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Automation and labour market inequalities: a comparison between cities and non-cities

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This paper reassesses the displacement effects of automation technologies from an urban perspective by highlighting heterogeneous effects in urban vs non-urban settings. Specifically, the paper argues that automation technologies in the form of robotisation do displace jobs and shrink the labour force, whatever the territorial context considered. However, this displacement effect particularly hits low-skilled workers in non-urban settings which suffer from the substitution pressure of robots and may exit the labour market. In urban contexts, instead, the low-skilled workers displacement effect is offset by reinstatement effects and, more relevantly, a reorientation of occupations towards more skilled, better paid ones, i.e., élite occupations, raising concerns about a widening of i inequalities in cities vs non-cities. The paper proves these statements in an analysis of the adoption of robot technologies in Italian cities in the period 2009–2019.

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INTRODUCTION

Recent years have been characterised by spectacular technological advances in multiple fields ranging from artificial intelligence to robotics, from internet of things to smart sensors, just to name a few of them[1–4].

The pace of technological development has achieved peak levels due to impressive improvements in ICTs, primarily chips[5], coupled with major achievements in (generative) artificial intelligence and new "large language models".

In this respect, the case of the startup ChatGPT, the chatbot developed by OpenAI, is exemplary. Released in November 2022, ChatGPT was used by 1 million people within one week and by 100 million people in two months for uses as diverse as school essays and wedding speeches. Microsoft embedded ChatGPT into its browser service, Bing, and rivals followed this move by releasing alternative chatbots[6].

The popularity of GhatGPT reignited once more the debate on the relationship between technology and society in general and technology and jobs in particular. In fact, the fear of technological unemployment is centuries old. The most famous historical example is the British Luddite movement that led to riots in the first decade of the 19th century. During the 1st industrial revolution, British weavers and textile workers, highly experienced and skilled craftsmen, fought against the introduction of mechanised looms and knitting frames and protested by destroying machineries and equipment[7].

Yet, the new generation of technologies show abilities which were somewhat unexpected even for their own creators, spanning from solving logic puzzles and writing computer code to identifying films from plot summaries written in emoji. Technological enthusiasts are confident of the new technologies potential to solve major societal challenges, including the development of new drugs and new materials and energy sources to fight climate change. Technological pessimists instead fear science-fiction disaster scenario, fatal consequences, disruption of social relationships and job-less future. This mixture of excitement and anxiety does not limit to the public debate but involves the business environment too. Elon Musk, founder of Tesla and Space-X as well as president of Twitter (now X), signed an open letter from the Future of Life Institute, an NGO, asking for a pause in the development of the most advanced form of artificial intelligence[6]. Few days later, Geoffrey Hinton, unanimously considered amongst the "Godfathers of AI" and "Godfathers of Deep Learning", resigned from his position of chief scientist at Google Brain, in order to be able to "freely speak out about the risks of A.I.", especially for jobs[8–10].

This renewed anxiety, however, is not fully, misplaced. In fact, the new technologies are able to perform cognitive and non-routine tasks, and thus have the potential to replace humans in a far larger spectrum of activities, including some white-collar tasks, such as summarising documents and writing code and not simply unskilled and routine ones.

This new technological scenario, therefore, brings to the forefront important societal challenges for the future of job markets. First, economic and employment growth are likely to decouple. By replacing, in principle, all kinds of jobs, the new technologies may lead to economic growth without inducing a parallel employment growth[11]. Possibly more importantly, the full-scale diffusion of the new technologies is deteriorating the outlook of the job markets not only from the quantitative perspective, i.e., the number of jobs being cut is likely to be greater than that of those being created, but primarily from the qualitative point of view, i.e., the types of jobs being cut and/or created and thus the composition of the labour force. Both effects lead to important redistributive consequences. First, the contraction of the number of jobs is likely to depress the wage share, as robustly documented in the US case[4]. Second, the selective and unbalanced displacement and creation effects of the new technologies on different occupational categories is likely to amplify inequalities in the job market. With the new technologies

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being substitute to most tasks and complementary to and/or reinstating of advanced, cognitive and non-routine ones, only a very tiny proportion of individuals can ultimately gain from their large-scale diffusion, leaving the position of most unaltered if not deteriorated, at least in relative terms, making income distribution consequences especially worrisome[12].

