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Job polarization in Italy: structural change and routinization

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ABSTRACT

Job polarization in Italy: structural change and routinization

This paper analyzes the role of structural change and the routinization hypothesis as concurrent explanations for job polarization in Italy over a fifteen-year period: 2004-2019. We observe that, even though the structural change pattern of Italian employment is characterized by the pronounced contraction of the most routine-intensive sector of the economy – i.e. the manufacturing sector – the disappearance of routine employment is a more generalized phenomenon that is affecting transversally all sectors. Indeed, by means of a standard shift-share decomposition method, the contraction of routine employment in Italy turns out to be marginally driven by the structural change pattern and the decline of the manufacturing sector – with only a negligible 20 percent of the total contraction attributable to the between-industry dimension. We find instead robust evidence in favor of the technological argument. The routinization hypothesis is tested with OLS and 2SLS models by exploiting industry-province cell variations and results point out that routine-tasks specialization does significantly increase employment in low-skill occupations for 6 out of 8 broad industries covering around 90 percent of non-farm private employment.

KEYWORDS: technological change, polarization, employment, structural change, routinization

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1. Introduction

Many advanced economies have experienced significant job polarization in the last decades, with an increase in the employment shares and relative wage growth of both low-wage and high-wage workers at the expense of middle-wage workers (OECD 2017; Acemoglu and Autor 2011; Goos *et al.* 2014).

Most of the available literature provides empirical evidence in favor of the technological argument based on the so-called 'routinization hypothesis' also referred to as *Routine-replacing technical change* (RRTC) or *Routine-biased technological change* (RBTC).

According to this theory, such occupational-composition shifts are triggered by the substitution effect of computer capital (robots, software technology and more in general ICTs) towards routine-tasks that are mostly performed by medium-skilled/medium-wage jobs and the simultaneous complementarity effect towards cognitive-tasks performed by high-skilled occupations. In this scenario, the effect of technology towards low-skilled manual tasks is supposed to be neutral or somehow ambiguous. Hence, low-skilled jobs employment shares are expected to decrease sensibly less than those of the medium-skilled – or even to increase – leading to job polarization (among others, see Autor *et al.* 2003; Autor and Dorn 2013; Goos *et al.* 2009, 2014).

A wide range of studies tried to investigate alternative explanations to the routinization hypothesis. For instance, Goos *et al.* (2009, 2014) analyze job polarization in Europe by looking also at the role played by income inequality and the offshoring of job-tasks, but still find routinization to be the main driver of the patterns observed. Mazzolari and Ragusa (2013) for the U.S. show that consumption spillovers from high-skilled workers towards low-skill time-intensive services explain around 1/3 of the increase in the demand for the least skilled workers from the 1990s. Firpo *et al.* (2011) examine both the role of technology and labor market institutions to explain the wage polarization phenomenon and find evidence in favor of technology.

A relevant contribution on job polarization in the US is that offered by Autor *et al.* (2015). The authors disentangle the role of international trade – namely, imports from China – from the role of routinization for what concerns both employment trends and job polarization. They show that imports from China tend to reduce employment in the manufacturing sector in both routine and high-skilled jobs (shifting employment from manufacturing towards non-manufacturing sectors) – whereas the process of routinization does reduce employment in routine-jobs within both manufacturing and non-manufacturing activities.

Over the past two decades most advanced economies have experienced a decline in the employment of the manufacturing sector (around 20%) and a growth in service. This process along with technological change has contributed to labor market polarization: the shares of low-skilled and (particularly) high-skilled jobs have increased, while there has been a hollowing out of middle-skilled jobs (OECD 2019).

