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ABSTRACT

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This paper analyzes the relation between specialization in routine tasks and the growth of low-skill jobs in Italian provinces. At this aim we use data of the Labour Force Survey (RCFL-ISTAT) integrated with information about the Italian provinces' specialization in routine tasks derived from the Occupational Information Network (O*NET). Following the empirical strategy proposed by Autor and Dorn (2013), we find the following results. First, in the period between 2004 and 2017, the routine tasks specialization leads to a significant increase in the growth of low-skill/low-wage occupations at province level. Second, if we focus on university-educated workers, the impact of provinces' specialization in routine tasks on the growth of low-skill/low wage jobs slightly increases. This result suggests that the local employment specialization in routine tasks might be also associated with increasing over-education patterns in Italy. Finally, our findings are robust to an econometric strategy that controls for endogeneity issues.

KEYWORDS: tasks, low-skill jobs, employment, provinces

JEL CODES: J23, J24, J20

1. Introduction

Since the early 90's, the composition of European employment has increasingly polarized – i.e. medium-paid occupations lost employment shares in favor of low-paid and high-paid ones. Such U-shaped polarization patterns have been detected both in European and in U.S labor-market data, even in light of the major differences existing among European countries, where a coexistence of divergent occupational wage and employment patterns arise (Fernández-Macías, 2012). For the U.S. case, see Acemoglu and Autor (2011) and Autor and Dorn (2013), while for Europe see Dustmann *et al.* (2009) and Spitz-Oener (2006), for Germany Machin (2011). Goos and Manning (2007) for UK; Centeno and Novo (2009) for Portugal; Goos *et al.* (2009, 2014) and Michaels *et al.* (2010) for Europe. While the empirical literature has quite commonly recognised a polarisation trend both for employment and wages, the explanations around that are less uniform: routinisation of tasks (Acemoglu and Autor 2011; Autor *et al.* 2003; Goos *et al.* 2009, 2014), consumption spillovers (Manning 2004; Mazzolari and Ragusa 2013), offshoring of tasks (Thoenig and Verdier 2003; Feenstra and Hanson 2003; Grossman and Rossi-Hansberg 2012), labour markets and institutions (Mishel *et al.* 2013; Firpo *et al.* 2011; Di Nardo *et al.* 1996) and different technological vergimes (Croci Angelini *et al.* 2009). Among these explanations, the *routine-replacing technical change* (RRTC) has received increasing attention due to the idea that computer capital (robots, software technology and – more in general – ICTs) is more likely to substitute for routine tasks – mainly performed by workers employed in occupations that are generally located in the middle of the skill distribution – while it complements for non-routine tasks (especially for what concerns high-skilled labor, which is intensive in non-routine cognitive tasks – see Autor *et al.* 2003). More recently, the evolution of employment has been related to spacial dynamics reflecting economic, social and institutional specificities (Ciarli *et al.* 2018; Charnoz and Orand 2017). These works highlight the relevance of the geographical dimension, stressing that the nature of the link connecting technological change, human capital and employment dynamics also depends on the characteristics of local labour markets (Moretti 2013). In other words, local labour markets are considered to be a relevant dimension for the analysis of occupational variations given the co-localization of supply and demand for employment. According to Autor and Dorn (2013), local labour markets specializing in routine tasks adopt ICT-type technologies, by reallocating employment to poorly qualified work in the service sector.

On the basis of these two streams of literature, this paper aims to explore the relation between local specialization in routine employment and occupational changes in low qualified jobs. To this aim, we adopt the spatial-framework approach used in Autor and Dorn (2009, 2013) and in Autor *et al.* (2015) to test if those Italian provinces more specialized in routine tasks have registered an increase in low-skilled jobs. Few studies have previously focused on the Italian case by exploiting data on tasks allowing measuring the degree of exposure of different local labor markets to *labour-saving* technology. Although the specialization of a province in routine tasks is a very rough indicator for the introduction of *labour-saving* technology (Fernández-Macías *et al.* 2016) disregarding aspects of work organization and features of industries specificities, in this work we consider that the higher the specialization of a province in routine tasks, the higher the extent of *labour-saving* technology in that province. This would imply – relative to a less routine-specialized province – a higher contraction of routine occupations and a higher expansion in both high-skilled and low-skilled non-routine jobs (see Autor and Dorn 2013). On this ground, this work aims to explore the existence of a relation between initial specialization in routine tasks and the emergence of a pattern of job polarization that might be related to the adoption of *labour-saving* technology. We do so by using survey microdata from the Italian Labor Forces Survey (RCFL) and occupational task information provided by the Occupational Information Network (O*NET). The results obtained document that also in Italy – similarly to the U.S. – it is possible to observe a clear relationship between the provincial specialization in routine tasks and changes in the employment composition. In particular, we analyze the relation between the provincial specialization in routine tasks and the growth of employment in low-skilled/low-wage occupations among 95 Italian provinces over the period 2004-2017.

The remainder of the paper is organized as follows: section 2 reviews the literature and outlines the main contributions of our analysis, while section 3 describes the data and provides some preliminary descriptive evidences. Section 4 presents and describes the results obtained with the empirical analysis. Section 5 concludes.

