without controls, thus estimating the lower and upper bounds of the parameter (i.e. the potential magnitude of the omitted variables bias). Since the stability of the model coefficients could be determined by the inclusion of uninformative controls, Oster (2019) suggests

Table 5: Models with instrumental variables

Model	**(10)**	**(11)**	**(12)**
Employment density (logarithm)	0.055***	0.045***	0.059***
	(0.020)	(0.016)	(0.007)
Share of developable surface	0.255***	0.231***	0.244***
	(0.036)	(0.032)	(0.031)
Distance to the nearest freshwater body		-0.099***	-0.097***
		(0.025)	(0.024)
River density		0.406***	0.426***
		(0.148)	(0.139)
South dummy	-0.230***	-0.204***	-0.187***
	(0.041)	(0.032)	(0.023)
Coastal, border, and minor island dummies	Yes	Yes	Yes
Constant	-0.425***	-0.395***	-0.466***
	(0.103)	(0.086)	(0.043)
Observations	611	611	611
Partial R-squared of the first stage	0.201	0.199	0.683
F statistic of the first stage	25.128	24.668	183.444
P-value of overidentifying restrictions test	0.338	0.192	0.172
P-value of endogeneity test	0.040	0.005	0.000
Geographical centrality instruments	Yes	Yes	Yes
Historical accessibility instruments	Yes	Yes	Yes
Seismic and flood risk instruments	Yes	Yes	Yes
Geological soil composition instruments	Yes	Yes	Yes
Historical population density instruments	No	No	Yes

All models are computed with the two-stage least squares (2SLS) estimator. The (logarithm of the) employment density is instrumented with the centrality, the density of roman roads, the degree of seismic and flood risks, and the soil profile differentiation of the LLMA. The historical population density (measured in 1921) is added to the set of instruments only in Model (12). All specifications include the constant term, controls for the share of developable surface as well as coastal, border, and minor island dummies. The partial adjusted R-squared of the first stage is reported to assess the relevance of the excluded exogenous variables. The p-value of the Durbin chi-squared statistic is reported to assess whether the (logarithm of the) employment density can be considered as endogenous in the models. The p-value of the Sargan's chi-squared statistic is reported to test the hypothesis that the additional instruments are exogenous. Standard errors robust to heteroskedasticity and intra-cluster correlation at the level of regions are reported in parentheses. Stars from one to three indicate statistical significance at 10%, 5%, and 1% levels, respectively.

consider that the importance of the omitted variables for the results boils down to the intensity of the correlation between the unobservables and the error term. Specifically, what matters for assessing the extent of omitted variable bias is the size of this correlation compared to that between the predictor of interest (density, in our case) and the controls, on the one hand, and the regressand, on the other. Oster (2019) provides a test measuring the relevance that unobservables should have with respect to observables (i.e., the density and the other controls) to drive the coefficient of the main independent variable to zero. For this aim, if the estimated bounds include zero, then the true effect of the treatment on the outcome variable is null, and the omitted variables should have a much greater impact

complementing their approach by also examining the effects of omitted variables on the coefficient of determination.

on the regressand than the observables.

We run Oster's test for the two baseline OLS regressions that respectively exclude and include the South dummy – i.e., Model (4) in Table 3 and Model (6) in Table 4. Our results show that, in both cases, our identified set does not include zero. Consequently, we can conclude that the OLS specifications in Tables 3 and 4 do not suffer from omitted variables bias.

Oster's methodology is based on the assumption that all covariates must be exogenous, i.e., uncorrelated with the error term. Although our controls refer to the physical geography of the LLMAs and the South dummy, we cannot totally rule out the possibility that they can be correlated with other important omitted variables.

To address this concern, we turn to the framework proposed by Diegert et al. (2022). They relax the assumption of exogeneity and instead employ multiple sensitivity indexes to bound the coefficient of interest in the presence of endogenous unobservables. In particular, for each share of explained variance in TFP due to unobservables compared to observables, the test computes an interval of the employment density coefficient that is compatible with the postulated level of endogeneity without imposing restrictions on the other parameters. The specific proportion at which zero lies within this interval provides the maximum degree of endogeneity associated with a significant impact of density on local productivity. This threshold in our case is 0.52, which makes it unlikely that omitted variables cancel out the effect of agglomeration on TFP.[44]

To further explore the robustness of our estimates, we resort to a different type of bounding analysis based on the kinky least squares (KLS) regression. Unlike Oster's method, KLS directly places constraints on the correlation between density and the error term (Kiviet, 2020, 2023; Kripfganz and Kiviet, 2021). This methodology relies neither on instrument availability nor exclusion restrictions. Instead, it corrects the bias in OLS estimates for all values on a grid of endogeneity correlations and provides consistent estimates in accordance with the postulated endogeneity range.

As already mentioned, a comparison between the coefficients of the OLS and IV regressions indicates that the elasticity of the TFP with respect to density estimated in the former case should be biased upwards and, therefore, that there should be a positive correlation between density and the error term. Based on that, Figure D.2 in the Appendix reports the main results based on KLS and IV for comparison. It turns out that the estimated parameter for density remains positive and significant throughout the majority of the values within the range of the postulated degree of endogeneity.[45]

[44] In unreported evidence, we further generalise the test by assuming that covariates might be correlated with unobservables but not necessarily to their maximum degree. Results are still consistent with the fact that density should have a positive impact on local TFP.

[45] Our educated guess is that such a correlation might be confined in the interval between 0 and 0.3, a threshold commonly used in the literature.

