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ABSTRACT

What Drives the Urban Wage Premium? Evidence along the Wage Distribution

This paper aims at disentangling the role played by different explanations on the urban wage premium along the wage distribution. We analyze the wage dynamics of migrants from lower to higher density areas in Italy, using quantile regressions and individual data. The results show that unskilled workers benefit more from a wage premium accruing over time, while skilled workers enjoy a wage premium when they migrate as well as a wage increase over time. Further, we find that for unskilled workers the wage growth over time is mainly due to human capital accumulation, consistently with the "learning" hypothesis, while for skilled workers it is the "coordination" hypothesis that matters.

JEL Classification: J31, J61, R23

Keywords: urban wage premium, human capital, spatial sorting, wage distribution, quantile fixed effects

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1. Introduction

The existence and extent of the urban wage premium have been widely investigated in the spatial economic literature, and various different theories have been proposed. The most widely accepted explanation refers to urbanization externalities in terms of reduced transport costs, technology and knowledge spillovers, cheaper inputs and proximity to consumers (Glaeser, 1998, Kim, 1987, Ciccone and Hall, 1996). According to this theoretical framework, workers moving to cities should immediately experience wage level increases, while those leaving cities should experience wage losses (wage level effect). More recently, a "learning" explanation has been proposed, i.e. in cities human capital accumulation is faster (Moretti, 2004). In this framework, workers moving to cities will only experience wage increases over time (wage growth effect), while those leaving cities will not necessarily suffer wage losses. Another explanation that entails the possibility of a wage growth effect being generated is the "coordination" hypothesis, since cities enhance the probability of a better match between workers and firms, and this probability increases with the time spent in cities (Kim, 1990, Yankow, 2006). Furthermore, the literature has also pointed out the importance of controlling for the sorting of workers, since the urban wage premium could be the outcome, at least partially, of skilled workers being sorted into cities (Combes et al., 2008, Mion and Naticchioni, 2009, Matano and Naticchioni, 2012).

From the empirical point of view, the first paper that discussed and tested the role played by the different explanations is Glaeser and Marè (2001), which analyzes the determinants of the urban wage premium in the US using data from the National Longitudinal Survey of Youth (NLSY), the Panel Study of Income Dynamics (PSID) and the 1990 US census. In particular, the authors analyze the

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migration flows from rural-to-urban areas (and vice versa), in order to disentangle the wage growth effect from the wage level effect. Glaeser and Marè (2001) also perform fixed effects estimates to control for the sorting of workers. Their results show that a non-negligible part of the urban wage premium accrues to workers over time and is retained when they leave cities, consistently with the wage growth explanation. Nonetheless, the authors also find evidence of the wage level effect.

More recently, other papers have extended the analysis of Glaeser and Marè (2001) to investigate further the determinants of wage growth in cities, focusing on the within- and between-jobs wage growth components which represent a proxy of the "learning" and "coordination" hypothesis (Yankow, 2006, Wheeler, 2006, Baum-Snow and Pavan, 2012).

The original contribution offered by this paper lies in extending to the whole wage distribution the analysis of the role played by the different theoretical explanations in accounting for the urban wage premium, which represents an unexplored field of research in the spatial economic literature, to the best of our knowledge.

We make use of the Italian employer-employee INPS (the Italian Social Security Institute) database, from 1986-2003. In the first part of the paper we analyze the wage dynamics of migrants from lower to higher, and from higher to lower, density provinces, by means of a quantile regression approach. Moreover, since previous empirical studies showed that the sorting of workers captures a significant part of the impact of spatial externalities on wages, both at the conditional mean (Combes et al., 2008, Mion and Naticchioni, 2009) and along the wage distribution (Matano and Naticchioni, 2012), the analysis takes into account the workers' unobserved heterogeneity by carrying out quantile fixed-effect estimations.

Our analysis shows that for unskilled workers, i.e. those at the 10th percentile, the wage premium takes place mainly over time, consistently with the wage growth level effect. As for skilled workers, i.e. those at the 90th percentile of the distribution, the wage level and the wage growth effects have a similar magnitude, suggesting that they are able to capture both the benefits of agglomeration economies and the dynamic gains accruing over time.

We also take into account the recent analysis presented in De la Roca and Puga (2013), who claim that even fixed effects estimates may be biased when dynamic effects are not considered. To capture these dynamics effects, De la Roca and Puga (2013) introduce in the estimation different experience variables, focusing on where experience has been acquired. Implementing a similar specification on the sample of young workers, we show that the estimates of the wage level and wage growth effects do not substantially change in comparison to baseline estimates, with the only difference being a slight reduction in the wage growth effect, especially for the upper tail of the wage distribution. Interestingly, we also find that while experience displays decreasing returns along the wage distribution, experience acquired in top cities (Rome and Milan) is associated to increasing returns along the distribution. We also carry out additional robustness checks, which basically confirm our baseline estimates.

Since our analysis suggests that the wage growth effect plays a role for both skilled and unskilled workers, in the second part of the paper we focus on the drivers of the wage growth effect, i.e. on disentangling the "learning" from the "coordination" explanation. We consider the sample of migrants from lower to higher density provinces after migration, using quantile fixed effects regressions. As a proxy for between-jobs wage growth we use the job-change dummy (as in Baum-Snow and Pavan, 2012), while as a proxy for within-job wage growth we use the job tenure variable (Topel, 1991). Once controlled for sorting, our findings show that skilled workers benefit more from better matching opportunities in cities, enjoying greater returns to job changes. As for unskilled workers, they benefit more from higher human capital accumulation, i.e. greater returns to tenure, once in cities. Similar results are derived using the sample of stayers in low- and high-density provinces. This suggests that the wage dynamics detected for the migrants can be extended to different groups of workers in the economy, thereby reassuring about the possible endogeneity of the migration choices.

Our results clearly bring out the importance of investigating the determinants of the urban wage premium along the wage distribution, since the relevance of the different explanations differs between skilled and unskilled workers. Further, it is also worth stressing that taking into account the whole wage distribution affords new insights that prove more revealing than when conventional measures of skills are applied, such as educational levels.[1]

The structure of the paper is as follows. In Section 2 we review the theoretical and empirical literature on the urban wage premium. In Section 3, we describe the data, define the spatial variable and present some descriptive statistic, while Section 4 sets out the empirical analysis, discusses the main results and presents a set of robustness checks. The conclusions are drawn in Section 5.

2. Related Literature

This paper aims at disentangling the role played by different explanations, characterized by different timing, for the urban wage premium: agglomeration economies (Ciccone and Hall, 1996, Kim, 1987, Glaeser, 1998), which imply that workers who migrate from non-urban to urban areas should enjoy an immediate wage premium (wage level effect); the "learning" (Glaeser, 1999, Moretti, 2004, Glaeser and Resseger, 2010) and "coordination" (Kim, 1990, Helsey and Strange, 1990) hypotheses, which imply that essentially wages in cities increase with time spent in the cities (wage growth effect). The literature has also shown that sorting matters, i.e. skilled workers are attracted by cities (Combes et al., 2008, Mion and Naticchioni, 2009, Matano and Naticchioni, 2012).

At the empirical level, the seminal paper is Glaeser and Marè (2001), which makes use of US data (1990 census, NLSY and PSID) to analyze the migration flows from rural-to-urban areas (and vice versa), in order to distinguish the wage growth effect (interpreted as human capital accumulation) from the wage level effect (agglomeration economies). Their findings show that the wage growth effect plays

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[1] According to the 1996 data of the European Community Household Panel, almost 50% of Italian graduates were not employed in the top quartile of the wage distribution, and around 20% had a wage lower than the median. This suggests a substantial heterogeneity within educational levels, heterogeneity that can be investigated by using quantile regressions.

an important role. A similar finding is found by Lehmer and Moller (2010) for Germany: the urban wage premium is due more to a wage growth effect related to human capital accumulation than to a wage level effect, especially for more experienced workers.

Other related papers have investigated further the main finding emphasized by Glaeser and Maré (2001), i.e. the wage growth effect and its determinants. Using the NLSY data, Wheeler (2006) shows that, on average, wage growth tends to be positively associated with the size of the local market. Further, he also points out that faster wage growth is related to job changes rather than to within-job wage growth, supporting the coordination explanation. On the same topic, Yankow (2006) shows that there is no statistical difference between urban and non-urban workers in the average wage gain from a single job change. However, he finds evidence that in cities there is a significantly higher frequency of job changes, entailing a higher cumulative wage growth related to job changes.

Baum-Snow and Pavan (2012) use the NLSY data for the US to develop a structural on-the-job-search model that includes all the relevant explanations that affect the urban wage premium (unobserved ability, search frictions, quality job matching, human capital accumulation and endogenous migration). They find out that human capital accumulation is more important among large and small cities, while wage level effects are more important among medium and small-sized cities.[2]

Another related paper is De la Roca and Puga (2013), who claim that fixed effects estimates may be biased when dynamic effects are not taken into account. Using administrative data for Spain, they estimate a wage regression where, apart from controlling for cities and individual fixed effects, they introduce various experience variables, i.e. proxy for dynamic gains, related to where experience has been acquired and where it has been used. They show that in bigger cities workers obtain an immediate static premium and accumulate more valuable experience,

[2] Also Gould (2007) carries out a structural analysis showing that cities offer a wage premium only to white-collar workers. For an in-depth survey on urban wage premium and human capital externalities see Heuermann et al. (2010).

which persists after workers move elsewhere, and which is greater for workers with higher innate ability.

All these studies focus on the analysis of the determinants of the urban wage premium evaluated at the conditional mean. The original contribution of this paper is to extend the analysis along the whole wage distribution. Some papers have already focused on related, but different, distributional/inequality issues, using either aggregate data (Wheeler, 2004, Moller and Haas, 2003) or individual level data (Matano and Naticchioni, 2012, Combes et al., 2012). None of them, however, has focused on disentangling the static and dynamic components of the urban wage premium along the wage distribution, which is the focus of this paper.