2. Literature review

Since its formulation (Autor *et al.* 2003), several studies have adopted the task-based framework to study the relation between technological progress and recent labor markets dynamics, see Goos and Manning (2007) for U.K., Spitz-Oener (2006) and Dustmann *et al.* (2009) for Germany, Goos *et al.* (2009, 2014) for Europe, Acemoglu and Autor (2011) for the U.S. and Europe, and Autor and Dorn (2013) for the U.S. Focusing on the phenomenon of employment polarization – i.e. a U-shaped pattern of employment growth along the skill distribution, reducing medium-skilled occupations employment shares relative to those of both high-skilled and low-skilled occupations – and on the related RRTC explanation, this literature has provided evidences on the decline of routine jobs and the polarization of the labor market across several developed economies.

For the United States, well-known studies in which local-level employment shares variations have been used to provide evidences on the effects of RRTC are Autor and Dorn (2009, 2013), and Autor *et al.* (2015). In particular, Autor and Dorn (2013) represent the main point of reference, together with Goos *et al.* (2014), for the implementation of this study. Autor and Dorn (2013) develop a spatial equilibrium model where the falling price of automating routine tasks causes faster RRTC in regions more endowed with routine labor (i.e. more specialized in routine-intensive activities, hence more exposed to automation). As for changes in the composition of employment, the model predicts: 1) greater adoption of computer technology and consequent displacement of routine labor; 2) larger inflows of high-skilled workers – caused by the complementarity with technology; 3); greater reallocation of low-skilled routine workers into low-wage service occupations (jobs that involve assisting or caring for others, thus are difficult to automate). The empirical framework developed by them tends to confirm these predictions, providing important evidences on the relationship between automation and job and wage polarization in the U.S over the period 1980-2005.

The literature on job-polarization in the old continent has not focused yet on the regional dimension of routinization, but has nonetheless provided evidences on the relationship between RRTC and job-polarization. As for overall Europe, Goos *et al.* (2009, 2014) use EU-LFS and O*NET data, and analyze employment shares variations of 21 different ISCO-88 sub-major groups (i.e. 2-digits) in 16 western European countries over the period 1993-2010. In this study, occupations are sorted according to their (imputed) average wage, and classified as high-paid, medium-paid and low-paid occupations. Goos *et al.* (2009) show that job-polarization is pervasive in Europe, and find that measures of routine intensity better explain the contraction of medium-paid jobs and the increase of high and low-paid ones. Following a similar approach, Goos *et al.* (2014) decompose occupation employment shares variations in a within and a between-industries component. They show that within-industries there is a significant relative demand shift away from both routine and "offshorable" jobs, finding that the much more important effect is towards routine-intensive occupations. Further, they develop a theoretical framework in which both the within-industries and between-industries components are modelled as a result of RRTC. Bringing their model into the data, they show that both dimensions of RRTC are important in accounting for overall job-polarization in Europe.
Indeed, several elements have been disregarded by this literature such as the relevance of path-dependence in technology generation and adoption as well as sectoral specificities strongly influencing the introduction of technologies and the organization of work. Given that, in this work we aim at exploring whether the specialization of Italian provinces in routine tasks may trigger a relative expansion of employment in low-skilled occupations as a consequence of the introduction of routine-replacing technologies in the economy. Therefore, with reference to the existent literature on the topic, our study contributes in the following ways.
First, it focuses on the Italian case, by linking provinces' degree of specialization in routine tasks and job polarization. Few studies have explicitly focused on Italy (see Naticchioni *et al.* 2008; Naticchioni *et al.* 2010). Second, it exploits the spatial dimension of the labor market. The advantage of this approach is that – rather than focusing on the negative correlation between the routine task index and changes in the employment shares of single occupations – it addresses the relationship between RRTC and employment polarization in a local perspective, more appropriate in the case of an economically and geographically heterogeneous country such as Italy is. Third, we address whether the relationship between RRTC and the growth of low-skilled manual jobs is a phenomenon strictly related to low and medium-skilled workers (as it is in the U.S., see Autor and Dorn 2013) or whether in Italy the magnitude of the phenomenon results to be larger once that university-educated workers are included in the picture. Our results show that this seems to be indeed the case.

3. Data

3.1 Data sources

The main data source of this analysis is the Italian Labor Force Survey (RCFL), provided by the Italian National Statistical Institute (ISTAT). In RCFL data, occupations are classified in 121 different categories according to the Italian *Classificazione delle Professioni* (CP01), whereas the narrowest territorial repartition is codified at provincial level. We focus on the period 2004-2017 for 95 provinces by excluding the self-employed and non-marketed sectors, while measuring employment as *N* multiplied by official RCFL weights[1]. Since at the 1-digit level the Italian Classification of Occupations CP is substantially the same compared to the International Standard Classification of Occupations (ISCO), in this section we provide some stylized fact by using both ISCO and CP occupational major groups according to the available classification in our data[2].

