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Spatial Externalities in Big Cities and Duality of the Labour Market

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Spatial Externalities in Big Cities and Duality of the Labour Market

Esternalità spaziali nelle grandi città e dualità del mercato del lavoro

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April 2021

Abstract

This article investigates the dynamics of the spatial wage premium for workers employed on temporary and permanent contracts. We use an employer-employee database that covers the universe of young Italian employees for 2005-2016. On controlling for individual observed and unobserved heterogeneity and endogeneity of the relationship, our findings indicate that workers hired on a temporary basis do not enjoy the same benefits from agglomeration externalities as workers on permanent contracts. Nonetheless, the likelihood of a temporary worker switching to a permanent contract, as well as its wage premium, increases with city size, thus partially offsetting the spatial dynamics disadvantage.

Questo articolo studia le dinamiche del premio salariale spaziale per i lavoratori assunti con contratti a tempo determinato e indeterminato. Utilizziamo dati di tipo employer-employee che coprono l'universo dei lavoratori italiani giovani per il periodo 2005-2016. Dopo aver controllato per le caratteristiche osservabili e non osservabili degli individui e per l'endogeneità della relazione oggetto di studio, i risultati dell'analisi mostrano che i lavoratori assunti con contratto a tempo determinato non godono degli stessi benefici dovuti alle esternalità di agglomerazione rispetto ai lavoratori assunti con contratto a tempo indterminato. Tuttavia, la probabilità che un lavoratore con contratto a tempo determinato passi ad un contratto a tempo indeterminato, così come il suo premio salariale, aumenta con le dimensioni della città, compensando così in parte lo svantaggio spaziale dinamico.

Keywords: Urban Wage Premium, Human Capital, Fixed-Term Contracts, Spatial Sorting, Instrumental Variables Estimates.
Parole chiave: Premio salariale urbano, capitale umano, contratti a tempo determinate, sorting spaziale, stime a variabili strumentali.
JEL Classification: R10, R23, J31, J41.

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1. Introduction

The role of spatial externalities in enhancing workers' productivity and wages has been widely investigated in the theoretical and empirical literature. From a theoretical point of view, various explanations have been proposed to explain the determinants of this wage premium. On the one hand, the literature has pointed out the role of "static" agglomeration externalities (lower transport costs, technological spillover, intermediate inputs and firm risk sharing, proximity to consumer, etc.) that generate a wage premium on workers' moves to high-density cities (Kim, 1987; Ciccone and Hall, 1996; Glaeser, 1998). On the other hand, the literature has shown the relevance of "dynamic" agglomeration externalities that entail a wage premium arising over time spent in cities (Glaeser, 2006, Glaeser and Maré, 2001, De la Roca and Puga, 2017, Matano and Naticchioni, 2016). The latter may be due to "learning" externalities, since cities stimulate knowledge spillovers and enhance human capital accumulation (Glaeser, 1999, Moretti, 2004, Glaeser and Resseger, 2010), or to "matching" externalities, since the quality of job matches in cities is higher (Yankow, 2006, Helsley and Strange, 1990; Kim, 1990).

The empirical literature has analyzed the urban wage premium focusing both on average wages (Combes et al. 2008, 2012, Mion and Naticchioni, 2009, De la Roca and Puga, 2017) and on wages of workers classified by specific occupation/education levels or position in the wage distribution (Carlsen et al., 2016, Korpi and Clark, 2019, Matano and Naticchioni, 2012, 2016). Their findings suggest strong confirmation of the existence of spatial externalities, which do not entail a uniform impact along these workers' characteristics.

A dimension that has not so far been considered in the literature is the duality of the labour market. Nowadays this topic is extremely relevant due to the considerable increase in the incidence of fixed-term contracts over the last few decades in Europe, subsequent to the progressive deregulation of the labour market. The relevance of this has prompted a growing literature studying the consequences of this form of contractual arrangement on workers' and firms' productivity. The relationship with spatial externalities has yet to be analyzed. However, the channels along which spatial externalities work might not be equally effective when workers are hired with fixed-term contracts. In fact, temporary workers might not be able to accumulate as much human capital as permanent workers in cities, since firms are less prone to offer training and incentivize learning for these workers. Besides, the quality matching between workers and firms might be rather less since job changes for temporary workers may not be in response to better job offers, but to the need to find a new job due to contract expiration.

The aim of this paper is to analyze the relationship between spatial externalities and the duality of the labour market. In particular, the purpose of the analysis is to study the impact of fixed-term contracts on the dynamics of workers' gains from agglomeration and analyze the channels at work behind these impacts. We also provide suggestive evidence about static differences. Further, we will go on to address the likelihood of conversion of temporary contracts to permanent contracts in cities.

We use a unique matched employer-employee database from 1998-2016 for Italy provided by the INPS (Italian Social Security) Institute. We focus on young male workers aged between 18-35 on entering the labour market. In order to derive a timespan to reconstruct their job careers, we focus the empirical analysis on the years 2005-2016 (De la Roca and Puga, 2017). The sample consists of 16,589,176 contract-worker-year observations, for 2,221,585 workers. The unit of spatial analysis is the local labour market.

The empirical analysis is structured as follows. First, we investigate the dynamics of the spatial wage premium analyzing the return to experience accumulated in big cities (De la Roca and Puga, 2017) when workers are employed on temporary or permanent contracts. We employ an individual fixed effects strategy to control for the presence of unobserved individual characteristics that might be correlated with the likelihood of having a temporary contract (Booth et al., 2002, OECD, 2015, Lass and Wooden, 2019) or with possible sorting of workers in big cities (Combes et al. 2008, 2012). We take into account the endogeneity of the relationship between wages and spatial variables using an IV strategy and employing deeply lagged spatial variables as instruments. Second, we explore the channels (learning and matching, Wheeler, 2006) behind the dynamics of the spatial wage premium, analyzing the wage growth between and within jobs and type of contract. Third, we estimate the likelihood of transition from temporary to permanent contracts to test whether larger cities hold out better chances of getting a permanent occupation.

The findings show that the experience accumulated in the largest Italian cities is more valuable than the experience accumulated in the other cities, in line with De la Roca and Puga (2017). However, this result holds only for workers hired on an indefinite basis. For each additional year spent in the largest cities, permanent workers get a 1% extra return to experience compared to permanent workers residing in other cities. Workers hired on a temporary basis do not enjoy significant wage gains by working in big cities.[1] Moreover, on investigating the channels behind these impacts, the results show the relevance of both learning and matching externalities for

[1] We provide suggestive evidence that also static agglomeration benefits in the largest Italian cities (Rome and Milan) are lower when workers are hired on fixed-term contracts (-1.2%). Consequently, the wage gap between temporary and permanent workers is wider in big cities.

permanent workers, while for temporary workers mild evidence of an on-the-job learning premium is detected. Further, and interestingly, in Rome and Milan, and more in general in higher density cities, there is a higher wage premium when a worker moves on from a temporary to a permanent contract, as well as a higher likelihood of contract conversion.

Overall, these results provide further evidence on the heterogeneous effects of spatial externalities. In particular, they show how, on the one hand, the benefits from agglomeration externalities are reduced when workers are hired on fixed-term contracts. This is a relevant finding considering the high percentage of young workers hired on this form of contract.[2] On the other hand, they show that this disadvantage is (at least) partially offset should the workers get a permanent contract.

The paper is structured as follows. Section 2 introduces the literature reference and the Italian institutional setting. Section 3 describes the data. Section 4 presents the empirical specification, while Section 5 presents the results. Section 6 concludes.

2. Related Literature and Italian Institutional Setting

2.a Related Literature

The spatial economic literature has extensively investigated the urban wage premium. From a theoretical point of view, the driving mechanisms can be classified into static and dynamic (Glaeser and Marè, 2011, Duranton and Puga, 2004, De la Roca and Puga, 2017). Urbanization externalities in terms of reduced transport costs, technology spillovers, firms' proximity to consumers and cheaper inputs are static mechanisms since they contribute to generating a wage premium that arises immediately on a worker's move to a city (Kim, 1987; Ciccone and Hall, 1996; Glaeser, 1998). On the other hand, learning externalities due to faster human capital accumulation in cities, and matching externalities, due to higher efficiency of the matching process between workers and firms, are dynamic mechanisms since they contribute to generating wage premium over time spent in cities (Wheeler, 2006, Glaeser and Marè, 2011, Duranton and Puga, 2004).