Stimulated by these concerns, a lively debate has been developing in the last years about the employment and redistribution effects of the diffusion of the new technologies, with most evidence about automation technologies measured in terms of robot adoption. An automation anxiety was the result of the identification and quantification of the displacement effect of robot adoption[7,13]. Some of these studies went a step further and highlighted the compression of low-skilled workers wage share, but with important nuances depending on the countries, period, groups of workers examined (see for the US[14], for the EU[15], for Japan[16], for France[17], for Germany[18], for Italy[19]).

Despite the important advances achieved, the spatial heterogeneity of the labour market outcomes deriving from the adoption of the new automation technologies remains largely unexplored. Disappointingly, most of the works have been developed by exploiting spatial data settings, without contrasting the automation effects across different types of settlements (i.e., urban vs non-urban). For example, ref. [20], implement some robustness cheques on the metropolitan location of workers. On the other hand[21], as well as[14], respectively, studied the role of ICT and robot adoption for the labour market within urban environments (i.e., US commuting zones). A similar approach was used in the analysis developed for Germany[18] and for Italy[19].

However, this approach remains insufficient to understand whether automation effects harming especially less-skilled, routine and manual workers take place irrespective of *where* the new technologies are adopted. Instead, the effects of technologies may strongly vary according to the labour market structure of each area and to the availability of skills' supply. Urban labour markets could find some shelter with respect to manufacturing ones where these occupations are primarily concentrated. The presence of a large mix of sectors, of an extremely differentiated labour force and of advanced, skill-intensive and non-routine occupations[22], in fact, could make urban areas more likely to experience a reorientation of their labour force towards more skilled (and better paid) occupations. However, the reorientation of the labour demand could take place because of two alternative mechanisms, with opposite effects in terms of wage inequalities. On the one hand, low-skilled workers displaced by the new technologies could switch to advanced and well-paid occupations, possibly created in response to new technological needs[12]. In this case, automation would work as an income equaliser mechanism, by allowing the upgrading and upskilling of displaced workers for new (reinstated) jobs. This effect would primarily take place in urban settings, which represent a nursery environment for the creation of new complex and advanced jobs. On the other hand, urban labour markets could evolve into élite job markets where the fraction of high-skilled and high-paid jobs increases simply as an effect of the exit of displaced low-skill and low-paid workers from the labour market. This effect too would primarily take place in urban settings, where existing complex and advanced jobs are concentrated, but leading to the opposite effect of widening the gap and the inequalities between labour market insiders and outsiders.

This paper aims to fill this gap by examining the effects of automation technologies adoption, measured as robot penetration rate as common practice in the literature, on wage inequalities in Italian cities, measured at NUTS3. Italy represents an ideal case for the empirical verification, for multiple reasons. First, it presents highly differentiated spatial settings, ranging from metropolitan areas to industrial and rural ones, across all parts of the country. Moreover, Italy is characterised by a persistent divide between macro-areas (i.e., North, Centre and South) in terms of technological intensity and propensity to introduce the new technologies. Lastly, Italian cities are characterised by heterogeneous sectoral mix and specialisations, with some still showing a strong industrial vocation and tradition.

In particular, by focusing on the employment compositional outcome of the adoption of automation technologies, the paper complements existing studies on the Italian cases which primarily focus on the displacement effect of these technologies. In doing so, the paper emphasises the income inequality effect by highlighting the impacts of technologies on labour demand, assuming the capacity of the supply to adjust to changes in demand. More importantly, the paper adds to the existing literature by unpacking the nexus between technology adoption, inequalities and cities. By highlighting the heterogeneous effects of automation technologies adoption across territories, the paper warns against superficial interpretations considering urban labour markets being sheltered from the present automation wave and emphasises their role as income inequality multiplier.