5.5. Simulation

We end this section with a series of simple simulations. Our goal is to provide insights into the magnitude of the estimated impact of both density and spatial fixed effects on TFP. To this aim, we rely on the different models estimated for Eq. (3) to predict variations in the productivity of a generic area as its density and location change. Specifically, Table 6 takes as reference the median LLMA of the South (i.e., a labour market with an employment density of 33.3 workers per square kilometre) and uses the coefficients estimated in Models (4), (5), and (11) to predict the expected variation in productivity as its density increases up to the median of northern LLMAs (i.e., equal to 114.9 workers per square kilometre, approximately 3.5 times that of the South) and/or the spatial unit is shifted to the North. The three scenarios reported in Table 6 describe respectively: *a*) the case in which only the density shifts, keeping the first-nature characteristics and the North-South productivity gap due to factors that exclude agglomeration and geography constant; *b*) the case where we let the TFP difference unrelated to density and natural advantages move while holding agglomeration and other geographical features constant; *c*) the case in which density and the productivity gap vary, maintaining first-nature determinants unchanged.

Using the elasticities of 0.110, 0.080, or 0.045 and increasing the density from the southern to the northern median value while holding all other covariates fixed (i.e., scenario *a*), the growth in density increases the productivity in the range of 14.6% to 5.8%. Factors influencing TFP beyond agglomeration (i.e., scenario *b*), contribute to an improvement in productivity between 17.3% and 22.6% when the LLMA is moved from the South to the North. A higher density combined with the relocation to northern area (i.e., scenario *c*) is associated with a TFP increase of about 30% in both OLS and IV models. In summary, after adjusting their elasticity downwards to account for the endogeneity bias, the role of agglomeration taken alone is relevant, although the magnitude of the effects unrelated to density and other geographical controls could be even larger than that.

Table 6: Estimated TFP variations in response to variations in density and localization

Model	**(4)**	**(6)**	**(11)**
Estimator	OLS	OLS	IV
Employment density (logarithm)	0.110***	0.080***	0.045***
	(0.007)	(0.007)	(0.016)
South dummy		-0.160***	-0.204***
		(0.022)	(0.032)
Southern LLMA staying in the South with employment density equal to the median of the North macro-area (*a*)	14.6%	10.4%	5.8%
Southern LLMA moving to the North with employment density equal to the median of the South macro-area (*b*)	0.0%	17.3%	22.6%
Southern LLMA moving to the North with employment density equal to the median of the North macro-area (*c*)	14.6%	29.6%	29.7%

The reference LLMA is located in the South. The median employment density of northern and southern spatial units is equal to 33.3 and 114.9 workers per square kilometre, respectively. All the other covariates are held at their median values, whereas the geographical dummies are held at their base level (i.e., zero).

Policy implications of these results are that we can certainly think of improving TFP in the South by increasing the density of economic activity in those areas. This conclusion is strengthened thanks to our evidence showing that returns from agglomeration are not that different between the northern and southern regions of Italy (see Section 5.2). However, this is not the end of the story in several respects. As already explained, it is not at all easy to design policy interventions that improve density also due to the presence of externalities surrounding public action (Duranton and Venables, 2018) and the strong hysteresis effects deriving from historical factors (think again about the contribution of industrial districts to the take-off of the Italian manufacturing sector). Moreover, our findings point to the fact that other determinants besides density could play a role in improving the productivity of southern firms. Investments in both education and the efficiency of local courts will likely help enhance TFP in the South even beyond the beneficial effects they might have through increasing the density of economic activity. All these topics, although highly relevant, are beyond the scope of this paper and should find a place on a future research agenda.

6. Agglomeration versus selection

The evidence collected so far shows that the substantial differences between the northern and southern LLMAs in terms of productivity are due to a lower agglomeration of the latter regions, on the one hand, and to alternative factors captured by additional controls (i.e., first-nature advantages and the South dummy), on the other.

In this section, we explore an alternative determinant of the uneven spatial distribution of TFP related to the hypothesis that market selection processes operate with heterogeneous intensity in different territories (i.e., the northern and southern macro-areas), determining specific patterns of productivity for the active firms. This idea derives from key contributions in the international trade literature (see Melitz, 2003; Melitz and Ottaviano, 2008) in which companies are modelled *ex-ante* heterogeneous in terms of TFP: more competitive markets lead to a larger share of inefficient businesses exiting, thereby increasing average efficiency through a selection effect.

As already discussed in Section 2, this selection effect would be observationally equivalent to explanations of productivity differences based on agglomeration economies if selection is tougher in denser LLMAs. In this sense, a positive link between the spatial concentration of firms and local TFP could be compatible with both agglomeration economies and selection models. Similar arguments would apply to other controls if there was a correlation between these variables and the intensity of the market selection forces (e.g., if selection was more severe in more accessible places). The productivity gap in favour of the northern territories, on average denser and more heavily endowed with natural advantages, could be attributed (at least in part) to the functioning of selection processes.

A possible solution to the observational equivalence problem has been proposed by Combes et al. (2012), who designed a methodology that disentangles multiple effects, extending an analysis based on differences between conditional means to one exploring discrepancies in the full TFP distribution. Such an approach can help distinguish the role of agglomeration forces or natural advantages from selection effects. Specifically, agglomeration economies would shift the entire productivity distribution to the right because they affect all firms in those locations while selection processes would affect the TFP distribution by shifting only its (left) truncation point (i.e., the minimum level of productivity needed to survive in the LLMA) to the right because they cut a larger share of inefficient companies.

The test developed by Combes et al. (2012) estimates, through non-parametric techniques, the dilating factor D, the shifting factor A, and the left-truncating factor S that differentiate two productivity distributions. The advantage of this approach is twofold. First, it exploits only the information conveyed by the empirical cumulative distribution of log-productivity for a specific set of companies without imposing any parametric assumption on its shape. Second, unlike the standard quantile regression, the test compares all percentiles of two distributions and not only specific ones, thereby improving the robustness and the efficiency of parameter estimation. However, this degree of generality is achieved at a cost since the procedure allows only the differences between two distributions to be analysed. In this sense, the technique essentially implements a univariate test, enabling us to compare the TFP distributions of firms in two sub-samples of spatial units according to the value of a specific variable (e.g., the companies located in northern versus southern LLMAs or those located in more agglomerated versus less agglomerated LLMAs).