The empirical evidence has widely confirmed the existence of the urban wage premium, focusing generally on average wages (Combes et al. 2008, Mion and Naticchioni, 2009, Glaeser and Marè, 2001). More recently, some studies have considered the heterogeneity of the urban wage premium according to specific workers' characteristics such as education and skill levels (Matano and Naticchioni, 2016, Carlsen et al. 2016, De la Roca and Puga, 2017, Korpi and Clark, 2019). Their findings have shown that high-skilled workers are able to reap greater benefits from

[2] According to Eurostat in 2016, 55% of workers aged 15-24 are employed on a temporary contract, while the figure comes to 24% for those aged 25-34, and 14% for workers aged 15-64.

agglomeration economies from both the "static" and "dynamic" point of view (De la Roca and Puga, 2017, Matano and Naticchioni, 2016). Low-skilled workers still benefit from agglomeration economies, but to a lesser extent. Moreover, their gains mostly accrue from higher human capital accumulation in cities (Matano and Naticchioni, 2016). Furthermore, these studies also highlight the relevance of the sorting of workers and firms in agglomerated areas, which capture part of the impact imputed to spatial externalities.

So far, no studies have considered the duality of the labour market. This topic is important since the 1980s and 1990s saw fairly drastic deregulation of fixed-term contracts, which led to a massive adoption of this form of contractual arrangement in many European countries. In particular, according to the OECD, in Italy the percentage of workers employed on temporary contracts rose from 8.5% in 1998 to 14% in 2016, in line with the EU28 average (14.2%). Moreover, the incidence proved all the higher the lower the age group considered, reaching 55% in the case of the very young workers (15-24).

Firms may choose to adopt fixed-term contracts for different reasons. They allow firms to be more flexible and to adjust to changes in demand without incurring adjustment costs. Adoption of this kind of contract is in fact stimulated by increase in firing costs for the firm (Cao et al., 2011). Furthermore, they allow for screening of workers, and firms are thus able to select only the most productive workers for open-end contracts (Nielen and Schiersch, 2016). They may also be offered when the firm is dealing with an initially low or unknown quality job match, while in the case of an initially high quality match the firm may be more inclined to offer a permanent contract (Cao et al., 2011).

The empirical literature has widely investigated the effects of adoption of fixed-term contracts on the workers' wages and the firms' productivity. The overall findings have proved somewhat ambiguous. Some studies have shown negative effects on workers' and firms' productivity (Dolado and Stucchi, 2008, Addessi, 2014, Cappellari et al. 2012, Boeri and Garibaldi 2007), while others have shown that the productivity gap between temporary and permanent workers actually remains negligible (Nielen and Schiersch, 2016, Garnero et al., 2016). Other papers have focused on the wage gap between fixed-term and permanent workers, showing general penalization for fixed-term workers (Dias da Silva and Turrini, 2015, Picchio, 2006, De la Rica, 2004, Hagen, 2002, Booth et al. 2002).

As for the connection between spatial externalities and the duality of the labour market, to the best of our knowledge there are as yet no theoretical frameworks addressing this issue. Nonetheless, it is possible that the benefits from agglomeration externalities are dampened when workers are hired on fixed-term contracts since some of the channels through which spatial externalities occur might not work efficiently. In fact, in cities the quality of the match between workers and firms is superior due to the higher number of matches (Duranton and Puga, 2004). However, while for permanent workers job-to-job shifting is generally the case with the availability of a better job offer, for temporary workers this might not apply. They could be obliged to accept an offer below their expectations due to the expiration of their contract; in turn, this decreases the likelihood of a good quality match. As a consequence, temporary workers might not enjoy the wage premium deriving from the higher quality of job match in cities. Also, the learning channel might not work well. In cities, human capital accumulation is faster (Glaeser and Resseger, 2010) because of knowledge spillovers and face-to-face interactions. However, there may be fewer learning opportunities for temporary workers because firms have less incentive to provide training to workers employed with this type of contractual arrangement (Arulampalam et al. 2004, Booth et al. 2012, Shire et al., 2009). Investment in human capital formation is only profitable for firms in the long run (Nielen and Schiersch, 2016). Also, the matching and learning mechanisms might be linked since the lower propensity of the firms to invest in human capital accumulation could be directly related to the low quality of the job-match of temporary workers (Akgunduz and Van Huizen, 2015).[3] These theoretical insights may possibly imply heterogeneous impacts of spatial externalities on temporary and permanent workers.

2b. Italian Institutional Settings

As far as the institutional setting is concerned, Italy has implemented several labour market reforms that have led to increased adoption of fixed-term contracts by firms. These contracts are characterized by lower hiring and firing costs, thus enabling the firms to ease adjustment to changes in economic conditions.

Fixed-term contracts were introduced in 1962 (law 230/1062) as an exception to the regular permanent contract. The circumstances in which they could be used were very strictly defined (replacing workers on leave, seasonal jobs or special activities with limited duration) and consequently adoption of this form of contract was very limited at the time. In 1997, an initial reform was brought in with the Treu law (196/1997), which liberalized apprenticeships and fixed-term contracts and regulated collaboration contracts. New rules were introduced for the extension of fixed-term contracts beyond their set limits.[4]

[3] It is nonetheless worth noting that the learning channel might also work more efficiently for temporary workers. In fact, knowledge spillovers in denser areas could be higher since higher labour turnover increases the diffusion of knowledge (Duranton and Puga, 2001).

[4] In particular, the contract could be extended beyond its legal limit for a maximum of 20 days for contracts with periods shorter than 6 months (30 days for longer periods) with higher wages. Also, a new fixed-term contract

In 2001, another major reform (decree 368/2001) further eased restrictions on fixed-term contracts and in particular abolished the specific “reasons” to use this kind of contract, introducing a single generic reason of a “technical, organizational, production or replacement nature”, which was to be written in the contract. Thus, the circumstances under which a firm could hire a worker on a temporary contract significantly increased. The aim was to allow firms to respond rapidly to changes in economic circumstances. Also, the law established that quantitative limits on the percentage of workers a firm could hire on a temporary contract should be regulated through collective agreements. Moreover, the maximum length of the fixed-term contracts was established to be no more than 36 months. The initial contract could be renewed only once if it was for a duration of less than 36 months, and the total duration of the contract (initial and extension) could not exceed this limit. The rest of the conditions remained the same with regard to the possibility of extending the contract for a short period of time beyond its limits (10/20 days depending of the initial duration of the contract) and the possibility to make another contract after a minimum spell of no contract (10/20 days). Finally, the Biagi Law (law 30/2003) made a number of changes in the national legislation, introducing new additional forms of atypical contracts and reforming in particular the apprenticeship contract.[5] To come into force, the latter two reforms (2001 and 2003) had to wait for the renewal of collective agreements for each industry, which took place in the subsequent years starting from 2005 (Cappellari et al. 2012). More recently, the Poletti reform (decree 34/2014) abolished the need to justify the fixed-term contracts and extended the possibility of renewal up to 5 times. The maximum length of fixed-term contracts remained set at 36 months, while the “Dignità” decree (decree 87/2018) shortened the length of fixed-term contracts and the maximum number of renewals.

3. Data description

We use administrative employer-employee panel data for the universe of Italian workers employed in the private sector, provided by the Italian Social Security Institute (INPS). These are worker-contract-year observations with information on several characteristics of workers such as age, gender, occupation, workplace, employment contract (part-time/ full-time and temporary/permanent), real gross yearly wage, and number of weeks worked. For firms, there is information on the plant location (province), the size (number of employees), and the sector. We focus the analysis on 2005-2016, but we use data going back as far as 1998 in order to reconstruct

could be signed after a minimum of 10 days from the expiration of the previous one should its duration be no longer than 6 months (20 days for longer periods). If the firm failed to comply with these restrictions the contract was converted into a permanent one.

[5] For an excellent review see Tealdi, 2011.

the workers' employment history (similarly to De la Roca and Puga, 2017).[6] As units of analysis we focus on young male full-time[7] workers aged between 18-35[8] when they entered the labour market (no earlier than 1998) and employed in the private sector, in order to reconstruct complete work histories. Also, the analysis is carried out considering workers on standard labour market contracts (blue-collar, white-collar and managers). We delete outlier observations with null or negative wages, and we eliminate observations with wages higher (lower) than the 99th (1st) percentile of the real wage distribution. We end up with a database made up by 16,589,176 observations for 2,221,585 individuals. As main dependent variable we use the real weekly wage in euro, with wages deflated using the Italian CPI (base year 2014).[9]

As spatial unit of analysis we use the Local Labour Market (LLM),[10] which can be assimilated to a metropolitan area, exploiting information on 610 LLMs in Italy.[11] We focus our analysis on the first two major Italian cities (Rome and Milan, RM) and the four other most populated LLMs (Naples, Turin, Palermo and Bologna, NTPB).[12] We also use the population density to estimate average spatial effects, with data going back to 1921 to construct the instrument for the IV analysis.

Table 1 shows the descriptive statistics of the variables of the empirical analysis for all workers and separately for temporary and permanent workers from 2005 to 2016. Panel A presents the statistics for all cities, Panel B for Rome and Milan, while Panel C considers the other four largest Italian cities.