Observing the fact that manufacturing has lost ground in the U.S. since the 1950s, Báráeny and Siegel (2018) offer a novel perspective on the polarization of the labor market based on a structural change driven explanation. The authors believe that the long run phenomenon of polarization of employment and wages is closely linked to the shift of U.S. employment from manufacturing to services. They document that job polarization in the U.S. has started since the 1950's because of structural change – and show that since the 1980's computer capital may have overlapped its effects on a pattern of employment polarization that was already at work because of the secular decline of the manufacturing sector in favor of the service sector. Nevertheless, in a more recent work Barany and Siegel (2019) review their previous analysis and stress the importance of sector-biased technological change for what concerns the structural transformation of the economy. Interestingly, they also show evidence of heterogeneity in the increase in the productivity of routine workers compared to abstract (high skill) and manual (low skill) workers across different sectors.

Compared to Autor *et al.* (2015) and Barany and Siegel (2018, 2019), we investigate whether structural change (regardless its determinants, whether they are import from China or sector-biased technical change – see Swiecki 2017; Herrendorf *et al.* 2014) may be considered as the main driver of the decline of routine jobs in Italy, or whether the contraction of routine employment is mostly a within-industry phenomenon that may be possibly related to RBTC.

In order to test the routinization hypothesis within each of the industries examined, we follow the empirical approach of Autor and Dorn (2013), (see also Autor *et al.* 2015), but exploit within-industry variations for each territorial unit rather than Commuting Zones.

The reason why we focus on Italy is twofold. First, computer technology adoption has suffered a certain delay compared with other advanced economies, like Germany and the US (see Brunetti *et al.* 2020, and Basso 2020). Second, the deep historical North-South divide makes the geographical dimension of the economy arguably more important than in other countries, possibly leading to different degrees of labor market polarization among northern, central and southern regions (see Brunetti *et al.* 2020).

A number of studies already documented job polarization in Italy. Using individual level data from the Labour Force Survey (LFS), Biagi *et al.* (2018) compare polarization across Italy and other European countries, and show that though countries differ in terms of cultures, institutions and labor market conditions, they share similar routinization trends. More recently Basso (2020), by using yearly Italian LFS data over 2007-2017, shows that occupation-industry cell employment shares changes are negatively correlated with occupational measures of routine-tasks importance[1]. Differently, Brunetti *et al.* (2020) address employment polarization and routinization in a spatial perspective. Employing Italian LFS data at the province level, they compute a routine-tasks specialization measure for each province by mapping U.S. occupational information into a detailed 3-digits Italian classification of occupations. By means of this measure, following Autor and Dorn (2013) they show that provinces more specialized in routine-tasks experienced higher increase in low-skill/low-paid elementary jobs employment shares – leading to job polarization.

We contribute both to the spatial literature on technology and polarization by offering two main advancements. First, we aim at investigating the role played by structural change and the routinization hypothesis as concurrent explanations for employment polarization in Italy. In particular – compared

[1] In particular, Basso compares different sets of job-tasks indicators (namely, Autor and Dorn 2013; Goos *et al.* 2009; D'Amuri and Peri 2014), but find highly significant correlations only in the case of the occupational routine-tasks measure from D'Amuri and Peri (2014). However, as the analysis aggregates indicators for only 21 occupational groups (i.e. ISCO 2-digits), the author warns that possible misclassification of occupations may have generated some measurement error in the analysis.

with the recent study by Brunetti *et al.* (2020) and Basso (2020) – we investigate for the first time how much of the contraction of routine employment in Italy may be attributable to the secular decline of the manufacturing sector (and of other routine-intensive industries)[2]. Second, we include for the first time in the existing literature the sectoral dimension within the strand of analysis on the relationship between routine-tasks specialization and the growth of low-skilled occupations (i.e. the empirical literature relying on the analytical framework elaborated in the cornerstone contribution of Autor and Dorn, 2013 – such as Charnoz and Orand 2017; Consoli and Sánchez-Barrioluengo 2019; Brunetti *et al.* 2020)[3].

Regarding the first aspect, structural change, we document that the continuous decline in the manufacturing sector may only partially account for job polarization – as the contraction of routine employment transversely occurred across almost all broad industry branches. Therefore – by means of a standard shift-share decomposition method (see Goos *et al.* 2014, and Spitz-Oener 2007) – we decompose the total contraction in a between and a within-industry component, and find that the disappearance of routine jobs in Italy is mainly a within-industry phenomenon. For the second aspect, the routinization hypothesis, we test the technological argument by means of spatial OLS and 2SLS fixed-effects regression models, and provide robust evidence of a link between routinization and job polarization in all industries with the exception for the finance sector and the restaurants and accommodation sector.