3. Institutional Setting and Data Description

Italy is generally conceived as a fairly immobile country. Actually, the Italian labour market is much more mobile than usually thought. Italian job flows are higher than those of most European countries (Gomez-Salvator et al., 2004), and wage differentials and inequalities are rather high, and increasing along the period considered (OECD, 2011). As far as the Italian wage setting is concerned, since the beginning of the nineties there is a two-level wage bargaining system. The first level concerns a national collective bargaining, which has to preserve the purchasing power of wages at the sector level by incorporating –at least partially- expected inflation rate in wage increases, while the second level of bargaining (either at the regional or firm level) allows rent sharing through performance-related pay schemes at the region/firm level (see Cappellari et al., 2012, for a description of the Italian institution setting).

As for the data, we use a panel version of the Italian administrative database provided by INPS and elaborated by ISFOL (the Italian Institute for the Development of Vocational Training).[3] It is an employer-employee dataset,

[3] The sample scheme of the database follows individuals born on the 10th of March, June, September and December and therefore the proportion of this sample in the Italian employee population is approximately of 1/90. The panel version was constructed considering only one observation per year for each worker. For those workers who have more than one observation per year we selected the

constructed for the period 1986-2003 by merging the INPS employee information with the INPS employer information database. The units of the analysis are industrial- (manufacturing and mining) and service-dependent workers, both part-time (converted into full-time equivalent) and full-time. We focus on standard labour contracts, including both blue and white collars. Moreover, we take into account prime-age male workers, as in Glaeser and Maré (2001) and Mion and Naticchioni (2009), among others. In particular, we focus on individuals aged between 25 and 49 (when they first enter the database).[4] We consider only those workers that are in the dataset for at least three years, in order to get more reliable within estimations.[5] By doing so, we eventually have an unbalanced panel of 49,526 workers for 463,247 observations. As for worker characteristics, the database contains individual information such as age, gender, occupation, workplace, worker status (part-time or full-time), real gross yearly wage and the number of months, weeks and days worked. For firms, we have the plant location (province), the size (number of employees), and the sector.

Using INPS provincial data on industrial and service employment for the period 1986-2003, we can define the employment density, which represents the proxy for urban agglomeration. It is defined as in Combes (2000), Ciccone and Hall (1996), Mion and Naticchioni (2009) and Matano and Naticchioni (2012): employment in province p at time t out of the province area in square km. The spatial breakdown is hence given by the province (*provincia*), classified in 95 units.[6]

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longest contract in terms of weeks worked. We also eliminated the observations below (above) the 0.5th (99.5th) percentile of the wage distribution.

[4] We do not consider, as standard in this literature (Topel, 1991), women and older workers since their wage dynamics is also affected by non-economic factors.

[5] Note that in our sample we consider only workers with observations continuously available, i.e. available for consecutive years, since if data are missing for some years it is not possible to establish the patterns of worker's career dynamics. Moreover, we do not consider migrants before and after ten years from migration, since we claim that ten years are a sufficient time span to investigate the wage dynamics before and after the migration.

[6] The Italian provinces follow the European NUTS3 classification. We make use of 95 provinces, which was the number of provinces in the first year of analysis (1986). In recent years the number of provinces has risen to 103. Therefore, we reclassified the individuals belonging to the new provinces into the corresponding initial 95-province classification. Note that Italian provinces are more than administrative areas, and that they have to be thought as functional aggregates, encompassing local labour markets. From an historical point of view, Italian provinces can be related to the Italian Renaissance period, characterized by many flourishing cities and the accompanying surrounding areas.

We define the following groups in order to classify workers' movements: migrants from lower to higher density provinces, i.e. workers who move to a province with higher density with respect to the one they come from; migrants from higher to lower density provinces, i.e. workers who move to a province with lower density with respect to the one they come from; stayers, defined as workers who never change province. To provide a spatial characterization of stayers, we split this group into stayers in high density provinces (HD) and stayers in low density provinces (LD) on the basis of the (time average) median value of the density, computed on individual observations.[7]

Table 1 shows the descriptive statistics for the different workers' groups. As expected, the average wage of stayers is lower in LD provinces, while the average wage for migrants is close to those of stayers in HD provinces. Migrants are also generally slightly younger and are relatively more concentrated in white collar occupations, as stayers in HD provinces. Further, migrants from lower to higher density provinces as well as stayers in HD provinces work in larger firms. Finally, migrants and stayers in HD provinces are relatively more concentrated in the service sector, while greater representation in the industry sector is found for stayers in LD provinces.

[table 1 around here]

4. Empirical Analysis

4.1. The Extent of the Wage Level and the Wage Growth Effect along the Wage Distribution

We use a quantile regression approach to investigate the role of the wage level and the wage growth effect in determining the urban wage premium along the wage distribution. Following Glaeser and Marè (2001), we estimate a wage regression with dummies that capture the exact path of migration:

[7] Note that if an individual moves more than once between different sized provinces, he/she may "score" more than once in the analysis. We do not consider workers moving three or more times between different sized provinces, who in any case account for a very small fraction of the workers in the sample.

$$\ln(w_{i,t}) = \alpha_\theta + B'_\theta * I\_Char_{i,t} + \beta_\theta * Firmsize_{i,t} + \sum_{j=1}^{T_i} \gamma_{j,\theta}^{l-h} I_{j,t}^{l-h} + \sum_{j=1}^{T_i} \gamma_{j,\theta}^{h-l} I_{j,t}^{h-l} + \varphi_{s,\theta} + \lambda_{r,\theta} + \delta_{t,\theta} + \varepsilon_{i,t,\theta}$$

where θ refers to the percentile, i to individuals, s to sectors, r to regions, t to time and j stands for the dummies concerning year intervals before ("10 to 5", "4 to 3", "2 to 1"), after ("1 to 2", "3 to 4", "5 to 10") and for the migration year ("0")), with $j \in T_i$ is the individual time span.

The dependent variable in our regressions is the (log) real gross weekly wage in euro.[8] As for the variables of interest, $I_{j,t}^{l-h}$ (with j=(-10-5,…,+5-+10)) stands for a dummy variable that takes on a value of one when the worker, at time t, moved (will move) j years before (after) from a lower to a higher density province, while $I_{j,t}^{h-l}$ stands for a dummy variable that takes on a value of one if the worker, at time t, moved (will move) j years before (after) from a higher to a lower density province. Hence, the estimates of γ_j^{l-h} and γ_j^{h-t} reflect the dynamics of wages before or after a move.

As for the other variables, the term $I\_Char_{i,t}$ is a set of observed individual characteristics (age, age squared, blue collar dummy) and $Firmsize_{i,t}$ is the proxy for firm heterogeneity,[9] while φ_s, λ_r, δ_t are sector, region (NUTS2 level) and time dummies respectively. We carry out estimates for the 10th, 25th, 50th, 75th and 90th percentiles.

Table 2 shows the cross sectional quantile regression results. The omitted category is 'stayers in LD provinces'. We also provide the coefficients for the stayers in HD provinces. It is worth noting that stayers in HD provinces earn significantly more than stayers in LD provinces. This confirms that the bulk of wage differences across the space dimension is also due to stayers, as emphasized by Mion and Naticchioni (2009). Moreover, the urban wage premium for stayers in

[8] Wages have been deflated using the national Consumer Price Index (FOI index, *Indice dei Prezzi al Consumo per le Famiglie di Operai e Impiegati*, ISTAT). The base year is 2002. We do not apply cost of living adjustments for two main reasons. First, because we are interested in the firms' willingness to pay higher wages and not in the location choice of workers. Second, because Baum-Snow and Pavan (2012) show that using wages not deflated by cost of living does not prove a major problem when working with differenced data. In our analysis this consideration applies since we work with deviations from within individual average.

[9] We proxy the firm heterogeneity using the firm size, since firm productivity and wages are positively related with firm size (Postel-Vinay and Robin, 2006).

HD provinces with respect to those in LD provinces increases along the wage distribution, ranging from 1.5% at the bottom of the wage distribution to 4.4% at the top. This means that skilled workers have a greater advantage in working in HD areas, consistently with Matano and Naticchioni (2012).

Let us now move on to the analysis of the groups of migrants, starting from the migrants from lower to higher density provinces. It is interesting to note that using quantile regressions allows for better characterization of the wage dynamics of migrants, both before and after migration. More specifically, from table 2 it emerges that skilled workers, at the 90th percentile, experience a wage increase even before migration, suggesting that the sample of migrants at the 90th percentile is positively selected, consistently with the intuitions of Borjas (1987). On the contrary, migrants at the 10th percentile represent a negative selection of the reference group of workers, since they experience a wage loss just (1-2 years) before migration. For workers at the median, instead, the wage dynamics just before migration is only slightly higher than that of the workers remaining in LD provinces. These findings suggests that unskilled workers mainly decide to migrate to a dense region after a negative shock in their current job, while for skilled workers the migration to dense regions is a tool to improve their already increasing wage dynamics.

As for the extent of the wage level and wage growth effect along the wage distribution, we begin with some considerations on the analysis of average wages, derived by using Ordinary Least Square. It may be noted that the wage level effect – the difference in wages within a year after the migration with respect to 1-2 years before the migration- is negligible (0.1%) while the greatest part of the wage increase occurs after migration: the wage growth effect amounts to 8.6% (12.1% minus 3.5%). These findings are consistent with those of Glaeser and Maré (2001), who emphasize the importance of the wage growth effect.

Similar patterns are derived when considering the median, and this is hardly surprising since the distribution of the dependent variable, i.e. the log weekly wage, should come fairly close to a symmetric distribution. In particular, it emerges that at the median the entire wage premium arises essentially some years after migration, since the wage level effect is even negative but negligible (-0.3%).

Different and more interesting findings are derived when the tails of the wage distribution are taken into account. On the one hand, for workers at the bottom of the wage distribution (10th percentile) there is a slight negative wage level effect (-1.1%, from -2.4% to -3.5%). Nonetheless, in the years following migration wages tend to rise and after 3-4 years these workers earn significantly more than unskilled workers in LD provinces (+3.8%); the premium increases further after 5-10 years (+5.1%). This is in line with the wage growth hypothesis.