Such a method allows us to test whether the effects of market selection processes on the TFP distribution lie behind what we have so far classified as pure agglomeration economies and first-nature advantages, and, in particular, whether different selection mechanisms can explain part of the productivity gap between the northern and southern regions of Italy.

The theoretical model proposed by Melitz and Ottaviano (2008) that inspired this empirical test assumes that the intensity of selection effects depends on the size of the demand in the *local* market. However, Accetturo et al. (2018) argue against the spatial segmentation of demand in most of the manufacturing sectors. In line with this argument, when comparing LLMAs in terms of their density, accessibility, or geographic location, we could not expect to detect a heterogeneous intensity of selection processes due to the different size of local demand. Nevertheless, the toughness of the local competitive process may still depend on other characteristics that are instead mainly local and differentiate the above-mentioned groups of LLMAs. For instance, a denser (or northern) geographical area could display tougher competition and, hence, stronger selection effects due to its local labour market, or the markets of local intermediate inputs and local institutions.[46] It is in this spirit that we must interpret the results from the following test.

To implement this methodology, we split the entire sample of firm-level log-productivity

[46] In particular, there is strong evidence that the denser spatial units in the North are characterised by a higher efficiency of local courts (e.g., Accetturo et al., 2022; Cugno et al., 2022). This extends to the application of bankruptcy laws, which help to improve the competitive tone of the local market, thereby increasing local TFP through selection.

obtained from Eq. A.5 in the Appendix,[47] into two groups according to different variables.[48] The results are presented in Table 7, comparing the distribution of TFP for firms in the North and South of Italy.[49] From the previous sections, however, we know that LLMAs in southern regions are, on average, less dense and more disconnected (i.e., less accessible) than those located in northern ones, meaning that even in the way we perform the test, we are not only comparing the macro-areas to which they belong. In this sense, with the aim of attributing to specific variables any evidence of selection effects affecting productivity, we also propose other partitioning rules based on the level of agglomeration (see Table D.12 in the Appendix) and the degree of geographical accessibility to identify forces that may contribute to a shift (or truncation) in the distribution of TFP. We also perform the test with the comparison between firms in the northern and southern regions, but limited to the sub-periods from 1995 to 2008 and from 2009 to 2019 to verify whether the temporal aggregation may hide the demographic contribution of the companies to the variation in the distribution of the TFP.[50]

The results in Table 7 are clear-cut. Most of the North-South differences in productivity are explained by the three parameters (i.e., A, D, and S). In particular, the rightward shift of the distribution is equal to about 0.20 in Model (1). Note that the pseudo coefficient of determination is 99.5%. By observing the constrained specifications from (2) to (4) that alternately exclude dilation and truncation effects (i.e., D and S are respectively set to 1 and 0), the agglomeration parameter, which corresponds to a rightward shift, turns out to be by far the main determinant. We still find evidence consistent with a compression of the productivity distribution for the companies located in northern LLMAs.[51,52] Moreover, the

[47] As illustrated in Section 4.1, data have been averaged across years and netted out for sectoral effects.

[48] Combes et al. (2012) compare the TFP distribution of establishments located in large versus small metropolitan areas of France, thus verifying whether the local productivity (i.e., the toughness of selection forces) depends on local market size. They conclude that firm selection cannot explain the heterogeneity of spatial productivity. The same test has been subsequently applied to analyse the productivity differentials in Ukraine before and after market deregulation (Shepotylo and Vakhitov, 2015) and for plants belonging to the same industry (silk-reeling) located in a more or less concentrated fashion (Arimoto et al., 2014). In all these cases, selection turns out to have little role in explaining productivity differentials. In contrast, Ding and Niu (2019) and Howell et al. (2020) show that the higher productivity observed in large Chinese urban agglomerations is shaped by both selection and agglomeration forces.

[49] The underlying tests have been carried out by resorting to the `estquant` library (Kondo, 2017).

[50] To elaborate more on this point, we also checked that the entry-exit dynamics are not diverging in the two macro-areas in the years of interest and, most importantly, that the entry-exit rates in the sample we employ are comparable to the true entry-exit rates in the economic system. Unreported evidence shows that both entry and exit rates are consistently higher in the South by a few percentage points and decrease slightly over time. Moreover, by comparing the demographics of the 264,166 firms in our sample with available Eurostat data, we confirm that our sample proves to be significantly representative.

[51] This implies an under-representation of the companies at both tails of the productivity distribution in the North once the shift between the two distributions is taken into account.

[52] The D parameter significantly lower than one combined with the positive shift indicates that less productive firms enjoy relatively larger benefits from agglomeration in areas with higher average TFP. This effect emerges in the comparisons between northern and southern LLMAs, but also in those shown in the Appendix between more (or less) dense and accessible spatial units. However, although statistically

Table 7: Comparison of the productivity distributions in southern versus northern LLMAs

Model	**(1)**	**(2)**	**(3)**	**(4)**
Relative shift (A)	0.202∗∗∗	0.204∗∗∗	0.224∗∗∗	0.223∗∗∗
	(0.003)	(0.003)	(0.004)	(0.003)
Relative dilation (D)	0.895∗∗∗	0.910∗∗∗		
	(0.010)	(0.006)		
Relative truncation (S)	-0.000		-0.000	
	(0.001)		(0.001)	
Constrained specification	No	Yes	Yes	Yes
Pseudo R-squared	0.995	0.973	0.930	0.922
Bootstrap replications	1,000	1,000	1,000	1,000
Firms in southern LLMAs	56,404	56,404	56,404	56,404
Firms in northern LLMAs	207,762	207,762	207,762	207,762
Total firms	**264,166**	**264,166**	**264,166**	**264,166**

The test was conducted with 1,000 replications. We constrain the baseline Model (1) to ignore truncation ($S = 0$) in Model (2), dilation ($D = 1$) in Model (3), or both effects in Model (4). We report bootstrap standard errors in parentheses. Stars from one to three indicate statistical significance at 10%, 5%, and 1% levels, respectively.

selection parameter is not statistically significant. Based on this, we have no elements to confirm the hypothesis that northern firms are more efficient than southern ones because of the tougher competition to which they are exposed in the LLMAs where they are located. This result seems at odds with those obtained by Rungi and Biancalani (2019), who find that North-South productivity gaps are driven by the presence of relatively more inefficient companies in the left tail of the distributions. Apart from dilation effects, our findings are largely in line with Combes et al. (2012) for France and Accetturo et al. (2018) for Italy.

