Are the best jobs created in largest cities? Evidence from Italy 1993-2016

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ABSTRACT

The gap in the employment dynamics between larger urban areas and other areas has widened dramatically in recent decades in advanced economies. A proposed explanation for this trend argues that the technological change occurs with greater intensity in larger urban areas than in medium and small cities, since it interacts with the urban agglomeration forces. In particular, more qualified, better paid jobs are expected to grow more in larger cities. This work focuses on the dynamics of most paying jobs and their spatial distribution across different-size cities in Italy in the period between 1993 and 2016. We investigate whether their share has grown and whether its growth has actually been concentrated in the larger cities. Using Bank of Italy's Survey of Household Income and Wealth (SHIW), we find that the share of most paying jobs has increased in aggregate but its growth in large cities was much weaker than in medium and small cities and even negative after 2008.

We also estimate a probit IV model of the worker's probability of being employed in a most paying job across cities. The results show that being in a bigger city does not increase the chances of getting a better paid job. Furthermore, a shift-share decomposition reveals that the weak growth of most paying jobs in larger cities is only partly explained by the sectoral shifts.

Our evidence can be explained by the slow diffusion of new technologies in the Italian economy. Moreover, it is consistent with studies showing the poor performance of the largest urban economies in Italy.

JEL: J24, J31, O14, O18, O33, R11.
KEYWORDS: employment change, technological change, most paying jobs, cities, local labour markets, agglomeration.

1. Introduction

Economic research has mainly focused on technological explanations, formalised through the skill-biased technological change (SBTC) and the routine-biased technological change (RBTC) models, to explain the observed patterns of change in the structure of employment and the growing wage inequalities that have occurred in advanced economies. The SBTC model predicts an upgrading of employment, i.e. an increase in the share of most paying, most skilled employment, as skills complement technology, and a decrease in the share of less paid jobs (Acemoglu 2002, Card and DiNardo 2002), while the RBTC model predicts a polarization, i.e. a decrease in the share of middle, mostly routinary jobs and an increase in the shares of lowest and most paying jobs (Autor et al. 2003). As a consequence, the impact of technology on the lowest and middle shares remains apriori uncertain as these two hypotheses make different predictions while, on the contrary, both converge in predicting that new technologies will increase the share of most paying jobs.

Anyway, the change in the occupational structure tends to be spatially uneven**.** In particular, the main spatial differentiation observed in recent decades is that between the largest urban areas from the other areas (Florida 2002, Moretti 2012, Mazzolari and Ragusa 2013, Autor 2019). A growing body of literature argues that the technological change occurs with greater intensity in larger urban areas as the agglomeration effects that typically occur in such areas interact with technological change, thereby reinforcing it (Davis e Dingel 2020, Koster and Ozgen 2021, Eeckhout et al. 2021). Thus, the employment change pushed by technological change, whether in the form of upgrading or polarisation, should be more intense in urban areas and, as a consequence, the growth of the share of most paying jobs is expected to be larger in large cities. This trend implies a *great divergence* between larger and smaller cities in the concentration of most paying jobs, with the gap between the two types of areas tending to widen over time (Moretti 2012, Kemeny and Storper 2023). These predictions have been empirically confirmed both in the US and, more recently, in a few European countries (Davis et al. 2020, Koster and Ozgen 2021, Rosés and Wolf 2021).

As for Italy the available evidence is much less clear as some studies have found that the employment structure followed a polarisation while others report an upgrading pattern and still others a weak and downward-biased polarisation or even a downgrading of employment. These two latter patterns imply a very modest growth or even a reduction of the share of most paying jobs. Moreover, the strength of the interaction of technological change and agglomeration effects can be questioned on the basis of structural characteristics of the Italian economy. On the one hand, technological change is relatively hindered by the specialisation and fragmentation of the production system. On the other hand, studies on urban economies found that the largest cities generate only weak agglomeration benefits and, conversely, high congestion costs (Accetturo et al. 2019). Under these conditions, it is doubtful *ex-ante* that the larger cities are able to drive technological change and that the growth of most paying jobs there is higher than in medium and small cities.

To the best of our knowledge no study has investigated so far the differentiation between larger cities and the rest of the areas in the change in employment structure. This study aims at filling this gap. We contribute to the existing literature by providing a territorial analysis in which, for the first time, the influence of urban agglomerations on the structure of employment in Italy are under scrutiny. Our analysis focuses on the dynamics of most paying jobs and documents what has been, within the pattern of change of the structure of employment, their evolution over the period between 1993 and 2016, and their spatial distribution between urban areas of different sizes. More specifically, we ask whether, the share of most paying jobs has grown and, consistent with hypothesis of an interaction between technological change and urban agglomerations, whether its growth has actually been concentrated in the larger cities.

The subject investigated has relevant implications. First, as the most paying jobs are directly linked to higher education level of the workforce and to technological change, their spatial distribution and their change over time can provide valuable insights into the dynamics of productivity in the whole economy as well as across sub-national areas. In the hypothesis of an interaction of technological change and agglomeration effects larger cities are designated as the environment where most innovations are generated. This implies growing inequalities between different places, with the larger cities attracting most of the dynamic entrepreneurs and skilled labour and capturing the bulk of the benefits of technological change at the expense of smaller cities (Odendahl et al 2019, Buciuni and Corò 2023). Such a development could trigger the territorial divide between the largest urban areas and the smaller and more peripheral areas. Moreover, these inequalities also tend to create left-behind places (Fiorentino et al. 2024) and to affect political orientations, leading to reduced trust in institutions and political discontent (Rodriguez-Pose 2018, Mitsch et al. 2021). On the other hand, if the interaction between technological change and agglomeration effects is jammed, as is to be expected in an economy characterised by hindered technological change and weak urban agglomeration benefits, the impetus for innovation is reduced and, ultimately, productivity growth at the macroeconomic level will be lower.

We follow the approach pioneered by Goos and Manning (2007) and Autor and Dorn (2013) and use the Survey of Household Income and Wealth (SHIW) conducted by the Bank of Italy. After partitioning employment into cells defined by sector/ occupation combinations, we rank cells by the mean wage and classify them in lowest-, middle-, and most-paying jobs. As a territorial unit we consider the 995 Local Labour Markets (LLMs) as defined by Istat on the basis of the 1981 Census and distinguish them between large, medium and small cities according to their population size[1]. Then we analyse the change in the shares of employment across cities of different size over the long period from 1993 to 2016.

Our results show, for the whole economy, an upgrading of employment until 2008 and a polarisation but downward biased afterwards, with the share of most paying jobs increasing in aggregate in both periods. However, in sharp contrast with the hypothesis of an interaction between technological change and urban agglomeration effects, its growth in large cities is much weaker than in medium and small cities and even negative after 2008. Consequently, there is no divergence.

Since the share of most paying jobs may differ across areas as a result of sorting effects, we estimate the individual probability of being employed in a most paying job. This allows us to account for individual characteristics, which can be related to job position. Furthermore, by instrumenting city size with altitude of the main centre within each LLM, we limit the risk of endogeneity of city size. Estimates reveal that the city size does not affect the probability of most paying jobs, irrespective of the period considered.

Furthermore, through a shift-share analysis we decompose the observed average change in the share of most paying jobs into two components. The *between-sectors* component measures the effect of the sectoral shifts occurred in the economy, while the *within-sectors* component corresponds to the change in the share within sectors and represents a proxy for the effect of technological change. The result shows that the weak growth of most paying jobs in larger cities is partly explained by sectoral shifts, however the *within* component is very limited and even smaller in larger cities.

Overall, our findings show that, contrary to the predictions in the literature, larger cities were not the place where most of the best jobs were created. We provide plausible explanations for this result.

[1] Throughout the article we use the terms city and local labour market interchangeably.

In the rest of the paper, after discussing the related literature in the next section, section 3 presents data in detail, section 4 illustrates the methodology, section 5 shows and comments the results. Section 6 concludes.

2. Literature background and hypotheses

The interaction between the change in employment structure and agglomeration effects

A large number of studies report evidence that the change in the employment structure, and with it the creation of most paying jobs, in recent decades has been concentrated particularly in larger urban areas. Autor (2019) shows that technological change it is a disproportionately an urban phenomenon. In densely populated areas, historically with a higher concentration of highly skilled labour, the level and relative concentration of it has further increased over the decades. Davis e Dingel (2020) show that larger cities specialize in skill-intensive activities. Michaels et al. (2014) find that non-routine jobs are concentrated in US metro areas. Berger and Frey (2016) argue that, following the computer revolution, the creation of new, more skilled and abstract jobs shifted towards cities better endowed with analytical and interactive skills.