In more detail, we combine Italian employment survey data with U.S. occupational-task information in order to: 1) explore the sectoral dimension of the decline of routine employment in Italy; 2) analyze the relationship of local industries' specialization in routine-tasks with the relative increase in low-skilled/low-paid occupations employment shares. As for point 1), we document that during the 15 years before the spread of the Covid pandemics the structural change pattern of the Italian economy was consistent with the secular decline of manufacturing observable in all advanced economies (-10.2 percentage points). Nevertheless, we also show that – although the manufacturing sector is the most intensive in routine employment (more than a half of manufacturing employment in 2004 is represented by routine jobs) – over the reference period routine occupations have suffered considerably important contractions across all 8 industries analyzed in our study. Moreover, with the aim of quantifying the contribution of the structural change pattern observed in our data on the progressive contraction of routine employment, we adopt a standard shift-share decomposition method (see for instance Spitz-Oener 2007; Goos *et al.* 2014). In particular, we first decompose the total contraction of routine occupations nationally (-13.4 p.p.) in a within and a between-province component, and then split each within-province contraction in a within and a between-industry component. This simple computational exercise reveals that the contribution of structural change on the decline of routine employment in Italy is rather marginal – since only a negligible 20 percent of the total contraction is attributable to the between-industry dimension, whereas the within-industry component accounts for 80 percent (respectively, 2.5 p.p. vs. -10.5 p.p.). Then, we proceed by

[2] In particular, Basso (2020) addresses the role of sectoral shifts on the contraction of a cluster of 2-digits occupations classified as 'middle-paid' jobs, while we rely instead on a 3-digit occupational measure allowing us to classify the most routine-intensive jobs in the economy (see also Brunetti *et al.* 2020)

[3] The empirical analysis of Brunetti *et al* (2020) – and of all other studies adapting Autor and Dorn (2013) framework to non U.S. data – neglects the sectoral dimension within each LLM.

addressing point 2) with the goal of assessing whether the technological argument applies when analyzing the polarization of the Italian labor market from an industry-based viewpoint. Following Brunetti *et al.* (2020) for Italy, Charnoz and Orand (2017) for France and Consoli and Sánchez-Barrioluengo (2019) for Spain, we adapt Autor and Dorn (2013) spatial-equilibrium empirical framework to our data. However, compared with the existing literature that only relies on aggregate industry information at the local labor market level by using regional or province level data, we enhance the empirical setting by identifying as unit of analysis 95x8=760 province-industry cells. Our estimates show that the start-of-period local industries' specialization in routine-tasks does significantly predict the subsequent increase in low-skill jobs employment shares in almost all industries examined with the exception of the finance sector and of the restaurants and accommodation industry. On aggregate, the model predicts a 2.3 p.p. larger expansion of elementary jobs employment shares in province-industry cells scoring at the 75th percentile of our measure of local industry routine-tasks specialization relative to those at the median. This effect doubles when accounting for endogeneity issues. Hence, the effective impact of local industries routine-tasks specialization on the growth of low-skilled/low-paid jobs results to be substantially twice the one estimated in a simple OLS setting – a result that is very similar to that obtained in Autor and Dorn (2013) in a regional setting for the U.S.

The reminder of the paper is organized as follows: section 2 describes the data, provides relevant descriptive statistics and discusses the main results of the shift-share decomposition analysis. In section 3 results of our empirical analysis are thereby reported. Section 4 concludes.