On average, observations for temporary contracts constitute around 23% of the total sample observations, a percentage that is slightly lower in the largest Italian cities. In terms of individual and firm characteristics, Panel A of Table 1 shows that on average workers in the sample are 30 years old, younger when hired on temporary contracts (27). The average experience[13] is 5.6 years, significantly lower in the case of temporary contracts (2.8), as expected. Moreover, fixed-term contracts are found mostly in the larger firms. As far as occupation is concerned, workers hired on

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[6] The year choice is motivated by the fact that data on temporary contracts was first collected by INPS in 1998. Therefore, we are able to reconstruct the complete experience of workers on temporary or permanent contracts starting from 1998.
[7] Part-time workers have been converted into full-time equivalent workers.
[8] The choice of focusing on the young workers is due to the fact that this is the age group most affected by the introduction of fixed-term contracts, as pointed out in the introduction. Also, we do not consider women, as is standard practice in this literature, since their wage dynamics are often affected by noneconomic factors (Topel, 1991, Mion and Naticchioni, 2009, De la Roca and Puga, 2017).
[9] FOI (*Indice dei Prezzi al Consumo per le Famiglie di Operai e Impiegati*) index.
[10] Throughout the paper we will use the terms LLM and city as synonyms.
[11] The LLMs in Italy number 611. We exclude the small LLM of Buddusò (Sardinia), because we do not have the data for the instrument available.
[12] In particular, in 2011 the LLMs of Rome and Milan accounted for an average of 3,582,336 individuals. The four other largest LLMs (Naples, Turin, Palermo and Bologna) accounted for an average of 1,493,038 individuals, while the rest of the Italian LLMs had an average of 76,523 individuals (2011 Population and Housing Census Commuting data, ISTAT).
[13] Experience is calculated in months and converted into years.

a temporary basis are relatively employed more in blue collar occupations with respect to those hired on a permanent basis. In the largest Italian cities (Panel B and C of Table 1), there are no significant differences with respect to national averages as far as age and experience are concerned. Significant differences arise when we take into account the occupation distribution and the average firm size. As for the former, it is possible to observe that the percentage of blue collar occupations decreases with increase in the size of the cities, while the percentage of white collars and managers increases accordingly. As for the latter, as expected, the larger the city, the larger proves the average firm size. The highlighted differences between temporary and permanent workers remain the same for all the cities. Considering our main variable of interest, the real weekly wage, the average real weekly wage is 457 euro, which drops to 369 euro in the case of temporary contracts and rises to 484 euro for permanent contracts, thus revealing an average raw wage gap of 31% between temporary and permanent workers. In Rome and Milan, the average wages are higher for workers employed in both temporary and permanent contracts. Also, the wage gap between temporary and permanent workers is wider (51%). The values for the four other largest cities in terms of wages and wage gap are close to the average of Italian cities.

[Table 1 around here]

4. Empirical Strategy

In this section we present the empirical analysis, which consists of three parts. First, we analyze the dynamics of the wage premium in big cities, considering workers' wage trajectories when employed on temporary and permanent contracts. Building on De la Roca and Puga (2017), we estimate the following regression equations:

$$ln(w_{i(c),t}) = \alpha_1 + B^{'} * Char_{i,t} + \beta * Firmsize_{i,t} + \gamma_1 * ExpTemp_{i,t} + \gamma_2 * ExpPerm_{i,t} + \gamma_3 * ExpTempRM_{i,t} + \\ + \gamma_4 * ExpPermRM_{i,t} + \gamma_5 * ExpTempNTBP_{i,t} + \gamma_6 * ExpPermNTBP_{i,t} + \tau_c + \varphi_s + \delta_t + \varepsilon_{i,t} \quad (1)$$

$$\hat{\tau}_c = \alpha + \lambda * \log\_pop\_densit\, y_c + u_c \quad (2)$$

where i stands for individual, c for city, s for sector and t for time.

The dependent variable, $ln(w_{i(c),t})$ is the logarithm of the real weekly wage. $Char_{i,t}$ represents the individual control variables, i.e. occupation dummies (blue collars, white collars and executives) and a dummy for being employed on a temporary contract. $Firmsize_{i,t}$ stands for the logarithm of the firm size. The experience variables are our variables of interest, since their returns provide an estimation of the dynamic spatial wage premium. Following De la Roca and Puga (2017), we introduce in the estimation variables capturing both generic experience, and experience acquired in the largest Italian cities (RM and NTBP). In order to capture the heterogeneity between contracts typologies, workers' experience is considered separately for the years spent working on temporary or permanent contracts: $ExpPerm_{it}$, $ExTemp_{it}$ $ExpPermRM_{it}$, $ExTempRM_{it}$ $ExpPermNTBP_{it}$ and $ExTempNTBP_{it}$. We insert linear as well as quadratic terms for the experience variables, in order to take into account possible non-linearity in the relationship analyzed.[14] Finally, τ_c, φ_s, δ_t are respectively city (610 LLMs), sector (Ateco91, 2 digit-level) and time dummies. Standard errors are clustered at the local labour market level. As standard in the spatial economic literature (Combes et al., 2008), we carry out this estimation in two-steps, in the second step regressing the city fixed effects retrieved in the first step on the time-averaged city population density to get an estimation of the static urban wage premium for young workers.[15]

This estimation might be biased for several reasons. First, there might be sorting of workers into temporary contracts due to unobservable worker characteristics. To address this issue, we will apply (individual) fixed-effect estimates able to control for individual time invariant unobserved heterogeneity that might be correlated with the likelihood of holding a temporary contract (as in Booth, 2002, OECD, 2015, Lass and Wooden, 2019).[16] Also, fixed-effect estimations will allow us to take into account the possible sorting of higher (unobservable) skilled workers in big cities.[17] Second, there might be endogeneity due to simultaneity between wages and location choices. We apply an IV strategy using the level of population density in 1921 as instrument (Combes et al., 2008, 2010, Mion and Naticchioni, 2009, Matano and Naticchioni, 2012). The intuition is that deeply lagged levels of population density are correlated to the current levels of spatial variables, but they are assumed not to influence productivity and wages today.

[14] For the sake of presentation, the quadratic terms are not included in the equation specification, but always included in the estimation.

[15] We do not distinguish the static wage premium by type of contract. Nonetheless, we will also carry out estimates providing evidence on the difference in the spatial static wage premium between temporary and permanent workers.

[16] In fact, temporary workers might self-select into fixed-term contracts as in the case of less productive workers being more likely to be employed on fixed-term contracts and thus characterized by lower salaries. On the other hand, according to the Loh's (1994) model, it could even be the ablest workers that are more likely to accept a fixed-term contract, since their probability of being fired at the end of the contract period is lower.

[17] Using a fixed effect strategy means that identification of the city fixed effects is based on the sample of migrants. This might be a source of concern for correct estimation of city fixed effects. In particular, having controlled for observable and unobservable (time-invariant) worker characteristics, there might be a bias in the estimation whenever some time-variant unobservable characteristics of workers are correlated with the error term in equation (1) – such as an attractive wage offer in another city. Nonetheless, as pointed out in De la Roca and Puga (2017), even if people migrate only when they receive a high wage offer, as long as these wage offers have similar impact on moves to bigger and smaller cities, this bias may be small if migration flows across different sized cities are fairly balanced. This seems to be borne out in our case. Migrations to Italy's six main local labour markets (Rome, Milan, Naples, Bologna, Turin, Palermo) account for 266,522 observations, while migrations out of these cities account for 255,990, thus showing a balance between movements from and to the largest Italian cities. On the other hand, note that the estimation of the dynamic spatial effects, given by the returns to experience, uses all sample information.

For a better understanding of the results of this first estimation, we proceed by analyzing whether dynamic wage gains occur as a result of better on-the-job learning or more efficient job-matching process in cities. To carry out this analysis, we investigate the wage growth dynamics associated with individual jobs and job changes for each contract typology (Wheeler, 2006). More specifically, we compute between job wage growth as the difference between the (log) starting wage of a new job and the (log) final wage of the job that preceded and within job wage growth as the difference between the (log) final wage and the (log) initial wage of each specific job.[18] We obtain six variables capturing the wage changes across and within jobs according to the following statuses: within job wage growth when on a permanent or temporary contract, between jobs wage growth when moving on from one permanent contract to another, from a temporary to another temporary contract, from a temporary to a permanent contract and from a permanent to a temporary contract. Thus these components reflect both the wage growth associated with individual jobs and job changes for each specific contract, and the wage growth associated with switching kind of contract; to the best of our knowledge, this represents a novelty in the literature.