Recent developments in the literature offer theoretical explanations of the reasons why employment change and the increase in the share of most paying jobs are likely to be sharper in larger cities (Lin 2011, Cerina et al. 2019, Davis e Dingel 2020, Davis et al. 2020, Eeckhout et al. 2021). These explanations build on the interaction between the effects of agglomerations typically generated in an urban environment and the technological change. Koster and Ozgen (2021) show that sorting, competition and agglomeration are forces that concentrate analytic jobs in large cities. According to Eeckhout et al. (2021) the replacement of mid jobs by high jobs is stronger in large cities because these are more expensive and, as a result, firms make more IT investments to replace routine work.

As for European countries, Davis et al. (2020) confirm that the employment change in France was also mainly an urban phenomenon. Although polarisation affected all areas of the country, the decline in mid jobs was strongest in large cities. In addition, in the larger urban areas the lost mid jobs have been replaced by most paying jobs, while in the smaller ones by low paid jobs. Koster and Ozgen (2021), based on Dutch data, show that urban density not only exerts a negative effect on routine tasks intensity of jobs, but also favours a strong concentration of complex tasks. Similar results have been found by Hurley et al. (2019) and Hurley et al. (2019). Davis et al. (2020) report also a “great divergence” between areas as a result of a greater increase in the highly paid jobs in large cities. This is consistent with Moretti (2012) who argues that larger cities endowed with more high skills also attract new technologies and, due to the complementarity of technologies to skills, the demand for skilled workers further increases. OECD (2020) reports a divergence between metro areas e non-metro areas in terms of per capita GDP.

Employment change and the structural features of the Italian economy

As for the Italian case, the literature reports a wide variety of results on the pattern of change in the structure of employment. Some studies find a polarisation trend since the early 1990s (Goos et al. 2014) or the early 2000s (Cirillo 2016, Brunetti et al. 2020, Intraligi et al. 2024). For others, however, an upgrading emerged until around the crisis of 2008 (Olivieri 2012, Fernandez_Macias 2012, Fernandez_Macias and Hurley 2016, Eurofound 2014, Hurley et al. 2019) while thereafter a downward biased polarization (Aimone Gigio et al. 2021) or a downgrading prevailed (Basso 2020, Fernandez-Macias and Hurley 2016, Eurofound 2014, Hurley et al. (2019). As regards the most paying jobs, Basso (2020) shows that after 2007 there was no growth in their share and concludes that the available evidence casts doubt about the hypothesis that the new technologies adoption acted as the main driver of occupational change in the Italian economy. On the contrary, the growth of low value-added, less skilled services such as accommodation and food service activities explains the rise in the low-paid jobs. Aimone Gigio et al. (2021) find that growth of most paying jobs is somewhat higher in the North-Centre than in the South, however in each macro-area they grow less than lowest paying jobs.

Structural factors and trends that characterised the Italian economy in the period under consideration are important to outline the economic context in which our analysis takes place. First, the technological change appears to be weaker than in other advanced countries due to the sectoral specialisation of the production system and the prevalence of small and family firms (Brandolini and Bugamelli 2009, Bugamelli et al. 2012 and 2018). This is confirmed by the slowdown of the productivity since the mid-1990s. ICT investments lagged behind that of other comparable countries over the whole period we consider. The rise in part-time and fixed-term contracts reduced the accumulation of work experience of the youth and made on-the-job training, an investment complementary to innovation, less convenient for employers (Hoffman et al. 2022). At the end of that period the use of digital technologies according to the Digital Economy and Society Index is still lower than most of other European countries.

Although the literature clearly points to the importance of urban areas in leading employment change and the growth of the share of most paying jobs, the urban dimension has so far been completely neglected in Italian studies.[2] However, there are reasons to believe that the mechanisms behind the creation of most paying jobs in urban areas are relatively weaker in Italy due to the specific shortcomings of major urban areas documented in the available studies (Accetturo et al. 2019).

Wage premiums in Italian urban areas are relatively lower than those estimated for other countries (Lamorgese et al. 2019)[3]. This disadvantage also extends to firm-level productivity and the propensity to innovate. The explanations put forward to account for this poor performance of Italian cities include inefficient infrastructural endowments and rigid housing supply, which may result in high local congestion costs, low labour mobility due to deficiencies in the provision of welfare services and the relative spatial rigidity of nominal wages, dysfunctional firm organisation and inadequate quality of public administration that may inhibit the creation of learning and matching benefits associated with urban agglomeration (Accetturo et al. 2019). Whatever the explanation, in the presence of only weak benefits from urban agglomerations, the interaction mechanisms between technological change and agglomeration can be expected to be not very strong. This is likely to end up negatively affecting the creation of most paying jobs.

3. Data

We use data from the SHIW, a biannual survey conducted by the Bank of Italy on a sample of about 7.000 households per year on average, from which not only can we draw data on occupation, sector and education of workers, but we can also compute the yearly wage and the worked hours. This is the only Italian microdata source that contains both earnings and employment data over a long historical period, the first wave going back to 1977[4]. The paramount advantage of using this dataset is that we do not need to gather extra-information on earnings from other sources and rank jobs based on imputed wages (Eurofound 2014,

[2] Intraligi et al. (2024) and Brunetti et al. (2020) perform an analysis at the provincial level (NUTS3) but do not investigate the urban dimension.
[3] Di Giacinto et al. (2012) find more favourable results for cities but their study is limited to manufacturing sector.
[4] The only source available on earnings and employment, at once, before that date is Population Census. In particular, 1951-1961-1971 Census collect data on employment by education, sector and occupation, but only on a provincial basis. Moreover, from 1981 on, with the disappointment of economic historians, payroll information is no longer reported.

Hurley et al. 2019, Aimone Gigio et al. 2021, Basso 2020). Data on earnings are provided for employees as well as self-employed workers[5].

Our sample is made up of all employed individuals. We compute annual net earnings for each job (Y)[6]. As we need to derive the average hourly real earnings (YHR), we rule out all the individuals for whom the total amount of hours worked in a year is missing or equal to 0[7]. The yearly hours worked (H) are obtained as the product of the weekly hours (WH) by the number of months (M) declared in the survey multiplied by 4.33[8]. The nominal hourly earnings (YH), equal to the ratio Y/H, are finally deflated with the Consumer Price Index to obtain earnings in real terms (YHR) and make comparisons possible across time.

Period

Changes in the employment structure take time to occur. As a result, one needs a long time span to properly measure such changes. Census data would be the best source (e.g. Autor 2019), but in the Italian case they lack information on earnings. On the other hand, SHIW is a unique survey for the time span covered as well as for the quality and the completeness of the information gathered.

In order to have a homogenous set of information about sectors and occupations, we focus on the 24-year-long period from 1993 to 2016 (the latest year for which the Historical SHIW is available). This time span embodies the periods covered by most studies on employment change in Italy and allows us to compare the results obtained so far with ours. We find it useful to split the whole period in two sub-periods, 1993-2008 and 2008-2016. There are at least three main reasons for this partition. First of all, no doubt that global financial crisis in 2008 brought about a shock with significant structural impacts. For instance, in the period 1993-2008, total employment in Italy goes through a long expansionary cycle which abruptly comes to an end in 2009. Hence, it would make our results less comprehensible to overlook this shock and treat this period as one. Secondly, the division into these sub-periods was worthwhile to

[5] In the Italian Labour Force Survey only gross monthly earnings for employees, top-coded at 3,000 euros per month, are reported and as from 2009 only (Basso 2020). Through the paper, as often in the literature, we will use earnings and wages interchangeably to refer to overall labour income.

[6] For self-employed it amounts to gross earnings minus annual depreciation. In this case, earnings in the dataset can be even 0 or negative. If we have gross earnings but depreciation is a missing value, we assume depreciation equal to 0. As regards labour income coming from family firms, there is only one total amount for the whole household and the income is equally distributed among the working members.

[7] Throughout this paper we mainly use headcounts as measure of employment, although we also observe the total amount of worked hours. Earnings are always per hour. Averages are not weighted, but wage ranking remains basically the same when survey weights are used.

[8] 4.33 is the average number of weeks in a month (=52/12).

preserve comparability with other studies (Basso: 2007-2017; Olivieri: 1993-2009, Aimone Gigio et al.: 2011-2017). Finally, with reference to data, in 2008 NACE classification of economic activities was updated and revised. Although main economic sectors in SHIW have been reconstructed by the Bank of Italy according to a homogeneous scheme in the period under scrutiny in our analysis, we want to make sure that changes in the underlying classification do not affect our results significantly.

As a result, we consider three reference dates. For each of these dates, we add data from two consecutive surveys in order to have a greater number of observations: 1993-1995, 2006-2008, and 2014-2016, which from now on we will only label with the second year 1995, 2008 and 2016. This temporal aggregation helps us to reduce cyclical variations of employment and the impact of wage bargaining on the average annual earnings (contracts expire in different years and are renewed with some delay).

