Urbanization Externalities, Market Potential and Spatial Sorting of Skills and Firms*

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Abstract

Using a matched employer-employee dataset for Italy we look at the spatial distribution of wages among provinces. We find evidence of both urbanization and market potential externalities, with the second one being more relevant. However, spatial sorting of skills is at work and explains a great deal of spatial wage variability. We further show that this sorting is only partially due to migrations and it dampens estimates of spatial externalities. The evidence concerning the sorting of firm is instead weaker. In the paper, we also find support of self-selection of migrants based on skills and a moderate evidence of the wage growth hypothesis. Finally, we show that the well-established correlation between the employer size and workers' skills is not simply the outcome of a co-location phenomenon.

Keywords: Spatial Externalities, Panel-Data, Skills, Firms' Heterogeneity, Sorting.

JEL Codes: J31, J61, R23, R30.

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1 Introduction

Imbalances in terms of wages, GDP per capita, growth, and labor markets' outcomes are pervasive features of the economic landscape. Spatial disparities are in fact large in both developed and developing countries attracting a lot of political concern and, in the case of EU, they are so strategically important to be ranked at the top of the political agenda.[1] As for wages, Glaeser and Mare (2001) find that they are 33% higher is US cities compared to outside metropolitan areas. Data evidence on EU as a whole is less systematic. However, a number of country-based studies, like for instance Combes, Duranton and Gobillon (2004), show that wages vary considerably across space.

So far, many explanations have been put forward to explain such imbalances, concerning for instance the availability of natural resources, infrastructures, technology, the impact of crime, cultural and social factors, etc.[2] In this paper we focus, although not exclusively, on the role of spatial externalities and skills distribution, using information on individual wages from a matched employer-employee database for Italy. More specifically, we work on panel version of an administrative database provided by INPS (the Italian Social Security Institute), in which we can follow workers over time, merge information of individuals and firms characteristics, and follow workers when they migrate from one location to another. The advantage of using such a rich database is that we can control for both observable and non-observable individual and firm characteristics that may (and actually they do) interact with spatial externalities.

The starting point of our analysis is a spatial equilibrium model in which two types of externalities are considered simultaneously. The first one, which is more rooted in the literature, refers to the positive impact of economic density on local productivity (urbanization externalities). The second source of spatial disparities are those pecuniary externalities - that emerges in new economic geography models (NEG)- stemming from increasing returns to scale, transportation costs and proximity to demand.[3] Our model provides an example of how nominal wages can be positively related to these externalities. A contrary argument may be that wages are higher close to densely populated areas and thick markets (like cities), just because people need to be compensated for the higher cost of living. This is however just one aspect (the labor supply side) of the issue and can help to understand why labor does not flock to this high pay. By contrast, the compensation story does not explain why firms stay in cities and are capable to afford higher nominal wages.

The first contribution of this paper is the assessment of the absolute and relative importance of

[1] The reduction of income disparities among EU regions involve much of the political debate with Structural and Cohesion Funds, both aiming at the reduction of imbalances, correspond to approximately one third of the EU budget in the period 1994-1999.

[2] See Beeson and Eberts (1989) and Moretti (2004) among others.

[3] See Fujita, Krugman and Venables (1999), and Fujita and Thisse (2002) for a review of the literature.

density and market potential externalities. In fact, the existing literature either focus on one single externality or use very inaccurate measures of the other.[4] To this respect, our results suggest that both density and market potential have a positive and significant impact on wages. However, market potential has the strongest effect suggesting that, at least for Italy, pecuniary externalities play a crucial role in the spatial distribution of wages. These findings are coherent with those of Mion (2004) who provides evidence of sizeable market proximity externalities in Italy.

The interplay between individual skills (time-invariant individual characteristics measured by fixed effects) and spatial externalities is a second peculiar feature of our paper. That fact that skills' distribution may be at the hearth of systematic wage differences is well-known in labor economics. However, most of the research has focused on wage differential across industries and job qualifications rather than across space.[5] Combes, Duranton, and Gobillon (2004), using a very similar dataset, show that skills explain a great deal of the observable variation in French wages. Moreover, they are highly correlated with location-specific variables and in particular with economic density. Skills are thus sorted in space and this dampens estimates of the elasticity of wages with respect to density. Our results confirm their findings and further identify a sorting related to market potential that is coherent with the theoretical framework developed by Redding and Schott (2003). However, we step forward with respect to the existing literature by assessing how much of the spatial sorting of skills is due to migrations. Our results suggest that migrations play a little role with sorting being essentially due to non-movers. Furthermore, we show that the self-selection of migrants may be (coherently with Borjas, 1987) either positive or negative depending on the characteristics of the location of origin and destination, leading to an opposite sign bias that eventually cancels out.

A last issue we consider in the paper is the relation between firms' characteristics, skills and location. This work is, to our knowledge, the first empirical framework dealing with the connection between these three features. According to the recent literature on heterogeneous firms, and in particular with Melitz and Ottaviano (2005), firms should also be sorted in space with bigger and more productive firms being attracted by local market size. Thus, as larger firms are known to pay higher wages, controlling for firms' characteristics may further reduce the magnitude of spatial externalities. This result is only weakly confirmed by our estimation suggesting that the sorting of firms is not as important as the one of individuals. However, theory also suggests that there may be important complementarities between firms and individual characteristics. Indeed, Abowd, Kramarz,

[4] See Glaeser and Mare (2001), Mion (2004), and Hanson (2005). Combes, Duranton and Gobillon (2004) try to put some NEG features in their analysis using a very crude measure of market potential like the mean of the log of density in adjacent areas.

[5] Combes, Duranton, and Gobillon(2004), Glaeser and Mare (2001), and Duranton and Monastiriotis (2002) are relevant exceptions.

and Margolis (1999) show that firm size is strongly correlated with skills. However, the link between skills and firm size may be in principle due to a simple co-location effect of skilled workers and big firms in cities. However, we show that there exist a strong correlation between skills and plant-size *conditionally* on spatial characteristics like density and market potential (that are precisely those that are linked to co-location), suggesting that there is a deeper complementarity between workers and firms[6].

The rest of the paper is organized as follows. In Section 2 we present a spatial model that combines both NEG and urbanization externalities and we discuss how to measure these forces. In Section 3 we present the data and some descriptive statistics, while in Section 4 we point out what a matched employer employee database can tell us more about space. Section 5 is devoted to the econometric analysis, in which we also deepen both the endogeneity and the self-selection issues. Finally, conclusions are reported in Section 6.

2 Theoretical Background

2.1 The Model

In this Section, we present an enriched version of Helpman (1998) model in which we introduce urbanization economies and consider more than two locations. The model helps clarify the kind of forces we want to analyze and provides an example of nominal wages depending positively on local economic density and market potential.

Imagine an economy consisting of Φ locations, two sectors (the manufacturing sector M and the housing sector H), and one production factor (labor). The M-sector produces a continuum of varieties of a horizontally differentiated product under increasing returns to scale, using labor as the only input. Each variety of this differentiated good can be traded among locations incurring in iceberg-type transportation costs.[7] Referring to two generic locations as j and k ($j, k = 1, 2, ..., \Phi$), we thus have that for each unit of good shipped from j to k, just a fraction $v_{j,k} = T(d_{j,k})$ of it arrives to destination, where $d_{j,k}$ is distance between the two locations and $T(.)$ is a decreasing function. The H-sector provides instead a homogeneous good, housing, that cannot be traded and whose amount in each location (H_j) is supposed to be exogenously fixed. Its price $P_{H,j}$ can therefore differ from one place to another and is determined by the equilibrium between local supply and demand.

Labor is supposed to be freely mobile, and its (exogenous) total amount in the economy is equal

[6] See for instance Yeaple(2005).

[7] The term transportation costs does not simply refer to shipment costs but in general to all costs and impediments of doing business in different markets, like information costs, language differences, etc.

to L. The equilibrium spatial distribution of our workers-consumers is thus determined by both wages (w_j), and prices prevailing in each location. We will denote L_j, with $\sum_{j=1}^{\Phi} L_j = L$, as labor in location j, and $\lambda_j = L_j/L$ as the corresponding share of total workers.