We regress the wage growths alternatively on the big city dummies and on city density, applying the same IV two-step methodology shown in the previous specification. In this way we can understand whether spatial dynamics gains are driven by higher on-the-job wage premia, thus providing evidence of learning externalities, or by job change wage premia, thus suggesting positive matching externalities. More specifically, we estimate the following equations:

$$WG_{i,j,t} = \alpha_1 + B' * Char_{i,j,t} + \beta * Firmsize_{i,j,t} + dRM_{i,j,t} + dNTBP_{i,j,t} + \varphi_s + \delta_t + \varepsilon_{i,j,t} \tag{3}$$

$$WG_{i,j,t} = \alpha_1 + B' * Char_{i,j,t} + \beta * Firmsize_{i,j,t} + \tau_c + \varphi_s + \delta_t + \varepsilon_{i,j,t} \tag{4}$$

$$\hat{\tau}_c = \alpha + \lambda * \log\_pop\_densit\, y_c + u_c \tag{5}$$

where subscripts and control variables remain the same as in the previous specification. Among the individual control variables we now include the individual fixed effects retrieved from the estimation of equation (1) in order to take into account workers' unobservable skills, and the (log) wage at the beginning of the job for within (between) wage growth. $WG_{i,j,t}$ represents in turn one of

[18] To carry out this part of the empirical analysis we follow the estimation strategy proposed in Wheeler (2006). In the first specification, Wheeler divides the wage growth components by the time elapsed within/between spells, and rescales them in annual terms. However, as he points out, the within job wage growth component computed in this way has the shortcoming that very short-lasting jobs (reported in annual terms) have the same weight in the estimation as long-lasting jobs. For the between components, the pitfall is that two different weights are given to jobs changes when the time spent between one job and another is different, whereas ideally they should count the same. For this reason, we adopt the second specification suggested in Wheeler (2006) where (log) wage changes are used. Nonetheless, we have also checked our results applying Wheeler's first original specification with similar results, available upon request.

the six wage growth components descripted. Equation (3) shows the estimation focusing on the largest Italian cities ($dRM_{i,j,t}$ and $dNTBP_{i,j,t}$ are dummies for being in Rome/Milan and in the other four largest cities respectively), while equation (4) and (5) show the two-step estimation using population density, to gauge average spatial elasticities. In the estimates of the between wage growth the occupation dummies and the firm size are related to the new job, while for the within wage growth they are set at the end of the job (as in Wheeler, 2006).[19]

The last part of the empirical analysis investigates the relationship between city size and the conversion rates from fixed-term to permanent contracts. The aim is to understand whether there is a higher likelihood in cities that fixed-term contracts represent a stepping-stone towards a steady position in the labour market. For this analysis we consider both all the workers' individual transitions from temporary to permanent contracts and only transitions out of the first temporary contract held when the worker enters the labour market beginning from 1998 (as in Petrongolo and Guell, 2007). We estimate the following equations:

$$P(Perm_{i,t} / Temp_{i,t-1}, X_{i,t-1}) = \alpha_1 + B' * Char_{i,t-1} + \beta * Firmsize_{i,t-1} + \gamma_1 * dRM_{i,t-1} + \gamma_2 * dNTBP_{i,t-1} + \\ + \varphi_{s(t-1)} + \delta_{t-1} + \varepsilon_{i,t-1} \qquad (6)$$

$$P(Perm_{i,t} / Temp_{i,t-1}, X_{i,t-1}) = \alpha_1 + B' * Char_{i,t-1} + \beta * Firmsize_{i,t-1} + \tau_{c(t-1)} + \varphi_{s(t-1)} + \delta_{t-1} + \varepsilon_{i,t-1} \qquad (7)$$

$$\hat{\tau}_c = \alpha + \lambda * \log(pop\_density_c) + u_c \qquad (8)$$

where $Char_{i,t-1}$ includes the individual and contract control variables (occupation dummies, worker skill level[20], the spell length and the workers' starting wage), $Firmsize_{i,t-1}$ is the log firm size, and $dRM_{i,t-1}$ and $dNTPB_{i,t-1}$ are the dummies related to the workers being located in Rome or Milan, and in Naples, Turin, Palermo and Bologna. All covariates refer to the spell on temporary contract. As in previous estimates we also assess the average spatial effects. Thus, we estimate the same regression equation (eq. 7) introducing city fixed effects which, in the second step, we regress on the (log) city density using an IV methodology (eq. 8). We estimate linear probability models with standard errors clustered at the local labour market level.

5. Results

5.1 Dynamic spatial wage premium

Table 2 presents the results of the dynamics wage premium arising from working in big cities. The full specification shown in equation 1 and 2 is presented step-by-step. We first carry out a simple

[19] The results are very similar setting the covariates in the starting job for the between wage growth, and at the beginning of the job for the within wage growth.

[20] Proxied by the fixed effects retrieved from estimation of equation 1.

OLS regression controlling for the individual and firm characteristics (column (1)). The results show an elasticity of wages with respect to generic experience of 5.5%, with a concave pattern. Also, workers employed on temporary contracts suffer a wage penalization of 8.8% with respect to those employed on permanent contracts. The other covariates have the expected signs: both white collars and managers have higher wages than blue collar workers, and wages increase with firm size. Considering the average of the city fixed effects for the main cities, it can be seen that workers employed in Rome or Milan get a static wage premium of 4.6% with respect to the average of Italian cities.[21] The wage premium in the four other largest cities is null due to negative fixed effects for the two Southern cities included in the sample (Naples and Palermo, -3.1%), which counterbalance those for the other two largest cities in the North (+2.7%), a finding that reflects Italy's North-South division whereas wages are significantly higher in the North than in the South. Turning to the second step estimation (Panel B of Table 2), the average static wage premium is 0.6%, but not statistically significant.

Column (2) of Table 2, shows the same estimation distinguishing experience when employed on temporary or permanent contracts. The results show that returns to general experience are not homogeneous across kinds of contracts. In fact, temporary workers enjoy higher (decreasing) returns to experience (6.4% per year) than permanent workers (4.1% per year). This finding is somewhat in line with a theory of compensating wage differential (Rosen, 1986) since over time the wage gap between temporary and permanent workers decreases.[22] It is also consistent with the findings in Booth et al. (2002). As for the other variables, the results remain similar to those in column (1). The only difference is that the wage penalization for temporary workers is now heavier, standing at 10.5%, indicative of the fact that the previous results had been incorporating the heterogeneous impact of experience.

Column (3) of Table 2 shows the OLS estimates of the full specification of equation 1, when experience in the largest Italian cities is also included. Other interesting findings emerge. The return to experience acquired in big cities for temporary workers is negative (-1.9% for Rome and

[21] Fixed effects are centered around their mean.

[22] According to the theory of compensating differentials, temporary workers should have higher wages than permanent workers as risk premium for their form of contractual arrangement. In Italy this is not the case, since on average they earn less than permanent workers, as in many other countries. Nonetheless, the wage gap over time shrinks, thus partially offsetting the starting wage disadvantage. The result arrived at could also be analyzed considering the average experience for temporary and permanent workers. Indeed, experience in temporary contracts is on average lower than the experience of permanent workers (as well as the standard deviation). Since the wage profile is expected to be steeper at the beginning of the worker's career, this might justify the difference in return to experience across workers' contracts. When computing standardized beta coefficients, we get a value of 0.14 for experience on temporary contracts and 0.34 for experience on permanent contracts, showing that an increase of one unit in the standard deviation of experience implies a higher increase in units of standard deviations of log wages when the experience is acquired on a permanent contract.

Milan and -1.7% for the four other largest cities, both convex), suggesting that for temporary workers returns to experience in big cities are lower than in average-sized cities. As for permanent workers, the findings show that in larger cities returns to experience are higher than in average-sized cities, in line with the previous empirical analyses (De la Roca and Puga, 2017, Matano and Naticchioni, 2016, Carlsen et al., 2016).[23] However, this effect is found only for the two largest Italian cities, Rome and Milan (+1.3%), while in the case of the four other largest cities the impact does not appear to be significant. This might again be due to the North-South division of Italy, as we will shortly show. As for the average city fixed effects, including the dynamic benefits in big cities, a drop can be seen in the static wage premium for Rome and Milan (which now stands at 2.7%), in line with De la Roca and Puga (2017). Hence, previous estimations of city fixed effects were partly capturing the dynamic benefits generated over time spent in big cities. Nonetheless, the average elasticity with respect to density (column (3), panel B) remains similar to previous estimation, 0.6%, again not statistically significant. Column (4) shows the fixed effects estimates of the full specification of equation 1 and 2. When taking into account worker sorting on unobservable characteristics, returns to experience are in general higher for workers employed on both temporary (+10.3%) and permanent contracts (+5.1%). In big cities the return to experience for workers hired on a temporary contract is now insignificant, suggesting negative sorting of temporary workers over time in space. For permanent workers there is a slight reduction (+1% per year in Rome and Milan). Moreover, the wage penalization for temporary workers falls to 7%, suggesting negative worker sorting also in the case of temporary contracts. The results for the city fixed effects show an average wage premium of 2% for permanent workers for being located in Rome or Milan, while again the average wage premium for being located in the four other largest cities is negligible (0.5%) and highly heterogeneous between Northern and Southern cities.[24] The second step confirms the previous results with an elasticity of wages with respect to city size of 0.8%, which is now statistically significant.[25] Finally, in column (5) of Table 2 we attempt to

[23] In Matano and Naticchioni (2016), returns to experience on average wages in the provinces of Rome and Milan are slightly higher (2%). Also, some wage gains in other major provinces of Italy are detected. These differences might be related to the sample considered (young vs all workers), the spatial unit of analysis (local labour market vs provinces) and the time period analysed (2005-2016 vs 1986-2003).