Territorial Unit

In order to explore the link between the change in the share of most paying jobs and urbanisation, we break down national territory according to population size. Instead of using administrative units, we use the LLM as a territorial unit (*Sistema Locale del Lavoro* in the ISTAT definition). LLM represents a territorial unit whose boundaries are defined using the flows of daily home-to-work trips. It corresponds to the area where a large part of the population lives and works and where, therefore, most social and economic relationships are exercised. In fact, they are more suitable to measure the agglomeration economies considered by economic theory and arising within the local areas (e.g. Duranton and Puga 2004).

We classify the Italian LLMs into three classes according to population thresholds[9]: large cities (>0.5 million), medium cities (0.1-0.5 million) and the less populated LLMs, that we define as small cities (<0.1 million). These thresholds are the same as those applied by Davis et al. (2020), which classify the largest 117 French metropolitan areas[10].

[9] Although population size and population density are strictly correlated and are both used in the literature (see the discussion in Lamorgese and Petrella 2016), size is better suited to our purposes as our theoretical framework focuses on larger as opposed to other medium and small cities.

[10] Davis et al. (2020) define large (above >0.5m inhabitants), medium-sized (0.1-0.5m) and small (0.05-0.1m) cities, so they exclude metropolitan areas below 50.000 inhabitants. By contrast, we classify all the LLMs, that is the whole Italian territory, not just cities; nonetheless, “small cities” is a convenient definition in our tripartition of territory. Moreover, the population threshold for large cities is the same as that applied by Di Giacinto et al. (2012) who also study agglomeration forces in LLMs and Accetturo et al. (2019) who contrast the Italian level of agglomeration compared to other advanced economies.

We use 1981 LLM definition (955 LLMs) in order to have a pre-determined measure of agglomeration[11]. According to our classification, we have 12 large cities (of which, 5 in the Mezzogiorno) corresponding to the 12 most populous regional capitals, 95 medium cities, and 848 small LLMs (Tab. 3.1). In the mid-1990s small cities absorbed the largest part of the population in the aggregate (23.6 million, about 41%) and in each macroarea, while residents in large cities represented the smallest part (25%). During the time span covered by our study the population living in the Centre-North has increased with the growth largely concentrated in small and medium sized cities. On the contrary, the population growth in the Mezzogiorno was negligible in the aggregate and even negative in small cities. The population in large cities have increased, albeit modestly, in the Centre-North while it remained almost constant in the Mezzogiorno.

Our final dataset is made up of all persons who work in the SHIW, associated to a LLM by municipality of residence[12]. Tab. 3.2 reports the size of our final sample by reference year and its distribution by group of jobs and class of LLM.

HERE TAB 3.1 AND 3.2

Classifying and ranking jobs

In order to rank jobs from lowest to most paying jobs we follow the analytical approach pioneered by Goos and Manning (2007), Goos et al. (2009, 2014) and Autor and Dorn (2013) and adopted by Eurofound (2014, 2017) for European countries, and in other contributions on Italy (Olivieri 2012, Basso 2020, Brunetti et al. 2020, Aimone Gigio et al. 2021). This requires, first, a detailed classification of employment on an occupational and sectoral basis and, second, a ranking of all sectoral-occupational combinations. Goos et al. (2009, 2014) considered 21 occupations in 16 countries, sorted them according to their (imputed) average wage and classified in three groups: high-paid, medium-paid and low-paid occupations. Eurofound (2014, 2017) and Aimone Gigio et al. (2021) use instead a matrix of jobs by occupation-sector[13].

The historical SHIW dataset provides us with occupation and sector for each person employed. Classifications are constant over the time-span covered by the survey. In particular,

[11] Our results are virtually unchanged when 1991 LLM are used. The number of LLMs has always been decreasing from 1981 onwards, as LLMs enlarge by embodying an increasing number of municipalities in each area, but overall the map of the LLMs is quite stable over time. Surprisingly enough, Davis et al. (2020) in their study over the period 1994-2015, define city size based on inhabitants in 2015.

[12] Sample size in 1995 is slightly smaller than the SHIW sample (10847 obs) because we fail to match some city codes of workers in the survey and those in the LLMs dataset.

[13] The number of distinct cells depends on the size of the matrix. As an example, in Hurley et al. (2019) there are 43 two-digit occupations and 21 one-digit sector.

we can exploit a uniform 9x9 occupation/sector classification (see Tab. 3.3). This job classification, albeit not detailed, allows us to overcome changes in classifications, which have occurred over time in the underlying official classifications[14].

Autor (2019) and Goos et al. (2014) consider all sectors and seemingly all occupations. Davis et al. (2020) use data on employees in private companies and exclude self-employment. As regards studies on Italy, Brunetti et al. (2020) focus on employees in the extra-agricultural private sector and exclude self-employment, Basso (2020) includes both employees and self-employed, and excludes the agricultural sector, PA and other public services, while Olivieri (2012) include all sectors as for employment, but refers only to employees in the private sector as for wages.

In this work, we exclude agriculture and PA (sector 1 and 9 in Tab. 3.3) while we include both self-employed and employees[15]. With reference to self-employed, it is worth reminding that with about five million self-employed workers, Italy is the European country with the highest number of self-employed workers (21.7% in 2019, 15.3% in EU28). Accordingly, excluding them would mean to neglect a substantial part of employment, which no doubt contributes to shape employment distribution across sectors and LLMs[16].

HERE TAB 3.3

In this empirical approach a crucial step is ranking jobs. Wage is one of the most frequently used criteria for this purpose although others, such as workers' education or indices of routinization of tasks are also applied. We too take advantage of information on wages, normally not available along with employment, provided by our dataset. In any case, as shown by Goos and Manning (2007) the wage ranking is closely correlated with rankings based on indices of routinization of tasks. Indeed, the best- and worst-paid jobs, which are concentrated in the tails of the wage ranking, are mainly non-routine jobs, while jobs in the middle of the wage ranking are mainly routine jobs. Moreover, it is worth noting that wage data avoid measurement errors affecting other indices (Aimone Gigio et al 2021).

We rank jobs by computing for each occupation/sector cell (63 cells defined as combinations of 9 occupations and 7 sectors) average hourly earnings[17]. In particular, we consider simple

[14] The sectoral classification changed in 2008 (from NACE Rev. 1 to NACE Rev. 2) and ISCO classification in 2011 (Basso 2020).
[15] We also include all positions, not only full-time full-year workers, as in Autor (2019).
[16] As our classification of occupations is quite simple, we would have lost too much information by excluding self-employed occupations. In that respect, this decision is also data-driven.
[17] Basso (2020) ranks 20 wage ventiles; Aimone Gigio et al. (2021) 9x20 sector/occupation cells; Hurley et al. (2019) 18x15 occupation/sector cells.

average by cell, even if we also compute the weighted average using weights provided in the Survey as a robustness check. This rank is defined in 1993-1995 and kept fixed over time and across LLMs[18].

Once they have been ranked, cells are aggregated into three groups of jobs that we term most paying, middle paying and lowest paying jobs. As Davis et al. (2020), we prefer an ad-hoc, theory-driven distribution, as sector and occupation provide some crucial information on the differences between jobs, along with wages. Furthermore, the empirical analysis necessitates mapping a large matrix of sectors/occupations into a simpler distribution. In addition, as we want to study the growth of most paying jobs across LLMs, we prefer our 9 (3x3) groups distribution to a finer distribution, e.g. of quintiles, to keep the sample size big enough in each cell.

Tab. 3.4 shows our rank of jobs along with hourly earnings (*yhr*) in each cell and the final three-groups classification (column "rank"). As can be noted, our groups are not the same size. As expected, some sector/occupation cells are much bigger than others (e.g. the cell including the industry workers) and their position within one group can significantly change the size of the group. When dividing the cells, we prefer to include industry blue collars and office workers in the middle-jobs group following the literature on employment change that consider them as mainly routine-task intensive jobs (e.g. Autor 2019).

HERE TAB 3.4

4. Empirical analysis

Our analysis aims at uncovering what has been the evolution of most paying jobs over the period between 1993 and 2016. More specifically, we consider the spatial distribution of most paying jobs between urban areas of different sizes and test whether, consistent with hypothesis of an interaction between technological change and urban agglomerations, the growth of most paying jobs has actually been concentrated in the larger cities and whether, as a result, there has been a divergence between the larger and smaller urban areas.

To this end, our empirical strategy consists of three main steps. Firstly, we document the pattern of change in the structure of employment and, in particular, the trend of most paying

[18] This is the usual assumption, which keeps the rank fixed and studies the change in the relative size of each group.

jobs across large, mid and small cities. We ask whether their share increased and, if so, whether it increased in larger cities more than in the other areas.