In order to address the topic of labor market polarization in Italy, the first step is to check whether low-wage occupations experienced a higher wage growth rate relative to medium-wage occupations. Table 1 reports Structure of Earnings Stata (SES) data on both mean and median occupational real hourly wages in Italy for the years 2006 and 2014 – while sorting occupations according to their mean hourly wage rank in 2006. Not surprisingly, from table 1 we can see that typical high-skilled jobs (such as managerial, professional and technical occupations) scores at the top-end of the distribution – while at the bottom-end we find traditionally low-skilled jobs such as agricultural workers and elementary occupations.

Table 1. Mean and median real hourly wage growth rate by broad occupation group in Italy (2006-2014)

ISCO occupations ordered by Italian 2006 mean wage rank	Mean wage			Median wage		
	2006	2014	%change	2006	2014	%change
Managers	36.81	38.63	4.92%	33.68	33.79	0%
Professionals	24.19	23.96	-0.93%	22.83	22.76	0%
Technicians and associate professionals	16.25	15.41	-5.16%	14.32	13.73	-4%
Clerical support workers	14.07	12,71	-9.66%	12.34	11.28	-9%
Plant and machine operators and assemblers	11.16	10.08	-9.68%	9.95	9.23	-7%
Service and sales workers	10.26	8.89	-13.36%	10.38	8.78	-15%
Craft and related trades workers	10.89	10.57	-2.86%	10.06	9.82	-2%
Skilled agricultural, forestry and fishery workers	11.83	11.16	-5.64%	10.69	10.48	-2%
Elementary occupations	9.59	9.41	-1.91%	8.70	8.88	2%

Note: Real hourly wages in euros (deflated with GDP deflator at 2010). Change is expressed as percentage growth rate. Wages are computed by excluding self-employed workers and workers employed in public administration, defense and compulsory social security. Source: SES (Eurostat)

Middling/routine-intensive broad occupational clusters (such as clerical support workers and plant and machine operators and assemblers), are placed towards the center of the distribution. In addition, occupational-wage growth rates follow a wage polarization pattern, with both high-wage and low-wage jobs experiencing a higher growth rate in their mean and median retributions when compared to medium-wage ones. This result is even more striking when looking at the relative increase of wages for elementary occupations. Indeed, between 2006 and 2014 the average hourly wage only contracted by 1.9 per cent for this group (above this figure, we only have managers and

[1] In particular, we drop the agriculture and fishing industries, the public sector and extraterritorial organizations and bodies from the analysis.

[2] At the 1-digit level, the main difference between ISCO and CP is that in the Italian classification of occupations (CP) ISCO major groups 6 & 7 are clustered in one single major group (i.e. major group 6 – "Craft, agricultural, forestry and fishery workers").

professional), while it is the only one to show an increase in the case of median retribution highlighting a high wage dispersion among employees in this occupational group.

Moving to table 2, we describe the educational attainment composition of these occupational clusters in Italy. Table 2 makes clear that elementary occupations not only represent the least paid occupational category (see table 1), but also represent the most intensive in low-skilled workers. Though contracting over time, indeed, we nonetheless observe that low educated individuals hold the highest share among workers employed in these occupations – i.e. 73 per cent in 2004 and 62 per cent in 2017 – always slightly more than the share held among craft and agricultural occupations (71 and 58 per cent, respectively).

Table 2. Share of employees by educational attainment in each occupational group (2004-2017)

Italian occupations ordered by Italian 2006 mean wage rank	**Educ. group**	**Educ. group share**		**Change**
		2004	**2017**	
	low	.095	.207	.112
Managers	*med*	.526	.470	-.056
	high	.379	.322	-.056
	low	.036	.010	-.026
Professionals	*med*	.326	.175	-.151
	high	.638	.815	.177
	low	.113	.082	-.030
Technicians and associate professionals	*med*	.744	.598	-.145
	high	.144	.319	.176
	low	.227	.138	-.089
Clerical support workers	*med*	.694	.685	-.009
	high	.079	.177	.098
	low	.692	.563	-.129
Plant and machine operators and assemblers	*med*	.302	.420	.118
	high	.006	.017	.011
	low	.514	.386	-.128
Service and sales workers	*med*	.461	.537	.076
	high	.025	.078	.052
	low	.713	.580	-.133
Craft, agricultural, forestry and fishery workers	*med*	.280	.407	.127
	high	.007	.013	.006
	low	.726	.624	-.102
Elementary occupations	*med*	.259	.338	.079
	high	.014	.038	.024

Note: in the Italian classification of occupations (CP), ISCO major groups 6 & 7 are clustered in one single major group (i.e. major group 6 - Craft, agricultural, forestry and fishery workers). Source: our calculations on RCFL data. Change is expressed in percentage points

In order to check whether in Italy the relative growth of employment in different occupations is following a job-polarization pattern, in table 3 we report the employment shares of Italian occupations as well as their changes over the period under analysis. Since socio-economic differences among Italian macro-regions are well-known in economics, we describe data by dividing the sample in three main geographical areas – i.e. northern, central and southern Italy. Table 3 depicts a rather clear picture about employment polarization in the Italian peninsula. Indeed, among all geographical areas, typical medium-skilled/routine occupational clusters (that is, clerical workers and plant and machine operators and assemblers) contracted over-time. In particular, moving from southern to northern regions, the magnitude of the contraction monotonically increases in the case of clerical workers, whereas that of plant and machine operators – though contracting more in northern Italy – appears roughly the same in the rest of the country (more than 5 p.p. among both central and southern regions). Similarly, changes in the employment share of elementary occupations (which, according to retributions and skills, represent the low tail of employment) also show a monotonic relationship with latitude. Indeed, while it slightly increases in the north, it contracts a bit more in the south relatively to the center. More importantly, elementary occupations contracted substantially less than middling occupations jointly considered among both central and southern regions, and contracted far less in comparison to the other low-skilled/low-wage occupational cluster – i.e. craft, agricultural, forestry and fishery workers).