The remainder of the paper unfolds as follows. The next sections present the empirical results and their discussion, together with some policy reflections. The description of the data and of the econometric approach applied in the empirical analysis conclude the paper.

RESULTS

Automation and displacement

The labour-saving nature of automation technologies is once more confirmed in the analysis of Italian data. Econometric results (see the Methods section for details), in fact, confirm that, after controlling for a series of cofounding variables, the intensity of automation diffusion (Table 1, columns 1, 3 and 5) and its growth (Table 1, columns 2, 4 and 6) negatively affects the participation to the labour market, here measured as employment to population ratio.

Quite interestingly, and consistently across all specifications, the participation to labour markets is higher in urban contexts as shown by the positive coefficient of the dummy variables flagging metropolitan NUTS3 regions (identified as the most populous NUTS3 regions at different threshold values, namely top 25%, top 20% and top 10%), a result certainly consistent with the literature on agglomeration economies[22]. Additionally, there is also same scaling effect, as the coefficients of the city dummy variables increase with the size of the city, as one can understand from comparing the coefficients of the dummy variable flagging the top 25% cities and the coefficient of the dummy variable flagging the top 10% cities (columns 1 and 2 vs. columns 5 and 6).

More importantly, the effect of automation technologies adoption seems universal across space. The interaction terms between the adoption variables and the city variables, regardless their specific measurement, are never significant. This result is also confirmed by the marginal effects of the automation variable computed for different territorial contexts (i.e., city vs. non-city). Table 2 summarises these results and clearly highlights that the magnitude of the negative effects of automation on employment participation are comparable across space and very stable in terms of magnitude, regardless the size of the cities considered.

Among the control variables, three of them are worth noticing. The local economic structure is crucial to increase labour participation. Regions with an agricultural vocation or strongly dependent on the public sector experience a worse outlook for the labour market. In terms of demographic variables, a larger female participation seems the most crucial element to sustain wider inclusion to the labour markets.

Table 1. Automation impact on employment to population ratio: estimation results.

Dependent variable: Employment to population ratio	1	2	3	4	5	6
Robot density	−0.005***		−0.005***		−0.005***	
	(0.001)		(0.001)		(0.001)	
Growth of robot density		−0.139***		−0.137***		−0.136***
		(0.042)		(0.042)		(0.041)
City dummy (p75)	0.033***	0.029***				
	(0.011)	(0.010)				
City dummy (p75) x robot density	−0.000					
	(0.001)					
City dummy (p75) x robot density growth		0.030				
		(0.039)				
City dummy (p80)			0.037***	0.034***		
			(0.013)	(0.012)		
City dummy (p80) x robot density			−0.000			
			(0.002)			
City dummy (p80) x robot density growth				0.020		
				(0.042)		
City dummy (p90)					0.058***	0.050***
					(0.014)	(0.014)
City dummy (p90) x robot density					−0.001	
					(0.002)	
City dummy (p90) x robot density growth						−0.024
						(0.044)
High-skill employment (%)	0.013	0.000	0.013	0.001	0.014	0.004
	(0.025)	(0.021)	(0.026)	(0.021)	(0.025)	(0.021)
Low-skill employment (%)	−0.009	−0.013	−0.009	−0.013	−0.009	−0.012
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Female employment (%)	0.055***	0.033	0.055***	0.032	0.055***	0.032
	(0.020)	(0.022)	(0.020)	(0.022)	(0.020)	(0.021)
<49 aged employment (%)	−0.018	−0.011	−0.018	−0.011	−0.018	−0.011
	(0.019)	(0.020)	(0.019)	(0.020)	(0.019)	(0.020)
Tertiary educated employment (%)	−0.010	−0.009	−0.010	−0.009	−0.009	−0.009
	(0.017)	(0.018)	(0.017)	(0.018)	(0.017)	(0.018)
Agriculture employment (%)	−0.129**	−0.212**	−0.124**	−0.210**	−0.127**	−0.221***
	(0.061)	(0.084)	(0.060)	(0.085)	(0.059)	(0.083)
Manufacturing employment (%)	−0.162	−0.087	−0.159	−0.084	−0.155	−0.084
	(0.105)	(0.112)	(0.104)	(0.111)	(0.103)	(0.107)
Public services employment (%)	−0.655***	−0.469***	−0.653***	−0.473***	−0.658***	−0.490***
	(0.104)	(0.115)	(0.104)	(0.116)	(0.104)	(0.115)
Constant	0.577***	0.509***	0.575***	0.510***	0.572***	0.509***
	(0.040)	(0.041)	(0.040)	(0.042)	(0.040)	(0.041)
R2	0.75	0.76	0.75	0.76	0.77	0.78
Observations	1174	856	1174	856	1174	856