Next, we estimate a probit model of the probability of being employed in a most paying job on worker-level microdata (Lin 2011, Koster and Ozgen 2021). According to the hypothesis of interaction of technological change and agglomeration effects, the size of the city should trigger technological change and, consequently, foster the local concentration of most paying jobs. Through the regression analysis we test whether, after controlling for sorting effects, the probability for a worker to be employed in a most paying job increases with the city size and whether this effect increases over the observe period.

Finally, we perform a shift and share decomposition of the change in the share of most paying jobs in large as well in the other cities to measure the extent of the effect of the sectoral shifts and the contribution of the *within* component, respectively.

4.1. The change in the share of the most paying jobs

As can be seen in Figure 4.1, over the whole period 1995-2016 the number of middle jobs is decreasing everywhere (as found by Davis et al. 2020 for France), however in small and medium-sized cities this is part of a polarisation of employment where both the lowest and the highest paid jobs are growing, whereas in large cities a downgrading is observed where only the lowest paid jobs are growing. If we distinguish between the two sub-periods, we see that before 2008 the most paying jobs decreased in the big cities, while it increased in the other cities. After 2008, the share of most paying jobs continues to decline in large cities, while we observe a downward-biased polarisation in small and medium-sized cities. This evidence contradicts the hypothesis that the growth of the most paying jobs is stronger in the larger cities. On the contrary, these are affected throughout the period by a decline in the share of better-paid jobs (-4.6% over the whole period). Thus, large cities do not seem to play the key role in the creation of high quality jobs that the hypothesis of an interaction between technology and agglomeration ascribes to them. On the contrary, there has been a sustained shift in employment in large cities from medium- and, above all, high-wage jobs to low-wage jobs whose share has increased by 7.5%. As a result, there is not divergence but convergence between cities. As shown in Tab. 4.1, the share of most paying jobs in large cities was initially 16.4%, that is 2.6 times that in small cities (6.3%) and almost 2 time that in medium-sized cities (8.4%), whereas by the end of the period the share in large cities is lower, equal to 11.7%, and these gaps narrowed to 1.3 and 1.2 respectively.

HERE TAB 4.1

Given the complementarity of technologies to skills, a more abundant supply of highly educated workers is required to boost the growth of most paying jobs. Moreover, as argued by Autor (2015), in case of an increase in the demand for skilled labour the supply does not fully accommodate in the short run due to the long time required to generate highly educated human capital. Therefore, in principle, the decreasing dynamics of most paying jobs in large cities could be attributed to a shortage of skilled labour.

Tab. 4.2 points out that large LLMs are persistently better educated than other ones. University graduates are relatively more numerous in large cities and, within each city category, are particularly concentrated in the better-paid jobs. Moreover, the share of graduates in large LLMs increases steeply from 10% to 22%.

HERE TAB 4.2

To better examine the relationship between the size of LLMs and the local supply of skills, we estimate the elasticities of university graduates and high school graduates with respect to the population based on 1991 and 2011 Census data. Tab. 4.3 shows that the elasticity of university graduates is significantly greater than 1, while the elasticity of high-school graduates is also higher than 1, but lower than that of those with a university degree. A 10% increase in population corresponds to a 12.1% increase in university graduates in 1991 and to a 11.3% increase in 2011, very close the values found by Davis et al. (2020) for France. University graduates increase more than proportionally to the population, which means that larger cities attract the most skilled workers throughout the period considered (Lamorgese and Petrella 2016) even this attraction weakens over time as the elasticity value becomes a little smaller in 2011, although still statistically significant.

HERE TAB 4.3

4.2 Estimates of probit model

The theory suggests that, all else equal, workers are more likely to be observed in a most paying job in bigger cities. This is confirmed also in our data as shown by Tab. 4.1. However, the share of most paying jobs we observe in data may differ across areas as a result of sorting of workers rather than as direct consequence of the city size. This is the case where, for example, workers with characteristics correlated to employment in most paying jobs tend to gather in larger cities.

Thus, to control for sorting, based on worker-level microdata from the SHIW, we estimate for each period considered in the aggregate analysis (1993-95, 2006-08 and 2014-2016) a probit model of the probability of being employed in a most paying job as a function of city size and a set of individual characteristics and LLM controls. The basic specification is

$$h_{ji} = \Phi\,(const + \beta_1 City\_size + \beta'_2 X_i) + \varepsilon_i \qquad (1)$$

where Φ is the cumulative standard normal distribution function and i=1..N denotes the i-th worker. The dependent variable h_j is a dummy taking value 1 if the worker is in a most paying job, 0 otherwise. *City_size* denotes the size of the LLM, which is the explanatory variable of interest. As explained below, we consider two different measures of the city size, first the dummy *LargeCity*, then the variable *Ln_pop*. X_i is a vector of controls. As workers' characteristics, we control for sex (*Sex*; male=1), education (*Edu*), measured by years of schooling, (*Age*) and age^2 (*Age^2*), and non-native worker (*Imm*). As regards city characteristics, besides *City_size* we include a dummy (*Mezzogiorno*) to control for LLM belonging to the North-Centre vs South, and local house prices (*hp*). To include house prices, we match the SHIW household samples with the house prices at the provincial level, using the province of the main centre in each LLM. House prices are from Consulente Immobiliare, a semi-annual survey conducted by market operators and published by Il Sole 24 Ore Media Group (Muzzicato et al. 2008). The data are divided into two property categories (new and recently built) and three locations (centre, semi-centre and outskirts). We take the simple average of all these prices as reference price for each province, while the reference year is the first in each period (1993, 2006, 2014). In all regressions, we use clustered standard errors by LLM to account for potential spatial correlation among units within the same LLM. Regressions are not weighted, but using SHIW weights does not change our results.

To begin with, we estimate a probit model where city size is measured by the dummy variable *LargeCity* which assumes value 1 if the worker resides in a large city as already defined in the descriptive analysis above (>0.5 million population), and 0 otherwise (Tab. 4.4). The estimated coefficient measures the effect of residing in a large city on the probability of being employed in a most paying job. The hypothesis of the interaction between technology and agglomeration effects implies that this coefficient takes a positive value and, furthermore, that this value is increasing over time assuming a progressive increase in technology diffusion.

Colums (1) (4) and (7) refer to the model without controls to show the basic correlation between agglomeration and most paying jobs. The correlation is positive but not statistically significant, except in the year 1995. Furthermore, the magnitude of the coefficient decreases over time. With the inclusion of controls (col. (2), (5) and (8)), the city size coefficient decreases in 1995, and remains non significant in 2008 and 2016. On the other hand, control variables are highly significant and with the expected sign. Consequently, R-squared increases significantly compared to the model without controls. This confirms that there are relevant sorting effects whereby workers with characteristics positively correlated with most paying jobs are more concentrated in large cities.

As expected, education and age[19] are strongly positively correlated with a high-job as well as being male. Interestingly enough, this latter correlation is not declining over time. Being a non-native worker negatively impacts on the probability as well as being resident in the Mezzogiorno. Finally, in colums (3), (6) and (9) we include house prices. Given the city size, a higher house price implies an outflow of workers from the city (Duranton and Kerr 2015, Olney and Thompson 2024). Assuming imperfect mobility of labour, the effect of the local house price on the average probability of employment in a most paying job depends on how largely different groups of workers, less or more skilled, and firms react. Therefore, the sign of the effect is uncertain a priori. However, its inclusion is useful as is allows us to control for local housing market conditions and, more generally, it represents a proxy for local congestion. The estimates are virtually unchanged and house prices are only slightly significant in 2008.

HERE TAB 4.4

The main indication from these estimates is that the larger share of most paying jobs in large cities observed in data shown in Tab. 4.1, with the exception of 1995, depends on sorting of workers with given characteristics rather than on population size. Consequently, the hypothesis that large cities drive the creation of most paying jobs is not confirmed. Furthermore, the correlation between city size and the share of most paying jobs becomes weaker over the course of the period, as was already visible in the data in Tab. 4.1.

In order to better investigate this relationship, we now assume as a measure of city size the logarithm of the resident population (*Ln_pop*). As a continuous variable, it is independent of any arbitrary classification of cities according to their size. In addition, to capture any non-

[19] The relation with Age is actually quadratic and hump-shaped, but the coefficient of squared term is very small. For 1995 for instance it becomes negative after the max=85 (years).

linearity in the relationship we also introduce the dummy *BigCity* which takes the value 1 in case the worker resides in one of the four largest cities in 1981[20], 0 otherwise. In the regressions without controls the coefficient of the variable *Ln_pop* (Tab. 4.5, col. (1), (3) and (5)) is positive but not statistically significant, with the exception of 1995. The introduction of the controls drastically reduces the magnitude of the coefficients and removes significance from the coefficient in 1995. This confirms that there are significant sorting effects. The variable *BigCity* is also always non-significant.