[24] We tried to detect whether the insignificant experience effect for the four other largest cities might be due to the influence of the two Southern cities included in the group, reflecting Italy's spatial North-South division. Therefore, we again ran the estimation of Table 2, column (3), excluding the Southern cities (Naples and Palermo) and found positive impacts for the experience had also in Turin and Bologna. This result applies to both temporary and permanent workers, with temporary workers showing strong concavity that implies lower returns than permanent workers after one year of experience (Table A1 in the Appendix).

[25] We also perform the estimates for columns (1) to (4) of Table 2 using a one-step strategy, rather than a two-step strategy to check the robustness of our findings. The results are shown in Table A2 in the Appendix and remain strongly consistent with the result using a two-step strategy. Besides, since the firm size might be considered a "bad" control, in the vein of Angrist and Pischke (2009), we replicate estimates of Table 2 excluding firm size from the analysis. The results remain confirmed (Table A3 in the Appendix).

provide some insights regarding the static spatial wage premium for temporary workers in the Italian largest cities. To this end, we interact the dummy for temporary contracts with the dummy for the largest cities and check whether these coefficients are statistically significant. Since in fixed effects the identification of these effects is based on a specific subsample of our observations[26], we claim only suggestive evidence about static effects. The results show that the wage difference between permanent and temporary workers is larger in the big cities. In particular, being in Rome or Milan further decreases the wage of a temporary worker with respect to a permanent worker by 1.2%. Combined with the average of city effects, this means that while a permanent worker on average has a static wage premium of 2.3% for working in Rome or Milan, the corresponding premium is 1.1% for a worker employed on a temporary contract. To clarify the picture, we plot these results (column (5) of Table 2) for workers when hired on a permanent (Figure 1) or a temporary contract (Figure 2). More specifically, in each figure we consider two identical workers differing only in terms of the city where they are employed (always remaining in Rome or Milan, or moving to Rome or Milan after two years of working experience) and we plot their earning premium over a five-year horizon with respect to a hypothetical individual with the same experience but throughout his/her career residing away from the main cities. The intercept represents the static wage premium (the average fixed effects of Rome and Milan) for each category of workers, which comes to 2.3% for a permanent worker (Figure 1) and 1.1% for a temporary worker (Figure 2). Over time, for workers hired on a temporary contract (Figure 2) the wage gap between those working in the largest cities and those working in other cities remains stable: the dynamic urban wage premium for this category of worker is insignificant. Hence, a worker with a temporary contract who moves to Rome or Milan gets only the static spatial wage premium. On the other hand, the spatial wage gap for a worker hired on a permanent contract (Figure 1) increases over time, due to the extra-valuable experience acquired in big cities. As a consequence, after five years the wage gap between two workers hired on a permanent contract but always living in different cities (Rome or Milan with respect to an average size city) is around 6%. Further, the worker moving to Rome or Milan after two years does not reach the same wage profile as that of the worker who has always resided in these cities because only after moving does he/she begin to accumulate extra valuable experience. Nonetheless, after spending three years in Rome or Milan his/her wage premium will be almost 5%.

[26] In particular, in fixed effects the temporary dummy is identified only for those workers who switch kind of contract at least once. The interaction effects are identified for those who have a temporary contract and move across cities and for those who change contract and stay in a large city for some time, holding a temporary contract. We also carried out general estimates separately for temporary and permanent workers to check the results on the static spatial wage premium. The results are shown in Table A4 in the Appendix and confirm the findings of column (5) of Table 2.

[Table 2 around here]

[Figure 1 and 2 around here]

5.2 Channels analysis

In this section we present the estimates of the impact of the spatial variables on the individual wage growths shown in specification equations (3) to (5). The purpose is to understand whether the spatial wage premium is driven by learning externalities (within-job wage growth) or by better quality job matches between workers and firms (between-job wage growth) or a combination of the two. We also seek to detect whether cities increase the wage premium associated with contract conversion. Table 3 shows the results.[27]

Panel A of Table 3 shows the results for the large cities. As for Rome and Milan, we can see that the dynamic gains previously detected for permanent workers are driven by both learning externalities and a better quality job matching, since both within-job and between permanent jobs wage growths are significantly higher in these cities (+5% and +3.7% in columns (1) and (3) respectively). As for the temporary workers, and in line with the previous results, we do not detect any clear advantage in switching across temporary jobs in Italy's largest cities (column (4)), while we find evidence of a positive, small within-job wage growth effect (+0.7% in column (2)). Considering the wage change across kinds of contracts, interestingly enough, in big cities the earning premium on moving on from a temporary to a permanent contract is on average 4% higher than in other cities (column (5)).[28] This means that even if the wage gap between temporary and permanent workers tends to get larger over time working in big cities, workers hired on a temporary contract have a higher reward when they switch to a permanent contract.[29] As for the four other largest cities and in line with the previous results, we failed to detect any clear dynamic advantage of residing in these cities with respect to cities of other sizes. As before, this is due to the effect of the Southern cities.[30] In Panel B of Table 3, we show the results using city density as main independent variable to check for average patterns with respect to city size. The results remain

[27] As for the descriptive statistics, within-job wage growth, both temporary and permanent is on average 5%, while the between permanent-permanent and temporary-permanent wage growth is on average 7%. The average between temporary-temporary wage growth is 2.4%, while the between permanent-temporary is 1.8%.

[28] There is also evidence of a wage premium when passing from a permanent to a temporary contract (2.1%, column (6)). In this respect, it is worth noting that the average wage growth when going from a permanent to a temporary contract (1.8%) is significantly lower than when going from a temporary to a permanent contract (7.1%). Hence, in absolute terms the spatial impact is significantly higher for workers who get a stable contract.

[29] In the estimates presented for the between components we also include workers who move into or out of cities during the contract change. As a robustness check we run the same estimation excluding these workers. The results remain consistent and are available upon request.

[30] When replicating the estimates excluding the Southern cities, for Turin and Bologna we detect patterns similar to those for Rome and Milan (Table A5 in the Appendix).

consistent with those shown for the Italian largest cities: with increase in city density, there is evidence of higher within- and between-job wage growth for permanent workers, higher but small within-job wage growth for temporary workers and higher wage premium for workers moving on from a temporary to a permanent contract.

[Table 3 around here]

Overall, the results of this section confirm that dynamic spatial wage gains mainly occur for workers on stable contracts, who enjoy the benefits generated by both learning and matching externalities, while workers on fixed-term contracts do not get the same benefits. Nonetheless, they enjoy a spatial wage premium once they succeed in getting a permanent contract.

5.3. Analysis of conversion rate from fixed-term to permanent contracts

The analysis has so far shown that the use of temporary contracts reduces the spatial wage benefits accruing over time spent in cities. In this section we analyze the conversion rates to understand whether the possibility of getting a permanent contract is higher in larger cities. As pointed out in the methodology section, we focus both on all the workers' individual transitions from temporary to permanent contracts and on the transitions out of the first temporary contract held when they entered the labour market beginning from 1998 (Petrongolo and Guell, 2007). The analysis considers 2,862,129 spells of temporary contracts, 632,556 of which in Italy's two biggest cities (Rome and Milan) and 295,331 in the four other largest cities in Italy.[31] Table 4 shows descriptive statistics on the overall rate of conversion of temporary contracts, by spell length, in all cities and by city size. The maximum spell of a temporary contract in Italy is no longer than 3 years.[32]

On the top panel in Table 4 it can be seen that 46% of workers on a temporary contract end up with (at least a month of) non-employment. Around 24% end up with another temporary contract, while 30% end up with a permanent contract. When assessing these conversion rates across cities there is no particular difference for the four other largest cities compared to an average sized city, while in Rome and Milan the percentage of new temporary contracts rises to 27%, compensating for a decrease in the percentage of those ending up in a period of non-employment (42%). Considering temporary spell lengths, it can be seen that the longer the spell, the greater is the probability for the worker to get a permanent contract, rising from 19% when the temporary contract lasts less than 7 months to 68% when it lasts more than 18 months. Conversely, the spell in non-employment decreases significantly: from 57% when the contract lasts less than 7 months to

[31] When taking into account only the first job spell, the analysis considers 781,629 individual job spells, of which 199,013 in Rome and Milan, and 80,981 in the other four largest cities.
[32] We drop 0.35% of observations where the contract spell is longer than 37 months.

around 17% when it is longer than 18 months. Also, the percentage of new temporary contracts decreases over spell lengths (from 24% to 15% respectively). These patterns do not appear to differ significantly across cities.