2. Data, measurements and descriptive statistics

In this section, we first describe the data sources and then illustrate our measure of industry specialization in routine-tasks. Then, we investigate whether the structural change pattern of the Italian economy might play any role in explaining the disappearance of routine jobs over the period under analysis. At this aim, in a first step we illustrate the national-level changes in the employment shares of 8 different broad economic activity branches as well as the over-time changes of routine occupations employment shares within these industries. Furthermore, in a second step, by relying on province-level data, we perform a standard shift-share decomposition method in order to separate and quantify the contribution of the relative growth of broad industries branches on the overall contraction of routine employment in Italy.

2.1 Data

In order to analyze employment polarization in Italy we make use of two different data sources. One that allows us to observe changes in the occupational composition of employment (the Italian Labor Force Survey, *Rilevazione Continua sulle Forze di Lavoro* – RCFL hereafter), while holding the task-content occupations constant, and another one offering information on the routine-tasks content of occupations (Occupational Information Network database -O*NET herafter).

The RCFL was conducted by the Italian National Statistical Institute (Istat) over the period 2014-2019 and provides survey data on a rich set of information about workers' employment status, occupation, economic sector of activity, geographical location, as well as important individual socio-demographic characteristics such as age, gender, education etc. Further, the RCFL database is endowed with individual-observation frequency weights allowing us to reconstruct the whole Italian population in each period observed. As standard in this literature, we focus on all employees in the non-farm private sector – i.e. we exclude the self-employed as well as all workers employed in the agriculture and fishing industries, the public administration and extraterritorial organizations and bodies. As for Italian local labor markets (LLMs), differently, we use as a proxy of Italian provinces (*provincia* – i.e. administrative divisions that equal the 3-digit Nomenclature of territorial units for statistics – NUTS 3), which is the narrowest territorial unit available in RCFL. By using this variable, we are able to divide the peninsula in 95 different spatial repartitions – that is, areas in which most of the employees live and work and where firms recruit the most of their workforce.

We then compute a routine-tasks index (*RTI*) for 121 different occupations by mapping information from the Occupational Information Network (O*NET) database (conducted by the U.S. Department of Labor) into a detailed 3-digit classification of Italian occupations (*Classificazione delle Professioni* - CP)[4]. So far, most of the studies for European countries have imputed U.S. job-task indicators by using single-digit or 2-digits occupational-classification levels of the International Standard Classification of Occupations (ISCO – see, for instance, Goos *et al.* 2009, 2014; Consoli and Sánchez-Barrioluengo 2019)[5]. By relying on a more detailed level of job classification, we therefore feel more comfortable in assuming that the task-content of jobs is not too different between Italy and the US – as argued, for instance, by Charnoz and Orand (2017) for France.

2.2 Industry specialization in routine-tasks, structural change and the decline of routine occupations

Our measure of interest, capturing the local-level industry specialization in routine-tasks, is the employment share of routine-jobs in a given province-industry cell. This is substantially in line with the routine share index (*RSH*) proposed by Autor and Dorn (2013) and adopted by Consoli and Sánchez-Barrioluengo (2019), Charnoz and Orand (2017) and more recently by Brunetti *et al.* (2020). However, compared with the aforementioned studies, the share is computed for each broad industry branch within each local labor market (LLM) – rather than just at the LLM level.

Besides, while in Autor and Dorn s' model each LLM has a different degree of specialization in routine-intensive industries – here we assume that each broad industry branch within each LLM has itself a different degree of specialization in routine-intensive 'sub-sectors', which may vary according to each LLM specific economic context. Arguably, it seems really not unreasonable to think that different industries in different LLMs have different production structures at the sub-sector level – that may

[4] We choose to rely on U.S. tasks information from O*NET-SOC 2006 inasmuch Italian tasks data from the Inapp-Istat survey (*Indagine Campionaria sulle Professioni* - ICP) does not allow us to consistently keep tasks constant for 3-digit occupations over the period 2004-2019.

[5] A notable exception is represented by the literature on the German case, which traditionally make use of job-tasks indicators by relying on the German BBIB/IAB survey. See, for instance, Spitz-Oener (2006) and Dustmann *et al.* (2009).

vary, for instance, for geographical or historical reasons – reflecting into different degrees of specialization in routine-tasks at the industry level in each LLM.