Standard errors in parentheses. Year and NUTS2 dummy included.
*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Automation, displacement and skills

Automation in the form of robotisation, however, primarily aims at replacing less-skilled, manual and routine jobs[14,23]. Results from Table 3 and Supplementary Table 1 in the Supplementary Information file confirm this conclusion while adding interesting and novel nuances to this general result, which is nonetheless consistent with the literature.

Specifically, Table 3 reports the marginal effects of the intensity of robotisation diffusion on the share of low-skill, mid-skill and high-skill employment by contrasting non-urban vs urban regions, identified as the most populous NUTS3 regions at different population threshold values, namely top 25%, top 20% and top 10%, as in Tables 1 and 2 above.

Interestingly, regardless the specific measurement used for the adoption and the city dummy variables, results consistently show that the labour displacement effect of automation on low-skill employment takes place in both urban and non-urban settings. While in principle, less-skilled, manual and routine occupations are primarily concentrated in manufacturing sectors, generally located in non-urban settings, the Italian case represents somewhat an exception to these general patterns, given the relatively high intensity of manufacturing activities also in urban areas[24], e.g. in the form of logistic functions, where a high density of robots is adopted. In fact, the marginal effects for low-skill employment are persistently negative and significant, without statistically significant different magnitude in the comparison between urban and non-urban settings.

Importantly, and once more consistent with the literature[14], mid-skill employment seems sheltered from the introduction of automation technologies, whatever the measurement of automation technologies adoption and city considered; the marginal effects of adoption intensity in fact never achieves the significance level, whatever the adoption and city dummy variables used. On the other hand, high-skill employment shows spatially heterogenous reactions to robotisation. While in urban settings, high-skill employment expands in association with automation, high-skill employment remains neutral in non-urban environments.

Table 2. Marginal effects of robot density and robot density growth on employment to population ratio for different city groups (top 25%, top 20% and top 10% population).

	Robot density	Robot density growth
Top 25% cities	−0.005***	−0.109**
	(0.001)	(0.055)
Noncity	−0.005***	−0.139***
	(0.001)	(0.042)
Top 20% cities	−0.005***	−0.118**
	(0.002)	(0.058)
Non-city	−0.005***	−0.137***
	(0.001)	(0.042)
Top 10% cities	−0.005***	−0.160***
	(0.002)	(0.059)
Non-city	−0.005***	−0.136***
	(0.001)	(0.041)

Standard errors in parentheses.
***$p < 0.01$; **$p < 0.05$.

DISCUSSION

The results displayed in Tables 1 to 3 highlight important messages and stimulate new reflections on the relationship between technology, employment and income inequalities, which stress the key role of cities in mediating this complex interplay.