[Table 4 around here]

Table 5 shows the results of estimation of the probability of conversion from temporary to permanent contracts. Column (1) in Table 5 shows that in Rome and Milan there is a higher likelihood of conversion (+2.9 percentage points). For the four other largest cities we do not find any significant evidence, much as was the case with the previous outcomes.[33] The same finding emerges when considering the probability of transition out of the first job spell in the individual work history (column (3), +2.8pp). Column (2) and column (4) in Table 5 (panel B) show the two-step estimates using the log city density. In line with the outcome for the largest cities, the results show that, on average, corresponding to the increase of city density is a higher conversion rate from temporary to permanent contracts (coefficient estimates of 0.033 for all spells and 0.026 for the first job spell). Hence, the likelihood of getting a permanent contract for temporary workers increases with city size.

[Table 5 around here]

Conclusions

In this paper we have analyzed the relationship between spatial externalities and the duality of the labour market. In particular, we have analyzed the dynamics of the spatial wage premium for workers employed on temporary and permanent contracts, as well as the driving channels. Moreover, we have examined the impact of spatial variables on transition rates from temporary to permanent contracts. The findings point to the following conclusions. First, workers employed on temporary contracts do not enjoy the same spatial benefits as permanent workers. More specifically, the dynamic advantages that arise over time spent in big cities accrue only for permanent workers through both learning and matching positive externalities. For temporary workers there is only mild evidence of learning externalities in big cities, thus suggesting that temporary workers have less ability to take advantage of the dynamic advantages arising in larger cities. Nonetheless, the greater the city size, the higher will be the wage premium related to the transition from temporary to permanent contracts, thus partially offsetting the spatial disadvantage. Further, the likelihood of conversion of a temporary to a permanent contract is also

[33] Also in this case this is due to the Italian North-South division, since when excluding the Southern cities of Naples and Palermo we do find positive and significant impacts (see Table A6 in the Appendix).

higher in larger cities. Hence, spatial externalities exert their impact on temporary workers mainly through transition to a stable job position.

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Tables and Figures

Table 1. Descriptive statistics of the variables of the analysis

Panel A	**All cities**			
	All Workers	Temporary	Permanent	Ratio Perm/Temp
Real weekly wage (euro)	457	369	484	1.31
Age (years)	30	27	31	1.14
Experience (years)	5.64	2.83	6.50	2.30
Firm size	17	27	17	0.65
Occupation:				
Blue Collars (%)	69.21	77.06	66.82	0.87
White Collars (%)	28.65	22.79	30.43	1.34
Managers (%)	2.14	0.15	2.75	18.33
N. of observations	16,589,176	3,869,792	12,719,384	
Panel B	**Rome and Milan**			
	All Workers	Temporary	Permanent	Ratio Perm/Temp
Real weekly wage (euro)	533	383	577	1.51
Age (years)	31	28	32	1.15
Experience (years)	5.76	2.68	6.65	2.48
Firm size	38	64	39	0.61
Occupation:				
Blue Collars (%)	55.70	66.08	52.67	0.80
White Collars (%)	38.75	33.47	40.29	1.20
Managers (%)	5.55	0.45	7.04	15.64
N. of observations	3,148,324	710,771	2,437,553	
Panel C	**Naples, Turin, Palermo and Bologna**			
	All Workers	Temporary	Permanent	Ratio Perm/Temp
Real weekly wage (euro)	449	380	467	1.23
Age (years)	31	28	31	1.13
Experience (years)	5.48	2.75	6.21	2.26
Firm size	38	71	38	0.54
Occupation:				
Blue Collars (%)	65.78	71.49	64.28	0.90
White Collars (%)	32.23	28.43	33.24	1.17
Managers (%)	1.98	0.08	2.49	31.13
N. of observations	1,995,078	417,356	1,577,722	

Source: Our elaboration from INPS data.

Table 2: Spatial dynamic gains in big cities. Dependent variable: log of real worker's wage per hour.

	(1)	(2)	(3)	(4)	(5)
Panel A	**OLS**	**OLS**	**OLS**	**FE**	**FE**
Experience	0.055***				
	[0.001]				
Experience^2	-0.002***				
	[0.000]				
Experience - temporary		0.064***	0.070***	0.103***	0.103***
		[0.001]	[0.001]	[0.002]	[0.002]
Experience^2 - temporary		-0.005***	-0.006***	-0.010***	-0.010***
		[0.000]	[0.000]	[0.000]	[0.000]
Experience - permanent		0.041***	0.039***	0.051***	0.051***
		[0.001]	[0.001]	[0.001]	[0.001]
Experience^2 - permanent		-0.001***	-0.001***	-0.001***	-0.001***
		[0.000]	[0.000]	[0.000]	[0.000]
Experience in RM - temporary			-0.019***	-0.000	0.001
			[0.005]	[0.010]	[0.011]
Experience^2 in RM - temporary			0.002**	-0.001	-0.002
			[0.001]	[0.001]	[0.002]
Experience in RM - permanent			0.013***	0.010***	0.009***
			[0.004]	[0.003]	[0.003]
Experience^2 in RM - permanent			-0.001***	-0.000***	-0.000***
			[0.000]	[0.000]	[0.000]
Experience in NTPB - temporary			-0.017**	-0.001	0.001
			[0.006]	[0.005]	[0.004]
Experience^2 in NTPB - temporary			0.004*	0.001	0.000
			[0.002]	[0.001]	[0.001]
Experience in NTPB - permanent			-0.000	-0.001	-0.002
			[0.002]	[0.002]	[0.002]
Experience^2 in NTPB - permanent			-0.000	-0.000	0.000
			[0.000]	[0.000]	[0.000]
White collar dummy	0.303***	0.302***	0.302***	0.186***	0.186***
	[0.010]	[0.010]	[0.010]	[0.005]	[0.005]
Manager dummy	0.973***	0.970***	0.962***	0.449***	0.450***
	[0.032]	[0.032]	[0.029]	[0.004]	[0.004]
Log firm size	0.023***	0.022***	0.022***	0.013***	0.013***
	[0.002]	[0.002]	[0.002]	[0.001]	[0.001]
Temporary dummy	-0.088***	-0.105***	-0.105***	-0.070***	-0.066***
	[0.004]	[0.003]	[0.003]	[0.002]	[0.002]
Temporary dummy*dRM					-0.012*
					[0.007]
Temporary dummy*dNTPB					-0.014***
					[0.004]
Sector and time dummies	yes	yes	yes	yes	yes
City fixed effects	yes	yes	yes	yes	yes
Observations	16,589,176	16,589,176	16,589,176	16,589,176	16,589,176
R-squared	0.48	0.48	0.48	0.75	0.75
RM average fixed effects	0.046	0.046	0.027	0.020	0.023
NTPB average fixed effects	-0.002	-0.002	0.015	0.005	0.009
Panel B					
Log Population Density	0.006	0.006	0.006	0.008**	0.009**
	[0.005]	[0.005]	[0.004]	[0.003]	[0.004]
Weak identification test (F-value)	39.17	39.17	39.17	39.17	39.17
Observations	610	610	610	610	610

Standard errors clustered at local labour market level in parentheses *** p<0.01, ** p<0.05, * p<0.1. Sector is codified according to Nace rev1.1, two-digit level. Log population density is instrumented using total population in 1921.

Table 3: Estimation of the impact of spatial variables on individual wage growth components.

	(1)	(2)	(3)	(4)	(5)	(6)
	Within Perm	Within Temp	Between P-P	Between T-T	Between T-P	Between P-T
Panel A	**OLS**	**OLS**	**OLS**	**OLS**	**OLS**	**OLS**
RM dummy	0.050***	0.007**	0.037***	-0.006	0.040***	0.021***
	[0.008]	[0.003]	[0.004]	[0.006]	[0.004]	[0.005]
NTPB dummy	-0.007	0.003	-0.013	-0.014	-0.005	-0.017
	[0.014]	[0.006]	[0.018]	[0.018]	[0.020]	[0.025]
Log real weekly wage	-0.598***	-0.435***	-0.861***	-0.949***	-0.914***	-0.990***
	[0.007]	[0.007]	[0.008]	[0.011]	[0.007]	[0.004]
Skills	0.558***	0.411***	0.714***	0.809***	0.731***	0.745***
	[0.003]	[0.009]	[0.010]	[0.028]	[0.007]	[0.019]
White collar dummy	0.165***	0.073***	0.199***	0.144***	0.180***	0.169***
	[0.003]	[0.002]	[0.006]	[0.004]	[0.002]	[0.002]
Manager dummy	0.430***	0.225***	0.572***	0.561***	0.553***	0.712***
	[0.006]	[0.019]	[0.007]	[0.025]	[0.020]	[0.010]
Log firm size	0.012***	0.013***	0.018***	0.013***	0.018***	0.013***
	[0.001]	[0.000]	[0.001]	[0.001]	[0.001]	[0.002]
Sector and time dummies	yes	yes	yes	yes	yes	yes
R-squared	0.31	0.23	0.53	0.54	0.54	0.61
Observations	2,866,713	857,144	2,637,360	1,474,403	1,109,529	948,931
Panel B						
Log real weekly wage	-0.614***	-0.439***	-0.869***	-0.956***	-0.925***	-0.995***
	[0.008]	[0.007]	[0.008]	[0.012]	[0.008]	[0.004]
Skills	0.569***	0.413***	0.721***	0.811***	0.738***	0.750***
	[0.003]	[0.009]	[0.010]	[0.029]	[0.007]	[0.019]
White collar dummy	0.165***	0.073***	0.195***	0.143***	0.176***	0.165***
	[0.003]	[0.002]	[0.006]	[0.004]	[0.003]	[0.002]
Manager dummy	0.432***	0.228***	0.568***	0.560***	0.547***	0.702***
	[0.007]	[0.020]	[0.008]	[0.024]	[0.018]	[0.010]
Log firm size	0.011***	0.013***	0.016***	0.012***	0.016***	0.011***
	[0.001]	[0.000]	[0.001]	[0.001]	[0.001]	[0.001]
Sector and time dummies	yes	yes	yes	yes	yes	yes
City fixed effects	yes	yes	yes	yes	yes	yes
R-squared	0.31	0.24	0.53	0.54	0.54	0.61
Observations	2,866,713	857,144	2,637,360	1,474,403	1,109,529	948,931
Second step						
Log Population Density	0.014***	0.007***	0.010**	0.001	0.013***	0.008
	[0.004]	[0.003]	[0.004]	[0.004]	[0.005]	[0.005]
Weak identification test (F-value)	39.42	39.42	39.42	39.42	39.42	39.42
Observations	610	610	610	610	610	610