Preferences do not directly depend upon the location where consumption and production take place, but only indirectly through prices. As usual in NEG models, preferences are described by the standard Cobb-Douglas utility function with CES type sub-utility for the differentiated product, i.e.:

$$U = (C_M)^{\mu} (C_H)^{1-\mu} \qquad 0 < \mu < 1 \tag{1}$$

where C_M stands for an index of the consumption of the M-sector varieties, while C_H is housing consumption. We assume that the modern sector provides a continuum of varieties of (endogenous) size N, the consumption index C_M is thus given by:

$$C_M = \left[\int_0^N c_m(s)^{\rho} ds \right]^{1/\rho} \qquad 0 < \rho < 1 \tag{2}$$

where $c_m(s)$ represents the consumption of variety $s \in [0, N]$. Hence, each consumer has a love for variety and the parameter $\sigma \equiv 1/(1-\rho)$, varying from 1 to ∞, represents the (constant) elasticity of substitution between any two varieties. If Y denotes the consumer income, then from utility maximization the demand function for a variety s is:

$$c_m(s) = p_m(s)^{-\sigma} \, \mu Y (P_M)^{\sigma-1} \qquad s \in [0, N] \tag{3}$$

where $p_m(s)$ is here the consumer-price (or delivered price) of our generic variety and P_M is the price-index of the differentiated product given by:

$$P_M \equiv \left[\int_0^N p_m(s)^{-(\sigma-1)} ds \right]^{-1/(\sigma-1)} \tag{4}$$

Technology is, by contrast, not the same across locations. Each variant of the differentiated product needs labor to be produced. The relation between the amount of labor used ($l_j(s)$) and the quantity of variant s produced ($c_j(s)$) is given by:

$$l_j(s) = f + \beta_j c_j(s) \tag{5}$$

where f and β_j are, respectively, the fixed and the marginal labor requirements. The fixed component is identical across space while, contrary to the standard formulation of Krugman (1991) and Helpman (1998), the marginal one is supposed to depend on the density of economic activities: $\beta_j = L_j^{-\eta}$.

The idea that market size has a positive impact on local productivity goes back to Marshall (1890) and have been formalized by Abdel Rahman, and Fujita (1990) among others. The urban literature has identified various mechanisms leading economic density to foster growth and productivity like knowledge cross-fertilization, increasing returns to scale in a non-tradable intermediate goods sector, matching of differentiated skills, etc. [8] Ciccone and Hall (1996) and Combes (2000) provide evidence in favor of the positive role of density, and these externalities are often referred to urbanization economies.

Firms know consumers' demand and choose prices in order to maximize their profits given by:

$$\pi_j(s) = p_{m,j}(s)c_j(s) - w_j[f + \beta_j c_j(s)] \tag{6}$$

where w_j is the wage paid by our generic firm and $c_j(s)$ is its output. However, when they look at demand structure, i.e. equation (3), they consider Y_j and $P_{M,j}$ as given. Since each of them has a negligible influence on the market, it may accurately neglect the impact of a price change over both consumers' income and the price index. Consequently, (3) implies that each firm faces an iso-elastic downward sloping demand with elasticity given by the parameter σ. Solving first order conditions yields the usual equilibrium relation between the optimal price, elasticity of demand, and marginal cost:

$$p_{m,j}(s) = \frac{w_j \beta_j}{1 - (1/\sigma)} \tag{7}$$

Under free entry, profits are zero. This implies, together with equation (7), that the equilibrium output is:

$$c_j(s) = (\sigma - 1) f / \beta_j \tag{8}$$

In equilibrium a firm's labor requirement is unrelated to firms' distribution. In fact, using equation (5) one gets:

$$l_j(s) = l = \sigma \ f \tag{9}$$

Now, combining equations (3), (7), and (9) we finally obtain the following reduced-form equation for wages that will be the theoretical basis for our estimations (in logarithm):

[8] See Duranton and Puga (2004) for a discussion of the microfoundations of agglomeration economies.

$$\ln(w_j) = \ln(\kappa) \;+\; \frac{(\sigma-1)\eta}{\sigma}\ln L_j \;+\; \frac{1}{\sigma}\ln\left(\sum_{k=1}^{\Phi} Y_k (P_{M,k}\, v_{j,k})^{\sigma-1}\right) \tag{10}$$

with $\kappa \equiv \rho\,[\mu/(\sigma-1)f]^{1/\sigma}$.

2.2 Measuring Spatial Externalities

Equation (10) states that nominal wages in location j depends positively on the local economic density (L_j) and on the weighted sum over space of incomes (Y_k) and prices ($P_{M,k}$) for all locations, with weights inversely related to distance ($v_{j,k} = T(d_{j,k})$). Helpman (1998) model is closed by perfect labor mobility of workers that leads to an equalization of real wages. Nominal wages are higher in locations where housing is more costly in order to compensate workers. On the labor demand side, firms can pay these higher nominal wages because they are more productive and can save on transportation costs when locating in these regions. It is on this kind of spatial labor market equilibrium that we build our investigation using wages differentials to recover spatial externalities.

In particular, the density related component in (10) stands for urbanization externalities and has a fully local nature. By contrast, the spatially weighted sum is the counterpart of those pecuniary externalities, stemming from transportation costs, product differentiation and increasing returns to scale, which leads to agglomeration of economic activities in NEG models. This term is much more tricky to deal with as it contains the local price variables $P_{M,k}$ for which proper data do not generally exist.

As for urbanization externalities, we measure them like in Ciccone and Hall (1996) and Combes (2000):

$$Dens_{j,t} = \ln\left[\frac{empl_{j,t}}{size_j}\right] \tag{11}$$

where $empl_{j,t}$ is employment in location j at time t, while $size_j$ is a location surface in square km. As standard, we consider the log, and we do the same for all the other location variables in order to interpret parameters as elasticities and ease comparison with previous studies.

The proxy we use for the spatially weighted component is instead based on the concept of market potential, as originally introduced by Harris (1954), which was developed to measure the "potential" demand for goods and services produced in a location $j = 1, 2, .., \Phi$, and in particular:

$$MP_{j,t} = \ln\left[\sum_{k\neq j} Y_{k,t}\; d_{jk}^{-1}\right] \tag{12}$$

where $Y_{k,t}$ is an index of purchasing capacity of location k (usually disposable income) at time t, and d_{jk} is the distance between two generic locations j and k. By comparing equations (10) and (12) one can notice that, apart for the time index, (12) is actually a particular specification of the spatially weighted term in (10), where the disposable income referring to location j is omitted, $P_{M,k} = 1 \; \forall \; k$, and $v_{j,k}^{\sigma-1} = T(d_{j,k}) = d_{jk}^{-1}$.[9] The choice to neglect the disposable income of location j variables, which is rather standard in the literature,[10] helps to mitigate both endogeneity problems and possible multicollinearity with the density variable.[11] Furthermore, the use of the power minus one function for $v_{j,k}^{\sigma-1}$ is justified by the gravity equation literature[12] and the trade nature of the model. It is true that there exist frameworks dealing with the structural estimation of NEG models, like Head and Mayer (2004) and Mion (2004), that use more sophisticated measures of market potential than (12). However, our goal here is to give a measure of the magnitude of agglomeration economies and not to estimate the underlying model parameter. To this respect Head and Mayer (2004), when comparing Harris' market potential with a more elaborated measure, did not find any strong evidence in favor of the latter in terms of predictive power.

Although we focus on the comparison between urbanization externalities and market potential, in the urban literature there is also a substantial interest for the so-called localization externalities, which concern the productivity gain stemming from the concentration of a specific industry in a given location (local specialization). Both the theoretical models of Henderson (1974) and Duranton and Puga (2004) and the empirical findings of Glaeser et al (1992) and Henderson (2003) suggest that these externalities play an important role in local growth and productivity. Consequently, we decide to include them in the analysis even though, compared to density and market potential, we are less able to tackle the related endogeneity issues. Nevertheless, as we will see later on, neglecting them does not alter substantially our results. As a proxy for such externalities, we use a measure of local sectoral specialization as in Combes (2000):

$$Spec_{j,s,t} = \ln \left[\frac{empl_{j,s,t}/empl_{j,t}}{empl_{s,t}/empl_t} \right], \tag{13}$$

where the specialization index for sector s in province j is defined as the ratio of the employment

[9] It is interesting to note that Harris (1954) did not provide any model to justify its concept of market potential. This is not surprising since general equilibrium models dealing with increasing returns to scale, space, and product differentiation have been introduced only recently. In particular, Fujita, Krugman and Venables (1999) show that market potential functions can be obtained from many spatial general-equilibrium models, thus providing the theoretical background for the use of such an approach.

[10] See Mion (2004) and Hanson (2005).

[11] High density provinces are usually characterized by a large disposable income. This means that, if we considered in the market potential index the disposable income for location j, then the correlation between density and market potential would be relatively high involving possible multicollinearity problems.

[12] See Disdiez and Head (2004).

share of sector s in province j divided by the same ratio at the national level.