First, automation is labour displacing. Differently from other studies conducted in Italy[19], our results align to the expanding literature at the international level pointing to a generalised labour displacement effect from the adoption of automation technologies at the local level. While effects can be positive for single adopting firms (see for example the case of France[17] and Spain[25]), at the territorial level these positive effects can be more than offset by the negative ones experienced by the competing non-adopting firms. The more aggregate the territorial level examined is, the greater this unbalance between adopting vs non-adopting firms can be, thus explaining the divergent results obtained in this work with respect to previous ones conducted at a more disaggregated spatial scale (i.e., local labour markets instead of NUTS3 regions as in our case).

Importantly, labour displacement is a dramatic consequence of modern technology adoption for all types of territorial settings; none of them looks sheltered by these negative consequences. Both urban and non-urban environments are affected alike suggesting that in the Italian context, characterised by a strong diffusion of manufacturing activities also in mid-sized and large cities, robotisation can represent a real challenge for local labour markets.

However, the occupational mix characterising the different territorial environments can explain the adjustment path that local labour markets can undertake when confronted with the present automation wave. In non-urban regions, the shrinking of employment to population ratio in relation to the diffusion of automation technologies ratio suggests that displacement of low-skilled workers is not sufficiently associated and compensated by a reinstatement effect of the same type of occupations[14]. Taken

Table 3. Marginal effects of robot density and robot density growth on employment share by skill level for different city groups (top 25%, top 20% and top 10% population).

	High-skilled workers	Mid-skilled workers	Low-skilled workers	High-skilled workers	Mid-skilled workers	Low-skilled workers
	Robot density			*Robot density growth*		
Top 25% cities	0.003	ns	−0.005	*0.278*	ns	−0.568
	(0.001)		(0.001)	(0.126)		(0.167)
Non-city	ns	ns	−0.004	ns	ns	−0.340
			(0.001)			(0.108)
Top 20% cities	0.004	ns	−0.008	*0.282*	ns	−0.517
	(0.001)		(0.001)	(0.141)		(0.189)
Non-city	ns	ns	−0.004	ns	ns	−0.374
			(0.001)			(0.106)
Top 10% cities	0.003	ns	−0.006	*0.336*	ns	*−0.546*
	(0.001)		(0.001)	(0.165)		*(0.251)*
Non-city	ns		−0.003	ns	ns	−0.361
			(0.001)			(0.131)

Standard errors in parentheses.
***$p < 0.01$; **$p < 0.05$.
ns not significant.

together, the results from Tables 1 to 3 indicate that automation displaces less skilled workers and push them out of the labour market.

Low-skilled workers are equally hit by automation also in urban areas, as shown in Tables 1 and 2. Yet, this displacement brings compositional effects in urban labour markets, as highlighted by results in Table 3. In particular, displaced workers could face wider job opportunities to be re-employed in the large and diversified labour markets generally present in big cities. These opportunities may include also the possibility to switch to advanced and well-paid occupations, possibly created in response to new technological needs[12]. This mechanism cannot be excluded on conceptual grounds. However, the joint reading of Tables 1 to 3 warns against this interpretation as the most likely one. The contraction of the labour force in response to automation, jointly with a shrinking of the low-skilled employment share, suggests that the high-skilled segment of the labour force is deemed to widen. Whereas the upgrading mechanism would mitigate the existing inequalities in urban labour markets, the expansion of the high-skilled employment share, and the displacement of low-skilled workers, unable to be re-employed in more complex, advanced and skilled occupations and their consequent exit from the labour market would amplify inequalities. Assuming that the labour supply adjusts to the demand, as it is highly reasonable in urban settings, all this suggests a worsening of income inequalities in urban environments, increasingly characterised by a dichotomy contrasting high-skilled, well-paid and élite workers versus low-skilled ones, at risk of becoming marginalised and outsiders.

The findings of the paper underline the existence of a displacement of low-skilled workers from robot adoption. These results open to further research directions, as the analysis of the displacement effect induced by technologies able to perform cognitive and non-routine tasks and the spatial effects of automation-induced displacement of low-skilled workers on nearby labour markets.