Formally, we follow Autor and Dorn (2013) approach and define as routine-jobs those occupations falling in the employment-weighted top third of the *RTI* measure at the starting period of our analysis (i.e. year 2004)[6]. In particular, our measure of local industries routine-tasks specialization can be formalized as follows:

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

where RSH_{ijt} is the routine-jobs employment share of industry *i* in province *j* at time t; L_{ijkt} is employment of occupation *k* in industry *i* in province *j* at time *t*; and 1[·] is an indicator function which takes the value of one if the occupation falls above the 66th percentile of our *RTI* measure. Table 1 summarizes our measure of local industry routine-tasks specialization for each of the 8 broad industry branches considered in this study.

Table 1. Local industries routine-tasks specialization in 2004

Broad economic activity branch	Mean	Std. dev.	Min	Max
Manufacturing	.544	.065	.258	.675
Construction	.142	.063	.000	.318
Trade	.283	.063	.091	.423
Restaurants and Accommodation	.066	.045	.000	.304
Transport and Communications	.313	.081	.087	.532
Financial activities	.308	.085	.000	.577
Services to persons/businesses	.404	.082	.103	.860
Other personal services	.124	.054	.000	.306
All industries	.343	.076	.173	.491

Note: 95 NUTS 3 statistical units in each row. Statistics weighted by local industry share of national industry employment in 2004. In the last row, statistic weighted by province share of national employment. Our calculations on RCFL data. Routine-tasks specialization measured according to equation (1).
Source: our calculations on RCFL data

Descriptive statistics in table 1 immediately disclose the fact that across different broad economic activity branches the concentration of routine employment varies considerably. Unsurprisingly, the manufacturing industry emerges as the most intensive in routine occupations – as routine-jobs represent around 54 per cent of total manufacturing employment in 2004 – i.e. far above the national employment share of routine occupations, amounting by construction to about 34 per cent of total non-farm private employment[7]. Interestingly, considerably above the national threshold, we also find

[6] This means that, by construction, routine occupations in 2004 amount to about 33 per cent of total non-farm private employment. See Brunetti *et al.* (2020) for further details about the mapping procedure and the construction of our measures of routine-tasks specialization. Appendix A table A1 reports the list of jobs included in our RSH measure.
[7] Please note that, as statistics in table 1 are weighted by local industry share of industry employment, the mean reflects the national-level share of routine occupations in the reference industry.

the "services to persons and businesses" industry, where routine occupations in 2004 account for about 40 per cent of total industry employment. Differently, substantially in line with the national routine employment share, we find sectors such as transport and communications, financial activities and trade – whereas in the case of other industry branches such as restaurant and accommodation, construction, and other personal services, routine occupations result to be less important, with an average (industry employment weighted) value of $RSH_{ij\,2004}$ scoring below 15 per cent. Accordingly, we can also notice that, in such 'non-routine intensive' industries, routine employment shares in some provinces can even reach a minimum value of zero (see table 1).

In sum, according to table 1 manufacturing and services to persons and businesses turn out to be the most routine-intensive sectors in the economy. Actually, this is in line with the RRTC theory – since in both cases we have, for different reasons, a high concentration of routine-jobs. Among manufacturing workers, we can find indeed higher shares of craft and production occupations (such as craft precision workers, or machine operators and assemblers – the so called 'routine-manual' jobs) – while in the case of the services to persons and businesses sector, we observe instead higher shares of clerical and technical occupations (such as office clerks or administrative and associate professionals – the so called 'routine-cognitive' jobs)[8].

To investigate whether the relative importance of routine occupations tend to be concentrated in specific areas of the Italian peninsula, in figure 1 we provide a graphical insight on the geographic distribution of our RSH measure for the two most routine-intensive industries – i.e. manufacturing and the services to persons and businesses sector.