In the case of skilled workers (90th wage percentile) the pattern is different. In fact, the wage level effect is positive and amounts to a 1.5% (from 5.4% to 6.9%). This finding suggests that for skilled workers agglomeration economies play a role in determining the urban wage premium. At the same time, there is evidence of a significant wage growth effect since the urban wage premium tends to increase over time (16.2% after 5-10 years).[10]

As for the migration from higher to lower density provinces, it is noteworthy that, regardless of the wage percentile considered, there is no evidence of wage losses just after migration relative to 1-2 years before, consistently with the wage growth hypothesis and in line with Glaeser and Marè (2001). Rather, there is even a slight increase (1-2%).

[table 2 around here]

However, these estimates might be biased since they do not take into account the role of the sorting of workers. Actually, part of the wage premium imputed to agglomeration economies, as well as human capital accumulation and quality matching, could be due to the sorting of skilled workers into cities. In order to tackle this issue, we perform fixed effects estimates that allow controlling for individual unobserved heterogeneity (Combes et al., 2008, Mion and Naticchioni, 2009, Matano and Naticchioni, 2012).

[10] Adding up the wage level effect (difference between coefficients just after the migration and 1-2 years before) and the wage growth effect (difference between coefficients after 5-10 years and just after the migration), it comes out that the total increase in wages is of 7.5% for workers at the 10th percentile, 6.8% for workers at the 50th percentile and 10.8% for workers at the 90th percentile.

Since we work in a quantile setting, we make use of the quantile fixed effects methodology proposed by Canay (2011).[11] The omitted category within each group of migrants is that of '5 -10 years before the migration'.

The results in table 3 confirm that sorting matters. In particular, considering the migrants from lower to higher density provinces, the difference in coefficients between 5-10 years after the migration and 1-2 years before the migration generally decreases relative to previous estimates, and the reduction is greater at the highest percentiles, consistently with Matano and Naticchioni (2012).

In terms of decomposition between the wage growth and wage level effect, for the median and the mean the results differ little from previous ones, i.e. the wage level effect remains quite small (around 1%) and most of the wage increase occurs over time: the wage growth effect is equal to 3.9% at the median (5.0% minus 1.1% just after migration) and 5.5% at the mean (6.1% minus 0.6%).

Similarly, for low skilled workers the wage premium is essentially due to a wage growth effect: there is an increase immediately after migration (+0.9%, from -4.7% to -3.8%), while most of the urban wage premium emerges over time (+7.7%, from -3.8% to 3.9%).

Different and indeed interesting patterns emerge for skilled workers (at the 90th percentile), since the urban wage premium is quite equally shared between the wage level effect (2.3%, from 3.5% to 5.8%), and the wage growth effect (2.8%, from 5.8% to 8.6%).

As for the migrants from higher to lower density provinces, fixed effects estimates generally confirm the cross sectional results. In particular there is no evidence of wage losses just after migration -relative to 1-2 years before migration- (consistently with the wage growth hypothesis).[12]

These findings suggest that while for unskilled workers the determinants of the urban wage premium appear to be due mainly to a wage growth effect, and hence

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[11] We have also run the same estimates using the procedure suggested by Koenker (2004). The results are very similar. They are available upon request.

[12] Note that also workers who move from higher to lower density provinces in general experience a wage increase, especially over time. This suggests that at least a part of the wage dynamics might be driven by migration choices. However, the magnitude of these wage increases is generally lower than the one generated when moving to a denser area, suggesting the existence of an urban wage premium due to spillovers generated in locations characterized by denser economic activity.

to the coordination and/or learning explanation, for skilled workers the urban wage premium is more uniformly distributed between the wage level and the wage growth effects.

[table 3 around here]

4.2. The role of dynamic gain

So far we have looked at the role of the wage growth and wage level effect in determining the urban wage premium along the wage distribution controlling for the sorting of workers. However, De la Roca and Puga (2013) claim that also fixed effects estimates may be biased when dynamic gains are not taken into account. In particular, they show that the earning premium for a given dense location can be biased upwards (downwards) if individuals with more valuable experience are more (less) likely to work in such a dense location. To capture these dynamics effects, De la Roca and Puga (2013) introduce in the estimation different experience variables, focusing on where experience has been acquired.

To deal with this issue we need the experience variable, which is not collected in the sample of prime age workers of our dataset.[13] Therefore we consider the sample of young workers (aged between 15-30) starting their first employment spell after January 1986, for whom we can compute the experience variable.[14] As a check, table 4 replicates for the group of young workers the fixed effects estimates derived on the group of prime-age workers (table 3). Results do not differ much, suggesting that the group of young workers displays similar spatial trends with respect to the one of prime age workers.[15] In particular, trends of wage level and wage growth effects are the same, while in terms of magnitude estimates on young workers

[13] This is mainly due to the fact that the data lack the information concerning the specific time period the individual entered the labour market.

[14] We cannot keep individuals recorded in the database as working from January 1986, since the formal beginning of all these jobs in the INPS database is forced to be January 1986. Note also that for the sample of young workers we assume that those individuals entering the sample did not previously had any working experience as self-employed or in the public sector. This seems to be plausible, since self-employed and public sector spells are less likely when young.

[15] Note that in the estimates of table 4 we put experience instead of age, since the two variables (in levels) are collinear in fixed effects estimates. Therefore, results can be compared with the ones related to prime age workers (table 3).

display slightly higher values for the 10th and 50th percentile and slightly lower for the 90th percentile.

[table 4 around here]

Using the sample of young workers, we introduce in the econometric specification the standard experience variable and two additional variables: the experience acquired in the two biggest Italian cities (Rome and Milan), and the experience acquired in the following four biggest Italian cities in terms of population (Palermo, Genoa, Turin and Naple). Table 5 shows the results for young workers when introducing the detailed experience variables. First of all, experience has a declining impact along the wage distribution, ranging from 5.3% at the 10th percentile to 2.2% at the 90th percentile. This suggests that unskilled workers benefit the most from experience in the labour market. However, experience acquired in Rome and Milan has an increasing (and concave) impact along the wage distribution. In particular, the returns to experience acquired in Rome and Milan range from 1.7% at the 10th percentile to 2.2% at the 90th percentile. As for the experience acquired in the other four main Italian provinces, magnitudes are lower but still increasing along the wage distribution (from 0.6% at the 10th percentile to 1.0% at the 90th percentile). The increasing trends for experience acquired in the two and four top cities mitigate the decreasing trend observed for the standard experience variable. Still the overall returns to experience are decreasing: for a worker who spent five years in Rome (or Milan) at the 10th percentile the overall returns are equal to 27.5% while at the 90th percentile are equal to 19.5%. The differences among percentiles would have been anyway greater without introducing the experience acquired in top cities.

[table 5 around here]

As for migration patterns, it is interesting to note that the introduction of experience variables only slightly affect the wage level effect, which is now equal to

0.3%, 0.8% and 1.6% at the 10^{th}, 50^{th} and 90^{th} percentile respectively. As for the wage growth effect, there is a general decrease, being now equal to 8.2%, 3.4% and 0.9% at the 10^{th}, 50^{th} and 90^{th} percentile respectively. Moreover, the reduction in the wage growth effect affects more the upper tail of the wage distribution, i.e. the decrease is around 60% at the 90^{th} percentile, 28% at the 50^{th} percentile and just 10% at the 10^{th} percentile. This means that experience acquired in top cities catches up part of the wage dynamics previously captured by migration dummies.[16]

4.3. Robustness Checks

In this paragraph we include a set of robustness checks of the baseline estimates of table 3.

First, we make use of provincial dummies instead of regional dummies, in order to check whether our results are driven by spatial unobserved heterogeneity within regions. Coefficients presented in table 6 are basically the same as baseline coefficients (table 3). In particular, workers at the 10^{th} percentile have a 1.1% wage level effect and a 7.6% wage growth effect, those at the 50^{th} percentile have a 1.4% wage level effect and a 4% wage growth effect, while the same values for the 90^{th} percentile are 2% and 2.6% respectively.

[table 6 around here]

Second, we consider an alternative measure of skills. Since education is not available in our data, we make use of occupational categories, performing fixed effects estimations on the sample of blue collar and white collar workers separately. Table 7 shows the results. As for blue collar workers estimates reveal that only the

[16] Note that De la Roca and Puga (2013) extend their approach by introducing interaction terms between the years of experience acquired by workers in main cities and the locations where the workers are currently employed. Their results show that these interactions are either not significant or small in magnitude, i.e. the value of experience is fully portable across cities. We have also run a robustness check introducing interaction terms between the experience acquired in main Italian cities and being currently employed in other (smaller or greater) provinces. Results show that our baseline estimates are not affected by the introduction of these interaction terms. Further, the impact of these interaction terms differ depending on the wage percentile considered. For the median and the average, estimates are consistent with those of De la Roca and Puga (2013), since they are either not significant or small in magnitude. Instead, in the lower and upper tail of the distribution, there are some significant effects, which suggest an interesting heterogeneity in dynamic gains across the wage distribution. These estimates are available upon request.

wage growth effect matters (1.9%), since the wage level effect is very close to zero (-0.3%). For white collar workers, proxy for skilled workers, the urban premium is due to a wage level effect (2.6%) and to a wage growth effect (5.5%). This evidence for blue and white collars is qualitatively consistent with previous estimates on unskilled (10th percentile) and skilled (90th percentile) workers.[17]

[Table 7 around here]

Third, we use a different spatial classification. In the baseline estimates (table 3) we consider as migrant to higher (lower) density province individuals moving to a province with higher (lower) employment density with respect to the one they come from. In this robustness check we make use of a dichotomic distinction between provinces: high density and low density provinces defined with respect to the (time average) median of density computed on individual observations. From table 8 it emerges that previous results are confirmed. Taking into account movements between low and high density provinces it is possible to observe that at the 10th and 50th percentiles the wage growth effect (8.2% and 4.7% respectively) is still more important than the wage level effect (1.7% and 1.6% respectively), while at the 90th percentile the wage level effect (3.1%) is greater than the wage growth effect (1.4%).

[table 8 around here]

Fourth, we tackle the issue of endogeneity of migration. In fact, migration decisions are not random and this can bias our estimates. We address this issue by considering the sample of displaced workers (as in Dustmann and Meghir, 2005, and Mion and Naticchioni, 2009), i.e. workers who have to change firm since their firm has closed down, which is an information included in our data. Table 9 shows the estimates derived from the sample of displaced workers. For workers at the 10th percentile the wage premium is still mainly driven by the wage growth effect

[17] One of the few differences with respect to the baseline estimate is that now the wage growth effect is higher for skilled workers.