Also, in the other partitioning cases provided in Appendix D, shift and dilation explain nearly all differences between distributions, i.e., market selection forces do not significantly determine the heterogeneous distribution of productivity in Italy.

7. Final remarks

The evidence collected in this paper confirms what a long strand of contributions has found for other countries, i.e., geographic concentration generates productivity advantages for the local incumbent firms. In our preferred estimation, the elasticity of TFP with respect to density in Italy is about 0.045, a magnitude that is comparable to those measured for other developed countries by scholars using methodologies similar to the ones employed in this work. Moreover, we find that the TFP-density nexus contributes to explaining a large share of the marked productivity gap between the northern and southern regions of Italy. In other words, companies in the South are less productive than those in the North to a relevant extent because they compete in less agglomerated local environments that are

significant, this effect has limited explanatory power. In Table 7, the pseudo R-squared when D is bound to 1 decreases from 99.5% in Model (1) to 93.0% in Model (3).

less capable of producing and capturing the positive externalities observed in the denser areas where northern firms are located.

We also deliver two other new and somewhat surprising facts complementing this evidence. First, the within-areas TFP-density elasticities are not significantly different between the southern and northern macro-areas. Second, we clearly exclude that market selection is an alternative mechanism (possibly associated with heterogeneous competition intensities) to explain the productivity gap in favour of the firms located in the North. On the basis of this evidence, the geographical concentration of economic activity seems to take on the role of precondition for industrial take-off in the less-developed southern regions of the country.

A note of caution is needed when interpreting our results. These refer to manufacturing industries and do not consider other important sectors, such as construction or services. From this perspective, some of our conclusions cannot be generalised to the entire economy, also considering the importance of those sectors for southern LLMAs.

In any case, the results of this study can be interpreted in light of the longstanding debate about the *questione meridionale* (i.e., southern question) in Italy. Our findings also speak to the literature on agglomeration economies in developing nations: southern Italy is a special case of a developing region that coexists in a unified country with other areas that are among the most advanced European regions.

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Appendix A. Estimation of the total factor productivity

Total factor productivity is estimated starting from the following production function:

$$Y_{i,t} = A_{i,t} \left(\sum_h s_h L_{h,i,t} \right)^{\alpha} K_{i,t}^{\beta} \tag{A.1}$$

where $Y_{i,t}$ denotes the physical output produced by the firm i at time t and $A_{i,t}$ is the TFP. As for labour input, the production function in Eq. (A.1) considers the possibility of using different h types of L_h employees, with $(h = 1, \ldots, H)$, each having a different efficiency represented by the s_h parameter. Furthermore, $K_{i,t}$ represents the capital stock owned by firm i at time t. Finally, α and β stand for the production function parameters to be estimated to recover the value of the TFP. The output we observe is the firm value-added, hence, our estimate is the following total factor productivity:

$$VA_{i,t} = P_{i,t} A_{i,t} \left(\sum_h s_h L_{h,i,t} \right)^{\alpha} K_{i,t}^{\beta} \longrightarrow P_{i,t} A_{i,t} = \frac{VA_{i,t}}{\left(\sum_h s_h L_{h,i,t} \right)^{\alpha} K_{i,t}^{\beta}} \tag{A.2}$$

where $P_{i,t}$ and $VA_{i,t}$ are the price of the output and the value-added of firm i at time t, respectively. As for the measure of capital stock, our proxy is the book value of the (deflated) data on tangible assets, net of amortisation and depreciation. Our monetary variables are deflated with the Eurostat sector-specific deflator of the value-added. Moreover, to account for the heterogeneity of the labour input, we follow both Fox and Smeets (2011) and Locatelli et al. (2019) and use the total wage bill paid by firm i at time t, $W_{i,t}$, as a proxy for $\sum_h s_h L_{h,i,t}$ in Eq. (A.1). Locatelli et al. (2019) discuss at length about the consequences deriving from alternative measures for labour inputs on the TFP differential across Italian macro-regions. Using logarithms, we get:

$$\log (VA_{i,t}) = \alpha \log (W_{i,t}) + \beta \log (K_{i,t}) + \varepsilon_{i,t} \tag{A.3}$$

where the error term, $\varepsilon_{i,t}$, includes our empirical TFP measure and the actual error term stemming from measurement errors in the production function inputs:

$$\varepsilon_{i,t} = \log (P_{i,t} A_{i,t}) + \mu_{i,t} \tag{A.4}$$

To estimate Eq. (A.3) and correct for input-output simultaneity, we employ the procedure developed by Wooldridge (2009). We then compute the residuals and define our empirical measure of TFP as follows:

$$TFP_{i,t} = \log (VA_{i,t}) - \hat{\alpha} \log (W_{i,t}) - \hat{\beta} \log (K_{i,t}) \tag{A.5}$$

Appendix B. Aggregation of the total factor productivity

Assume the following production function:

$$Y_r = A_r\ K_r^{\alpha}\ L_r^{1-\alpha} = A_r \left(\frac{K_r}{L_r}\right)^{\alpha}\ L_r \tag{B.1}$$

where Y_r is the aggregated output produced in the area r, and A_r is the TFP of aggregated production of the area. Note that sector and year subscripts are dropped for the sake of notation simplicity. L_r and K_r are the amount of labour and capital inputs by all the firms belonging to area r, i.e., $L_r = \sum_{i\in r} l_i$ and $K_r = \sum_{i\in r} k_i$. Assuming constant returns to scale, α stands for the production function parameter. Y_r can be also defined as:

$$Y_r = \sum_{i\in r} y_i = \sum_{i\in r} A_i\ k_i^{\alpha}\ l_i^{1-\alpha} = \sum_{i\in r} A_i \left(\frac{k_i}{l_i}\right)^{\alpha}\ l_i \tag{B.2}$$