In the next Section we will present the database used, the way we construct our regressors and instruments as well as some simple descriptive statistics that gives a flavor of the spatial variability of wages.

3 Data Description

3.1 Data Sources

In this paper we use an administrative database provided by INPS (the Italian Social Security Institute). More specifically, we work on a panel version of this database, elaborated by ISFOL[13], which matches employer and employee information, a similar database like the one used by Kramarz, Abowd, and Margolis (1999). The sample units are full-time workers[14] in all private sectors but agriculture, covering 14 years from 1985 to 1998. The sample scheme has been set up to follow individuals born on the 10^{th} of March, June, September and December, and therefore the proportion of this sample on the Italian employees population is approximately of 1/90.

As far as workers' characteristics are concerned, the database contains many individual information like age, gender, qualification, place and date of birth, workplace, date of beginning and end of the current worker contract, the social security contributions, if the worker is either part time or full time, the yearly wage, and the number of worked weeks and days.

For firms this database contains the following information: plant location (province), headquarter location (province), the average number of employees, the sector and the date of start up and the one of shut down (if any). This means that, contrary to other database, we are able to exactly identify where a job takes place since the headquarter and plant location are two separate information.

As far as job location is concerned, we use data on the 95 Italian provinces.[15] The choice of provinces represents a good compromise between a detailed classification of the Italian territory and data availability. Provinces are in fact sufficiently big to entirely cover cities area and small enough to provide a rich data variability. Mion (2004) uses the same spatial disaggregation in its structural analysis of agglomeration externalities. Data on yearly sectoral employment at the provincial level are provided by INPS and refers to the period 1986-1998. The corresponding sectoral decomposition

[13]For a detailed explanation of this database see Centra and Rustichelli (2005).

[14]Apprenticeships and part time workers are excluded from the dataset, since the attention is focused on standard labor market contracts (blue collar, white collar and managers). Further, self-employed are not included in INPS database.

[15]Actually, in 2005 the Italian provinces are 103. The transition between 95 and 103 took place in 1995. In this paper we consider the initial classification of 95 provinces, converting subsequent changes of definitions to the old classification.

is the ATECO 81, which splits the Italian economy in 52 sectors (at 2digit level). Province data on education (year 1991), and households' disposable income (period 1991-2000) are provided by the "Istituto Tagliacarne".

As for historical data, information about provinces population in 1861, 1881, and 1901 comes from a re-elaboration of population census by municipalities operated by ISTAT. Data on local sectoral specialization for the year 1951 comes from the "Ateco51-91" database, which is still provided by ISTAT. Finally, data on surface and crow-fly distances among provinces' centroids comes from Arcview GIS software.

3.2 Dataset Construction

In our empirical analysis we focus on the period 1991-1998 for which all individual and spatial data are jointly available. Our unit of analysis is a worker i at year t. As for job records of a worker, we consider only one employer-employee match per year. In particular, we assign to each individual i the monthly wage and job characteristics of the longest job record in year t. The choice of the monthly wage - reconstructed using yearly wage and worked weeks - is meant to control for both the actual time worked during a year as well as for differences in actual vs reported working time which can systematically vary across space.[16] We further eliminate those extreme observations below (above) the 1^{st} (99^{th}) percentile of the yearly wage distribution, and consider only workers with at least two observations in order to be able to perform a within transformation on our data. This lead us to an unbalanced panel of 92,579 individuals corresponding to 560,040 observations over the span 1991-1998.

However, in the paper we actually use a smaller dataset. In particular only male individuals with age between 24 and 39 (when they first enter in the database) are considered, *i.e.* 31,457 workers and 200,015 observations. The choice to consider only male workers is quite standard in the wage equation setting.[17] Women wage dynamics is in fact often affected by non-economic factors, meaning that standard economic and spatial covariates are less relevant in explaining their carriers. Furthermore, as we will see in Section 4, workplace changes are crucial for estimations and young male workers represents a relatively homogeneous category with respect to migration. Indeed, the related literature - like Borjas, Bronars, and Trejo (1992) and Dahl (2002) - usually focuses on them.[18]

[16] More precisely, as wage variable we use the yearly wage paid by the firm to the employee, divided by the number of worked weeks, and then reporting the week wage at the monthly level. We did not use the information of the worked days because Ginzburg (1998) claimed that this variable in the south could be underestimated, leading to higher daily wages in this region, which is indeed supposed to be the poorest Italian area.

[17] See for instance Topel (1991).

[18] It is for example well known that male prime-age workers are more mobile. Indeed, in our full sample of 92,579 workers 10.49% of them change location at least once in the observation period against the 13.54% of male prime-age.

Finally, the need to have a good measure of skills, that we measure as individual fixed effects, lead us to consider only workers with more than four observations ending up with a panel of 24,353 workers and 175,700 observations.[19]

The dependent variable in our regression is the (log) of before tax monthly wage in thousands of Italian liras. Data have been deflated and the base year is 1991. As for individual characteristics, we focus on the standard covariates usually used in a mincerian equation: age, age^2, and two other dummies for blue collar and white collar with the residual category being managers, as well as time and sectoral dummies.

Moreover, in order to capture firms' heterogeneity we use the log of firm size. The positive and strongly significant relation between wages and firm size has been extensively studied in labor economics. The seminal papers are probably the ones of Krueger and Summers (1988) and Brown and Medoff (1989). In particular, this literature points out a persistent positive effect of firm size on wages, identifying several different explanations.[20]

As spatial variables we consider employment density, market potential, and localization externalities as defined (respectively) in (11), (12), and (13). Descriptive statistics of the main variables used in our sample are given in Table 1.

3.3 A First Glance

From descriptive statistics, spatial imbalances come out quite clearly. The spatial distribution of wages is in fact far from being uniform across Italian provinces suggesting that location matters. This does not have to be taken for granted, since Italy is a country characterized by a very important centralized wage setting where, within each sector, contracts have to respect several national based constraints like a minimum wage. However, it is worth noting that firms are allowed to integrate the national contract with a company specific contract in which, for example, the minimum wage can be increased. Besides, since several standard economic theories suggest that fixing wages above the minimum wage level might represent an efficient solution for the firm (for instance the efficiency wage approach, the insider outsider and/or the wage setting in presence of unions etc.), it is not surprising that wages distribution is affected by economic location.

[19] Estimations of spatial externalities in the database of 31,457 workers, with all male prime-age workers for which more than two observations are available, are virtually identical. Moreover, when considering the largest database of 92,579 we found slightly smaller estimates but lower standard errors.

[20] For instance, some papers claim that only more productive and big size firms can afford to pay efficiency wages in order to attract and keep skilled workers (Krueger and Summers, 1988), while other papers stress the importance of unions power in big size firms and the consequent impact on wages. Further, another explanation concerns the fact that big size firms make use of a better screening device in order to select high skilled workers. For a survey concerning all this literature see Oi and Idson (1999).

To give some figures about spatial imbalances, the ratio between the highest average province wage (considering time averages over the period) and the lowest one is 1.52, and this ratio is increasing overtime (1.46 in 1991 and 1.56 in 1998). This result still holds if the different qualifications are taken into account. For instance, the same rate is equal to 1.40 for blue collar workers, 1.53 for white collar and 2.82 for managers. Even considering a less extreme indicator than the max/min like the $90^{th}/10^{th}$ percentile ratio we still derive a relevant wage variation. This ratio is in fact 1.24 for all workers, while being 1.22 for blue collar, 1.17 for white collar and 1.33 for managers.

In the paper, we will use matched employer-employee data. However, using aggregate data already gives a flavor of some of the conclusion we will draw. Considering the relation between province average wages (across individuals) and density (mean 1991-1998), it is possible to derive a clear positive correlation leading to an R^2 of 0.36. Market potential is also a powerful explanatory variable, with the R^2 of the regression on province average wages being 0.28. However, we find that individual skills, and in particular education, are more important in order to understand spatial wage disparities. In fact, the share of people with an High School degree in a given province explains alone 42% of the differences among aggregated wages. The spatial literature has paid little attention to the issue of skills and much more on spatial externalities: in this paper we contribute to fill this gap.

4 What Can Matched Employer-Employee Panel Data Tell us More About Spatial Imbalances?

One major goal of our empirical analysis is the estimation of the importance of spatial externalities for the distribution of wages and the model presented in Section 2 provides a theoretical ground for a positive impact of such externalities on nominal wages. However, most of the studies that has dealt with the measurement of spatial externalities, like Glaeser et al (1992), Ciccone and Hall (1996), and Mion (2004), use aggregate data on labor, wages and productivity. Using individual level data provides relevant steps forward in the analysis. First of all, it is possible to control for possible composition effects due to individual characteristics like age, gender and qualification. Indeed, in our data both the age and the gender of workers are strongly correlated with economic density and the same apply, although to a smaller extent, to market potential. For instance, female workers can be found more easily in big cities with the working population being a little older. Since female workers earn less and at the same time wages are positively correlated with age, the sign of the bias coming from omitting these individual control variables on economic density is (in this case) undetermined a priori.