(7.4%), even if there is also an important role for the wage level effect (3.4%). As for workers at the 90th percentile the wage level effect is even stronger than before (3.2%), while the wage growth effect is equal to 0.9%. Also these patterns are qualitatively consistent to those observed in table 3.[18]

[table 9 around here]

The fifth robustness check concerns the fact that in the baseline estimates we use an unbalanced panel of workers. This implies that the number of observations for the categories '5-10 years before' or '5-10 years after' a move is smaller than the number observed around the migration year. In order to handle this issue we focus on long-stay migrants, defined as individuals remaining in the sample at least 10 years. Results are included in table 10, and basically confirm baseline estimates, suggesting that findings are not driven by the characteristics of the panel data used. In particular, for the unskilled workers (10th percentile), the wage growth effect is the main determinant behind the urban wage premium (9.1%), while for skilled workers the urban wage premium is more balanced between the two components (2.2% for the wage level effect and 1% for the wage growth effect).

[table 10 around here]

As last robustness check we take into account the possible endogeneity of firm size. For this reason, we take off the firm size from the econometric specification of the quantile fixed effect regressions, and estimates are basically unchanged (table 11).

[table 11 around here]

[18] Using displaced workers to deal with the endogeneity of migration is the best we can do, since the literature has shown that it is rather difficult to find a convincing instrument for mobility decisions. Note also that the literature has mainly investigated the case in which migration can be assumed as exogenous. Combes et al. (2012) stress that the exogeneity assumption is less restrictive when the econometric specification "contains area and year effects", as in our case. Furthermore, the bias due to endogeneity is likely to be attenuated in the case that migration choices are driven by long-term expected wages, rather than by short-term wage shocks (Combes et al., 2012), which seems plausible in the case of European countries such as Italy and France.

4.4 Focus on the Wage Growth Effect: Disentangling the "Learning" and the "Coordination" Effects along the Wage Distribution

One of the findings of our paper is that a non-negligible part of the urban wage premium is related to a wage growth effect, consistently with Glaeser and Maré (2001). As stressed in the literature, the wage growth effect could be the outcome of either faster human capital accumulation (learning) or more efficient job searching and matching (coordination). Our aim in this section is to disentangle the roles of the "learning" and "coordination" effects.

We focus on the sample of migrants from lower to higher density provinces, once they have moved into a higher density province. We include variables that are considered in the literature as proxy for the within-job wage growth (tenure, using a quadratic specification) and for the between-jobs wage growth (dummy for job change, as in Baum-Snow and Pavan, 2012). We estimate the following regression:

$$\ln(w_{i,t}) = \alpha_\theta + B'_\theta * I\_Char_{i,t} + \beta_\theta * Firmsize_{i,t} + \gamma_1 * Tenure + \gamma_2 * TenureSq + \theta * JobChange +$$
$$+\phi_{s,\theta} + \delta_{t,\theta} + \varepsilon_{i,t,\theta}$$

where as before θ refers to the percentile, i to individuals, s to sectors, t to time.

The dependent variable is again the (log) real gross weekly wage in euro. The variables of interest are *Tenure, Tenure squared* –that capture firm specific human capital accumulation-, and the dummy *Job Change* that takes the value of one when a worker changes job in the corresponding year. All the other variables are the same as in the previous section. In table 12 we set out the estimates derived by means of the quantile fixed effect regression to control for the sorting of workers.

The results show that the impact of within- and between-jobs components on wages is not uniform along the wage distribution. In fact, the unskilled workers' wage growth (10^{th}-25^{th} wage percentiles) is due mainly to positive – and concave - returns to tenure, suggesting that firm specific human capital accumulation plays a substantial role. For instance an unskilled worker (10^{th}/25^{th} percentile) who has moved to a higher density area gets a wage increase of 2.5%/0.5% after 5 years spent in the same firm. Further, the linear coefficient of the returns to tenure decreases along the wage distribution, becoming negative at the 90th percentile, even if the quadratic term switches to positive. This suggests that for skilled workers job tenure plays only a minor role.

As for the impact of job changes, this is positive for skilled workers (75th and 90th percentile), suggesting better matching opportunities in dense area, consistently with Wheeler (2006). Returns to job changes are instead negative for unskilled workers.

Combining these findings, it clearly emerges that in dense areas unskilled workers advance in their careers by remaining in their jobs, while skilled workers benefit by exploiting matching opportunities.[19]

[table 12 around here]

However, one might argue that the sample of migrants from lower to higher density provinces is not representative of the whole economy (Mion and Naticchioni, 2009, Baum-Snow and Pavan, 2012). For this reason, we carry out the same econometric specification -including tenure and job-to-job changes- on the sample of stayers using the dichotomic classification of LD and HD, i.e. stayers in the sense that they remain in the same LD or HD area although they may change jobs within the area. Since the results derived from the sample of stayers are very similar to those derived from the group of migrants (table 13), our findings may well be taken as representative of the whole economy.[20] [21]

[table 13 around here]

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[19] We have run the same estimates using the sample of young workers and introducing the detailed experience variables, as in table 5. Results are very close from a qualitatively point of view. They are available upon request.

[20] Note that estimates in tables 12 and 13 can change sign after some years (around 7-10) from the migration, due to the quadratic term. Nonetheless this change concerns a relatively few number of observations in the sample (around 1.2%), thus suggesting that this issue should not represent a main concern of the analysis.

[21] Note that there could be some degree of interaction between the tenure and job-to-job variables. We have therefore run the same estimates for migrants including one at a time the tenure variable and the job-to-job variable; results remain consistent, and are available upon request.

Moreover, we also verify whether there is a higher incidence of job changes in HD provinces, as argued in Yankow (2006), which would entail a greater cumulative wage growth. On the evidence of table 14 the overall job change incidence can be seen to be basically the same for the group of stayers in LD provinces (9%) and for the group of stayers in HD provinces (8.8%), and a similar incidence is observed for the group of migrants from lower to higher density provinces after migration (8.5%). However, since we work in a quantile framework we aim at enriching the analysis of Yankow (2006) by investigating whether the differences between different sized provinces in the incidence of job changes vary along the wage distribution. To do so we compute the incidence of job changes for the four quartiles of the wage distribution.

From table 14 it emerges that for the first three quartiles of the wage distribution there are decidedly negligible differences in the incidence of job changes between the groups of stayers in LD provinces and the stayers in HD. Interestingly, in the first quartile the incidence of job changes for migrants is almost two percentage points higher than for stayers. Since for this group returns to job changes are negative, this entails a stronger cumulative penalization for low skilled workers due to job mobility.

Further, it is interesting to note that at the fourth quartile the incidence of job changes for the group of stayers in high density provinces (7.5%) is higher than for the group of stayers in low density provinces (6.5%), while an intermediate values is observed for the group of migrants (7.1%). This evidence points out that skilled workers have a higher incidence of job change in HD provinces than in LD provinces. This also means that for skilled workers not only are the returns to each single job change higher in HD provinces (tables 12 and 13) but also the incidence of job changes, suggesting that the cumulative returns to job changes are even higher than those shown in tables 12 and 13.

[table 14 around here]

All these findings suggest that for skilled workers the driving force of wage growth dynamics in dense areas is largely a matter of better matching opportunities, while for unskilled workers it is related to human capital accumulation, in line with the learning explanation.[22]

5. Conclusions

In this paper we investigate whether, and if so to what extent, the determinants of the urban wage premium, in terms of agglomeration economies, human capital accumulation and quality matching, differ along the wage distribution. Having controlled for the sorting of workers by means of quantile fixed effect regressions, we arrive at the following findings.

First, the patterns of the urban wage premium are far from homogeneous along the wage distribution. In particular, skilled workers enjoy wage premiums that are balanced between a wage level effect at the time of migration and a wage growth effect. For low skilled workers the urban wage premium is due to a wage growth effect, since wages increase over time.

Our findings are robust to control for experience acquired in bigger cities, in line with recent literature (De la Roca and Puga, 2013). Interestingly, we also show that while experience displays decreasing returns along the wage distribution, experience acquired in top cities (Rome and Milan) is associated to increasing returns along the distribution. We also carry out other additional robustness checks, which confirm our baseline estimates.

Second, we further investigate the determinants of the wage growth effect in dense areas. For both migrants to higher density provinces and stayers in LD and

[22] Our findings are to some extent not consistent with those derived by Baum-Snow and Pavan (2012). However, the two papers differ for many aspects such as the sample, the econometric approach and the countries analysed, among others. To make the two approaches more comparable, we carry out a robustness check for the sample of prime age workers, using the age variable, proxy for experience in the labour market. In particular, we use a specification including the linear term of age separated for workers in LD and HD provinces, and the quadratic term in common between LD and HD provinces, as in Baum-Snow and Pavan (2012) for the experience variable. In the specification we also include the job change dummies and all the covariates of table 13 (excluding tenure). When focusing on the conditional mean, the results come closer to Baum-Snow and Pavan (2012), i.e. the coordination explanation plays a very negligible role. However, when considering the two tails of the distribution our findings are still confirmed: skilled workers benefit more from job changes while unskilled workers benefit more from human capital accumulation. These estimates are available upon request.

HD provinces, within-job wage growth is an important driver of the wage growth effect for unskilled workers, and this effect is stronger in HD provinces: unskilled workers benefit more from human capital accumulation in dense areas. On the contrary, for skilled workers it is more the between-jobs wage growth that matters and this effect is stronger in HD provinces: in dense areas there are better matching opportunities for skilled workers.

References

Baum-Snow, N., Pavan R., (2012), "Understanding the City Size Wage Gap", *The Review of Economic Studies*, 79(1): 88-127.

Borjas, G.J., (1987), "Self-selection and earnings of immigrants", *American Economic Review*, 77: 531–53

Canay, I. (2011), "A Simple Approach to Quantile Regression for Panel Data", *The Econometrics Journal*, 14 (3): 368-386.