By equating Eq. (B.1) with Eq. (B.2), and considered that profit maximisation requires that $k_i/l_i = K_r/L_r\ \forall i$, we obtain:

$$A_r \left(\frac{K_{r,t}}{L_{r,t}}\right)^{\alpha} L_r = \sum_{i\in r} A_i \left(\frac{k_i}{l_i}\right)^{\alpha}\ l_i\ \rightarrow\ A_r = \sum_{i\in r} \frac{l_{i,t}}{L_{r,t}}\, A_i \tag{B.3}$$

That is, under constant returns to scale, the aggregated TFP of the area coincides with the sum of firm-level productivities weighted by their share of labour input.

Appendix C. Additional descriptive statistics

This appendix provides several tables and figures to enrich the information on the data and phenomena we analyse in the paper. In particular, *i*) we map our definition of the North and South; *ii*) we report some additional descriptive statistics of the variables employed in our empirical analysis; *iii*) we present the aggregation of manufacturing industries used to estimate TFP; *iv*) we report the Shapley decomposition for OLS models in Table 3; and finally, *v*) we plot the time trend of TFP.

Table C.1: Descriptive statistics for northern and southern LLMAs

Northern LLMAs	**Count**	**Mean**	**Median**	**SD**	**Min**	**Max**
Total factor productivity	330	0.944	0.972	0.118	0.370	1.108
Employment density	330	200.806	114.857	308.377	7.972	3,324.195
Share of developable surface	330	0.442	0.382	0.333	0.020	1.000
Distance to the nearest freshwater body	330	0.131	0.096	0.124	0.000	0.619
River density	330	0.079	0.076	0.043	0.000	0.219
Coastal dummy	330	0.221	0.000	0.416	0.000	1.000
Island dummy	330	0.006	0.000	0.078	0.000	1.000
Border dummy	330	0.130	0.000	0.337	0.000	1.000
Southern LLMAs	**Count**	**Mean**	**Median**	**SD**	**Min**	**Max**
Total factor productivity	281	0.707	0.711	0.134	0.184	1.110
Employment density	281	103.946	33.338	279.777	4.585	2,718.200
Share of developable surface	281	0.470	0.411	0.274	0.022	1.000
Distance to the nearest freshwater body	281	0.506	0.353	0.459	0.001	1.971
River density	281	0.051	0.051	0.045	0.000	0.252
Coastal dummy	281	0.577	1.000	0.495	0.000	1.000
Island dummy	281	0.014	0.000	0.119	0.000	1.000
Border dummy	281	0.000	0.000	0.000	0.000	0.000

Table C.2: Correlation matrix

Variable	**(1)**	**(2)**	**(3)**	**(4)**
Total factor productivity	1.0000			
Employment density	0.1804	1.0000		
Share of developable surface	0.2405	-0.2419	1.0000	
Distance to the nearest freshwater body	-0.4650	-0.0669	0.0534	1.0000
River density	0.3580	-0.1201	0.2063	-0.3334

Table C.3: Shapley decomposition for the determinants of total factor productivity

Model	**(1)**	**(2)**	**(3)**	**(4)**
Employment density (logarithm)	100.00%	72.20%		43.10%
Share of developable surface		27.80%	18.81%	16.92%
Distance to the nearest freshwater body			52.12%	21.26%
River density			18.20%	10.37%
Coastal, border, and minor island dummies			10.86%	8.35%
Total	**100.00%**	**100.00%**	**100.00%**	**100.00%**

We compute Shapley values with the results of the ordinary least squares regressions in Table 3 on the determinants of the (logarithm of the) employment-weighted total factor productivity net of sector effects.

Table C.4: Descriptive statistics of the instruments

Instrumental variables	**Count**	**Mean**	**Median**	**SD**	**Min**	**Max**
Centrality	611	0.003	0.003	0.001	0.002	0.005
Roman road density	611	0.035	0.025	0.042	0.000	0.234
Seismic risk	611	0.140	0.142	0.066	0.030	0.277
Flood risk	611	0.040	0.019	0.062	0.000	0.479
Historical population density	611	531.673	292.672	1,007.416	27.085	16,115.908
Low differentiation of the soil profile	611	0.155	0.000	0.363	0.000	1.000
High differentiation of the soil profile	611	0.056	0.000	0.229	0.000	1.000

Geological data has been collected at the pixel level (the size of a cell is equal to 1 squared kilometre) and then aggregated for each LLMA by considering the mode of its distribution. The instrument on the historical agglomeration has been computed using the developability-adjusted density of population (in 1921).

Figure C.1: Map of northern and southern LLMAs

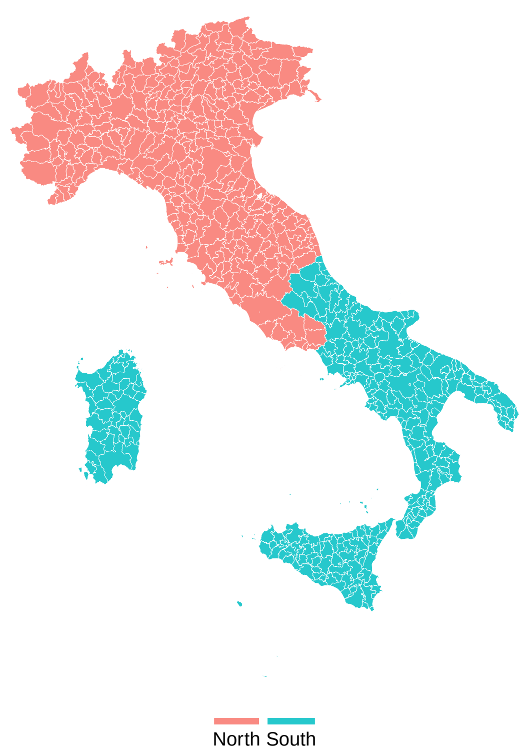


Table C.5: List of manufacturing industries and related two-digit ATECO classification