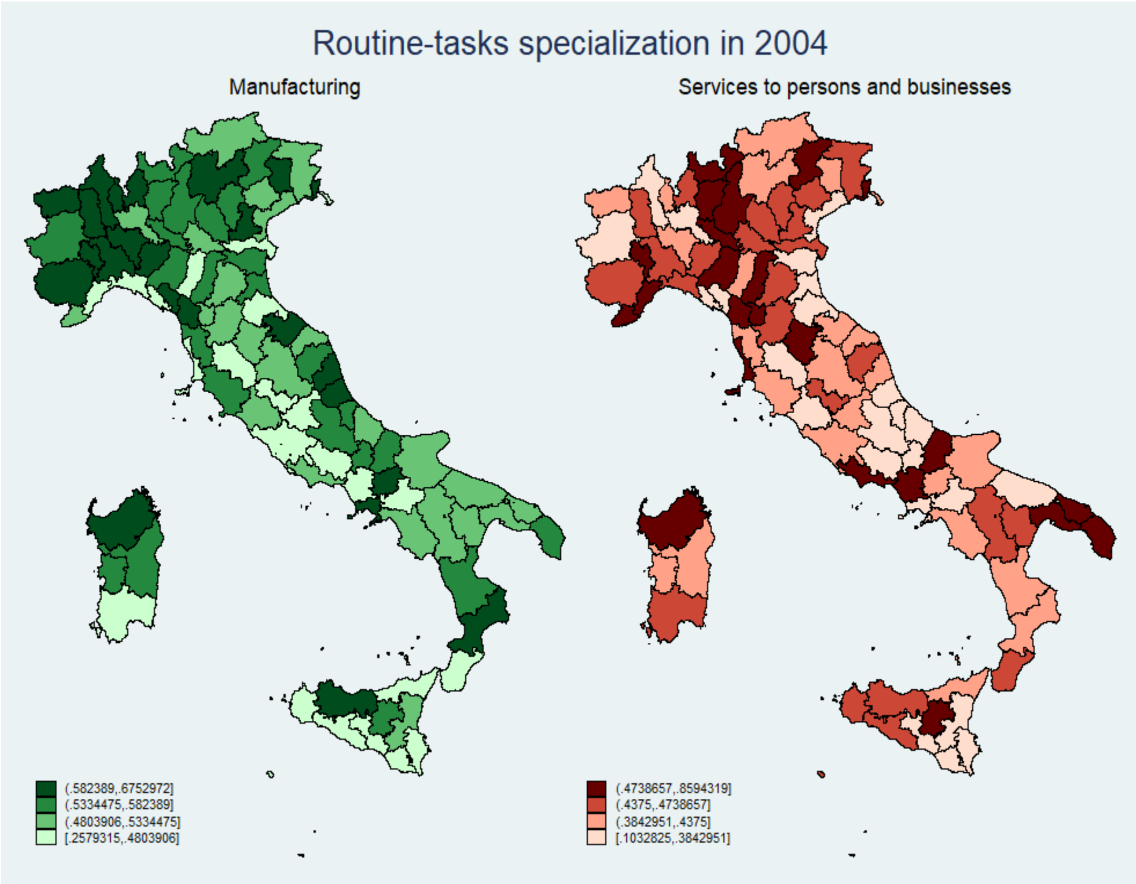
The graphical evidence provided in figure 1 discloses an interesting pattern. In particular, within both industries routine occupations employment shares results to be mostly concentrated in the northern side of the peninsula – though among southern provinces there are a few cases in which routine employment shares are considerably large[9]. Since northern Italian regions are historically more economically advanced compared to southern regions, this pattern is of no surprise. Indeed, similarly to the U.S. and other advanced economies (see Autor 2015) technical progress between the end of WWII and the age of computer technologies made Italian agricultural employment shrank in favor of skilled blue-collar and clerical and administrative occupations. However, as the Italian economy is historically characterized by a persistent North-South divide, mass-migration phenomena have led the growth in production and clerical jobs to mostly occur in northern regions.