A second point in using individual data is that the panel nature of observations allow us to control for a very important source of wage variation: unobserved time-invariant individual characteristics (skills). Education is certainly one important component of individual skills, but the use of individual fixed effects is crucial to capture other important time-invariant features that would be otherwise neglected. This choice is quite standard in labour economics[21], especially when the core of the analysis is not the estimate of the returns to education. Accounting for such individual effects turns out to be particularly interesting when their distribution across space is uneven. Glaeser and Mare (2001), Moretti (2004), and Redding and Schott (2003) provide the rationale for an interplay between skills and space. In particular, these frameworks suggest that skilled workers should be disproportionately found in regions characterized by high density and market potential leading to an up-ward bias of the estimate of spatial externalities.

Another important element we can deal with our data is firms' heterogeneity. On the one side, there is an important literature focusing on the positive relation between firm size and wages. Nevertheless, as long as there is no correlation between firm size and location characteristics, omitting the former would have no impact on the estimates of spatial externalities. To this respect, the recent literature on heterogeneous firms (started with the work of Melitz, 2003) has something to say about that. In particular, Melitz and Ottaviano (2005) build a model in which the size of the local market is positively related to firm size and productivity. The bottom line of their argument is that local competition (which is tougher in big markets) lead to a self-selection of bigger and more productive firms. Indeed, in our data firm size in positively correlated with density (0.12), and this correlation is strongly significant even after introducing sectoral dummies.[22] All of this suggests that controlling for firm size may provide useful insights to our spatial analysis. In order to better explore this topic we will also perform a more general estimation technique introduced by Abowd, Kramarz, and Margolis (1999) that, allowing simultaneously for firm and worker fixed effects, should enable us to better control for firms' heterogeneity than simply using firm size and sectoral dummies.

As for the interaction between individual and firm heterogeneity, theory further suggests that there may be some important complementarities at work. For example, Yeaple (2005) shows that firms who choose to be high tech are more productive, bigger and have a skill-biased technology. Consequently, big firms should be observed to hire more skilled workers and, even after controlling for skills, to have a residual productivity advantage. The positive link between firms' size and skills has already been documented empirically by Abowd, Kramarz, and Margolis (1999). However, we are able to go a bit further here by assessing whether the observed correlation is just due to co-location

[21] See for instance Krueger and Rouse (1998).

[22] The positive correlation between firm size and economic density has also been documented by Campbell and Hopenhayn (2002).

of both big firms and skilled workers in cities or not.

Econometric Specification and Identification

Once established the importance of using matched employer-employee data we can proceed in our empirical analysis. In particular we use an augmented mincerian equation that combines standard features of labor economics with spatial externalities:

$$w_{i,t} = \mathbf{B}_1^{'}\mathbf{I\_C}_{i,t} + \mathbf{B}_2^{'}\mathbf{F\_C}_{f(i,t),t} + \gamma_0 Spec_{j(i,t),\ s(f(i,t),t),\ t} + \gamma_1 Dens_{j(i,t),t} + \gamma_2 MP_{j(i,t),t} + \delta_t + u_i + \varepsilon_{i,t} \tag{14}$$

where subscript i refers to individuals, t to time, j to location, f to firms and bold variables refer to vectors. The dependent variable is the logarithm of before tax monthly wage, u_i is an individual effect (skills), and δ_t is a time effect. The term $\mathbf{I\_C}_{i,t} = \{Age_{i,t},\ Age^2_{i,t},\ Bc\ dummy_{i,t},\ Wc\ dummy_{i,t}\}'$ is a battery of individual characteristics while $\mathbf{F\_C}_{f(i,t),t}$ contains variables that controls for firm f features. The latter is given either by $\mathbf{F\_C}_{f(i,t),t} = \{\mathbf{i}_{s(f(i,t),t)}, \ln(FirmSize_{f(i,t),t})\}'$, where $\mathbf{i}_{s(f(i,t),t)}$ is a set of industry dummies and $\ln(FirmSize_{f(i,t),t})$ is log of firm f size (both time varying), or by a fixed effect $\mathbf{F\_C}_{f(i,t)}$ (one for each firm) as in Abowd, Kramarz, and Margolis (1999). Finally $Spec_{j(i,t),\ s(f(i,t),t),\ t}$, $Dens_{j(i,t),\ t}$ and $MP_{j(i,t),\ t}$ indicate specialization, density and market potential as defined in (13), (11) and (12). It is worth noting that in our notation both the sectoral index s (referring to the 52 Ateco81 sectors), the location index j (referring to the 95 provinces), and the firm index f depend ultimately upon the couple (i,t) because they vary when an individual changes sector and/or province and/or firm at time t.

Identification of spatial variables is important in our analysis. As long as OLS or GLS are used, both the between and within variance identify γ_0, γ_1, and γ_2 and there is no major issue. However, with our preferred within estimates, identification essentially comes (although not exclusively) from workers changing sector/location. For example, in the within dimension, only 14% of the variability of density is actually due to density changing over time in a given location with the remaining 86% coming from workers' migrations.[23] Now, it is well known that migrants are not a random sample from the population of origin, generating a possible self-selection problem. We will deal with this issue in Section 5.3. As for firms' characteristics, a similar problem arises for the within estimations of sectoral dummies and the coefficient of $\ln(FirmSize_{f(i,t),t})$, which are essentially identified by workers changing employer. However, our interest in these variables is very limited as we use them

[23]In order to compute these shares of the within variance we first attribute to each worker the same (initial) location for the entire period and then we compute the (without migration) within variance of density. Finally, we compare this within variance with the non-restricted variance that includes workers' movements.

just as controls in our spatial analysis. Finally, when using the Abowd, Kramarz, and Margolis (1999) estimator (AKM), spatial variables are identified by their time variability only.

5 Econometric Analysis

5.1 First Results

In order to give a clear overview of the relation between wages, skills, firms and spatial externalities we present in this Subsection estimations of (14) based on OLS, GLS, Within as well as the firm and individual fixed effects estimator (AKM) of Abowd, Kramarz, and Margolis (1999). Endogeneity of spatial variables and self-selection of migrants are discussed in the next two Subsections.

Table 2 shows the results obtained using our sample of male prime age workers for all sectors. Columns (1) to (5) contains (respectively) OLS, GLS, within without firm size, within with firm size and AKM. In all specifications, except AKM where sectoral dummies cannot be separately identified from firm effects,[24] a complete set of time and sectoral dummies are included.

First of all, our estimates on the impact of $Age_{i,t}$ and $Age^2_{i,t}$, and the two dummies for blue and white collar are in line with previous findings (Naticchioni and Panigo, 2004). Moreover, the impact of localization externalities, as proxied by our specialization measure, is always very low (between 0.55% and 0.01%) and weakly significant. This is consistent with previous works on Italy and in particular with Cingano (2003), who did not find any strong evidence in favor of a positive wage differential in highly specialized areas (Industrial Districts). These variables are not of direct interest in our analysis and thus we will not discuss them further.

The Spatial Sorting of Skills and Firms

As for density and market potential, going from column (1) to (3) it is quite straightforward to observe that taking into account individual effects dampens simple OLS results. Nevertheless, these variables are always significant and elasticities are in line with economic meaningful values. In fact, according to OLS, doubling density increases wages of 2.21%. Previous findings of Ciccone and Hall (1996) for US and Combes, Duranton and Gobillon (2004) for France found (respectively) something around 5% and 3%. Our rather low value is probably due to the already mentioned fact that Italy is characterized by a high degree of wage compression, for instance due to the sectoral minimum wages set at the national level. Further, taking into account individual effects further reduce this estimate. When considering (uncorrelatd) random effects the effect of density drops to 1.87%, while allowing

[24] Sectoral dummies can be separately identified from firm effects as long as firms change sector. However, there are few such changes in the data and even Abowd, Kramarz and Margolis (1999) do not deal with them.

this effects to be correlated with regressors in the within estimations of column (3) leads to only 0.74%.[25] These simple estimates suggest a strong positive correlation between individual skills, as measured by u_i, and density. Indeed, our within estimations give a (significant) correlation of 0.20 among the two, which suggests that sorting of skills in space is at work. These findings confirm those of Combes, Duranton and Gobillon (2004) for France.