HERE TAB 4.5

At this point we have to consider that the estimates obtained so far may be affected by endogeneity. In particular, there may be hidden determinants related to both the city size and the dependent variable. In particular, the location choices of workers who prefer larger cities can be correlated with unobserved characteristics, which in turn are correlated with the probability of employment in the most paying job (Lin 2011). Koster and Ozgen (2021) estimate a model similar to ours and suggest that endogeneity may depend on omitted consumption amenities. In that case there may be city characteristics associated with its size that attract workers with characteristics correlated with the probability of getting the best paid jobs. Endogeneity may also derive from unobserved locational choices of firms, e.g. certain local amenities or policies which may disproportionately attract certain firms that in turn require more high-profile workers. In all those cases, our estimates of city size effects would be biased and inconsistent.

To limit endogeneity risks, we adopt an IV estimation strategy. In particular, we take the altitude of the LLM's main urban centre[21] as an instrument for city size. The idea that natural conditions may represent an initial advantage or disadvantage for agglomeration of economic activity is rooted in the New Economic Geography (Krugman 1991, Henderson et al. 2018). In our case, elevation is supposed to be negatively correlated with city size (e.g. Cohen and Small 1998), but exogenous with respect to our dependent variable.

In Tab. 4.6 we report the results of estimations where *Ln_pop* is instrumented[22]. F-test for first-stage equation (the Kleibergen-Paap Wald F statistic when errors are not i.i.d is always

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[20] They are, in order of size, Rome, Milan, Turin, Naples. They are significantly bigger than the rest of Italian cities in 1981. Naples counted 1.6 million inhabitants in 1981. The next largest city was Palermo with 0.9 million.

[21] See Istat, https://www.istat.it/it/archivio/156224 (Principali statistiche geografiche sui comuni).

[22] We use the command ivprobit in Stata15, designed for IV estimates for probit model, when the endogenous variable is continuous, as in our case. 2SLS-IV is in fact not feasible in the more general nonlinear case. However, we checked that our results hold, when we use a linear probability model and a standard 2SLS-IV approach.

higher than 10, indicating a high explanatory power of our instrument). The estimated coefficients indicate that the city size continues to be non-significant. Apart from the initial year, the findings confirm that the city size does not significantly increase the probability of employment in a most paying job. In particular, the estimation with IV without controls (col. (1), (3) and (5)) removes significance from the population even in 1995. However, when controls are included (col. (2), (4) and (6)), the coefficient of *Ln_pop* takes a negative value in 1995, while the *BigCity* coefficient is positive, both statistically significant. This result suggests that in the 1995 there are unobserved variables that are positively correlated with the probability of employment in a most paying job, not captured by the regressors. The positive coefficient of *BigCity* reveals that at the beginning of the period in the four largest cities this probability was significantly higher. However, this diminishes over time. To appreciate the magnitude of the city size effect, the marginal effect from the coefficient estimated in 1995 for the complete model (col. (2)) are -0.0197 for the variable *Ln_pop* and 0.0694 for *BigCity*.

HERE TAB 4.6

4.3 How sectoral shifts and other structural trends may have affected the most paying jobs

The results of the analyses presented so far suggest that the largest cities have not led the growth in the share of most paying jobs. On the contrary, they experienced a net contraction of their share, a dynamic opposite to that predicted by the hypothesis of interaction between technological change and agglomeration effects. The question therefore arises as to what caused this trend. To find plausible explanations, it is necessary to recall some of the structural features of the economy.

First, the Italian economy is lagging behind in the diffusion of new technologies as a consequence of its structural features, namely its sectoral specialisation and the prevalence of small and family firms (Brandolini and Bugamelli 2009). Comparative analyses point out that technological change was relatively lower in Italy than in comparable countries (Bugamelli et al. 2012 and 2018). ICT investments lagged behind that of other comparable countries over all the period we are considering. The responsiveness of firms to new technologies and to the increasing availability of skilled labour has been be limited.

Secondly, our results are consistent with the findings of studies that have investigated the performance of urban economies in Italy (Accetturo et al. 2019, Ciani et al. 2017). According to them, wage premiums in urban areas are relatively lower than those estimated for other countries and this disadvantage also extends to firm-level productivity and the propensity to innovate (Lamorgese et al. 2019). Moreover, there is evidence that larger cities in last decades suffered from congestion problems and institutional weaknesses that may have prevented them from serving as innovation hubs.

Finally, the consequences of sectoral shifts must be considered. During the period considered, the economy underwent an intense change in its sectoral structure characterised by the contraction of the manufacturing sector and the growth in the weight of tertiary activities. In line with what has been suggested e.g. by Bárány and Siegel (2018), deep structural changes experienced by the advanced economies may play an important role in employment change. To the extent that these trends are not homogeneous between cities of different sizes, they may help to explain spatial differences in the trend of the share of most paying jobs.

The strong growth of the tertiary sector in Italy has been largely driven by the growth of low value-added services in which low jobs predominate, while growth in more qualified services normally located in larger cities has been weak. An important component of low jobs is concentrated in accommodation and food and other tourism-related activities (e.g. Basso 2020). In particular, cultural tourism, which, as documented by Petrella and Torrini (2019), is largely concentrated in large cities, is an important factor that has contributed to the more than proportional growth of the share of low jobs within them. Along with the growth of services, there has been a deindustrialisation process. The contraction of industry exacerbated the reduction in the share of most paying jobs. This effect was stronger in large cities where the reduction of industry was larger.

Fig. 4.2 shows that there have been major shifts in the sectoral structure. Over the entire period, industry has lost 15% of its initial weight while the non-business services sector has grown by 15%. The construction sector initially grew by up to almost 12%, but contracted after 2008, losing almost 4%. Already before 2008, industrial employment was declining, mainly due to the increased international trade and offshoring affecting the tradable sectors (Federico 2014). After 2008, industry underwent a profound restructuring process that aggravated the loss of employment.

Comparison between the largest cities and the other cities shows that the trends are quite homogeneous in qualitative terms, but the variations in the large cities are considerably larger. This implies that sectoral shifts may have affected the dynamics of the share of most paying jobs differently between cities of different sizes.

HERE FIG 4.2

Other factors also contributed to the remarkable and prolonged increase in the share of the less skilled, low value-added employment within tertiary sector. The ageing of the population in Italy and the increasing participation of women in the labour market have led to a growing demand for care services from households (De Philippis 2017). At the same time, on the labour supply side, there has been an increasing availability of immigrant workers, mainly low-skilled. The share of non-national residents over population in the age 15-64, has grown from 0.8 in 1991 to 9.7 in 2016 (Barbiellini Amidei et al. 2018). Given Italy's family-based model of welfare policies, which largely relies on the role of households rather than on public provision or services purchased on the market, households have acquired services directly by recruiting immigrants (Barone and Mocetti 2011). This has boosted low-skilled employment. As a result, the lowest paid jobs in non-business services increased (Rhodes 1996).

In addition, the diffusion of atypical, temporary contracts characterised by higher flexibility and lower costs has contributed to the growth of low-wage employment, especially of workers in low value-added services (Basso 2020, Herrero and Pérez-Ortíz 2023). The share of temporary workers in dependent employment in 1995 was 7.2%, while in 2016 it reached 13.3%. At the same time, the OECD index of the strictness of employment protection related to temporary contracts, which ranges between 0 (lowest protection) to 6 (highest protection), decreased from 4.75 to 1.63 in the period considered. The diffusion of temporary contracts, more intense among lower-skilled jobs, has created a two-tier labour market (Torrejòn Perez et al. 2023) and has contributed to the decline in productivity at the bottom of the distribution (Hoffman et al. 2022). Finally, employment in low-paid jobs may also have acted as a shock absorber in face of the structural decline of manufacturing and construction which was going on following the Great Recession. Indeed, the large destruction of middle paying jobs after 2008 may have pushed more workers previously employed in these jobs into less qualified activities further inflating the share low-paid jobs (Autor 2019).

4.4 *Shift and share decomposition*

The wider shift from industry to non-business services, mostly low value-added and poorly qualified, which occurred in the larger cities may *per se* have implied a loss of most paying jobs within them. To better quantify how sectoral shifts and technological change contributed, respectively, to the observed change in the share of most paying jobs we decompose it through a shift-share analysis into a *between-sectors* and a *within-sectors* component. The *between-sectors* component quantifies the effect of the change in the shares of employment by sector while keeping the incidence of most paying jobs within sectors constant. This component is a proxy for the contribution of sectoral shifts to the change in the share of most paying jobs. The sign of this component is uncertain ex-ante since it depends on which sectors increase and which decrease and the incidence of most paying jobs within them. On the other hand, the *within-sectors* component quantifies the effect of the change in the incidence of most paying jobs in the sectors while keeping the relative weight of each sector constant. This component is strictly correlated to the change in occupations and, according to Autor et al. (1998), Berman et al. (1998) and Goos et al. (2014), may be taken as a rough measure of the impact of technological change as it represents mainly a within-sectors phenomenon. As in both SBTC and RBTC more qualified, better paid jobs are expected to increase, in the event of technological change the *within-sectors* component is expected to contribute positively to the increase in the share of most paying jobs[23].