Table 3. Employment shares changes by broad occupational group in Italy (2004-2017)

Macro region	Italian occupations ordered by 2006 mean wage rank	2004	2017	Change
Northern Italy	Managers	.017	.028	.011
	Professionals	.039	.100	.061
	Technicians and associate professionals	.186	.218	.032
	Clerical support workers	.169	.122	-.047
	Plant and machine operators and assemblers	.175	.099	-.076
	Service and sales workers	.122	.190	.068
	Craft, agricultural, forestry, fishery workers	.200	.145	-.055
	Elementary occupations	.092	.096	.005
Central Italy	Managers	.017	.027	.010
	Professionals	.048	.122	.075
	Technicians and associate professionals	.171	.183	.013
	Clerical support workers	.163	.133	-.030
	Plant and machine operators and assemblers	.121	.070	-.052
	Service and sales workers	.153	.221	.068
	Craft, agricultural, forestry, fishery workers	.210	.144	-.067
	Elementary occupations	.116	.099	-.017
Southern Italy	Managers	.013	.025	.013
	Professionals	.034	.098	.064
	Technicians and associate professionals	.122	.155	.033
	Clerical support workers	.123	.114	-.009
	Plant and machine operators and assemblers	.133	.080	-.054
	Service and sales workers	.171	.262	.091
	Craft, agricultural, forestry, fishery workers	.259	.154	-.105
	Elementary occupations	.145	.112	-.033

Note: In the Italian classification of occupations (CP), ISCO major groups 6 & 7 are clustered in one single major group (i.e. major group 6 - Craft, agricultural, forestry and fishery workers). Source: our calculations on RCFL data. The macro-region repartition follows the one indicated by ISTAT. Change is expressed in percentage points

Table 3 not only points out that over the reference period the main features of employment polarization are detectable in Italy, but also that the magnitude of this phenomenon is larger in the north than in the south of the country.

The stylized facts described in this section point out that since the early 2000's job-polarization seems to be at work in Italy, and, therefore, that there is room for researchers to address whether the local specialization in certain types of tasks – see RRTC approach – may explain these outcomes. However, relying on the two canonical 1-digit "clerical" and "machine operators" occupation groups in order to measure Italian NUTS-3 regions' degree of specialization in routine tasks may reasonably appear too coarse. Hence, we first need to compute the routine task content of Italian occupations by using a less aggregated occupational classification – i.e. the Italian CP classification of occupations at the 3-digit level[3]. To construct such tasks indicators we rely on the same data source used in the U.S. literature – namely, the Occupational Information Network database (O*NET).

3.2 Measuring Italian provinces' specialization in routine tasks

To frame our analysis in a local perspective, we measure Italian provinces' specialization in routine tasks by simply computing routine occupations employment shares in each province. In doing this, we follow as close as possible the procedure proposed in Autor and Dorn (2013). More specifically, we compute the routine task index (RTI) for each occupation, and classify as "routine" only those occupations falling above the (employment-weighted) 66th percentile of this variable. In order to do so, we map a set of 16 O*NET tasks indicators indicated by Acemoglu and Autor (2011) into the Italian classification of occupations[4]. The mapping procedure is conducted in two steps. As a first step, we average the set of indicators (computed for each SOC-00 5-digits occupation) by ISCO-88 3-digit occupations. We do this operation by simply relying on the structure of multiple correspondences available in the official crosswalk. By following the same approach, in a second step we use the ISCO88-CP01 official crosswalk to average the resulting numbers by CP01 3-digits occupations[5]. Hence, we standardize data to have mean 0 and variance 1 by using RCFL occupations employment shares in 2004 as weights. Note that we aggregate the 6 task domains considered by Acemoglu and Autor (2011) into three main task-categories[6]. The resulting three composite indexes are then rescaled to positive values (adding one) to allow the log-transformation required by the RTI formula:

$$RTI_k = \ln\left(T^R_{k,o*net}\right) - \ln\left(T^C_{k,o*net}\right) - \ln\left(T^M_{k,o*net}\right), \tag{1}$$

[3] Indeed, highly routine-intensive jobs may as well be classified among other broad occupation groups - for instance, some job in technical occupations or in craft and related trades ones (with particular reference to the latter, think about jobs related to high-precision routine manual tasks).