Concerning market potential, spatial sorting is also at work. OLS estimates suggest that doubling market potential lead to a 10.88% increase in wages. Interestingly, in their aggregate analysis of the impact of market potential on sectoral EU wages, Head and Mayer (2005) find a very similar result. However, taking into account individual skills push down elasticity to 5% in the within estimates. The (significant) correlation between the u_i and market potential is 0.08 which is significantly lower than the one with density but still suggestive of a positive link between skills and those agglomeration externalities stemming from NEG models. This result is consistent with the theoretical and empirical findings of Redding and Schott (2003).

In columns (4) and (5), we further account for firms' heterogeneity by means of (respectively) firm size and firm fixed effects. This is, to our knowledge, the first empirical framework dealing with the firm content of spatial externalities. Considering column (4), the firm size elasticity with respect to wages is 1.94%, which is in line with previous findings for other countries. For instance, Brown and Medoff (1989) derive an elasticity value of around 3% for the US. As for the impact on spatial variables, considering firm size slightly decrease the elasticities of density (0.56%) and market potential (4.56%). Indeed, the size of firms is significantly correlated with both and in particular with density (0.12), which is the one that experiences the strongest fall. However, compared to the sorting of individuals, the sorting of firms entails a much weaker impact on spatial externalities.

These findings are confirmed by the more general AKM estimation in which the elasticity of density slightly falls to 0.66% while market potential remains substantially stable compared to estimation in column (3).[26] The idea that firms' heterogeneity may lead to dampen the magnitude of spatial externalities has been put forward by Baldwin and Okubo (2004). Our results suggest that the bias

[25] Although this elasticity might seem really low, Di Addario and Patacchini (2005) find a very close result. Using a similar database on individual wages where they also have information of workers' education the authors find that doubling density leads to a 0.53% increase in wages.

[26] In particular, we use the order dependent person first method. As for the conditioning variables Z we use the interactions between (mean) individual characteristics (age, age^2, density, and market potential) and (mean) firms characteristics (firm size, firm size^2, and a 9 industry classification based on Ateco 81 one digit). Separate identification of individual and firms effects require 'connections' within a group of workers and firms (see Abowd, Creecy, and Kramarz, 2002). In our estimations we have 24,353 individuals and 28,719 firms forming 15,186 groups. We use all groups and consequently have 37,886 separately identifiable individual and firm effects. It is important to stress that these fixed effects fully account for both individual and firm time invariant characteristics. The fact of having many groups is in fact only a constrain for the separate identification and comparability of firm and individual effects. Therefore, as comparison is only meaningful within a group, we do not report the correlation between the two effects and we base our analysis of the interaction between skills and firms' characteristics on individual effects and firm size.

induced by firms' heterogeneity is small, especially if compared to the one induced by individuals. Finally, it is worth noting that in the AKM estimation the identification of parameters γ_1 and γ_2 is due to the time-variability of density and market potential only. Parameters are not so different from column (4) where identification was basically driven by migrations, showing that the self-selection bias problem may not be so important for our estimations, as we will see later on.

The Interaction between Skills, Firms and Space

Another interesting issue we deal with is the relation between workers skills and firms attributes. Yeaple (2005) is an example of a model in which there are complementarities between the two sides of the market. The author shows that firms who choose to be high-tech are endogenously bigger and have a skill-biased technology. Consequently, big size firms are expected to hire more skilled workers and, even after controlling for skills, to have a residual productivity premium. This in indeed the case in our regressions where the firm-size effect is always significant. Furthermore, the correlation between the individual effects and firm size is very strong (0.35) and significant. A similar result is derived in Abowd, Kramarz, and Margolis (1999). However, the fact that we specifically deal with space in our framework allow us to go a bit further. Actually, the link between skills and firm size may be in principle due to a simple co-location effect. Melitz and Ottaviano (2005) suggest that big and more productive plants should locate in thick markets. At the same time, according to Glaeser and Mare (2001) and Moretti (2004), skilled workers should be expected to be found disproportionately in big cities. However, the partial correlation between individual effects and plant size *conditional* on spatial characteristics (density and market potential) is 0.33 which is just slightly smaller than the unconditional one and still highly significant. This suggests that co-location is not really an issue suggesting that there is a deeper underlying complementarity between skills and firm size.

Sectoral Robustness of the Spatial Sorting

An issue we also deal with in the paper is the sectoral scope of our analysis. One can in fact reasonably argue that there may be a considerable sectoral heterogeneity with respect to spatial externalities. In Table 3, which is the counterpart of Table 2, we show estimations of (14) obtained on the sub-sample of manufacturing workers. These estimates have the advantage of being based on a set of economic activities that are more directly comparable, still confirming that the sorting of skills (firms) is very strong (weak). Furthermore, all elasticities are still positive and significant with magnitudes comparable to those referring to all activities with two interesting exceptions. On the one hand, localization externalities seems to be stronger and more significant for manufacturing and this is somehow expected since the idea that specialization fosters growth and productivity is historically related to such activities. The other interesting difference concerns market potential. In the subsample of manufacturing, market potential seems to matter less: punctual estimates are in fact (in within and AKM estimations) almost half of their counterparts in the sample of all activities. This may suggest that other sectors, and in particular services -that usually display higher transportation costs- are more sensitive to market centrality. However, the difference between comparable estimates is not significant and caution is needed.[27]

5.2 Endogeneity

In this Subsection we explore the issue of endogeneity. Although within and AKM estimations can give useful insights on the issue of spatial sorting, the reliability of computed elasticities are in fact conditional upon the validity of the underlying moments' restrictions. In particular, it is assumed that $\mathrm{Cov}(\varepsilon_{i,s}, \mathbf{X}_{i,t})$, where $\mathbf{X}_{i,t}$ represents the vector of all covariates, is equal to zero $\forall\ s,\ t$. However, as pointed out by Combes, Duranton, and Gobillon (2004), some local characteristics are likely to be endogenous to local wages. For instance, provinces experiencing a positive technological shock at time t may attract migrants and thus lead to a positive correlation between density and/or market potential and the residual term. In particular, exogeneity of the location choice is violated whenever workers make their employment choice on the basis of the actual wages at date t. Combes, Duranton, and Gobillon (2004) show that the bias is much reduced in a dynamic context when workers make their employment decision on the basis of both current and future (expected) wages. Nevertheless, the issue of endogeneity of density, market potential and, to some extent, also of the sector choice (specialization) remains open. We deal with endogeneity by means of IV estimations that exploit the idea of Ciccone and Hall (1996) of using deeply lagged values of the endogenous variables as instruments. Crucially, test on over-identifying restriction accepts the validity of such instruments.[28] It is also important to stress that the AKM method cannot be used with endogenous covariates. Therefore, we use a within-IV with firm size and sectoral dummies as controls for firm heterogeneity.

In Table 4 we show our within-IV results, which we believe are the most reliable estimates of spatial externalities we can provide. In particular, column (1) represents our preferred specification. In Column (1) to (4) we use as instruments for spatial variables data on specialization in 1951, density of population in 1861, 1881, and 1901, as well as a proxy for market potential, calculated replacing aggregate disposable income of a province by its population in equation (12), for the years 1861, 1881,

[27] In AKM estimations of Table 3 we have 13,149 individuals and 13,843 firms forming 8,631 groups. We use all groups and consequently have 18,361 separately identifiable individual and firm effects.

[28] In a previous version of the paper we also experimented Dynamic Panel Data GMM estimation to solve endogeneity problems. However, results were very disappointing both in terms of parameter estimates and testing the over-identifying restrictions. The short span of the panel (8 years) and the issue of migration are probably the reason of this failure.

and 1901[29]. The use of deeply lagged levels of specialization, density and market potential obey to the logic (expressed in Ciccone and Hall, 1996) that, as long as early pattern of agglomeration do not reflect factors that influence productivity today, then they can be used as instruments. To this respect, the presence of a structural break would provide the condition for a natural experiment. Ciccone and Hall (1996) use late US 19th century data that are previous to both world war one and two, right after the civil war, and just at the beginning of railroad network construction. Our instruments of density and market potential for Italy meet these needs as the Italian State was created just after Garibaldi expedition in 1860 and the railroad network did not really develop until late 19th century. Unfortunately, we could not find very old data on specialization, even if this variable is not central in our analysis. Further, we will see that omitting localization externalities does not alter results. Crucially, the Sargan test on the one over-identifying restriction does not reject the validity of our instruments, and this is quite a strong result considering that with almost 200,000 observations the power of the test should be reasonably high.