We now try to investigate how employment shifts between the 8 sectors considered (i.e. structural change) cope with the phenomenon of polarization of the labor market that has been documented for Italy in several studies. Has the structural change pattern of the Italian economy played a role in this respect? In our view, it is not unreasonable to expect that the contraction of industries that are highly intensive in routine occupations (above all, the manufacturing sector) – or, alternatively, the expansion of industries that are barley endowed with routine jobs – might have influenced the observed polarizing pattern that characterizes the occupational composition of Italian employment.

[8] Interestingly, in 2004 about 60 per cent of manufacturing workers were craft and production workers, while about 60 per cent of workers in the services to persons and businesses industry were employed in technical (mostly administrative professionals) and clerical occupations. Descriptive evidences about the distribution of occupation by industry branch are available upon request.

[9] An analogous pattern is found by Brunetti *et al.* (2020) with aggregate province data.

Figure 1. Routine-tasks specialization by province in routine-intensive industries (2004)

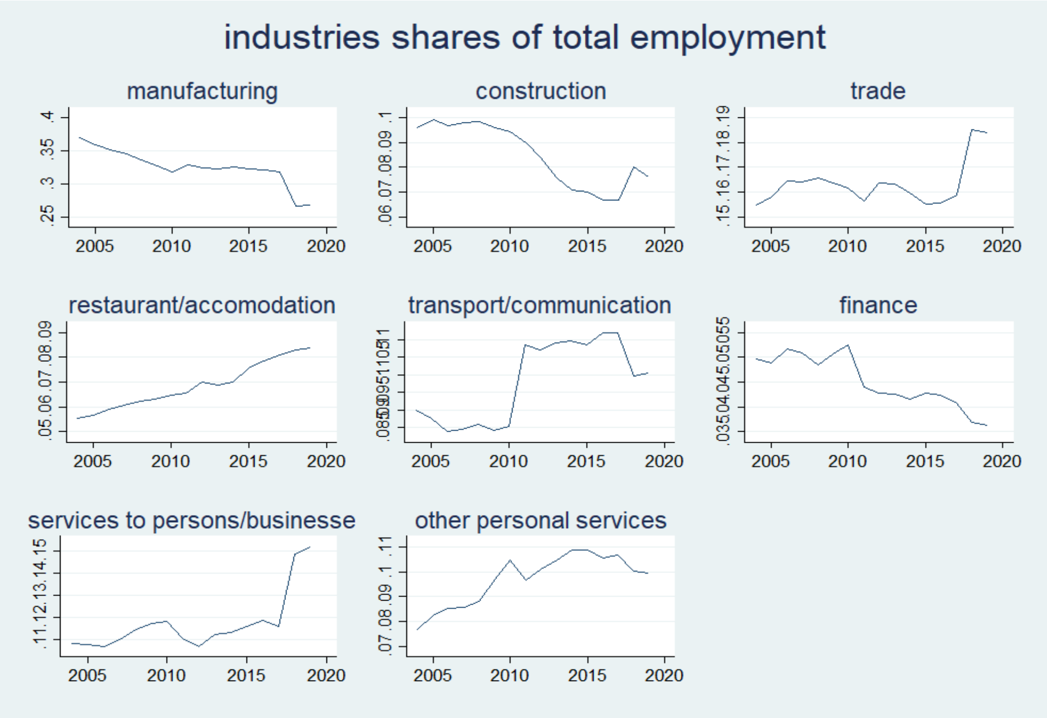


Note: routine-tasks specialization measured according to equation (1)
Source: our calculations on RCFL data

We first start by investigating descriptively whether routine-intensive (non-intensive) industries have effectively lost (gained) ground over the reference period. Figure 2 plots changes in the employment shares of national-level broad industry branches over the period 2004-2019, while table 2 reports the corresponding changes (also distinguishing between two different sub-periods – i.e. 2004-2012 and 2012-2019, before and after the economic crisis).