METHODS

Data

The data used in the empirical analysis come from multiple sources. The main data source is the *Italian Labour Force Survey – Rilevazione delle Forze Lavoro (RFL)*, which collects quarterly individual data on the employment condition of the Italian population, with 2009 as starting year (The information collected from the population constitutes the basis on which the official estimates of employment and unemployment are derived, as well as the information on the main aggregates of the labour supply—occupation, sector of economic activity, house worked, type and duration of contracts, training. The labour force survey is harmonised at European level as established by EU Regulation 2019/1700 of the European Parliament and of the Council and is part of those included in the National Statistical Programme, which identifies statistical surveys of public interest.). From RFL, by aggregating individual level micro-data at the NUTS3 level, we computed for each year of the period 2009–2019 (The time span covered aims to focus on the after-2008-crisis while excluding the years from 2020 onwards and the outbreak of the COVID pandemics. Moreover, the NUTS3 level breakdown of RFL micro-data is guaranteed starting from 2009.) the two dependent variables of the empirical analysis: the employment to population ratio and the employment share by occupational groups (low-skilled, mid-skilled and high-skilled). Low-skilled workers are those classified in one of the two 1-digit International Standard Classification of Occupations (ISCO) categories: plant and machine operators and assemblers (ISCO 8) or elementary occupations (ISCO 9). High-killed workers instead are those classified in one of the three 1-digit ISCO categories: managers (ISCOC 1), professionals (ISCO 2), technicians and associate professionals (ISCO 3). The mid-skilled group comprises the remaining occupations. Data has been aggregated at the NUTS3 level by using the RFL survey weights.

As for regression control variables, the source is the RFL from which NUTS3 level information on gender, education, sector of employment has been derived.

Data on robot adoption at the NUTS3 level has been obtained through apportionment of national data sourced from the International Federation of Robotics (IFR) in the period 2004–2017 by using a set of three weights accounting for the NUTS3 employment share in manufacturing, for the NUTS3 employment share in blue-collar occupations (i.e., ISCO 8) and the NUTS3 share of households with broadband, all computed with respect to the country. The first two weights follow the expectation that the robot adoption is more widespread in regions where industrial activities are more concentrated and the opportunity costs of robot adoption is more attractive while the third follows the expectations that technology adoption requires an adequate digital infrastructure. This approach is widely accepted and consistent with the literature[18,26,27]. A detailed presentation of the apportionment strategy is presented in Appendix. Moreover, because of the count nature of robot data, in the econometric analysis data on regional robot adoption is computed as a moving average over 3 years. In order to control for the size of the region, the robot stock is divided by the number of employees in the manufacturing sector, the largest destination sector of adoption, thus obtaining a measure of robot density at the NUTS3 level. On a similar vein, the growth of robot density is measured as the average annual compound growth rate in robot density over the five preceding years. Supplementary Fig. 1 in Supplementary Information file maps the growth of robot density (robots per 1000 employees) in the period 2005–2010; some unexpected peak values emerge in Southern provinces, probably due to very low values in manufacturing employment.

More controversial instead is operationalisation of the concept of city. Conceptually speaking, the city is a clear and well-accepted economic archetype characterised by the operation of agglomeration economies, thus with self-evident differences with respect to the non-city. This conceptual clarity, however, clashes with empirics. The literature in fact has amply debated issues in the identification of the city and its spatial boundaries, i.e., when an agglomeration is a city and where a city ends and a non-city starts[28].