Standard errors clustered at local labour market level in parentheses *** p<0.01, ** p<0.05, * p<0.1. Sector is codified according to ISIC 3.1, two-digit level. Log population density is instrumented using total population in 1921.

Table 4: Descriptive statistics on temporary contract conversion rates

All contracts	**All Cities**	**RM**	**NTPB**	**Other Cities**
New temporay contract	23.83%	27.41%	22.30%	22.90%
Permanent contract	29.92%	30.63%	28.94%	29.84%
Non-employment	46.25%	41.95%	48.76%	47.27%
Number of observations	2,862,129	632,556	295,331	1,934,242
By spell length:				
1) Less than 7 months	**All Cities**	**RM**	**NTPB**	**Other Cities**
New temporary contract	24.08%	28.62%	22.36%	22.89%
Permanent contract	19.10%	19.34%	17.90%	19.21%
Non-employment	56.82%	52.04%	59.74%	57.91%
2) Between 7 and 18 months	**All Cities**	**RM**	**NTPB**	**Other Cities**
New temporary contract	25.47%	27.67%	24.32%	24.91%
Permanent contract	44.27%	45.20%	42.64%	44.20%
Non-employment	30.26%	27.13%	33.03%	30.89%
4) More than 18 months	**All Cities**	**RM**	**NTPB**	**Other Cities**
New temporary contract	14.89%	16.20%	14.21%	14.54%
Permanent contract	68.06%	67.43%	67.14%	68.44%
Non-employment	17.05%	16.37%	18.65%	17.02%

Source: Our elaboration from INPS data.

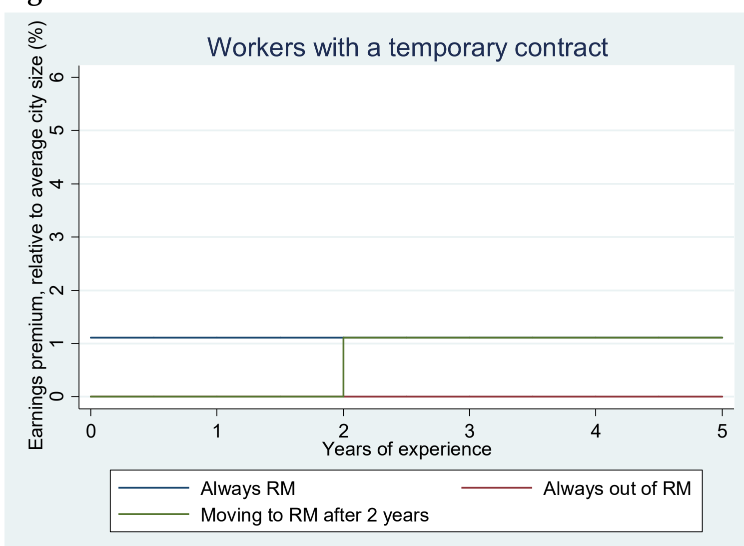
Table 5: Linear probability model of transition from temporary to permanent employment

	(1)	(2)	(3)	(4)
Panel A	**OLS**	**OLS**	**OLS**	**OLS**
Dummy RM	0.029**		0.028*	
	[0.013]		[0.016]	
Dummy NTPB	-0.005		-0.004	
	[0.015]		[0.016]	
Log real weekly wage	0.016***	0.013***	-0.006***	-0.008***
	[0.002]	[0.002]	[0.002]	[0.002]
Spell	0.021***	0.021***	0.024***	0.024***
	[0.000]	[0.000]	[0.000]	[0.000]
Skills	0.032***	0.040***	0.051***	0.056***
	[0.006]	[0.005]	[0.005]	[0.004]
White collar dummy	0.057***	0.053***	0.057***	0.054***
	[0.004]	[0.003]	[0.003]	[0.003]
Manager dummy	0.161***	0.148***	0.157***	0.146***
	[0.014]	[0.015]	[0.024]	[0.024]
Log firm size	-0.014***	-0.016***	-0.014***	-0.016***
	[0.001]	[0.001]	[0.001]	[0.001]
Sector and time dummies	yes	yes	yes	yes
City fixed effects	no	yes	no	yes
R-squared	0.20	0.21	0.25	0.26
Observations	2,862,129	2,862,129	781,629	781,629
Panel B		**IV**		**IV**
Log Population Density		0.033***		0.026***
		[0.006]		[0.005]
Weak identification test (F-value)		39.42		39.42
Observations		610		610

Standard errors clustered at the LLM level in parentheses *** p<0.01, ** p<0.05, * p<0.1. Sector is codified according to nace rev1.1, two-digit level. In column (3) log population density is instrumented with total population in 1921. Columns (1) and (2) refer to all spells, while columns (3) and (4) refer to the first spell.

Figure 1

Figure 2



Appendix

Table A1: Estimation of Dynamic Gains in Big Cities. Dependent variable: log of real worker's wage per hour. Excluding Naples and Palermo

	(1)		(2)
Panel A	**FE**	**Panel B**	**IV**
Experience - temporary	0.103***	Log Population Density	0.008**
	[0.002]		[0.003]
$Experience^2$ - temporary	-0.010***		
	[0.000]		
Experience - permanent	0.051***		
	[0.001]		
$Experience^2$ - permanent	-0.001***		
	[0.000]		
Experience in RM - temporary	0.000		
	[0.010]		
$Experience^2$ in RM - temporary	-0.001		
	[0.001]		
Experience in RM - permanent	0.010***		
	[0.003]		
$Experience^2$ in RM - permanent	-0.000***		
	[0.000]		
Experience in TB - temporary	0.008**		
	[0.004]		
$Experience^2$ in TB - temporary	-0.003***		
	[0.001]		
Experience in TB - permanent	0.005**		
	[0.002]		
$Experience^2$ in TB - permanent	-0.000		
	[0.000]		
Temporary dummy	-0.070***		
	[0.002]		
White collar dummy	0.186***		
	[0.004]		
Manager dummy	0.448***		
	[0.005]		
Log firm size	0.013***		
	[0.001]		
Sector and time dummies	yes		
City fixed effects	yes		
Weak identification test (F-value)			39.17
Observations	16,589,176		610

Standard errors clustered at local labour market level in parentheses *** p<0.01, ** p<0.05, * p<0.1. Sector is codified according to Nace rev1.1, two-digit level. Log population density is instrumented using total population in 1921.

Table A2: One-step estimation. Dependent variable: log of real worker's wage per hour.