We start by discussing column (1) which is the direct counterpart of column (4) of Table 2. As one can see, accounting for endogeneity alters the magnitude of spatial externalities. Compared to within estimation in column (4) of Table 2, density goes from 0.56% to 0.20% and is only significant at 10% level. By contrast market potential is just slightly affected going from 4.53% to 4.64%. This suggest that local economic density is much more affected by endogeneity than market potential and that our estimation for this variable might suffer from weak instrumentation. Nevertheless, differences with respect to the within estimations are not significant at 1% and caution is needed. Finally, the elasticity with respect to specialization is still not significant. As for the relative importance of density and market potential, all our estimations suggest that the latter is more important in explaining spatial wage variation. The elasticity corresponding to market potential is in fact always higher (with a gap that is statistically significant) and, when considering "standardized" elasticities, this result still holds with the one corresponding to density (market potential) being 0.0067 (0.0366).[30] Both absolute and standardized elasticities thus suggest that, at least for Italy, pecuniary externalities play a crucial role in the spatial distribution of wages. These findings are coherent with those of Mion (2004) who finds evidence of sizeable agglomeration externalities in Italy.

[29] Note that in this way we assume that disposable income is proportional to the population.

[30] Such standardized (or beta) coefficients are defined as the product of the estimated coefficient and the standard deviation of its corresponding independent variable, divided by the standard deviation of the dependent variable. They actually convert the regression coefficients into units of sample standard deviations giving a measure of how much variability of the dependent variable may be explained by the regressor. See Wooldridge (2003, Section 6.1) for a further description of this transformation.

Further Robustness Checks

In column (2) we perform the same estimation as in column (1) except for the fact the we now exclude both the specialization variable $Spec_{j(i,t),s(i,t),t}$ and the sectoral dummies $\mathbf{i}_{s(i,t)}$. Although we can reasonably instrument for the endogeneity linked to spatial variables, we cannot do the same for the sectoral dummies. The sector choice is in fact certainly endogenous and, although specialization in 1951 may not be such a bad instrument, we do not really have something to instrument sectoral dummies. The results we get for density and market potential are nevertheless almost identical. Furthermore, the Sargan test on over-identifying restrictions does not detect any bias from omitted variables. We interpret these results as an evidence that location and sector choice are quite independent from each other, implying that our estimates of agglomeration externalities are robust to the mispecification of the sector choice.

In column (3) we replicate, for comparability, the estimation methodology used by Combes, Duranton and Gobillon (2004). The authors assume in their estimation equation, which is very similar to (14), that there is a further time-location specific error component ($v_{j(i,t),t}$) that can be thought as an idiosyncratic technological shock. In order to control for this additional source of heterogeneity, the authors perform a first-step within estimation in which they include a full set of time-location dummies ($\beta_{j(i,t),t}$) that capture all the variation in the time-space dimensions. Subsequently, they recover the parameters of spatial externalities from a second step regression, in which the dependent variable is $\beta_{j(i,t),t}$, using a two-steps least squares estimator and deeply lagged values of covariates as instruments. Compared to our strategy, their methodology has the advantage of accounting for the heteroschedasticity that comes from time-location shocks $v_{j(i,t),t}$. In other words, although our IV estimates would still be unbiased, the standard errors may not. However, when they first recover their dummies without instrumenting, the endogeneity of spatial variables is still at work and can seriously bias their estimates of $\beta_{j(i,t),t}$. In order to get some insights on the relative advantages of the two procedures we have implemented their estimation techniques with the exception that we just considered location dummies in the first stage (i.e. $\beta_{j(i,t),t} = \beta_{j(i,t)}$). We do not have in fact enough time span and migrations to be able to identify all possible time-location effects. Comparing results of columns (1) and (3) reveals that the difference between the two sets of estimates is very small for density (which turns out to be not significant) but not negligible for market potential. We interpret the latter result as being due to an endogeneity bias. Indeed, the Sargan test in column (3) does not accept the validity of instruments in the second step. This may be due to the fact that first step estimates in the procedure of Combes, Duranton, and Gobillon (2004) suffers from endogeneity. However, this may also come from the restriction of the time-invariance of $\beta_{j(i,t),t}$ that we were forced to impose. Interestingly, the increase in standard errors that is expected as a consequence of heteroschedasticity is not dramatic and limited to density, suggesting that unobserved location heterogeneity is very small compared to that of individuals.

Finally, in column (4) we partition Italian provinces in four subsamples according to four macro areas (North-East, North West, Center, South).[31] For each subsample, we have thus performed separate estimations. Coefficients and standard errors reported are actually the average of the corresponding values of the four regressions. The reason of this exercise is twofold. On the one hand, we want to check whether spatial effects are possibly due to different returns on age, qualification, or firm size across space. On the other hand, we want to be sure that the North is not driving our results and particularly the one on market potential. As for the first issue, our estimations confirms that the positive impact of density and market potential on individual wages is robust even after introducing heterogeneity in returns to individual characteristics. In particular, both elasticities increases although the difference with pooled estimations is not significant. Moreover, looking at macro-area specific estimates, while the coefficient of density is very stable across space around its mean of 0.58% the same is not true for market potential that ranges from 2.24% for the North-East to the 10.12% of the South. This relatively unstable effect of market potential may be due to the fact that the Southern Italian economy heavily relies on the richer North that is (by contrast) much more export oriented.[32] In fact, we did not consider international demand in the construction of market potential and so the proximity of the North to the economic core of Europe is actually neglected. However, in all four cases estimates are positive and significant at 10% level suggesting that market proximity is a pervasive spatial force.

5.3 Migrations, Self-Selection, and Human Capital Accumulation

As we said in Section 4, migrations are the most important source of variability for identification of spatial externalities parameters in within estimations. However, the literature on migrations clearly points out that migrants are not a random sample from the population of origin, with skills being a crucial elements of this self-selection process (see, Borjas, 1987). However, it is not always the case that people migrating are the most skilled. As pointed out by Borjas (1987), selection may be either positive or negative depending on the characteristics of the location of both origin and destination. To this respect, Borjas, Bronas and Trejo (1992) find that the skills composition and the size of internal US migrations are well explained by interstate differences in the returns to skill: States that pay low

[31] The four macro areas are made by the following regions (according to the official classification): 1) Northwest: Valle d'Aosta, Piemonte, Liguria, Lombardia; 2) North-east: Veneto, Trentino, Friuli Venezia Giulia, Emilia Romagna; 3) Center; Toscana, Marche, Umbria, Lazio; 4) South; Abbruzzo, Molise, Campania, Puglia, Basilicata, Calabria, Sicilia and Sardegna.

[32] Interestingly, Mion (2004) also finds that market potential has a bigger impact for the South of Italy.

returns to skills will see their best workers leaving (positive selection), while States that pay high returns will experience an outflow of unskilled workers (negative selection).[33]

However, at first glace, it is not so clear how this self-selection mechanisms might bias our estimations. Why should for example more skilled workers experience a different wage change campared to less skilled when migrating? An answer, given implicitly by Moretti (2004), is that as long as returns to skills differ across space, then more (less) skilled workers that migrate to high (low) return to skills locations should receive a wage gain with respect to an average movers. We will see that this is indeed the case in our framework, and we start by describing the sorting of migrants in our data.

So far, we argued that the correlation between fixed effects u_i (our measure of skills) and density (0.20) is much higher than the one with market potential (0.08). On the other hand, the urban literature agrees on the fact that returns to skills (private *plus* social) is higher in big cities (see Moretti, 2004). Consequently, we now focus on the implications of self-selection and sorting of skills for the estimate of the density parameter only.[34] In particular we split provinces in low density (LD) and high density (HD) on the basis of the median of the (time average of) density in our database.[35] We then use the individual fixed effects obtained from the regression in column (4) of Table 2 and compute summary statistics of the distribution of skills of residents as well as of migrants (based on workplace) from and to LD and HD provinces.[36]

Table 5 provides a clear picture of the sorting across provinces. Looking at the first column, it is possible to claim that workers in HD provinces are much more skilled (0.0422) compared to the ones in LD provinces (-0.0520). The average skills gap corresponds to almost a 10% difference in wages between HD and LD provinces and standard errors (in parenthesis) reveal that this gap is highly significant. Moreover, migrations between the two groups of provinces (from LD to HD and from HD to LD) show that sorting of migrants is at work. This sorting is positive (as expected) from LD to HD provinces because the average skills of migrants (-0.0023) are significantly higher than those of the population of origin (-0.0520) although not as good as those of the population of destination (0.0422). The reverse is true, and so sorting is negative as expected, from HD to LD provinces. These findings are thus consistent with the idea that skills are a crucial element in migrations decisions and that higher returns to skills in big cities induce both a positive and negative sorting.[37]

[33] In the migration literature, returns to skills are relative to the average worker and the distribution is supposed symmetric. This means that, for the same average wage across space, a low skilled worker will receive a lower wage in a high returns to skills location.