Cappellari, L., Dell'Aringa, C., Leonardi, M. (2012), "Temporary Employment, Job Flows and Productivity: A Tale of Two Reforms," *Economic Journal*, Royal Economic Society, 122(562): F188-F215.

Ciccone, A., Hall, R. (1996), "Productivity and the Density of Economic Activity", *American Economic Review*, 86: 54-70.

Combes, P. (2000), Economic structure and local growth: France, 1984-1993, *Journal of Urban Economics*, 47: 329-355.

Combes, P., Duranton, G., Gobillon, L. (2008), "Spatial Wage Disparities: Sorting Matters!", *Journal of Urban Economics*, 63: 723-742.

Combes, P., Duranton, G., Puga D., Roux S., (2012), "Sorting and local wage and skill distributions in France", *Regional Science and Urban Economics*, 42: 913-930.

De la Roca J., Puga D., (2013), Learning by Working in Big Cities, Working Paper wp2013_1301, CEMFI.

Dustmann, C., Meghir, C. (2005), Wages, Experience and Seniority, *Review of Economic Studies*, 72: 77-108.

Glaeser, E.L. (1998), "Are cities dying?", *Journal of Economic Perspectives* 12:139–160.

Glaeser, E.L. (1999), "Learning in cities", *Journal of Urban Economics* 46: 254–277.

Glaeser, E.L., Maré, D.C. (2001), "Cities and Skills", *Journal of Labor Economics*, 19(2): 316-342.

Glaeser, E.L., Resseger, M.G. (2010), "The Complementarity Between Cities and Skills", *Journal of Regional Science*, 50(1): 221-244.

Gomez-Salvador, R., Messina, J., Vallanti, G. (2004), "Gross Job Flows and Institutions in Europe", *Labour Economics*, 11, 469-485.

Gould, E.D. (2007), "Cities, Workers, and Wages: A Structural Analysis of the Urban Wage Premium" *Review of Economic Studies,* 74: 477-506.

Helsey R.W., Strange W.C. (1990), "Matching and agglomeration economies in a system of cities", *Regional Science and Urban Economics,* 28: 189–212.

Heuermann D., Halfdanarson B., Suedekum J., (2010), "Human Capital Externalities and the Urban Wage Premium: two Literatures and their Interrelations", *Urban Studies*, 47(4): 749-767.

Kim, S. (1987) "Diversity in urban labor markets and agglomeration economies", *Papers of the Regional Science Association*, 62: 57–70.

Kim, S. (1990), "Labor heterogeneity, wage bargaining, and agglomeration economies", *Journal of Urban Economics,* 28: 160–177.

Koenker, R. (2004), "Quantile Regression for Longitudinal Data", *Journal of Multivariate Analysis*, 91(1): 74-89.

Lehmer F., Moller, J., (2010), "Interrelations between the urban wage premium and firm-size wage differentials: a microdata cohort analysis for Germany", *The Annals of Regional Science*, 45(1): 31-53.

Matano, A., Naticchioni, P. (2012), Wage Distribution and the Spatial Sorting of Workers, *Journal of Economic Geography*, vol.12(2), pp.379-408.

Mion, G., Naticchioni, P. (2009), The Spatial Sorting and Matching of Skills and Firms, *Canadian Journal of Economics*, Canadian Economics Association, 42(1): 28-55.

Moller, J., Haas, A., (2003), "The Agglomeration Differential Reconsidered: an investigation with German Micro Data 1984-1997". In J. Broecker, D. Dhose, R. Soltwedel (eds) *Innovation Clusters and Interregional Competition*, Berlin: Springler.

Moretti, E. (2004), "Human Capital Externalities in Cities", in Henderson J.V. and Thisse J.F. (eds.), *Handbook of Regional and Urban Economics*, Elsevier-North Holland, Amsterdam, 4.

OECD (2011), *Divided We Stand: Why Inequality Keeps Rising*, OECD Publishing.

Postel-Vinay, F., Robin, J.M. (2006), "Microeconometric Search-Matching Models and Matched Employer-Employee Data", in R. Blundell, W. Newey and T. Persson (eds.), *Advances in Economics and Econometrics: Theory and Applications*, Ninth World Congress, 2, Cambridge: Cambridge University Press.

Topel, R. (1991), Specific capital, mobility, and wages: Wages rise with job seniority, *Journal of Political Economy*, 99: 145-176.

Wheeler, C.H., (2004), "Wage inequality and urban density", *Journal of Economic Geography*, 4: 412-437.

Wheeler, C.H., (2006), "Cities and the growth of wages among young workers: Evidence from the NLSY", *Journal of Urban Economics,* 60(2):162-184.

Yankow, J., (2006), "Why do cities pay more? An empirical examination of some competing theories of the urban wage premium", *Journal of Urban Economics* 60(2): 139-161.

Tables

Table 1: Descriptive Statistics for Stayers and Migrants.

	Stayers Low Density (179,431)				Stayers High Density (197,125)			
Variables	**Mean**	**Std.Dev.**	**Min**	**Max**	**Mean**	**Std.Dev.**	**Min**	**Max**
Real Weekly Wage (log)	6.00	0.38	4.25	8.73	6.14	0.42	4.25	9.23
Age	42.05	8.06	25	66	42.47	8.06	25	67
Blue Collar	0.71	0.45	0	1	0.58	0.49	0	1
White Collar	0.29	0.45	0	1	0.42	0.49	0	1
Firm Size (log)	4.60	2.69	0	12.11	5.25	2.80	0	12.11
North West	0.23	0.42	0	1	0.51	0.50	0	1
North East	0.25	0.43	0	1	0.23	0.42	0	1
Centre	0.21	0.40	0	1	0.19	0.39	0	1
South	0.22	0.41	0	1	0.07	0.26	0	1
Island	0.11	0.31	0	1	0.00	0.00	0	0
Industry	0.66	0.47	0	1	0.59	0.49	0	1
Services	0.34	0.47	0	1	0.41	0.49	0	1
	Migrants Low-High Density (43,130)				**Migrants High-Low Density (43,561)**			
Variables	**Mean**	**Std.Dev.**	**Min**	**Max**	**Mean**	**Std.Dev.**	**Min**	**Max**
Real Weekly Wage (log)	6.16	0.49	4.27	8.87	6.16	0.50	4.25	9.04
Age	40.56	7.81	25	65	40.62	7.93	25	67
Blue Collar	0.52	0.50	0	1	0.52	0.50	0	1
White Collar	0.48	0.50	0	1	0.48	0.50	0	1
Firm Size (log)	5.25	2.66	0	12.07	5.15	2.54	0	12.11
North West	0.35	0.48	0	1	0.36	0.48	0	1
North East	0.25	0.43	0	1	0.25	0.43	0	1
Centre	0.20	0.40	0	1	0.18	0.38	0	1
South	0.14	0.35	0	1	0.15	0.36	0	1
Island	0.06	0.25	0	1	0.06	0.24	0	1
Industry	0.59	0.49	0	1	0.60	0.49	0	1
Services	0.41	0.49	0	1	0.40	0.49	0	1

Source: Panel INPS (processed by ISFOL) data. Number of observations in brackets.

Table 2: Wage Dynamics of Migrants. Quantile Regression.						
	q10	**q25**	**q50**	**q75**	**q90**	**mean**
Stayer in a High Density province	0.015***	0.015***	0.026***	0.036***	0.044***	0.032***
	[0.002]	[0.001]	[0.001]	[0.002]	[0.002]	[0.001]
Moving to a province of higher density:						
Observed 5-10 years before a move	0.036***	0.030***	0.030***	0.030***	0.043***	0.050***
	[0.004]	[0.004]	[0.003]	[0.005]	[0.010]	[0.004]
Observed 3-4 years before a move	0.017***	0.021***	0.031***	0.045***	0.057***	0.053***
	[0.006]	[0.004]	[0.005]	[0.005]	[0.007]	[0.004]
Observed 1-2 years before a move	-0.024***	0.004	0.018***	0.036***	0.054***	0.034***
	[0.007]	[0.003]	[0.002]	[0.003]	[0.006]	[0.003]
Observed within a year after a move	-0.035***	-0.008	0.015***	0.041***	0.069***	0.035***
	[0.007]	[0.005]	[0.004]	[0.006]	[0.011]	[0.004]
Observed 1-2 years after a move	0.007	0.016***	0.041***	0.076***	0.105***	0.073***
	[0.005]	[0.005]	[0.003]	[0.006]	[0.008]	[0.004]
Observed 3-4 years after a move	0.038***	0.041***	0.060***	0.099***	0.137***	0.099***
	[0.004]	[0.005]	[0.007]	[0.008]	[0.015]	[0.005]
Observed 5-10 years after a move	0.051***	0.054***	0.086***	0.125***	0.162***	0.121***
	[0.005]	[0.004]	[0.005]	[0.008]	[0.010]	[0.004]
Moving to a province of lower density:						
Observed 5-10 years before a move	0.029***	0.029***	0.037***	0.050***	0.072***	0.054***
	[0.005]	[0.004]	[0.004]	[0.005]	[0.008]	[0.004]
Observed 3-4 years before a move	0.008*	0.013***	0.036***	0.049***	0.067***	0.049***
	[0.005]	[0.004]	[0.005]	[0.005]	[0.010]	[0.004]
Observed 1-2 years before a move	-0.047***	-0.010**	0.017***	0.039***	0.066***	0.025***
	[0.006]	[0.004]	[0.004]	[0.005]	[0.008]	[0.003]
Observed within a year after a move	-0.028***	0.003	0.031***	0.062***	0.086***	0.052***
	[0.007]	[0.004]	[0.003]	[0.005]	[0.008]	[0.004]
Observed 1-2 years after a move	0.005	0.022***	0.044***	0.078***	0.103***	0.074***
	[0.005]	[0.005]	[0.004]	[0.007]	[0.007]	[0.004]
Observed 3-4 years after a move	0.034***	0.042***	0.059***	0.095***	0.126***	0.094***
	[0.007]	[0.006]	[0.003]	[0.007]	[0.011]	[0.005]
Observed 5-10 years after a move	0.045***	0.054***	0.063***	0.093***	0.131***	0.096***
	[0.007]	[0.003]	[0.004]	[0.008]	[0.008]	[0.004]
N. of Observations	463,247	463,247	463,247	463,247	463,247	463,247
N. of Individuals	49,526	49,526	49,526	49,526	49,526	49,526

Notes: Standard Errors in Parenthesis with ***,** and * denoting significance at 1%, 5% and 10% respectevely. Control variables are age, age squared, occupation dummies, firm size and regional, sector and time dummies.