The results in Tab. 4.7 show that in large cities the *between-sectors* component is large and negative (-3,0%). In particular, the sectoral shifts that weighed most heavily are the contraction of manufacturing (-2.5%) and the contraction of business services after the financial crisis between 2008 and 2016 (-1,9%). Moreover, the *within-sectors* component also makes a negative contribution (-1,6%). Actually, after 2008 it has a positive sign but it only concerns business and non-business services and its magnitude is modest, thus the negative effect prevails over the whole period. Even in medium and small cities, the *within-sectors* component is only positive due to the contribution of business and non-business services. Moreover, the *between-sectors* component is negligible (-0,1%). As in large cities, de-industrialisation contributes negatively but to a lesser extent than in large cities.

Overall, the decomposition indicates that sectoral shifts have indeed contributed to the wider contraction of the most paying jobs in large cities. However, the negative *within-sectors* component shows that technological change has not been sufficiently influential in creating high-skilled jobs. In the end, this result confirms that the largest cities did not drive the growth of most paying jobs.

HERE TAB 4.7

[23] Following Goos et al. (2014) it must be taken into account that technological change, in case of RBTC, may have also two between-sectors opposite effects, that to offset each other, on the share of most paying jobs. First, RBTC reduces the employment, for given level of output, more severely in sectors more intensive in routinary occupations. This effect implies polarization and, consequently, increases the share of most paying jobs. Second, in the same sectors RBTC lowers costs and output prices, so demand for output may increase. This contrasts the previous employment decrease and mitigates polarization and, as a consequence, it exerts a negative effect on the share of most paying jobs.

6. Conclusions

The change in the occupational structure is a spatially uneven phenomenon. The gap between larger urban areas and other areas has widened dramatically in recent decades. Indeed, a recent body of literature argues that the technological change occurs with greater intensity in larger urban areas than in medium and small cities, since in the former ones technological change interacts with the effects of urban agglomeration and thus reinforces. Thus, largest urban areas outpace the other areas and, in particular, more qualified, better paid jobs are expected to grow more in larger cities. However, so far no study has investigated the employment change in Italy and the spatial distribution of most paying jobs across cities of different sizes. This study fills this gap. Our analysis focuses on the dynamics of most paying jobs and documents their evolution over the period between 1993 and 2016. We investigate whether the share of most paying jobs has grown and whether its growth has actually been concentrated in the larger cities. The subject investigated has relevant implications. First, the creation of most paying jobs is strictly related to productivity growth in the economy. Second, if the growth of more productive and better paid jobs is concentrated in large cities spatial inequalities increase between the larger cities and the other areas. Our results show, for the whole economy, an upgrading of employment until 2008 and a polarisation but downward biased afterwards. The share of most paying jobs is increasing in aggregate in both periods but its growth in large cities is much weaker than in medium and small cities and even negative after 2008. Consequently, there is no divergence.

Since the share of most paying jobs may differ across areas as a result of sorting effects, we estimate the individual probability of being employed in a most paying job. Furthermore, we deal with risks of endogeneity by instrumenting city size. The estimates reveal that the being in a larger city does not increase the chances of getting a better paid job.

The shift-share decomposition of the observed average change in the share of most paying jobs reveals that the weak growth of most paying jobs in larger cities is partly explained by the sectoral shifts as measured by the *between-sectors* component and the *within* component, that represents a proxy of the (positive) effect of technological change, is very limited and even smaller in larger cities.

In sharp contrast with the idea of an interaction between technological change and urban agglomeration effects, the analysis shows that larger cities in Italy were not the place where most of the best jobs were created. On the contrary, they experienced a contraction of their share and a large increase in the share of the lowest paid jobs. To explain the evidence provided by our analysis we point to the influence of structural factors. First, the Italian economy is lagging behind in the diffusion of new technologies as a consequence its sectoral specialisation and the prevalence of small and family firms. Second, our results are consistent with the conclusions of studies that have shown the poor performance of large urban economies in Italy. Finally, sectoral shifts, namely the contraction of the manufacturing sector and the growth of service activities, hit the larger cities hardest and contributed to the sharp increase in lowest paid jobs, concentrated mainly in low value-added service activities.

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Table 3.1. Number of LLMs and population (millions) by class of LLM and macro-area

City size	Number / pop in million	Centre-North	Mezzogiorno	Italy
Small	Number of LLMs	494.0	354.0	848.0
	pop 1995	14.4	9.2	23.6
	pop 2016	15.4	9.0	24.4
Medium	Number of LLMs	64	31	95
	pop 1995	12.6	6.3	18.9
	pop 2016	14.2	6.4	20.6
Large	Number of LLMs	7	5	12
	pop 1995	9.1	5.1	14.3
	pop 2016	9.4	5.2	14.6

Notes: Istat data.

Table 3.2. Observations by city size and occupational group

City size	**Occupational group**	**1995**	**2008**	**2016**
Small	Lowest-paying	1711	1619	1334
Medium	Lowest-paying	1432	1245	1173
Large	Lowest-paying	865	701	731
Small	Middle paying	2304	2345	1631
Medium	Middle paying	2005	2031	1526
Urban	Middle paying	1436	1209	967
Small	Most paying	308	361	314
Medium	Most paying	338	371	337
Urban	Most paying	373	229	211
Tot obs		**10772**	**10111**	**8224**

Source: SHIW. 1995 refers to the sum of observations from 1993 and 1995 waves; 2008 to 2006 and 2008; 2016 to 2014 and 2016.

Table 3.3. Sectors and occupations in SHIW

Sector		Occupation	
			employee / salaried worker
1	agriculture	1	workers
2	industry	2	office worker /teacher /employee
3	construction	3	manager
4	retail,repair accomodation and food	4	director
5	transportation and communication		*self-employed*
6	financial services	5	professional
7	professional private serivces, business services, real estate	6	sole entrepreneur
8	households as employer and other private services	7	self-employed
9	PA, education, health and other public services	8	owner or worker in a family firm
		9	business partner or owner of a firm

Notes: Sectors and Occupations in Bank of Italy's Historical SHIW; variables: SETTP11, QUALP10. We include in sector 9 also the Extra-territorial Bodies sector.

Table 3.4. Jobs by sector and occupation ranked by hourly earnings

Sector	Occupation	yhr	obs cum	rank
construction	owner or worker in a family firm	2.32	35	lowest paying
retail,repair accomodation and food	owner or worker in a family firm	2.58	582	lowest paying
transportation and communication	owner or worker in a family firm	2.89	600	lowest paying
financial services	owner or worker in a family firm	2.95	604	lowest paying
industry	owner or worker in a family firm	2.98	717	lowest paying
households as employer and other private services	owner or worker in a family firm	3.03	729	lowest paying
retail,repair accomodation and food	self-employed	3.37	1496	lowest paying
transportation and communication	business partner or owner of a firm	3.49	1510	lowest paying
households as employer and other private services	workers	3.51	1919	lowest paying
retail,repair accomodation and food	workers	3.60	2727	lowest paying
professional private serivces, business services, real estate	workers	3.65	2774	lowest paying
industry	self-employed	3.73	3041	lowest paying
transportation and communication	self-employed	3.96	3151	lowest paying
households as employer and other private services	self-employed	4.01	3256	lowest paying
construction	workers	4.04	3835	lowest paying
professional private serivces, business services, real estate	self-employed	4.14	3965	lowest paying
retail,repair accomodation and food	sole entrepreneur	4.14	**4016**	lowest paying

Sector	Occupation	yhr	obs cum	rank
industry	workers	4.24	2583	middle paying
construction	self-employed	4.28	2762	middle paying
professional private serivces, business services, real estate	sole entrepreneur	4.33	2780	middle paying
professional private serivces, business services, real estate	business partner or owner of a firm	4.59	2827	middle paying
professional private serivces, business services, real estate	office worker /teacher /employee	4.62	3113	middle paying
professional private serivces, business services, real estate	owner or worker in a family firm	4.63	3137	middle paying
households as employer and other private services	office worker /teacher /employee	4.79	3299	middle paying
retail,repair accomodation and food	office worker /teacher /employee	4.83	3726	middle paying
transportation and communication	workers	4.86	3929	middle paying
financial services	self-employed	4.89	3952	middle paying
financial services	workers	5.03	3958	middle paying
construction	office worker /teacher /employee	5.24	4063	middle paying
households as employer and other private services	business partner or owner of a firm	5.37	4084	middle paying
construction	business partner or owner of a firm	5.47	4129	middle paying
households as employer and other private services	sole entrepreneur	5.62	4135	middle paying
industry	office worker /teacher /employee	5.64	4977	middle paying
financial services	professional	5.84	5017	middle paying
retail,repair accomodation and food	business partner or owner of a firm	5.98	5209	middle paying
industry	professional	5.99	5230	middle paying
retail,repair accomodation and food	manager	6.01	5286	middle paying
transportation and communication	office worker /teacher /employee	6.05	5470	middle paying
retail,repair accomodation and food	professional	6.13	5497	middle paying
construction	manager	6.43	5510	middle paying
financial services	office worker /teacher /employee	6.60	**5815**	middle paying