[4] The 16 O*NET indicators used in Acemoglu and Autor (2011, 1163) scores from 1 to 5 for each SOC-00 occupation. In particular, I use the last available update of the O*NET database used in Goos *et al.* (2009). More specifically, this paper make use of the O*NET-SOC 2006 version 11.0. Since O*NET data are subject to periodical updates with survey data, I prefer to use the newer O*NET-SOC 2006 version 13.0 (see the update summary available on the O*NET website). Indeed, O*NET releases between 1998 and 2003 were based on information provided, to some extent arbitrarily, by occupation analysts only. Since then, the database have been updated several times.

[5] As the Italian classification of occupations has been revised in 2012, in the statistical appendix we describe the methodology we use to consistently map O*NET indicators in the new classification for years 2012-2017.

[6] In particular, Acemoglu and Autor (2011) assign O*NET task indicators to the following six task categories: 1) non-routine cognitive analytical, 2) non-routine cognitive interpersonal, 3) routine cognitive, 4) routine manual, 5) non-routine manual interpersonal, 6) non-routine manual physical. To obtain three aggregate indicators for each occupation, I collapse these six categories into three main ones.

where T_k^R, T_k^C and T_k^M are the aggregate indicators of the intensity in, respectively, the routine, non-routine cognitive and non-routine manual task content of occupation k. Again, we standardize this measure on CP01 3-digits occupations to have mean 0 and standard deviation 1 by using 2004 occupational weights. Hence, following Autor and Dorn (2013), we define province specialization in routine tasks as follows:

$$RSH_{jt} = \left(\sum_{k=1}^{K} L_{jkt} \times 1[RTI_k > RTI^{66p}]\right) \times \left(\sum_{k=1}^{K} L_{jkt}\right)^{-1}, \quad (2)$$

where RSH_{jt} is the routine employment share in the province j at time t; L_{jkt} is province's j employment in occupation k at time t; and $1[\cdot]$ is an indicator function which takes the value of one if the occupation is intensive in routine tasks according to the described approach.

Table 4. Routine-intensive occupations and routine tasks index

CP01 code	CP01 nomenclature	RTI_k
723	Wood-products machine operators	.515
732	Food and related products machine operators	.587
741	Locomotive engine drivers and related workers	.597
728	Other machine operators not elsewhere classified	.624
633	Handicraft workers in wood, textile, leather and related materials	.636
727	Assemblers	.636
731	Agricultural and other mobile plant operators	.658
721	Metal- and mineral-products machine operators	.699
331	Administrative associate professionals	.740
634	Craft printing and related trades workers	.761
411	Office clerks	.766
412	Numerical clerks	.766
712	Metal-processing plant operators	.798
714	Wood-processing- and papermaking-plant operators	.805
863	Manufacturing laborers	.833
632	Potters, glass-makers and related trades workers	.837
725	Printing-, binding- and paper-products machine operators	.907
724	Other wood-products machine operators	.922
726	Textile-, fur- and leather-products machine operators	.929
645	Fishery workers, hunters and trappers	.948
611	Miners, shot-firers, stone cutters and carvers	.982
651	Food processing and related trades workers	1.147
743	Agricultural engine drivers	1.880
744	Other engine drivers	1.880
513	Shop, stall and market salespersons and demonstrators	1.940
615	Painters, building structure cleaners and related trades workers	2.057
654	Pelt, leather and shoemaking trades workers	2.215
631	Precision workers in metal and related materials	2.219

Notes: Our calculations on RCFL data. By construction, routine occupations should represent 33.3 per cent of total employment in 2004. Nonetheless, we drop approximately 0.5 per cent of total employment from the routine cluster. We do this inasmuch some occupations – even if having a relatively low RTI – scores in the top tercile of the RTI measure despite they appear extremely far away from the concept of routine job developed in the literature (e.g. in the case of occupation 211 – mathematicians – with a RTI of .629). This is plausibly due to some little inconsistency in the O*NET-to-CP mapping procedure. See the appendix for more details

Table 4 reports the nomenclature of those occupations identified as “routine-intensive” by following the outlined procedure. Table 5 describes the distribution of *RSHj* – i.e. the provincial specialization in routine tasks variable described in equation (2).

Table 5. Provinces’ specialization in routine tasks in Italy: descriptive statistics (2004-2017)

Variable	Min.	Max.	Mean	Median	Std.	Italy
$RSH_{j,2004}$	.173	.49	.344	.356	.076	.328
$RSH_{j,2017}$	.139	.47	.262	.254	.058	.257
ΔRSH_j	-.034	.02	-.082	-.102	.018	-.071

Notes: sample is composed by 95 provinces. Summary statistics weighted by region share of national population in each period

After having built our measure of provincial specialization in routine tasks, we check whether: 1) the start of period *RSH* is positively correlated with some provincial proxy of technology adoption, 2) provinces with higher start of period *RSH* experienced higher contraction in routine jobs employment shares, 3) a correlation between the start of period *RSH* and the relative growth of low-wage/low-skilled elementary occupations employment shares applies. With reference to point 1, we use Eurostat data on the percentage growth rate of the per capita R&D expenditure between 2004 and 2016 by regions[7]. The population-weighted correlation between this variable and the start of period *RSH* computed at the provincial level is of 0.57, and it is significant at the one percent level. This result suggests that regions specialized in routine tasks might have experienced a higher adoption of technology also due to a higher concentration of manufacturing firms. As for point 2, in table 6 we run a regression of RSH on its over-time variations in a pooled OLS setting. Remarkably, the negative coefficient we can see in column 1 of table 6 remains highly significant also when including fixed effects at provincial level (column 2).