Alternative measures have been proposed and, in this paper, we follow a solid tradition using the administrative approach and the NUTS classification to identify cities[28–34]). A particular advantage of this approach is that the NUTS3 classification remains constant over our period of analysis. Specifically, the identification of cities is based on different population size thresholds, with data at administrative level: the 25% most populous NUTS3 regions, the 20% most populous NUTS3 regions and the 10% most populous NUTS3 regions, the latter corresponding to a population threshold of 1 million inhabitants. The variable city, therefore, is a dummy flagging with 1 the regions that are in the top 25% (respectively 20% or 10%) of the population distribution and flagging with 0 the remaining ones. (The list of the top 10% cities are: Bari, Bergamo, Bologna, Brescia, Catania, Firenze, Milano, Napoli, Palermo, Roma, Salerno, Torino. The top 20% cities include: Caserta, Genova, Lecce, Monza Brianza, Padova; Treviso, Venenzia, Verona, Vicenza. The top 25% cities include: Cosenza, Foggia, Messina, Modena, Perugia.). As the analyses reported in Tables 1 to 3 show, results are robust to alternative coding of the city dummy variable.

Econometric approach

Results displayed in Tables 1 to 3 are the output of two sets of econometric estimates.

Specifically, the empirical model tested in Tables 1 and 2 takes the following form, consistent with the literature:

$$\text{employment to poulation ratio}_{r,t} = \alpha\left(\text{automation}_{r,t-1}\right) + \beta\left(\text{city dummy}_r\right) + \gamma X_{r,t-1} + \varepsilon_r \quad (1)$$

where r stands for the NUTS3 region, t for the year of observation in the period 2009–2019. The automation variable is measured as robot penetration rate or its annual compound growth rate in the 5 preceding years as noted in the previous section while the city dummy is identified as a dummy flagging the most populous NUTS3 regions identified according to three different threshold values: top 25%, top 20% and top 10%. The term $X_{r,t-1}$ includes a series of control variables. As consistent with the literature[4,12,14,15,18,19,21,23], the control variables capture:

- the regional sectoral structure (e.g., the role of manufacturing and private service against agriculture and public services), controlling for the labour-intensive characteristics of each sector;
- the median age of the labour force, controlling for the different opportunities of finding a job at older ages;
- the female employment rate, controlling for the different opportunities of finding a job being a female rather than a male;
- the tertiary educated labour force share, controlling for the education level of the labour force;
- the composition of the labour force, i.e., the share of high-skilled and low-skilled employment[14].

Importantly, this model has been expanded to include the interaction between the automation and the city dummy variables as to compute the marginal effects of automation across different territorial settings displayed in Table 2.

Admittedly, possible endogeneity issues may affect the estimates. To limit such a bias, the independent variables are introduced in the model lagged in time, an approach widely used in the literature. Even if this solution does not overcome the problem completely, it mitigates possible endogeneity bias in estimates.

Estimates have been obtained in a panel setting with random effects, because of the presence of time invariants variable, chiefly the city dummy, while controlling for year and NUTS2 level region fixed effects with robust standard errors. The results of the Hausman test, performed on Model 1 of Table 1, confirms this approach (Chi2 = 8.99, with $p = 0.98$).

Concerning the empirical model tested in Supplementary Table 1 in the Supplementary Information file and Table 3, the estimated equation takes the following form, consistent with the literature:

$$\text{employment share}_{r,s,t} = \alpha\left(\text{automation}_{r,t-1}\right) + \beta\left(\text{city\_dummy}_r\right) + \gamma Z_{r,s,t-1} + \delta X_{r,t-1} + \varepsilon_r \quad (2)$$

where r stands for the NUTS3 region, s for the skill level (low, medium or high), t for the year of observation in the period 2009–2019. The automation and city variables are measured as in Eq. 1. The term $Z_{r,s,t-1}$ captures a series of control variables which are skill-group specific, namely, the median age of the labour force, the female employment rate, the tertiary educated labour force share and the share of high-skilled and low-skilled employment as consistent with the literature. The variables capturing the regional sectoral structure $X_{r,t-1}$ (e.g., the role of manufacturing and private service against agriculture and public services), instead, have been considered at the regional level, without disaggregating by skill level.

Estimates have been obtained in a pooled panel setting while controlling for year and NUTS2 level region fixed effects with robust standard errors.

DATA AVAILABILITY

Data used in the analysis is available upon request.

CODE AVAILABILITY

Codes used in the analysis are available upon request.

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