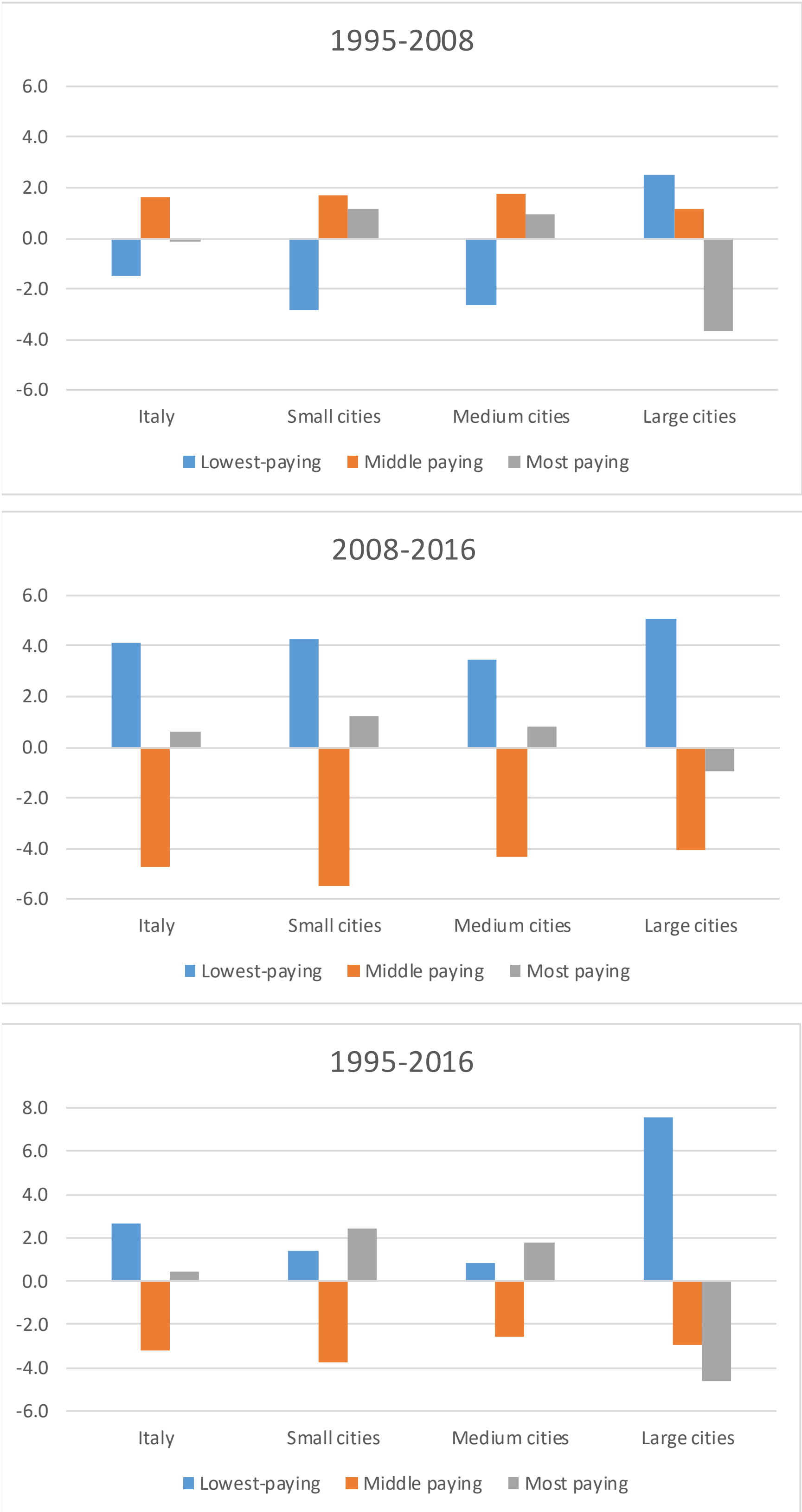
Notes: Private sector, excluding Agriculture. Average hourly earnings in 1993-1995 waves. Source: SHIW.

Table 3.4. Jobs by sector and occupation ranked by hourly earnings (continued)

Sector	Occupation	yhr	obs cum	rank
industry	business partner or owner of a firm	6.62	133	most paying
households as employer and other private services	manager	6.72	143	most paying
households as employer and other private services	professional	6.77	171	most paying
construction	professional	7.03	242	most paying
professional private serivces, business services, real estate	professional	7.19	467	most paying
industry	manager	7.37	642	most paying
transportation and communication	sole entrepreneur	7.54	646	most paying
construction	director	7.63	650	most paying
professional private serivces, business services, real estate	director	7.68	659	most paying
transportation and communication	professional	7.69	663	most paying
industry	sole entrepreneur	7.86	689	most paying
construction	sole entrepreneur	8.16	725	most paying
professional private serivces, business services, real estate	manager	8.60	760	most paying
transportation and communication	manager	8.70	790	most paying
financial services	manager	9.00	895	most paying
retail,repair accomodation and food	director	9.40	908	most paying
households as employer and other private services	director	10.77	912	most paying
industry	director	11.82	963	most paying
financial services	business partner or owner of a firm	11.93	965	most paying
financial services	director	12.22	1000	most paying
transportation and communication	director	13.59	1012	most paying
financial services	sole entrepreneur	18.09	1016	most paying

Notes: Private sector, excluding Agriculture. Average hourly earnings in 1993-1995 waves. Source: SHIW.

Figure 4.1. Changes in shares of employment



Notes: Percentage points. Private sector, excluding Agriculture. Source: SHIW. Weighted averages by SHIW weights.

Table 4.1. Shares of employment by city size and occupational group

Occupational group	1995	2008	2016
		Italy	
Lowest paying	36.4	34.9	39.1
Middle paying	54.1	55.7	51.0
Most paying	9.5	9.3	9.9
		Small cities	
Lowest paying	39.2	36.3	40.5
Middle paying	54.6	56.3	50.8
Most paying	6.3	7.4	8.7
		Medium cities	
Lowest paying	36.4	33.7	37.2
Middle paying	55.3	57.0	52.7
Most paying	8.4	9.3	10.1
		Large cities	
Lowest paying	31.9	34.5	39.5
Middle paying	51.7	52.8	48.7
Most paying	16.4	12.7	11.7

Notes: Percentage points. Private sector, excluding Agriculture. Source: SHIW. Weighted averages by SHIW weights.

Table 4.2. Shares of university graduates by city size and occupational group

Occupational group	1995	2008	2016
		Other cities	
Lowest paying	0.5	3.0	4.9
Middle paying	2.5	7.7	11.7
Most paying	27.7	34.4	48.7
All groups	3.5	8.1	12.1
		Large cities	
Lowest paying	2.2	3.9	8.1
Middle paying	6.7	13.8	19.0
Most paying	37.5	49.9	71.8
All groups	10.2	15.3	22.0