Code	**Description (identifier)**
CA	Manufacture of food products (10) Manufacture of beverages (11) Manufacture of tobacco products (12)
CB	Manufacture of textiles (13) Manufacture of wearing apparel (14) Manufacture of leather and related products (15)
CC	Manufacture of wood, wood and cork products, except furniture; manufacture of straw articles and plaiting materials (16) Manufacture of paper and paper products (17) Printing and reproduction of recorded media (18)
CE	Manufacture of chemicals and chemical products (20)
CG	Manufacture of rubber and plastic products (22) Manufacture of other non-metallic mineral products (23)
CH	Manufacture of basic metals (24) Manufacture of fabricated metal products, except machinery and equipment (25)
CI	Manufacture of computer, electronic and optical products (26)
CJ	Manufacture of electrical equipment (27)
CK	Manufacture of machinery and equipment not elsewhere classified (28)
CL	Manufacture of motor vehicles, trailers, and semi-trailers (29) Manufacture of other transport equipment (30)

Appendix D. Robustness checks

This appendix reports a series of robustness tests and additional econometric results that complement our main findings shown in the main body of the paper.

First, we introduce a number of alternative proxies to measure the spatial concentration of economic activity, such as *i*) the (logarithm of the) employment density restricted to the manufacturing sector, *ii*) the (logarithm of the) firm density (Henderson, 2003), *iii*) the (logarithm of the) firm density restricted to the manufacturing sector, *iv*) the (logarithm of the) population density, and *v*) the (logarithm of the) nightlight intensity (Henderson et al., 2021). The descriptive statistics and correlations for these additional variables are reported in Tables D.6 and D.7, respectively. The results of the related models, shown in Table D.8, are stable across the alternative definitions, confirming similar findings in the previous literature.

Table D.6: Descriptive statistics for alternative measures of agglomeration

Variable	Count	Mean	Median	SD	Min	Max
Employment density	611	156.260	69.831	299.255	4.585	3,324.195
Manufacturing employment density	611	40.107	17.667	78.148	0.428	1,302.109
Firm density	611	50.965	23.116	106.060	2.566	1,388.329
Manufacturing firm density	611	5.579	2.595	10.902	0.215	132.724
Population density	611	645.848	311.492	1,261.263	32.990	15,172.417
Nightlight intensity	611	2.999	1.943	3.017	0.224	22.928

The nightlight intensity data has been collected at the pixel level (the size of one cell is equal to 225 square arc seconds at the equator) and subsequently aggregated for each LLMA by considering the mean of its distribution.

Table D.7: Correlation matrix for alternative measures of agglomeration

Variable	(1)	(2)	(3)	(4)	(5)
Employment density	1.0000				
Manufacturing employment density	0.6628	1.0000			
Firm density	0.9713	0.5114	1.0000		
Manufacturing firm density	0.8694	0.8417	0.8142	1.0000	
Population density	0.9516	0.5149	0.9744	0.8144	1.0000
Nightlight intensity	0.3041	0.2818	0.2536	0.2670	0.2980

Table D.8: Models with alternative measures of agglomeration

Model	**(6)**	**(A1)**	**(A2)**	**(A3)**	**(A4)**	**(A5)**
Employment density (logarithm)	0.080***					
	(0.007)					
Manufacturing employment density (logarithm)		0.075***				
		(0.007)				
Firms density (logarithm)			0.072***			
			(0.007)			
Manufacturing firms density (logarithm)				0.071***		
				(0.006)		
Population density (logarithm)					0.072***	
					(0.007)	
Nightlight intensity (logarithm)						0.097***
						(0.012)
Share of developable surface	0.265***	0.224***	0.273***	0.262***	0.268***	0.036
	(0.033)	(0.032)	(0.034)	(0.035)	(0.034)	(0.035)
Distance to the nearest freshwater body	-0.092***	-0.084***	-0.103***	-0.109***	-0.113***	-0.106***
	(0.024)	(0.024)	(0.027)	(0.028)	(0.030)	(0.028)
River density	0.458***	0.401***	0.478***	0.451***	0.458***	0.453***
	(0.137)	(0.124)	(0.145)	(0.141)	(0.146)	(0.148)
South dummy	-0.160***	-0.145***	-0.192***	-0.190***	-0.223***	-0.228***
	(0.022)	(0.020)	(0.023)	(0.022)	(0.024)	(0.024)
Coastal, border, and minor island dummies	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-0.576***	-0.441***	-0.455***	-0.295***	-0.621***	-0.165***
	(0.045)	(0.035)	(0.037)	(0.025)	(0.054)	(0.023)
Observations	611	611	611	611	611	611
Adjusted R-squared	0.625	0.661	0.589	0.602	0.583	0.594

The dependent variable is the (logarithm of the) employment-weighted total factor productivity net of sector effects. The main regressor is either the (logarithm of the) developability-adjusted employment density in Model (6), the (logarithm of the) manufacturing employment density in Model (A1), the (logarithm of the) firm density in Model (A2), the (logarithm of the) manufacturing firm density in Model (A3), the (logarithm of the) developability-adjusted population density in Model (A4), or the (logarithm of the) average nightlight intensity in Model (A5). All specifications include the constant term, controls for the share of developable surface, the distance to the nearest freshwater body (in hundreds of kilometres), and the river density as well as coastal, border, and minor island dummies. Standard errors robust to heteroskedasticity and intra-cluster correlation at the level of regions are reported in parentheses. Stars from one to three indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Second, we consider various sets of spatial controls to check whether the main econometric results are robust to alternative definitions of northern and southern LLMAs. Furthermore, more granular indicator variables could better capture the effects of unobservables and reduce biases resulting from omitted variables. In Table D.9, we estimate the baseline specifications with either geographical breakdown, region, or province dummies. Results indicate that such more detailed fixed effects do not add much to the variance explained by the South dummy.[1] We show in Table D.10 the corresponding Shapley decompositions. Note that the increasing contribution attributed to spatial controls when more granular indicator variables are included in the specification is achieved more disproportionately at the expense of first-nature covariates than density.[2]

[1] The adjusted R-squared of the models increases from 62.5% when considering only 2 macro-areas to 65.7% when including 110 province dummies.