Table 3: Wage Dynamics of Migrants. Quantile Fixed Effects Regression (Canay, 2011).						
	q10	**q25**	**q50**	**q75**	**q90**	**mean**
Stayers	-	-	-	-	-	-
Moving to a province of higher density:						
Observed 5-10 years before a move	-	-	-	-	-	-
Observed 3-4 years before a move	-0.016***	-0.003	0.005**	0.010***	0.024***	0.001
	[0.005]	[0.003]	[0.002]	[0.002]	[0.003]	[0.003]
Observed 1-2 years before a move	-0.047***	-0.015***	-0.002**	0.012***	0.035***	-0.009***
	[0.004]	[0.002]	[0.001]	[0.002]	[0.003]	[0.003]
Observed within a year after a move	-0.038***	-0.006***	0.011***	0.029***	0.058***	0.006**
	[0.004]	[0.002]	[0.001]	[0.002]	[0.004]	[0.003]
Observed 1-2 years after a move	0.009**	0.021***	0.031***	0.046***	0.064***	0.033***
	[0.004]	[0.001]	[0.001]	[0.002]	[0.004]	[0.003]
Observed 3-4 years after a move	0.028***	0.031***	0.039***	0.052***	0.062***	0.045***
	[0.003]	[0.002]	[0.003]	[0.003]	[0.005]	[0.004]
Observed 5-10 years after a move	0.039***	0.040***	0.050***	0.069***	0.086***	0.061***
	[0.003]	[0.002]	[0.002]	[0.002]	[0.004]	[0.004]
Moving to a province of lower density:						
Observed 5-10 years before a move	-	-	-	-	-	-
Observed 3-4 years before a move	-0.030***	-0.009***	0.005***	0.015***	0.025***	0.001
	[0.005]	[0.003]	[0.002]	[0.003]	[0.005]	[0.003]
Observed 1-2 years before a move	-0.042***	-0.007***	0.012***	0.029***	0.055***	0.005*
	[0.003]	[0.002]	[0.001]	[0.002]	[0.004]	[0.003]
Observed within a year after a move	-0.031***	0.001	0.022***	0.040***	0.072***	0.018***
	[0.006]	[0.003]	[0.002]	[0.002]	[0.005]	[0.003]
Observed 1-2 years after a move	0.006**	0.025***	0.034***	0.046***	0.061***	0.033***
	[0.003]	[0.002]	[0.001]	[0.002]	[0.004]	[0.003]
Observed 3-4 years after a move	0.032***	0.039***	0.043***	0.050***	0.068***	0.045***
	[0.004]	[0.003]	[0.002]	[0.002]	[0.005]	[0.004]
Observed 5-10 years after a move	0.030***	0.035***	0.042***	0.057***	0.074***	0.045***
	[0.002]	[0.001]	[0.001]	[0.002]	[0.005]	[0.004]
N. of Observations	463,247	463,247	463,247	463,247	463,247	463,247
N. of Individuals	49,526	49,526	49,526	49,526	49,526	49,526

Notes: Standard Errors in Parenthesis with ***,** and * denoting significance at 1%, 5% and 10% respectevely. Control variables are age, age squared, occupation dummies, firm size and regional, sector and time dummies.

Table 4: Wage Dynamics of Migrants. Sample of Young Workers (15-30). Quantile Fixed Effects Regression.						
	q10	**q25**	**q50**	**q75**	**q90**	**mean**
Experience	0.057***	0.045***	0.038***	0.032***	0.026***	0.041***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Experience squared	-0.002***	-0.001***	-0.001***	-0.001***	-0.000***	-0.001***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Moving to a province of higher density:						
Observed 5-10 years before a move	-	-	-	-	-	-
Observed 3-4 years before a move	-0.024***	-0.013***	0.002	0.015***	0.027***	0.000
	[0.006]	[0.003]	[0.003]	[0.003]	[0.003]	[0.004]
Observed 1-2 years before a move	-0.056***	-0.019***	0.004**	0.026***	0.045***	-0.003
	[0.004]	[0.002]	[0.002]	[0.003]	[0.002]	[0.004]
Observed within a year after a move	-0.047***	-0.009***	0.016***	0.037***	0.064***	0.011**
	[0.006]	[0.003]	[0.002]	[0.003]	[0.005]	[0.004]
Observed 1-2 years after a move	0.008**	0.024***	0.037***	0.049***	0.071***	0.037***
	[0.003]	[0.002]	[0.001]	[0.002]	[0.003]	[0.004]
Observed 3-4 years after a move	0.036***	0.046***	0.052***	0.062***	0.069***	0.052***
	[0.005]	[0.003]	[0.002]	[0.003]	[0.004]	[0.005]
Observed 5-10 years after a move	0.045***	0.053***	0.063***	0.073***	0.087***	0.067***
	[0.004]	[0.002]	[0.002]	[0.002]	[0.006]	[0.005]
Moving to a province of lower density:						
Observed 5-10 years before a move	-	-	-	-	-	-
Observed 3-4 years before a move	-0.018***	-0.010***	0.003	0.013***	0.030***	0.004
	[0.005]	[0.002]	[0.002]	[0.002]	[0.006]	[0.004]
Observed 1-2 years before a move	-0.051***	-0.020***	0.001	0.025***	0.055***	-0.003
	[0.003]	[0.001]	[0.002]	[0.003]	[0.004]	[0.004]
Observed within a year after a move	-0.055***	-0.018***	0.008***	0.030***	0.055***	0.001
	[0.006]	[0.003]	[0.002]	[0.003]	[0.003]	[0.004]
Observed 1-2 years after a move	-0.005**	0.012***	0.024***	0.035***	0.049***	0.020***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.003]	[0.004]
Observed 3-4 years after a move	0.013**	0.026***	0.034***	0.039***	0.049***	0.030***
	[0.006]	[0.002]	[0.002]	[0.003]	[0.006]	[0.005]
Observed 5-10 years after a move	0.016***	0.029***	0.038***	0.050***	0.066***	0.038***
	[0.006]	[0.002]	[0.002]	[0.004]	[0.004]	[0.005]
N. of Observations	286,258	286,258	286,258	286,258	286,258	286,258
N. of Individuals	36,077	36,077	36,077	36,077	36,077	36,077

Notes: Standard Errors in Parenthesis with ***,** and * denoting significance at 1%, 5% and 10% respectevely. Control variables are occupation dummies, firm size and regional, sector and time dummies.

Table 5: Wage Dynamics of Migrants. Sample of Young Workers (15-30). Detailed Experience. Quantile Fixed Effects Regression.						
	q10	**q25**	**q50**	**q75**	**q90**	**mean**
Experience	0.053***	0.042***	0.034***	0.029***	0.022***	0.037***
	[0.001]	[0.000]	[0.000]	[0.000]	[0.001]	[0.000]
Experience squared	-0.002***	-0.001***	-0.001***	-0.000***	0.000	-0.001***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Experience in Rome and Milan	0.017***	0.018***	0.020***	0.021***	0.022***	0.020***
	[0.001]	[0.000]	[0.000]	[0.000]	[0.000]	[0.001]
Experience squared (Rome and Milan)	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Experience in other 4 major provinces of Italy	0.006***	0.006***	0.006***	0.007***	0.010***	0.007***
	[0.001]	[0.000]	[0.000]	[0.000]	[0.001]	[0.001]
Experience squared in other 4 major provinces of Italy	-0.000***	-0.000***	-0.000***	-0.000***	-0.001***	-0.000***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Moving to a province of higher density:						
Observed 5-10 years before a move	-	-	-	-	-	-
Observed 3-4 years before a move	-0.020***	-0.009**	0.006**	0.019***	0.031***	0.005
	[0.006]	[0.004]	[0.003]	[0.003]	[0.003]	[0.004]
Observed 1-2 years before a move	-0.047***	-0.012***	0.011***	0.032***	0.053***	0.004
	[0.004]	[0.002]	[0.002]	[0.002]	[0.005]	[0.004]
Observed within a year after a move	-0.044***	-0.003	0.019***	0.040***	0.069***	0.015***
	[0.008]	[0.004]	[0.002]	[0.002]	[0.004]	[0.004]
Observed 1-2 years after a move	0.008*	0.025***	0.037***	0.050***	0.070***	0.038***
	[0.004]	[0.003]	[0.002]	[0.003]	[0.004]	[0.004]
Observed 3-4 years after a move	0.034***	0.043***	0.049***	0.058***	0.068***	0.049***
	[0.005]	[0.002]	[0.002]	[0.003]	[0.004]	[0.005]
Observed 5-10 years after a move	0.038***	0.045***	0.053***	0.066***	0.078***	0.058***
	[0.003]	[0.003]	[0.003]	[0.003]	[0.004]	[0.005]
Moving to a province of lower density:						
Observed 5-10 years before a move	-	-	-	-	-	-
Observed 3-4 years before a move	-0.023***	-0.017***	-0.003	0.006**	0.023***	-0.002
	[0.004]	[0.003]	[0.002]	[0.003]	[0.005]	[0.004]
Observed 1-2 years before a move	-0.062***	-0.031***	-0.011***	0.013***	0.043***	-0.015***
	[0.004]	[0.002]	[0.002]	[0.002]	[0.003]	[0.004]
Observed within a year after a move	-0.064***	-0.030***	-0.003	0.019***	0.044***	-0.010**
	[0.006]	[0.004]	[0.003]	[0.003]	[0.005]	[0.004]
Observed 1-2 years after a move	-0.014***	0.003	0.015***	0.025***	0.039***	0.011**
	[0.003]	[0.002]	[0.002]	[0.002]	[0.005]	[0.004]
Observed 3-4 years after a move	0.008	0.020***	0.027***	0.032***	0.042***	0.024***
	[0.006]	[0.002]	[0.002]	[0.002]	[0.005]	[0.005]
Observed 5-10 years after a move	0.012***	0.026***	0.034***	0.046***	0.062***	0.036***
	[0.004]	[0.002]	[0.003]	[0.003]	[0.004]	[0.005]
N. of Observations	286,258	286,258	286,258	286,258	286,258	286,258
N. of Individuals	36,077	36,077	36,077	36,077	36,077	36,077

Notes: Standard Errors in Parenthesis with ***,** and * denoting significance at 1%, 5% and 10% respectevely. Control variables are occupation dummies, firm size and regional, sector and time dummies. The other 4 major provinces of Italy are: Genoa, Naple, Turin and Palermo.