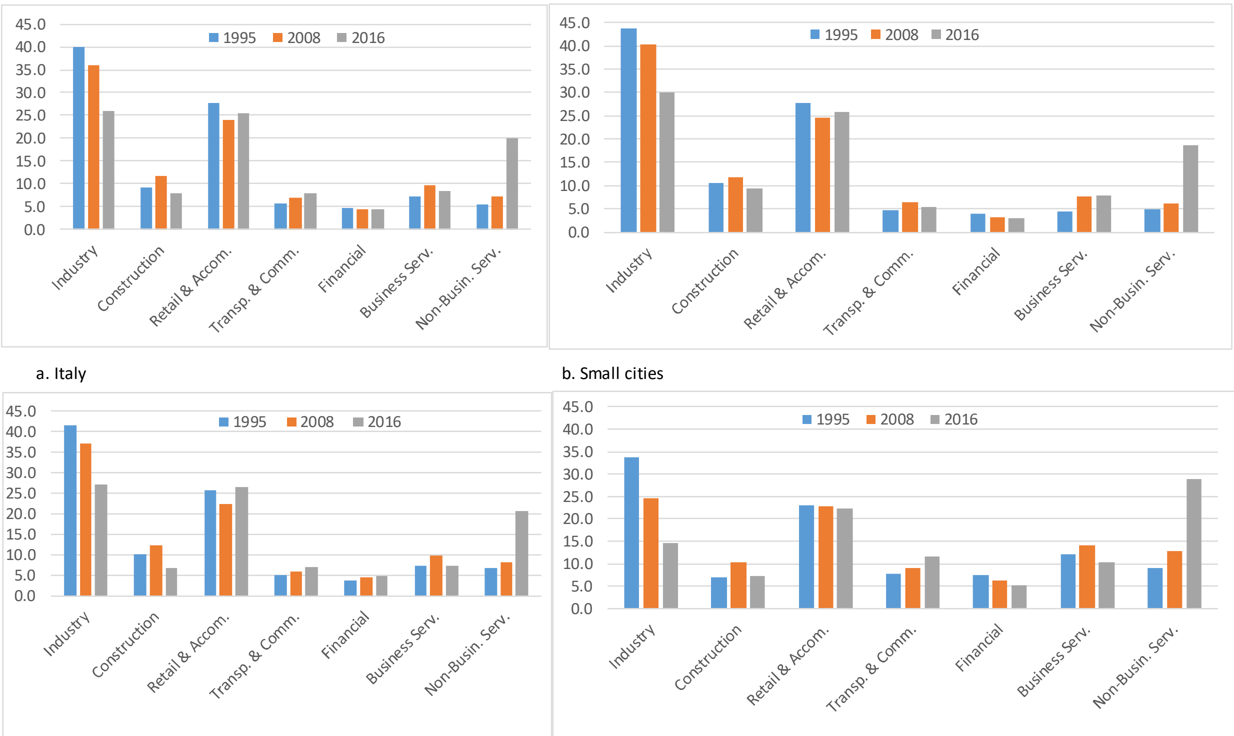
Notes: Percentage points. Private sector, excluding Agriculture. Source: SHIW. Weighted averages by SHIW weights.

Table 4.3. Elasticity of education to population in 1991 and 2011

	(1)	(2)	(3)	(4)	(5)	(6)
		1991			2011	
Var. dip.= Log of:	university graduates	high-school graduates	less educated	university graduates	high-school graduates	less educated
log(pop)	1.21***	1.12***	0.94***	1.13***	1.04***	0.95***
	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)
Constant	-6.03***	-3.18***	-0.13***	-3.91***	-1.70***	-0.67***
	(0.12)	(0.07)	(0.03)	(0.09)	(0.05)	(0.04)
Observations	784	784	784	611	611	611
R-squared	0.936	0.973	0.993	0.969	0.987	0.989

Notes: Log of number of workers by education level (graduated, high school, medium school or lower) over log of population by LLMs. Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Figure 4.2. Shares of employment by sector and city size



a. Italy

b. Small cities

c. Medium cities

d. Large cities

Notes: Percentage points. Private sector, excluding Agriculture. Source: SHIW. Weighted averages by SHIW weights.

Table 4.4. Probability of most-paying jobs in large cities

(OLS estimates)

		1995			2008			2016	
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
LargeCity	0.324***	0.171***	0.168**	0.087	-0.040	-0.127	0.040	-0.025	0.065
Edu		0.195***	0.195***		0.184***	0.184***		0.206***	0.206***
Age		0.085***	0.085***		0.069***	0.069***		0.080***	0.081***
Age^2		-0.001***	-0.001***		-0.000**	-0.000**		-0.001***	-0.001***
Sex		0.321***	0.321***		0.418***	0.420***		0.374***	0.374***
Imm		-0.134	-0.134		-0.712***	-0.718***		-0.881***	-0.877***
Mezzogiorno		-0.256***	-0.255***		-0.067	-0.029		-0.191***	-0.245***
hp1995			0.000						
hp2008						0.067*			
hp2016									-0.097
Constant	-1.407***	-5.833***	-5.837***	-1.330***	-5.732***	-5.818***	-1.264***	-6.360***	-6.230***
Observations	10,772	10,772	10,772	10,111	10,111	10,110	8,224	8,224	8,224
Pseudo_R2	0.0115	0.266	0.266	0.000698	0.225	0.226	0.000155	0.268	0.268

Notes: Probit model; robust standard errors, errors clustered by LLM; pvalues: *** p<0.01, ** p<0.05, * p<0.1. LargeCity is a dummy taking value 1 if LLM population is =>0.5 million inhabitants.

Table 4.5. Probability of most-paying jobs and city size
(OLS estimates)

	1995		2008		2016	
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Ln_pop	0.210***	0.046	0.099	0.008	0.063	0.009
BigCity		0.191		-0.215		0.245
Edu		0.371***		0.343***		0.386***
Age		0.170***		0.151***		0.168***
Age^2		-0.001***		-0.001***		-0.001***
Sex		0.634***		0.803***		0.693***
Imm		-0.252		-1.601***		-2.030***
Mezzogiorno		-0.479***		-0.087		-0.458***
hp1995		0.002				
hp2008				0.078		
hp2016						-0.192*
Constant	-4.843***	-11.684***	-3.441***	-11.331***	-2.905***	-12.060***
Observations	10,772	10,772	10,111	10,110	8,224	8,224
Pseudo_R2	0.0119	0.269	0.00260	0.226	0.00108	0.271

Notes: Probit model; robust standard errors, errors clustered by LLM; pvalues: *** p<0.01, ** p<0.05, * p<0.1. BigCity is a dummy taking value 1 if worker resides in one of the four largest cities in 1981: Rome, Milan, Turin, Naples; see footnote 20.

Table 4.6. Probability of most-paying jobs and city size
(IV estimates)

	1995		2008		2016	
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Ln_pop	-0.030	-0.159**	0.019	-0.033	0.019	0.065
BigCity		0.470**		-0.055		-0.003
Edu		0.197***		0.184***		0.205***
Age		0.085***		0.069***		0.082***
Age^2		-0.001***		-0.000**		-0.001***
Sex		0.314***		0.422***		0.371***
Imm		-0.145		-0.708***		-0.887***
Mezzogiorno		-0.194***		-0.024		-0.280***
hp1995		0.019*				
hp2008				0.072		
hp2016						-0.164*
Constant	-0.943	-4.130***	-1.540**	-5.465***	-1.485**	-6.889***
		0				
Observations	10,772	10,772	10,111	10,110	8,224	8,224
F-test first stag	13.08	25.26	19.55	21.39	30.48	42.05

Notes: Probit model; robust standard errors, errors clustered by LLM; pvalues: *** p<0.01, ** p<0.05, * p<0.1. BigCity is a dummy taking value 1 if worker resides in one of the four largest cities in 1981: Rome, Milan, Turin, Naples; see footnote 20. F-test first stage is the Kleibergen-Paap rk Wald F statistic, accounting for clustered errors.

Table 4.7. Shift-share decomposition of the change in in most-paying jobs by city size

	Small and Medium cities								
		1995-2008			2008-2016			1995-2016	
Sector	Within	Between	**Total**	Within	Between	**Total**	Within	Between	**Total**
Industry	0.0	-0.3	**-0.3**	-0.2	-0.7	**-0.9**	-0.2	-0.9	**-1.2**
Construction	0.3	0.2	**0.5**	-0.3	-0.5	**-0.7**	0.0	-0.2	**-0.2**
Non-Business Services	0.4	0.0	**0.3**	1.1	0.6	**1.6**	1.5	0.5	**2.0**
Business Services	-0.3	0.7	**0.4**	1.4	-0.3	**1.1**	0.9	0.6	**1.5**
Total	**0.4**	**0.6**	**1.1**	**2.0**	**-0.9**	**1.1**	**2.2**	**-0.1**	**2.1**

	Large cities								
		1995-2008			2008-2016			1995-2016	
Sector	Within	Between	**Total**	Within	Between	**Total**	Within	Between	**Total**
Industry	-1.3	-1.3	**-2.7**	-0.7	-1.1	**-1.7**	-1.9	-2.5	-4.4
Construction	-0.1	0.4	**0.3**	-0.6	-0.3	**-0.9**	-0.6	0.0	-0.6
Non-Business Services	0.2	0.2	**0.4**	0.7	1.0	**1.7**	1.0	1.2	2.1
Business Services	-2.1	0.3	**-1.7**	1.8	-1.9	**0.0**	0.0	-1.8	-1.8
Total	**-3.3**	**-0.4**	**-3.7**	**1.2**	**-2.2**	**-1.0**	**-1.6**	**-3.0**	**-4.6**

Notes: Percentage points. Private sector, excluding Agriculture. Source: SHIW. Weighted averages by SHIW weights.