Table 6. Province specialization in routine tasks and changes in routine occupations employment shares

Routine occs. share $_{-1}$	-0.240***	-1.223***
	(0.027)	(0.113)
Province FE		**X**
R^2	0.220	0.683

Notes: Dep. Var.: change in share of employment in routine occupations within NUTS-3 regions (2004-08/08-12/12-17). N=285 (3 periods x 95 NUTS-3 regions). Standard errors in parentheses are clustered by NUTS-3 regions. All models include a constant, time period effects, and are weighted by start of period region share of national population. *** p<0.01, ** p<0.05, * p<0.1

We run the simple univariate regression described in equation (3), where $\Delta ELM_{j,2004-2017}$ is the change in elementary occupations employment shares in province *j* over the period 2004-2017,

[7] For NUTS-2 regions Umbria, Molise and Basilicata, the end of period R&D expenditure is that of 2014 because of missing data in 2016.

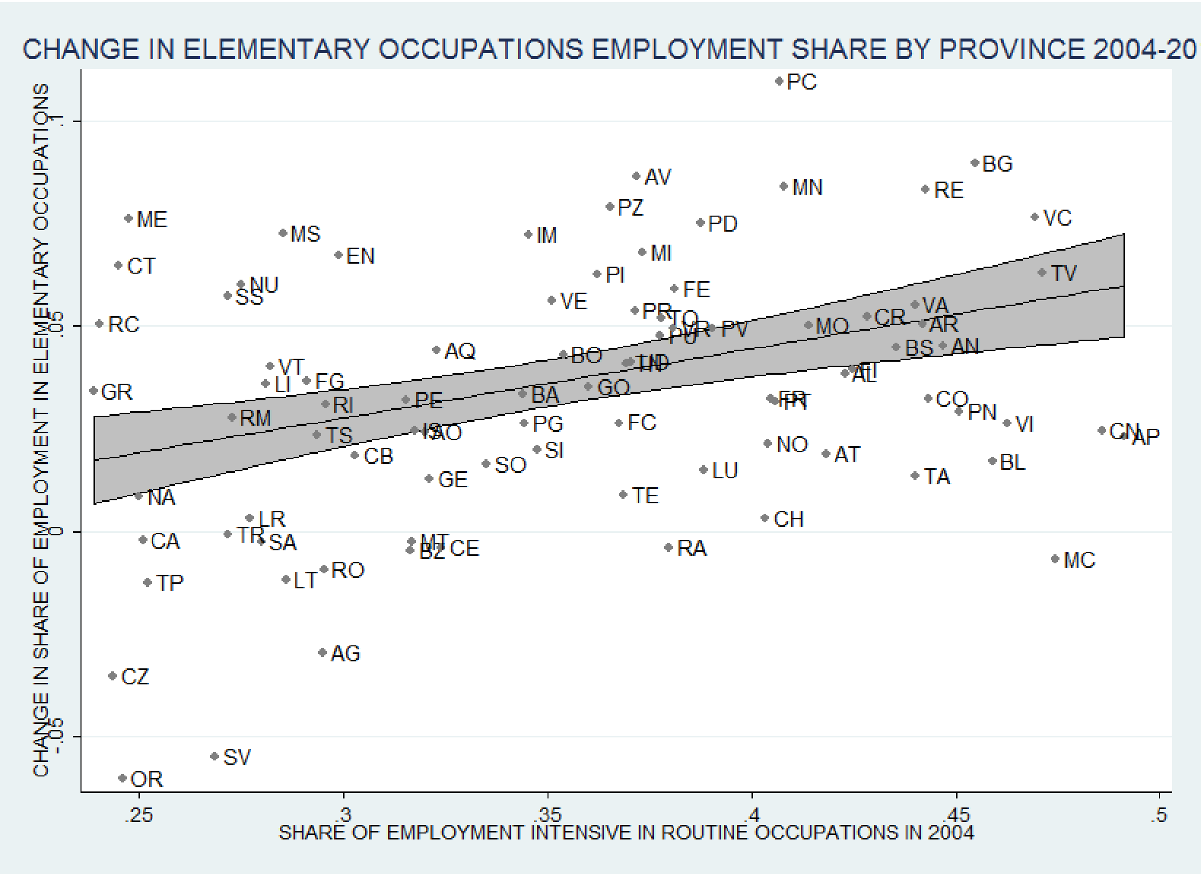
$RSH_{j,2004}$ is province *j* routine occupations employment share in 2004, and weights are equal to the start of period province *j* share of national population[8]. We obtain the following results:

$$\Delta ELM_{j,2004-2017} = -\,0.023 + 0.169 \times RSH_{j,2004} + \; e_{jt}, \qquad (3)$$

$$(t{=}4.00) \qquad N{=}95,\ R^2{=}0.175$$

We also detect a substantially significant positive correlation between RSH and $\Delta ELM_{j,2004-2017}$. More specifically, our estimated coefficient on *RSH* predicts a 3.3 percentage-points increase in elementary occupations employment shares for regions with a start-of-period routine share of 0.33. To provide a graphical insight about the relationship under analysis, in figure 1 we describe the output of the regression model in equation (3) by displaying the bivariate scatter-plot and the corresponding estimated regression line.