Table 6: Wage Dynamics of Migrants. Provincial Dummies. Quantile Fixed Effects Regression.					
	q10	**q25**	**q50**	**q75**	**q90**
Stayers	-	-	-	-	-
Moving to a province of higher density:					
Observed 5-10 years before a move	-	-	-	-	-
Observed 3-4 years before a move	-0.019***	-0.004***	0.005***	0.011***	0.023***
	[0.003]	[0.002]	[0.001]	[0.003]	[0.004]
Observed 1-2 years before a move	-0.047***	-0.016***	-0.002*	0.013***	0.039***
	[0.003]	[0.002]	[0.001]	[0.002]	[0.003]
Observed within a year after a move	-0.036***	-0.005	0.012***	0.031***	0.059***
	[0.006]	[0.003]	[0.002]	[0.003]	[0.003]
Observed 1-2 years after a move	0.011**	0.022***	0.033***	0.048***	0.063***
	[0.005]	[0.002]	[0.002]	[0.002]	[0.005]
Observed 3-4 years after a move	0.031***	0.033***	0.041***	0.054***	0.064***
	[0.005]	[0.002]	[0.002]	[0.003]	[0.005]
Observed 5-10 years after a move	0.040***	0.042***	0.052***	0.069***	0.085***
	[0.003]	[0.002]	[0.002]	[0.002]	[0.004]
Moving to a province of lower density:					
Observed 5-10 years before a move	-	-	-	-	-
Observed 3-4 years before a move	-0.028***	-0.007***	0.005***	0.015***	0.025***
	[0.005]	[0.003]	[0.002]	[0.003]	[0.005]
Observed 1-2 years before a move	-0.042***	-0.007***	0.012***	0.029***	0.053***
	[0.003]	[0.002]	[0.001]	[0.002]	[0.004]
Observed within a year after a move	-0.033***	0.002	0.021***	0.041***	0.073***
	[0.005]	[0.002]	[0.002]	[0.002]	[0.006]
Observed 1-2 years after a move	0.005	0.024***	0.035***	0.047***	0.064***
	[0.004]	[0.002]	[0.002]	[0.002]	[0.003]
Observed 3-4 years after a move	0.030***	0.039***	0.043***	0.052***	0.069***
	[0.003]	[0.002]	[0.001]	[0.003]	[0.004]
Observed 5-10 years after a move	0.030***	0.034***	0.044***	0.058***	0.076***
	[0.003]	[0.002]	[0.002]	[0.002]	[0.004]
N. of Observations	463,247	463,247	463,247	463,247	463,247
N. of Individuals	49,526	49,526	49,526	49,526	49,526

Notes: Standard Errors in Parenthesis with ***,** and * denoting significance at 1%, 5% and 10% respectevely. Control variables are age, age squared, occupation dummies, firm size and provincial, sector and time dummies.

Table 7: Wage Dynamics of Migrants by Skill Levels. Quantile Fixed Effects Regression.

	Blue Collars	White Collars
Moving to a province of higher density:		
Observed 5-10 years before a move	-	-
Observed 3-4 years before a move	-0.010**	-0.002
	[0.004]	[0.004]
Observed 1-2 years before a move	-0.036***	-0.004
	[0.004]	[0.004]
Observed within a year after a move	-0.039***	0.026***
	[0.004]	[0.005]
Observed 1-2 years after a move	-0.022***	0.051***
	[0.004]	[0.005]
Observed 3-4 years after a move	-0.014***	0.055***
	[0.005]	[0.005]
Observed 5-10 years after a move	-0.020***	0.081***
	[0.005]	[0.005]
Moving to a province of lower density:		
Observed 5-10 years before a move	-	-
Observed 3-4 years before a move	-0.011***	-0.002
	[0.004]	[0.004]
Observed 1-2 years before a move	-0.032***	0.011***
	[0.004]	[0.004]
Observed within a year after a move	-0.037***	0.040***
	[0.004]	[0.005]
Observed 1-2 years after a move	-0.032***	0.056***
	[0.004]	[0.005]
Observed 3-4 years after a move	-0.027***	0.064***
	[0.005]	[0.005]
Observed 5-10 years after a move	-0.034***	0.058***
	[0.005]	[0.005]
N. of Observations	287,085	176,162
N. of Individuals	33,163	20,044

Notes: Standard Errors in Parenthesis with ***,** and * denoting significance at 1%, 5% and 10% respectevely. Control variables are age, age squared, occupation dummies, firm size and regional, sector and time dummies.

Table 8: Wage Dynamics of Migrants. High and Low Density Provinces: Spatial Dichotomic Classification. Quantile Fixed Effects Regression.

	q10	q25	q50	q75	q90
Stayers living in a HD Province	-	-	-	-	-
Moving to a HD province:					
Observed 5-10 years before a move	-	-	-	-	-
Observed 3-4 years before a move	-0.030***	-0.004	0.002	0.004	0.021***
	[0.009]	[0.003]	[0.002]	[0.002]	[0.005]
Observed 1-2 years before a move	-0.063***	-0.025***	-0.011***	0.004	0.033***
	[0.008]	[0.002]	[0.002]	[0.003]	[0.005]
Observed within a year after a move	-0.046***	-0.011***	0.005*	0.032***	0.064***
	[0.008]	[0.004]	[0.003]	[0.004]	[0.009]
Observed 1-2 years after a move	0.008***	0.016***	0.029***	0.047***	0.067***
	[0.003]	[0.004]	[0.004]	[0.004]	[0.005]
Observed 3-4 years after a move	0.029***	0.031***	0.041***	0.052***	0.072***
	[0.005]	[0.005]	[0.003]	[0.005]	[0.008]
Observed 5-10 years after a move	0.036***	0.036***	0.052***	0.066***	0.078***
	[0.007]	[0.004]	[0.002]	[0.002]	[0.005]
Moving to a LD province:					
Observed 5-10 years before a move	-	-	-	-	-
Observed 3-4 years before a move	-0.021***	0.002	0.017***	0.030***	0.048***
	[0.006]	[0.005]	[0.002]	[0.004]	[0.008]
Observed 1-2 years before a move	-0.030***	0.007**	0.029***	0.054***	0.092***
	[0.005]	[0.003]	[0.002]	[0.003]	[0.006]
Observed within a year after a move	-0.046***	0.006*	0.038***	0.059***	0.101***
	[0.007]	[0.004]	[0.003]	[0.004]	[0.010]
Observed 1-2 years after a move	0.006	0.035***	0.050***	0.068***	0.084***
	[0.005]	[0.003]	[0.002]	[0.003]	[0.006]
Observed 3-4 years after a move	0.034***	0.051***	0.057***	0.066***	0.083***
	[0.006]	[0.004]	[0.002]	[0.006]	[0.008]
Observed 5-10 years after a move	0.032***	0.042***	0.051***	0.064***	0.087***
	[0.006]	[0.003]	[0.002]	[0.004]	[0.007]
N. of Observations	457,800	457,800	457,800	457,800	457,800
N. of Individuals	46,822	46,822	46,822	46,822	46,822

Notes: Standard Errors in Parenthesis with ***,** and * denoting significance at 1%, 5% and 10% respectevely. Control variables are age, age squared, occupation dummies, firm size and regional, sector and time dummies.

Table 9: Wage Dynamics of Migrants. Displaced Workers. Quantile Fixed Effects Regression.					
	q10	**q25**	**q50**	**q75**	**q90**
Stayers	-	-	-	-	-
Moving to a province of higher density:					
Observed 5-10 years before a move	-	-	-	-	-
Observed 3-4 years before a move	-0.030*	-0.017*	-0.015***	-0.007	0.025
	[0.017]	[0.010]	[0.004]	[0.010]	[0.015]
Observed 1-2 years before a move	-0.072***	-0.038***	-0.018***	-0.002	0.015
	[0.007]	[0.006]	[0.003]	[0.008]	[0.010]
Observed within a year after a move	-0.038**	0.003	-0.001	0.000	0.047***
	[0.019]	[0.010]	[0.002]	[0.006]	[0.016]
Observed 1-2 years after a move	-0.011	0.002	0.005**	0.009*	0.031***
	[0.007]	[0.004]	[0.002]	[0.005]	[0.009]
Observed 3-4 years after a move	0.003	0.009**	0.009***	0.016***	0.017***
	[0.011]	[0.005]	[0.002]	[0.006]	[0.006]
Observed 5-10 years after a move	0.036***	0.036***	0.043***	0.045***	0.056***
	[0.005]	[0.003]	[0.002]	[0.004]	[0.008]
Moving to a province of lower density:					
Observed 5-10 years before a move	-	-	-	-	-
Observed 3-4 years before a move	-0.052***	-0.031**	-0.020***	-0.021**	-0.022
	[0.017]	[0.012]	[0.005]	[0.008]	[0.025]
Observed 1-2 years before a move	-0.062***	-0.043***	-0.033***	-0.008	0.047**
	[0.009]	[0.010]	[0.004]	[0.010]	[0.023]
Observed within a year after a move	-0.063***	-0.038***	-0.029***	-0.016***	-0.006
	[0.018]	[0.008]	[0.002]	[0.006]	[0.010]
Observed 5-10 years after a move	-0.034*	-0.014**	-0.013***	-0.008	-0.005
	[0.020]	[0.006]	[0.003]	[0.005]	[0.010]
Observed 3-4 years after a move	-0.008	0.002	-0.002	-0.005	-0.004
	[0.010]	[0.006]	[0.004]	[0.003]	[0.014]
Observed 5-10 years after a move	0.022***	0.013***	0.010***	0.004	0.014***
	[0.003]	[0.003]	[0.001]	[0.003]	[0.005]
N. of Observations	40,120	40,120	40,120	40,120	40,120
N. of Individuals	6,149	6,149	6,149	6,149	6,149

Notes: Standard Errors in Parenthesis with ***,** and * denoting significance at 1%, 5% and 10% respectevely. Control variables are age, age squared, occupation dummies, firm size and regional, sector and time dummies.