[34] We also derived for market potential similar findings; although less clear results.

[35] The HD provinces are Torino, Varese, Milano, Vicenza, Venezia, Trieste, Bologna, Roma, Genova, Como, Bergamo, Treviso, Padova, Modena, Firenze, and Napoli. Note that the median is computed across individual observations.

[36] Some individuals moving more than once may actually "score" on more than one category. The same apply to the analysis resumed in Tables 6, 7, and 8.

[37] Migrations within each group (LD to LD and HD to HD) suggest that sorting exists only among HD provinces.

However, one can wonder to what extent these results hold when considering long-term migrations. To answer this question we report in Table 6 the same summary statistics with the difference that migrations are now defined as working in a province different from the one where the worker was born. Furthermore, the first column now shows the distribution of skills based on birthplace instead of workplace. As one can see, the sorting of migrants is qualitatively identical. However, there is an additional remark to underline: the sorting of migrants has a little impact on the overall sorting of skills across provinces. Although the sorting of migrants widens the skills gap between LD and HD provinces - comparing average skills based on birthplace in column (1) of Table 6 with those based on workplace in column (1) of Table 5 - the difference is relatively small. Those who are born in one of the two groups and do not move are already sorted in space and, although 15% of people change group within the working age, this flow does not have a major impact.

Although the sorting of migrants has little impact on the overall sorting of skills, it is potentially very important for our estimations of the urbanization economies due to a possible self-selection bias. Due to higher returns to skills in HD provinces and the double sign of sorting, the bias is expected to be positive (negative) for workers migrating to HD (LD) provinces. Table 7 shows that this is indeed the case. We perform the same estimation as in column (4) of Table 2, but we restrict out attention to migrants (based on workplace), and report only the coefficient on density. Estimations of column (1), (2), and (3) refer (respectively) to all migrants, migrants from LD to HD provinces, and migrants from HD to LD provinces. When moving to HD cities, "relatively" skilled workers receive a higher wage increase than the average of migrants. By contrast, "relatively" low skilled people going to LD provinces experience a below average wage drop which is, by the way, not statistically different from zero. These results confirm our a priori and prove that a bias exist. However, the sign of this bias goes in opposite directions depending on the type of migration and possibly cancels out.

However, the fact that people moving from HD to LD cities do not seem to experience a significant wage drop is also consistent with the wage growth story of Glaeser and Mare (2001). If urbanization externalities have a dynamic content, meaning that human capital (skills) is a stock and its accumulation is faster in cities, then wages do not necessarily fall when people that have accumulated skills in big cities move back to the periphery. Moreover, the gains of people migrating towards HD provinces should not be entirely reflected by their wages immediately after migration because such wages will be increasing over time. This implies that within estimations of spatial externalities might actually be downward bias. We test the consistency of this story with our data in Table 8. Following Glaeser and Mare (2001), we construct a dummy for non-movers living in HD provinces and different

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This is not really an issue for us as long as the return to skills are reasonably homogeneous in this group.

dummies for movers. For workers leaving or moving to a HD provinces we use two set of interacted year dummies to examine the wage dynamics before and after the migration. The first column refers to OLS estimations and the residual category are non-movers living in LD provinces. The second column refers to within estimations and the residual category is all non-movers. All other variables in equation (14) have been used as additional regressors. As one can see, there is some evidence of the wage growth hypothesis only in OLS estimations, where wages increase over time for people moving to HD provinces while no relevant wage losses are observed for people leaving HD locations. However, the evidence on within estimation is more mixed.

6 Conclusions

In this paper we use wages from a matched employer-employee panel data on Italian workers in order to estimate the magnitude of urbanization externalities and market potential. Our results suggest that these externalities are positive and significant. Moreover, both absolute and standardized elasticities suggest that market potential has the stronger impact. These findings are coherent with those of Mion (2004) who finds evidence of sizeable pecuniary externalities in Italy.

We also provide evidence that spatial sorting is at work in the sense that "good" workers and big firms are disproportionately located in provinces characterized by high density and/or good access to consumers' markets. The sorting of workers is stronger than that of firms and can explain a great deal of spatial wage variability. We further investigate the issue of self-selection of migrants and wage growth. Data reveals, coherently with Borjas (1987), both a positive and a negative sorting of migrants depending on the characteristics of the location of departure and arrival. The relative bias is thus both positive and negative possibly cancelling out. At the same time, we find a weak support for Glaeser and Mare (2001) wage growth story.

Another issue we deal with is the relation between the firm-size premium, individual skills and location. Our results suggest, coherently with Abowd, Kramarz, and Margolis (1999), that the correlation between the size of the employing firm and skills is very strong. However, this correlation is not simply the outcome of a co-location phenomenon, suggesting that a deeper complementarity relationship is at work.

A final remark concern the interpretation of our results. Although we show that taking into account the uneven distribution of firms and individual characteristics dampens simple estimates of spatial externalities, we do not believe this should be interpreted as a signal that these externalities are not important. Rather, we believe that spatial models should devote more efforts to understand the mechanisms underpinning the spatial sorting of agents and in particular of workers.

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Table 1. Summary Statistics

Variable	Observ.	Mean	Std. Dev.	Min	Max
ln(wage)	175700	6.4824	0.3625	3.1180	8.2036
Age	175700	34.1257	5.0713	24.0000	46.0000
Age^2	175700	1190.2820	350.7040	576.0000	2116.0000
Firmsize	175700	4.6278	2.7433	0.0000	12.2699
Bc Dummy	175700	0.6528	0.4761	0.0000	1.0000
Wc Dummy	175700	0.3319	0.4709	0.0000	1.0000
Specialization	175700	0.0622	1.0412	-8.7156	4.9706
Density	175700	3.9525	1.2167	0.6903	6.2398
Market Potential	175700	8.5566	0.2864	7.7637	9.0872
Specialization in 1951	175700	-0.0679	0.8887	-7.2878	3.6926
Density pop in 1861	175700	4.7640	0.6980	2.9671	6.7048
Density pop in 1881	175700	4.9202	0.6847	3.0494	6.8617
Density pop in 1901	175700	5.0708	0.7029	3.1931	6.9914
Market Potential in 1861	175700	12.5091	0.0667	12.4026	12.7018
Market Potential in 1881	175700	12.6485	0.0638	12.5404	12.8337
Market Potential in 1901	175700	12.7721	0.0633	12.6706	12.9480

All variables (except Sex, Age, Ageˆ2 , Bc Dummy, and Wc Dummy) are, coherently with their definition in the text, expressed in natural logarithm. Wages are in log of thousands liras while Market Potential is in log of billions liras. Both are in real terms (base 1991). Market Potential and Density in 1861-1901 are computed on the basis of inhabitants.

Table 2. Regression results for male prime-age workers: all industries. Dependent variable ln(wage)

	(1)	(2)	(3)	(4)	(5)
Age	0.0481***	0.0485***	0.0456***	0.0466***	0.0464***
	(0.0015)	(0.0010)	(0.0080)	(0.0080)	(0.0075)
Age^2	-0.0005***	-0.0005***	-0.0005***	-0.0005***	-0.0005***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Firmsize				0.0194***	
				(0.0004)	
Bc Dummy	-0.7619***	-0.3567***	-0.2132***	-0.2149***	-0.2162***
	(0.0049)	(0.0037)	(0.0041)	(0.0041)	(0.0038)
Wc Dummy	-0.4891***	-0.1771***	-0.1452***	-0.1466***	-0.1468***
	(0.0049)	(0.0031)	(0.0031)	(0.0031)	(0.0029)
Specialization	0.0055***	0.0030***	0.0015*	0.0008	0.0001
	(0.0006)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Density	0.0221***	0.0187***	0.0074***	0.0056***	0.0066***
	(0.0005)	(0.0008)	(0.0010)	(0.0011)	(0.0010)
Market Potential	0.1088***	0.0912***	0.0500***	0.0453***	0.0516***
	(0.0021)	(0.0039)	(0.0058)	(0.0058)	(0.0054)
Estimation mehtod	OLS	GLS	Within	Within	AKM
Time & Sector Dummies	Yes	Yes	Yes	Yes	Time only
Firm effects	No	No	No	No	Yes
Corr(u_i, Xb)			0.2559	0.3075	
R^2	0.5249	0.4974	0.3596	0.4412	
N. of individuals	24353	24353	24353	24353	24353
N. of identifiable firm effects					13533
N. of observations	175700	175700	175700	175700	175700

Standard errors in parentheses with ***, ** and * respectively denoting significance at the 1%, 5% and 10% levels.