	(1)	(2)	(3)	(4)
	IV	**IV**	**IV**	**IV FE**
Experience	0.055***			
	[0.001]			
Experience^2	-0.002***			
	[0.000]			
Experience - temporary		0.069***	0.073***	0.105***
		[0.002]	[0.002]	[0.002]
Experience^2 - temporary		-0.006***	-0.006***	-0.010***
		[0.000]	[0.000]	[0.000]
Experience - permanent		0.041***	0.039***	0.051***
		[0.001]	[0.001]	[0.001]
Experience^2 - permanent		-0.001***	-0.001***	-0.001***
		[0.000]	[0.000]	[0.000]
Experience in RM - temporary			-0.016***	0.001
			[0.006]	[0.010]
Experience^2 in RM - temporary			0.001	-0.001
			[0.001]	[0.001]
Experience in RM - permanent			0.018***	0.010***
			[0.004]	[0.003]
Experience^2 in RM - permanent			-0.001***	-0.000***
			[0.000]	[0.000]
Experience in NTPB - temporary			-0.016***	-0.002
			[0.006]	[0.005]
Experience^2 in NTPB - temporary			0.004*	0.001
			[0.002]	[0.001]
Experience in NTPB - permanent			-0.003	-0.001
			[0.004]	[0.002]
Experience^2 in NTPB - permanent			-0.000	-0.000
			[0.000]	[0.000]
Log population density	0.018	0.018*	0.010	0.008**
	[0.011]	[0.011]	[0.008]	[0.004]
Temporary dummy	-0.082***	-0.103***	-0.103***	-0.069***
	[0.004]	[0.003]	[0.003]	[0.002]
White collar dummy	0.308***	0.307***	0.306***	0.187***
	[0.010]	[0.010]	[0.010]	[0.005]
Manager dummy	0.987***	0.984***	0.969***	0.451***
	[0.030]	[0.030]	[0.027]	[0.004]
Log firm size	0.025***	0.024***	0.023***	0.014***
	[0.002]	[0.002]	[0.002]	[0.001]
Sector and time dummies	yes	yes	yes	yes
Weak identification test (F-value)	99.74	100.36	91.92	230.87
Observations	16,589,176	16,589,176	16,589,176	16,589,176

Standard errors clustered at local labour market level in parentheses *** p<0.01, ** p<0.05, * p<0.1. Sector is codified according to Nace rev1.1, two-digit level. Log population density is instrumented using total population in 1921.

Table A3: Estimation of Dynamic Gains in Big Cities. Dependent variable: log of real worker's wage per hour. Excluding firm size

	(1)	(2)	(3)	(4)
Panel A	**OLS**	**OLS**	**OLS**	**FE**
Experience	0.055***			
	[0.001]			
Experience^2	-0.002***			
	[0.000]			
Experience - temporary		0.076***	0.081***	0.107***
		[0.002]	[0.001]	[0.002]
Experience^2 - temporary		-0.007***	-0.007***	-0.010***
		[0.000]	[0.000]	[0.000]
Experience - permanent		0.041***	0.038***	0.053***
		[0.001]	[0.001]	[0.001]
Experience^2 - permanent		-0.001***	-0.001***	-0.001***
		[0.000]	[0.000]	[0.000]
Experience in RM - temporary			-0.013***	-0.001
			[0.003]	[0.010]
Experience^2 in RM - temporary			0.000	-0.001
			[0.001]	[0.001]
Experience in RM - permanent			0.016***	0.010***
			[0.003]	[0.003]
Experience^2 in RM - permanent			-0.001***	-0.000***
			[0.000]	[0.000]
Experience in NTPB - temporary			-0.014**	-0.001
			[0.005]	[0.004]
Experience^2 in NTPB - temporary			0.003*	0.001
			[0.002]	[0.001]
Experience in NTPB - permanent			0.002	-0.000
			[0.002]	[0.002]
Experience^2 in NTPB - permanent			-0.000***	-0.000
			[0.000]	[0.000]
Temporary dummy	-0.058***	-0.085***	-0.085***	-0.061***
	[0.005]	[0.004]	[0.003]	[0.002]
White collar dummy	0.318***	0.315***	0.315***	0.190***
	[0.011]	[0.010]	[0.011]	[0.005]
Manager dummy	1.000***	0.996***	0.987***	0.455***
	[0.027]	[0.028]	[0.026]	[0.004]
Sector and time dummies	yes	yes	yes	yes
City fixed effects	yes	yes	yes	yes
Observations	16,589,176	16,589,176	16,589,176	16,589,176
R-squared	0.47	0.47	0.47	0.74
RM average fixed effects	0.052	0.051	0.027	0.023
NTPB average fixed effects	-0.003	-0.002	0.011	0.004
Panel B				
Log Population Density	0.014***	0.013***	0.011***	0.012***
	[0.005]	[0.005]	[0.004]	[0.004]
Weak identification test (F-value)	39.17	39.17	39.17	39.17
Observations	610	610	610	610

Standard errors clustered at local labour market level in parentheses *** p<0.01, ** p<0.05, * p<0.1. Sector is codified according to Nace rev1.1, two-digit level. Log population density is instrumented using total population in 1921.

Table A4: Estimation of Static Gains in Big Cities. Dependent variable: log of real worker's wage per hour. Separate estimations for workers with temporary and permanent contracts

	Temporary		Permanent	
	(1)	(2)	(3)	(4)
Panel A	**FE**	**FE**	**FE**	**FE**
RM dummy		0.004		0.028***
		[0.011]		[0.005]
NTPB dummy		-0.018		0.010*
		[0.014]		[0.006]
Experience	0.078***	0.079***	0.065***	0.065***
	[0.001]	[0.001]	[0.001]	[0.001]
Experience Squared	-0.004***	-0.004***	-0.002***	-0.002***
	[0.000]	[0.000]	[0.000]	[0.000]
White collar dummy	0.194***	0.195***	0.146***	0.147***
	[0.006]	[0.006]	[0.006]	[0.006]
Manager dummy	0.580***	0.582***	0.394***	0.394***
	[0.018]	[0.019]	[0.008]	[0.008]
Log firm size	0.016***	0.016***	0.013***	0.013***
	[0.001]	[0.001]	[0.001]	[0.001]
Sector and time dummies	yes	yes	yes	yes
City fixed effects	yes	no	yes	no
R-squared	0.61	0.61	0.82	0.82
Observations	3,564,026	3,564,026	12,574,938	12,574,938
RM average fixed effects	0.010		0.026	
NTPB average fixed effects	-0.015		0.006	
Panel B				
Log Population Density	-0.003		0.011***	
	[0.005]		[0.003]	
Weak identification test (F-value)	39.17		39.17	
Observations	610		610	

Standard errors clustered at local labour market level in parentheses *** p<0.01, ** p<0.05, * p<0.1. Sector is codified according to ISIC 3.1, two-digit level. Log population density is instrumented using total population in 1921.

Table A5: Estimation of the impact of spatial variables on individual wage growth components. Excluding Naples and Palermo

	(1)	(2)	(3)	(4)	(5)	(6)
	Within Perm	Within Temp	Between P-P	Between T-T	Between T-P	Between P-T
	OLS	**OLS**	**OLS**	**OLS**	**OLS**	**OLS**
RM dummy	0.053***	0.008**	0.042***	-0.003	0.043***	0.025***
	[0.008]	[0.003]	[0.005]	[0.006]	[0.005]	[0.006]
TB dummy	0.030***	0.009***	0.032***	0.017**	0.030***	0.031***
	[0.005]	[0.002]	[0.008]	[0.007]	[0.009]	[0.005]
Starting Wage	-0.599***	-0.436***	-0.861***	-0.949***	-0.914***	-0.990***
	[0.007]	[0.007]	[0.008]	[0.011]	[0.007]	[0.004]
Skills	0.559***	0.411***	0.714***	0.809***	0.731***	0.745***
	[0.003]	[0.009]	[0.010]	[0.028]	[0.007]	[0.019]
White collar dummy	0.165***	0.073***	0.198***	0.143***	0.179***	0.168***
	[0.003]	[0.002]	[0.006]	[0.003]	[0.002]	[0.002]
Manager dummy	0.428***	0.225***	0.571***	0.560***	0.552***	0.711***
	[0.006]	[0.019]	[0.007]	[0.024]	[0.019]	[0.010]
Log firm size	0.012***	0.013***	0.018***	0.013***	0.018***	0.013***
	[0.001]	[0.000]	[0.001]	[0.001]	[0.001]	[0.002]
Sector and time dummies	yes	yes	yes	yes	yes	yes
R-squared	0.31	0.23	0.53	0.54	0.54	0.61
Observations	2,866,713	857,144	2,637,360	1,474,403	1,109,529	948,931

Standard errors clustered at local labour market level in parentheses *** p<0.01, ** p<0.05, * p<0.1. Sector is codified according to ISIC 3.1, two-digit level.

Table A6: Linear probability model of transition from temporary to permanent employment. Excluding Naples and Palermo

	(1)	(2)
	OLS	**OLS**
Dummy RM	0.031**	0.031**
	[0.013]	[0.016]
Dummy TB	0.022***	0.024***
	[0.008]	[0.008]
Log real weekly wage	0.016***	-0.006***
	[0.002]	[0.002]
Spell	0.021***	0.024***
	[0.000]	[0.000]
Skills	0.032***	0.052***
	[0.006]	[0.005]
White collar dummy	0.056***	0.056***
	[0.004]	[0.003]
Manager dummy	0.161***	0.156***
	[0.014]	[0.024]
Log firm size	-0.014***	-0.014***
	[0.001]	[0.001]
Sector and time dummies	yes	yes
R-squared	0.20	0.26
Observations	2,862,129	781,629

Standard errors clustered at the LLM level in parentheses *** p<0.01, ** p<0.05, * p<0.1. Sector is codified according to nace rev1.1, two-digit level. In column (3) log population density is instrumented with total population in 1921. Columns (1) and (2) refer to all spells, while columns (3) and (4) refer to the first spell.