[2] The share of variance in TFP explained by agglomeration shrinks from 25.7% to 19.8% when the set

Table D.9: Models with alternative groups of spatial controls

Model	**(6)**	**(A6)**	**(A7)**	**(A8)**
Employment density (logarithm)	0.080***	0.085***	0.082***	0.086***
	(0.007)	(0.008)	(0.007)	(0.010)
Share of developable surface	0.265***	0.273***	0.252***	0.256***
	(0.033)	(0.033)	(0.038)	(0.044)
Distance to the nearest freshwater body	-0.092***	-0.096***	-0.063***	-0.099**
	(0.024)	(0.019)	(0.016)	(0.035)
River density	0.458***	0.455***	0.383**	0.373**
	(0.137)	(0.144)	(0.136)	(0.149)
Spatial control dummies	Macro-areas	Breakdowns	Regions	Provinces
	(2 levels)	(5 levels)	(20 levels)	(110 levels)
Coastal, border, and minor island dummies	Yes	Yes	Yes	Yes
Constant	-0.576***	-0.625***	-0.561***	-0.573***
	(0.045)	(0.057)	(0.050)	(0.071)
Observations	611	611	611	611
Adjusted R-squared	0.625	0.628	0.650	0.657

The dependent variable is the (logarithm of the) employment-weighted total factor productivity net of sector effects. The main regressor is the (logarithm of the) developability-adjusted employment density (measured in 2001). The spatial control dummies are either macro-areas in Model (6), geographical breakdowns in Model (A6), regions in Model (A7), or provinces in Model (A8). All specifications include the constant term, controls for the share of developable surface, the distance to the nearest freshwater body (in hundreds of kilometres), and the river density as well as coastal, border, and minor island dummies. Standard errors robust to heteroskedasticity and intra-cluster correlation at the level of regions are reported in parentheses. Stars from one to three indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Table D.10: Shapley decompositions with alternative groups of spatial controls

Model	**(6)**	**(A6)**	**(A7)**	**(A8)**
Employment density (logarithm)	25.69%	25.13%	22.74%	19.75%
Share of developable surface	13.82%	13.48%	10.12%	8.18%
Distance to the nearest freshwater body	13.30%	13.20%	11.47%	10.46%
River density	7.17%	6.98%	6.26%	5.64%
Spatial control dummies	34.65%	35.82%	44.52%	51.81%
	Macro-areas	Breakdowns	Regions	Provinces
	(2 levels)	(5 levels)	(20 levels)	(110 levels)
Coastal, border, and minor island dummies	5.36%	5.39%	4.89%	4.16%
Total	**100.00%**	**100.00%**	**100.00%**	**100.00%**

We compute Shapley values with the results of ordinary least squares regressions in Table D.9 on the determinants of the (logarithm of the) employment-weighted total factor productivity net of sector effects. The spatial control dummies are either macro-areas in Model (6), geographical breakdowns in Model (A6), regions in Model (A7), or provinces in Model (A8).

Third, we decompose the entire observation window by considering different sub-samples of years (i.e., that cover the periods from 1995 to 2008 and from 2009 to 2019) to investigate whether our findings are sensitive to estimation over shorter time intervals. This additional set of models is reported in Table D.11. The estimates confirm all the baseline results.[3]

of macro-area dummies is replaced with province indicator variables.

[3] Note that we use the employment density measured in 2001 and 2011 for the specifications computed

Table D.11: Models with different sub-samples of years

Model	**(A9)**	**(A10)**	**(A11)**	**(A12)**
Period	Years from 1995 to 2008		Years from 2009 to 2019	
Employment density (logarithm)	0.117***	0.081***	0.097***	0.073***
	(0.010)	(0.008)	(0.005)	(0.007)
Share of developable surface	0.321***	0.282***	0.260***	0.233***
	(0.049)	(0.042)	(0.031)	(0.024)
Distance to the nearest freshwater body	-0.175***	-0.107***	-0.121***	-0.073***
	(0.035)	(0.035)	(0.016)	(0.012)
River density	0.599***	0.388***	0.710***	0.560***
	(0.161)	(0.122)	(0.179)	(0.163)
South dummy		-0.190***		-0.131***
		(0.030)		(0.019)
Coastal, border, and minor island dummies	Yes	Yes	Yes	Yes
Constant	-0.875***	-0.639***	-0.628***	-0.465***
	(0.072)	(0.052)	(0.035)	(0.043)
Observations	609	609	611	611
Adjusted R-squared	0.496	0.563	0.514	0.563

The dependent variable is the (logarithm of the) employment-weighted total factor productivity net of sector effects. The main regressor is the (logarithm of the) developability-adjusted employment density measured either in 2001 for Models (A9) and (A10) or in 2011 for Models (A11) and (A12). All specifications include the constant term, controls for the share of developable surface, the distance to the nearest freshwater body (in hundreds of kilometres), and the river density as well as coastal, border, and minor island dummies. Standard errors robust to heteroskedasticity and intra-cluster correlation at the level of regions are reported in parentheses. Stars from one to three indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Fourth, we provide further applications of the univariate test developed by Combes et al. (2012) to verify whether differences in productivity between LLMAs can be determined by the intensity of selection mechanisms associated with possibly density-related variables. In Section 6 we have shown that the difference of productivity of northern and southern firms is mainly due to a rightward shift of the TFP distribution (i.e., driven by agglomeration and not by selection effects). Finally, we compared the productivity distributions between *i*) firms located in agglomerated versus non-agglomerated LLMAs; *ii*) firms located in more versus less accessible areas; *iii*) different sub-periods. Even in these cases, shift and dilation explain almost all the differences between the distributions.