Figure 1. Change in elementary occupations employment share by province in Italy (2004-2017)



Notes: Model weighted by start of period provincial region share of national population. Elementary occupations are defined with CP01 major group 8 (ISCO 9) by excluding manufacturing laborers - i.e. CP01 863

[8] Since the Italian CP01 occupation 863 (manufacturing laborers) is included in the definition of routine jobs, elementary occupations employment shares are computed by excluding occupation 863 from the broad 1-digit occupation group.

Figure 1 adds further evidences to the north-south geographical pattern of job-polarization detected in table 3 in two aspects: 1) it adds to the picture the routine share variable; 2) it reveals a certain degree of variability in the main trends. On one hand, indeed, we can see that not all southern provinces experienced a contraction in elementary occupations – though almost all provinces in the north exhibit an increase in the low-skilled jobs. On the other hand, we can observe that even if routine labor results to be prevalently concentrated in the north due to the presence of higher shares of manufacturing firms, not all high RSH provinces are located in northern Italy (e.g. Rovigo, Massa Carrara). Instead, some locations in central Italy and southern Italy (e.g. Macerata, Ascoli Piceno, Taranto) result to be relatively more endowed with routine employment than several other northern provinces. The descriptive evidences provided in this section indicates that – since the early 2000's – job-polarization patterns are detectable in Italy, and they might be related to some form of technological input such as the expenditure in R&D occurring in those areas with an higher concentration of routine occupations[9].

4. Main results

We are now interested in assessing the existence and, if so, the magnitude of a significant impact of routine specialization on the job-polarization pattern previously detected. Our main response variable is the growth in the employment shares of the least-paid and least-skilled jobs in the labor market (in their paper, low-skilled service jobs). This is because the fundamental feature of job polarization is the relative increase of employment at the very low-tail of the skill distribution – mainly composed by jobs that are particularly hard to automate[10]. In the Italian labor market data, these occupations are represented by the so-called "elementary occupations" – corresponding to major group 9 of the International Standard Classification of Occupations. Moreover, since the Italian labor market is traditionally characterized by well-known over-educational patterns, in our empirical analysis we also try to assess whether specialization in routine tasks in Italy results to have a wider impact on job-polarization once that high-educated workers are included in the picture.
Formally, we stack elementary occupations employment shares first differences over three different periods (2004-2008, 2008-2012, 2012-2017) and estimate a pooled OLS regression model of the form:

$$\Delta ELM_{j,t} = \delta_t + \beta RSH_{j,t} + \mathbf{X}'_{j,t} + e_{jc} \tag{4}$$

where $\Delta ELM_{j,t}$ is the change in elementary occupations employment shares in province *j* between t_1 and t_0, $RSH_{j,t}$ is province *j* routine occupations employment share in t_0 and $\mathrm{X}'_{j,t}$ is a vector of socio-demographic control variables in t_0. We also include a full set of time-period dummies, province fixed effects (where indicated) and weight models by start of period region share of national

[9] Since RCFL survey data do lack of complete and detailed information about workers' earnings, we cannot address the issue of wage polarization in our paper. Therefore, in the next section we address the relationship between RRTC and job-polarization only.
[10] Indeed - by assuming increasing high-paid employment relative to medium-paid employment - a relative contraction of low-paid employment would configure an upgrading process rather than a polarizing one.

population. We report the results obtained in table 7. As already mentioned, we are also interested in assessing the existence of possible differences in the impact of RRTC for different educational attainment compositions of elementary-occupations. Therefore, in table 7 we run a set of different regressions that are repeated in the same way for each of the two different definitions of elementary occupations we adopt (i.e. – all educational attainments and non-university educated only) for a total of 6 regression models.

Table 7. Routine employment share and growth of elementary occupations within Italian provinces

Panel A: OLS	**ALL EDUCATIONAL ATTAINMENTS**			**NON-GRADUATES ONLY**		
Routine occs. share $_{-1}$	0.081***	0.150***	0.281***	0.078***	0.146***	0.262***
	(0.018)	(0.046)	(0.095)	(0.018)	(0.045)	(0.088)
X'$_{-1}$		**X**	**X**		**X**	**X**
Province FE			**X**			**X**
Obs.	285	285	285	285	285	285
R^2	0.293	0.317	0.485	0.301	0.323	0.486
Panel B: 2SLS						
Routine occs. share $_{-1}$	0.069***	0.121*	0.488**	0.067***	0.130*	0.467**
	(0.022)	(0.071)	(0.203)	(0.021)	(0.069)	(0.208)
KP *rk* Wald F statistic	91.1	20.3	10.0	91.1	20.3	10.0
Obs.	285	285	285	285	285	285
Centered R^2	0.293	0.316	0.465	0.300	0.323	0.466