Table 10: Wage Dynamics of Long-Stay Migrants. Quantile Fixed Effects Regression.					
	q10	**q25**	**q50**	**q75**	**q90**
Stayers	-	-	-	-	-
Moving to a province of higher density:					
Observed 5-10 years before a move	-	-	-	-	-
Observed 3-4 years before a move	-0.019**	-0.001	0.006**	0.013***	0.019***
	[0.008]	[0.004]	[0.003]	[0.003]	[0.003]
Observed 1-2 years before a move	-0.054***	-0.017***	0.005**	0.030***	0.054***
	[0.010]	[0.003]	[0.002]	[0.003]	[0.007]
Observed within a year after a move	-0.052***	-0.010*	0.022***	0.043***	0.076***
	[0.010]	[0.006]	[0.003]	[0.003]	[0.005]
Observed 1-2 years after a move	0.008	0.019***	0.033***	0.049***	0.061***
	[0.006]	[0.003]	[0.003]	[0.002]	[0.005]
Observed 3-4 years after a move	0.024***	0.032***	0.041***	0.051***	0.059***
	[0.007]	[0.002]	[0.003]	[0.003]	[0.006]
Observed 5-10 years after a move	0.039***	0.042***	0.053***	0.071***	0.086***
	[0.004]	[0.002]	[0.002]	[0.002]	[0.005]
Moving to a province of lower density:					
Observed 5-10 years before a move	-	-	-	-	-
Observed 3-4 years before a move	-0.033***	-0.006	0.008***	0.020***	0.036***
	[0.005]	[0.004]	[0.002]	[0.003]	[0.007]
Observed 1-2 years before a move	-0.058***	-0.017***	0.003	0.032***	0.054***
	[0.005]	[0.004]	[0.003]	[0.004]	[0.005]
Observed within a year after a move	-0.057***	-0.021***	0.012***	0.036***	0.066***
	[0.008]	[0.005]	[0.004]	[0.004]	[0.006]
Observed 1-2 years after a move	-0.012***	0.010***	0.023***	0.039***	0.050***
	[0.005]	[0.003]	[0.002]	[0.003]	[0.007]
Observed 5-10 years after a move	0.016***	0.025***	0.033***	0.037***	0.054***
	[0.005]	[0.004]	[0.003]	[0.004]	[0.006]
Observed 5-10 years after a move	0.024***	0.028***	0.036***	0.051***	0.067***
	[0.003]	[0.002]	[0.002]	[0.002]	[0.005]
N. of Observations	421,369	421,369	421,369	421,369	421,369
N. of Individuals	41,454	41,454	41,454	41,454	41,454

Notes: Standard Errors in Parenthesis with ***,** and * denoting significance at 1%, 5% and 10% respectevely. Control variables are age, age squared, occupation dummies, firm size and regional, sector and time dummies.

Table 11: Wage Dynamics of Migrants. Quantile Fixed Effects Regression. Excluding Firm Size.					
	q10	q25	q50	q75	q90
Stayers	-	-	-	-	-
Moving to a province of a higher density:					
Observed 5-10 years before a move	-	-	-	-	-
Observed 3-4 years before a move	-0.017***	-0.004	0.005***	0.010***	0.021***
	[0.004]	[0.003]	[0.002]	[0.003]	[0.003]
Observed 1-2 years before a move	-0.049***	-0.015***	-0.003**	0.011***	0.034***
	[0.004]	[0.001]	[0.001]	[0.002]	[0.003]
Observed within a year after a move	-0.041***	-0.006**	0.011***	0.028***	0.059***
	[0.006]	[0.003]	[0.001]	[0.002]	[0.005]
Observed 1-2 years after a move	0.008**	0.022***	0.033***	0.048***	0.066***
	[0.004]	[0.002]	[0.002]	[0.002]	[0.004]
Observed 3-4 years after a move	0.028***	0.032***	0.042***	0.054***	0.064***
	[0.003]	[0.002]	[0.002]	[0.002]	[0.003]
Observed 5-10 years after a move	0.041***	0.043***	0.054***	0.072***	0.089***
	[0.003]	[0.002]	[0.002]	[0.004]	[0.008]
Moving to a province of a lower density:					
Observed 5-10 years before a move	-	-	-	-	-
Observed 3-4 years before a move	-0.025***	-0.008***	0.005***	0.015***	0.026***
	[0.005]	[0.003]	[0.002]	[0.002]	[0.006]
Observed 1-2 years before a move	-0.044***	-0.007***	0.012***	0.028***	0.054***
	[0.003]	[0.002]	[0.001]	[0.002]	[0.004]
Observed within a year after a move	-0.033***	0.002	0.023***	0.039***	0.070***
	[0.005]	[0.003]	[0.002]	[0.003]	[0.004]
Observed 1-2 years after a move	0.006**	0.027***	0.034***	0.045***	0.060***
	[0.003]	[0.002]	[0.001]	[0.003]	[0.004]
Observed 3-4 years after a move	0.030***	0.040***	0.043***	0.051***	0.067***
	[0.004]	[0.002]	[0.001]	[0.002]	[0.004]
Observed 5-10 years after a move	0.033***	0.036***	0.044***	0.057***	0.074***
	[0.004]	[0.002]	[0.002]	[0.003]	[0.004]
N. of Observations	463,247	463,247	463,247	463,247	463,247
N. of Individuals	49,526	49,526	49,526	49,526	49,526

Notes: Standard Errors in Parenthesis with ***,** and * denoting significance at 1%, 5% and 10% respectevely. Control variables are age, age squared, occupation dummies, regional, sector and time dummies.

Table 12: Returns to Tenure and to Job Changes. Sample of Migrants from Lower to Higher Density Provinces after the Migration. Quantile Fixed Effects Regressions.

	q10	q25	q50	q75	q90	Mean
Job-to-Job	-0.031***	-0.020***	-0.005	0.013***	0.024***	-0.003
	[0.009]	[0.004]	[0.004]	[0.004]	[0.008]	[0.005]
Tenure	0.015***	0.006***	0.002**	-0.002	-0.006**	0.003*
	[0.002]	[0.001]	[0.001]	[0.002]	[0.002]	[0.002]
Tenure squared	-0.002***	-0.001***	-0.000**	0.000**	0.001***	-0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Age	0.075***	0.068***	0.067***	0.064***	0.061***	0.069***
	[0.003]	[0.001]	[0.001]	[0.001]	[0.002]	[0.003]
Age squared	-0.001***	-0.001***	-0.001***	-0.001***	-0.000***	-0.001***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Firm size	0.013***	0.012***	0.012***	0.011***	0.010***	0.012***
	[0.001]	[0.000]	[0.000]	[0.000]	[0.001]	[0.002]
Blue collar dummy	-0.060***	-0.058***	-0.062***	-0.065***	-0.082***	-0.067***
	[0.004]	[0.002]	[0.001]	[0.002]	[0.004]	[0.014]
Constant	3.973***	4.230***	4.318***	4.473***	4.641***	4.328***
	[0.053]	[0.018]	[0.020]	[0.030]	[0.053]	[0.088]
N. of Observations	19,503	19,503	19,503	19,503	19,503	19,503
N. of Individuals	4,003	4,003	4,003	4,003	4,003	4,003

Notes: Standard Errors in Parenthesis with ***,** and * denoting significance at 1%, 5% and 10% respectevely. The other control variables are sector and time dummies.

Table 13: Returns to Tenure and to Job Changes in High (HD) and Low Density (LD) Provinces. Sample of Stayers. Quantile Fixed Effects Estimates.

	q10	q25	q50	q75	q90	mean
Job-to-Job HD	-0.019***	-0.008***	0.002	0.019***	0.041***	0.007***
	[0.004]	[0.002]	[0.002]	[0.002]	[0.003]	[0.002]
Job-to-Job LD	-0.034***	-0.021***	-0.010***	0.004	0.020***	-0.008***
	[0.004]	[0.003]	[0.002]	[0.002]	[0.005]	[0.002]
Tenure HD	0.019***	0.010***	0.005***	0.003***	0.001	0.009***
	[0.001]	[0.000]	[0.000]	[0.000]	[0.001]	[0.001]
Tenure squared HD	-0.001***	-0.001***	-0.000***	-0.000***	0.000	-0.001***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Tenure LD	0.013***	0.005***	0.000	-0.003***	-0.007***	0.003***
	[0.001]	[0.000]	[0.000]	[0.000]	[0.001]	[0.001]
Tenure squared LD	-0.001***	-0.001***	-0.000***	0.000	0.000***	-0.000***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Age	0.061***	0.055***	0.052***	0.049***	0.045***	0.054***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.001]	[0.001]
Age squared	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Firm size	0.017***	0.015***	0.014***	0.014***	0.011***	0.014***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Blue collar dummy	-0.070***	-0.073***	-0.076***	-0.083***	-0.099***	-0.083***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]	[0.003]
Constant	4.210***	4.455***	4.593***	4.743***	4.941***	4.480***
	[0.007]	[0.006]	[0.006]	[0.010]	[0.016]	[0.020]
N. of Observations	190,386	190,386	190,386	190,386	190,386	190,386
N. of Individuals	24,869	24,869	24,869	24,869	24,869	24,869

Notes: Standard Errors in Parenthesis with ***,** and * denoting significance at 1%, 5% and 10% respectevely. The other control variables are sector and time dummies.

Table 14: Incidence of Job Changes along the Quartiles of the Wage Distribution. Samples of Stayers in LD, Stayers in HD, and Migrants from Lower to Higher Density Provinces after the Migration.

	Stayers in LD	Stayers in HD	Migrants from lower to higher density provinces
Overall	9.0	8.8	8.5
1th quartile	11.4	11.8	13.3
2nd quartile	8.7	8.5	8.2
3rd quartile	7.4	7.7	6.7
4th quartile	6.5	7.5	7.1