The productivity distribution of agglomerated areas (i.e., those with density below and above the median of the distribution) is mostly obtained by shifting rightward the distribution of those LLMAs with a low degree of concentration. However, the A coefficient is about half of the value obtained when comparing the TFP of the northern and southern areas, thus indicating that relevant differences other than agglomeration economies uniformly affect the productivity of firms: *first-nature* advantages, and possibly heterogeneous infrastructural or institutional endowments.

with the sub-sample of years from 1995 to 2008 and from 2009 to 2019, respectively.

Table D.12: Comparison of the TFP distributions in non-agglomerated versus agglomerated LLMAs

Model	**(1)**	**(2)**	**(3)**	**(4)**
Relative shift (A)	0.115***	0.116***	0.118***	0.121***
	(0.004)	(0.003)	(0.004)	(0.003)
Relative dilation (D)	0.952***	0.965***		
	(0.019)	(0.009)		
Relative truncation (S)	-0.000		0.001	
	(0.001)		(0.001)	
Constrained specification	No	Yes	Yes	Yes
Pseudo R-squared	0.964	0.914	0.634	0.890
Bootstrap replications	1,000	1,000	1,000	1,000
Firms in non-agglomerated LLMAs	41,784	41,784	41,784	41,784
Firms in agglomerated LLMAs	222,382	222,382	222,382	222,382
Total firms	**264,166**	**264,166**	**264,166**	**264,166**

The test was conducted with 1,000 replications. We constrain the baseline Model (1) to ignore truncation ($S = 0$) in Model (2), dilation ($D = 1$) in Model (3), or both effects in Model (4). Agglomerated LLMAs are those with a developability-adjusted employment density above the median of its distribution. We report bootstrap standard errors in parentheses. Stars from one to three indicate statistical significance at 10%, 5%, and 1% levels, respectively.

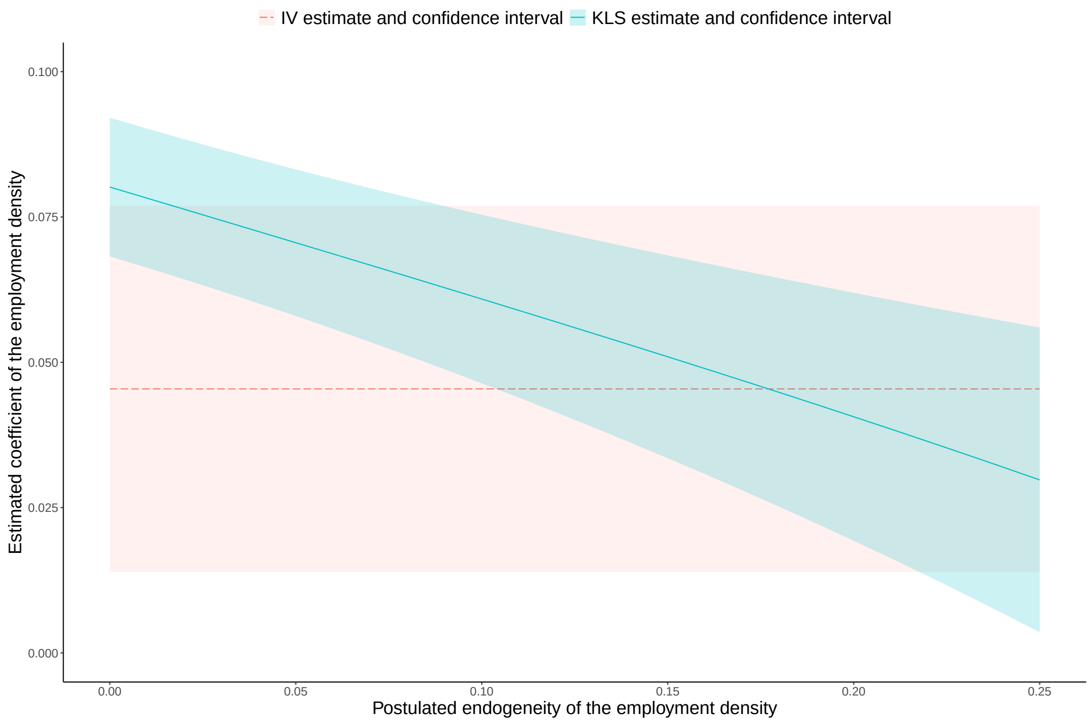
We also tested our baseline specifications on different aggregation procedures for the TFP, as defined in Eq. (1). In unreported evidence, we obtain that the coefficient of the density increases, passing from an average weighted by the share of the employment to an average weighted by the share of wages and the share of value added.[4]

As a final check for our empirical analysis, we computed our measure of productivity using the alternative methodologies based on the works by Olley and Pakes (1996), Levinsohn and Petrin (2003) and Ackerberg et al. (2015). In unreported evidence, we find that all the results hold when using the TFP resulting from the former estimation technique. The latter two procedures do not converge and do not deliver reasonable values for the input coefficients. In particular, Kim et al. (2019) observe that, given their non-linear nature, these methods might provide results that are unstable and extremely sensitive to the initial conditions. For these reasons and considering the additional motivations advanced in Fox and Smeets (2011), we keep our estimates based on the approach of Wooldridge (2009).

Finally, Figure D.2 reports the comparison of the results of KLS and IV regression as illustrated in Section 5.4. As can be seen, the estimated density parameter remains positive and significant for most values within the range of the postulated degree of endogeneity.

[4] Similar evidence is reported in Jacob and Mion (2024).

Figure D.2: Kinky least squares estimation



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