Notes: N=285 (3 periods for 95 provinces). Dependent variable: change in share of employment in elementary occupations by provinces (2004-08/08-12/12-17). Standard errors in parentheses are clustered by provinces. All models include a constant, time period effects and are weighted by start of period province share of national population. The vector of covariates X' controls for eight different provinces' start of period socio-demographic conditions: graduate/non-graduate employment ratio, unemployment rate, share of population with age >65 and shares of employment of immigrant, low-tech manufacturing, female, part-time, and temporary workers. In Panel B estimates are the share of routine occupations is instrumented by interactions between the 1993 industry mix instrument and time dummies. *** p<0.01, ** p<0.05, * p<0.1

As we can see from columns 1 to 3 in Panel A of table 7, the significance of the coefficient on the routine share variable is highly robust to the different specifications we adopt. In particular, the coefficient on RSH in Panel A column 1 increases in magnitude when adding our set of control variables $\mathbf{X}'_{j,t}$ in column 2, and still holds when absorbing the most of the variation in our data by including a full set of province fixed-effects (column 3). Moving to columns 4 to 6, among elementary occupations we consider non-university educated workers only. It is interesting to note that, though with similar significance, coefficients on the routine share in this case are slightly smaller than those that are observable in columns 1 to 3. These results seem to point out that, as expected, the consequence of routinization in Italy are likely to be detrimental also for the working careers of the most educated individuals, and our guess is that this outcome may be due to younger workers undertaking elementary jobs in regions where more RRTC is at work.

Since the routine share variable may be correlated with unobservables of cyclical nature that are likely to simultaneously affect changes in elementary occupations employment shares, we conclude this section by trying to address the possible endogeneity concerns related to our OLS estimations. We adapt the instrumental variable approach proposed in Autor and Dorn (2013) to RCFL data. We can reduce the possible endogeneity of the treatment variable by using province employment data from year 1993 – i.e. 11 years before the start of period of our empirical analysis. Formally, we exploit the 2-digits NACE industry classification to build our instrumental variable as follows:

$$\widetilde{RSH_j} = \sum_{i=1}^{I} E_{i,j,1993} \times R_{i,-j,1993}, \quad (5)$$

where $E_{i,j,1993}$ is the employment share of industry *i* in province *j* in 1993 and $R_{i,-j,1993}$ is the 1993 routine share of industry *i* in all Italian provinces excluding the region in which province *j* is contained[11]. We are comfortable in believing that – our instrumental variable is still suitable to address the bias that may affect our OLS estimations. Indeed, compared to other advanced economies, Italy is well known as one of the less innovative ones. Therefore, it is quiet plausible to look at the early nineties as a period in which the unobservable regional characteristics driving contemporary innovations still have to fully take place. Moreover, Italy in 1993 was experiencing both an economic and political transition period, hence, the case for exogeneity of our instrumental variable can be considered as even more plausible.

The 2SLS estimations obtained with this strategy are reported in Panel B of table 7. As indicated by the Kleibergen-Paaprk Wald F statistic, the instrument indeed is rather strong – though in full-fledged models (columns 3 and 6) the inclusion of province fixed-effects almost kills the instrument predictive power. Nevertheless, it is worth noting that in this case the first-stage F statistic is exactly at the threshold of 10 – result which may appear even surprising in light of the severe fixed-effects setting adopted. Overall, the OLS results displayed in Panel A table 7 are confirmed by the 2SLS estimations in Panel B.

In sum, the empirical evidences provided in this section document that job polarization in Italy is likely to be driven by RRTC – as already shown in the literature in the case of the U.S. and of other advanced economies in Europe. Moreover, we think that the existence of this phenomenon in the Italian labor market of the XXI century is highly consistent with the well-known lag in innovation that affected the Italian economy in the last decades. In other words, it is really not unreasonable to think that the technology-induced changes in the occupational composition of employment in Italy may have took place 10 or 15 years later than in the U.S., the U.K. or Germany – i.e. highly-innovative economies for which these phenomena are documented since the early 90's (see Goos and Manning 2007; Goos *et al.* 2009, 2014; Spitz-Oener 2006 and Dustmann *et al.* 2009). Finally, we believe that possible interesting future lines of research should assess whether job polarization patterns documented in this analysis do reflect into different occupational wage dynamics. Indeed, a more comprehensive study on job polarization would require the simultaneous consideration of

[11] More specifically, calculations are elaborated on 20 regions and 53 NACE economic sectors.

several drivers such as changes in labour market institutions (unionization vs. de-unionization) as well as integration of local production structures in the global value chains.

5. Conclusions

In this paper we analyzed the impact of RRTC on the growth of low-skill jobs across Italian provinces labor markets. With this aim, we used microdata from the Italian Labor Forces Survey (RCFL) over the period 2004-2017 and occupational task information provided by the Occupational Information Network (O*NET). Following the empirical strategy proposed by Autor and Dorn (2013), we show that in Italy provincial specialization in routine tasks leads to a significant increase in the growth of low-skill occupations. Further, our findings seem to point out that employment polarization on Italian province labor markets is associated with an increase in occupational over-education patterns. Then, one may argue that province labor markets with higher specialization in routine tasks tended to partly reallocate highly educated workers into low skill jobs, with potentially detrimental consequences for economic growth.

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