Table 3. Regression results for male prime-age workers: manufacturing only. Dependent variable ln(wage)

	(1)	(2)	(3)	(4)	(5)
Age	0.0539*** (0.0019)	0.0446*** (0.0013)	0.0453*** (0.0073)	0.0468*** (0.0074)	0.0473*** (0.0071)
Age^2	-0.0006*** (0.0000)	-0.0005*** (0.0000)	-0.0004*** (0.0000)	-0.0004*** (0.0000)	-0.0004*** (0.0000)
Firmsize				0.0228*** (0.0007)	
Bc Dummy	-0.8263*** (0.0070)	-0.3927*** (0.0054)	-0.2404*** (0.0060)	-0.2417*** (0.0060)	-0.2398*** (0.0058)
Wc Dummy	-0.5322*** (0.0071)	-0.1997*** (0.0046)	-0.1625*** (0.0045)	-0.1653*** (0.0046)	-0.1632*** (0.0044)
Specialization	0.0084*** (0.0009)	0.0058*** (0.0011)	0.0046*** (0.0013)	0.0033** (0.0013)	0.0035*** (0.0012)
Density	0.0207*** (0.0007)	0.0190*** (0.0012)	0.0081*** (0.0015)	0.0060*** (0.0016)	0.0075*** (0.0015)
Market Potential	0.1084*** (0.0031)	0.0875*** (0.0058)	0.0251*** (0.0095)	0.0233*** (0.0095)	0.0333*** (0.0091)
Estimation mehtod	OLS	GLS	Within	Within	AKM
Time & Sector Dummies	Yes	Yes	Yes	Yes	Time only
Firm effects	No	No	No	No	Yes
Corr(u_i, Xb)			0.1915	0.2229	
R^2	0.5146	0.4879	0.3525	0.4245	
N. of individuals	13149	13149	13149	13149	13149
N. of identifiable firm effects					5212
N. of observations	87056	87056	87056	87056	87056

Standard errors in parentheses with ***, ** and * respectively denoting significance at the 1%, 5% and 10% levels.

Table 4. GMM regression results for male prime-age workers: all industries. Dependent variable ln(wage)

	(1)	(2)	(3)	(4)	(5)
Age	0.1009***	0.1007***	0.0316***	0.0073***	0.0072***
	(0.0019)	(0.0042)	(0.0036)	(0.0018)	(0.0019)
Age^2	-0.0005***	-0.0005***	-0.0003***	-0.0001***	-0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Firmsize	0.0157***	0.0186***	0.0159***	0.0141***	0.0108***
	(0.0012)	(0.0014)	(0.0017)	(0.0015)	(0.0017)
Bc Dummy	-0.1406***	-0.1277***	-0.1211***	-0.1904***	-0.1837***
	(0.0085)	(0.0091)	(0.0105)	(0.0103)	(0.0111)
Wc Dummy	-0.0821***	-0.0708***	-0.0572***	-0.0866***	-0.0815***
	(0.0058)	(0.0061)	(0.0065)	(0.0069)	(0.0075)
Specialization	0.0011	-0.0181*	-0.0172*	0.0030	-0.0114
	(0.0015)	(0.0106)	(0.0097)	(0.0041)	(0.0070)
Density	0.0042*	-0.1602***	-0.1034***	0.0264***	0.1717***
	(0.0024)	(0.0188)	(0.0175)	(0.0089)	(0.0366)
Market Potential	0.0422***	-0.0901	-0.6503***	-0.0176	0.0164
	(0.0137)	(0.1804)	(0.2004)	(0.0246)	(0.1717)
Lag $w_{i,t}$			0.3164***	0.8035***	0.7944***
			(0.0567)	(0.0124)	(0.0137)
Lag Specialization					0.0113**
					(0.0046)
Lag Density					-0.1156***
					(0.0299)
Lag Market Potential					-0.0255
					(0.1574)
Model estimeted in	Diff	Diff	Diff	Diff&Lev	Diff&Lev
Instruments Diff.	T-4 to T+4	T-4 to T-3	T-4 to T-3	T-4 to T-3	T-4 to T-3
Instruments Lev.				T-3 to T-2	T-3 to T-2
Time & Sector Dummies	Yes	Yes	Yes	Yes	Yes
Hansen test degr. freed.	138	24	32	63	60
Hansen test	671.44***	108.17***	155.25***	587.96***	483.81***
Test for AR(1)	-29.41***	-28.33***	-10.11***	-32.59***	-25.21***
Test for AR(2)	-6.32***	-7.05***	1.27	8.21***	7.62***
N. of individuals	24353	24353	24353	24353	24353
N. of observations	175700	175700	175700	175700	175700

Standard errors in parentheses with ***, ** and * respectively denoting significance at the 1%, 5% and 10% levels.

Table 5. Skills distribution across provinces and migrants characteristics based on workplace

		Migration Flows	
	Whole population	LD provinces (destination)	HD provinces (destination)
LD provinces (origin)	-0.0520*** (0.0021)	-0.0665*** (0.0076) [1184]	-0.0023 (0.0083) [1037]
HD provinces (origin)	0.0422*** (0.0023)	-0.0060 (0.0083) [1042]	0.1038*** (0.0102) [881]

Standard errors in parentheses with ***, ** and * respectively denoting significance at the 1%, 5% and 10% levels. Number of migrants are in square brackets

Table 6. Skills distribution across provinces and migrants characteristics based on birthplace

		Migration Flows	
	Whole population	LD provinces (destination)	HD provinces (destination)
LD provinces (origin)	-0.0380*** (0.0023)	-0.0326*** (0.0054) [2235]	0.0594*** (0.0049) [2839]
HD provinces (origin)	0.0417*** (0.0028)	0.0202** (0.0089) [885]	0.1211*** (0.0079) [1278]

Standard errors in parentheses with ***, ** and * respectively denoting significance at the 1%, 5% and 10% levels. Number of migrants are in square brackets

Table 7. Analysis of migrations. Dependent variable ln(wage)

	(1)	(2)	(3)
Density	0.0039*** (0.0015)	0.0060*** (0.0022)	0.0001 (0.0021)
Migrants	All	LD to HD	HD to LD
Estimation method	Within	Within	Within
R^2	0.3738	0.3283	0.2798
N. of individuals	3297	1037	1042
N. of observations	23632	7506	7519

Standard errors in parentheses with ***, ** and * respectively denoting significance at the 1%, 5% and 10% levels. Regressions contains Age, Age^2, Firmsize, Bc Dummy, Wc Dummy, Specialization, Market Potential as well as year and sectoral dummies.

Table 8. Analysis of the wage growth hypothesis. Dependent variable ln(wage)

	(1)	(2)
Non movers living in HD province	0.0501***	dropped
	(0.0012)	
Moving to a HD province:		
Observed 4 or more years before a move	-0.0142*	-0.0096*
	(0.0081)	(0.0056)
Observed 2-3 years before a move	0.0018	-0.0083*
	(0.0066)	(0.0048)
Observed 1 year before a move	0.0030	-0.0146**
	(0.0078)	(0.0051)
Observed 1 year after a move	0.0305***	0.0044
	(0.0083)	(0.0054)
Observed 2-3 years after a move	0.0379***	0.0021
	(0.0072)	(0.0052)
Observed 4 or more years after a move	0.0594***	0.0073
	(0.0095)	(0.0064)
Leaving from a HD province:		
Observed 4 or more years before a move	0.0264***	0.0107**
	(0.0075)	(0.0053)
Observed 2-3 years before a move	0.0165**	0.0107
	(0.0066)	(0.0048)
Observed 1 year before a move	-0.0006	0.0022
	(0.0077)	(0.005)
Observed 1 year after a move	-0.0096	-0.001
	(0.0087)	(0.0055)
Observed 2-3 years after a move	-0.0125*	-0.0029
	(0.0074)	(0.0053)
Observed 4 or more years after a move	0.0087	0.002
	(0.0104)	(0.0069)
Estimation method	OLS	Within
R^2	0.5325	0.4026
N. of individuals	24353	24353
N. of observations	175700	175700

Standard errors in parentheses with ***, ** and * respectively denoting significance at the 1%, 5% and 10% levels. Regressions contains Age, Age^2, Firmsize, Bc Dummy, Wc Dummy, Specialization, Market Potential as well as year and sectoral dummies.