Time-series plotted in figure 2 make clear the main feature of the structural change pattern of the Italian economy – i.e. the progressive decline of the manufacturing industry. This trend is of no surprise, since it characterizes all advanced economies of the XXI century (see OECD 2019). Indeed, as shown in table 2, the manufacturing sector represents the economic activity branch that has experienced the largest change in its national employment shares – by losing more than 10 percentage points of the national employment over the period 2004-2019. Conversely, with the exception of the relatively small contractions registered in the case of the construction industry and the financial sector (-2 p.p. and -1.3 p.p., respectively), we can see that all other industries experience an increase in their employment shares – with a more pronounced growth in the case of the services to persons and businesses sector (+4.3 p.p.).

Figure 2. The structural change pattern of the Italian economy (2004-2019)



Note: industries shares of total national non-farm private employment.
Source: our calculations on RCFL data

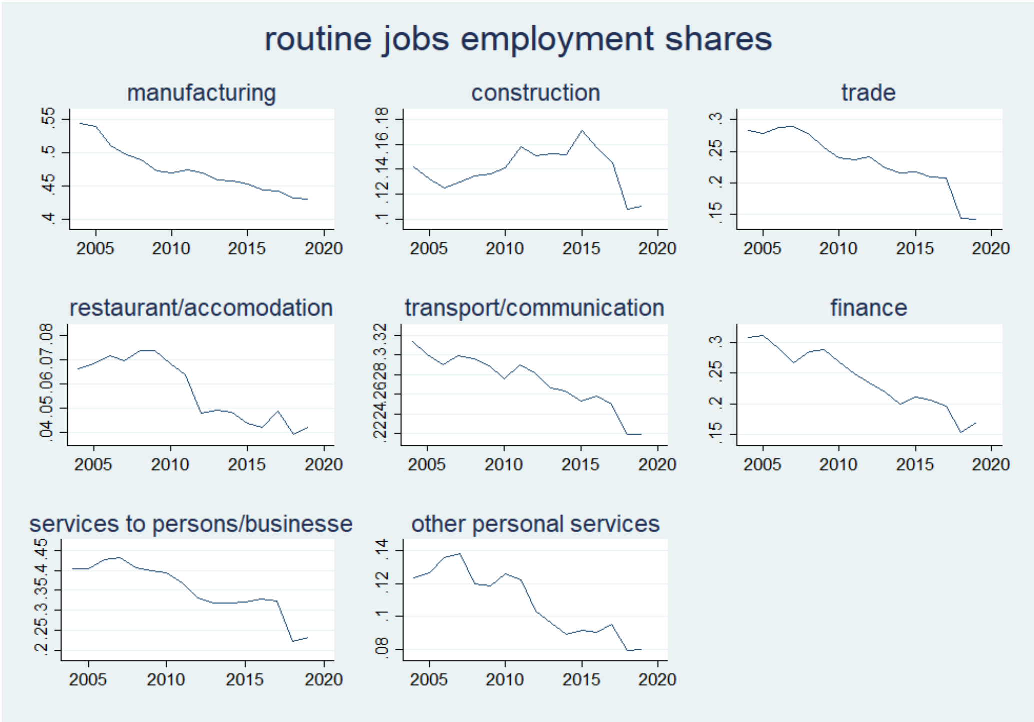
Table 2. Broad industry branches share of national employment

	Share of total employment			Change		
	2004	**2012**	**2019**	**2004-2012**	**2012-2019**	**2004-2019**
Manufacturing	.370	.324	.268	-.046	-.056	-.102
Construction	.096	.084	.076	-.012	-.080	-.020
Trade	.155	.164	.184	.009	.020	.029
Restaurants and Accommodation	.055	.070	.084	.015	.014	.029
Transport and Communications	.090	.107	.109	.017	.002	.019
Financial activities	.049	.043	.036	-.006	-.007	-.013
Services to persons/businesses	.108	.107	.151	-.001	.044	.043
Other personal services	.077	.101	.099	.024	-.002	.022

Source: our calculations on RCFL data

Since we observe that the services to persons and business sector (see table 1) is relatively intensive in routine-jobs, we may wonder – for instance – whether such growth has limited or not the contraction of routine employment which may be attributable to the decline of the manufacturing industry. Of course, this could be the case if we assume that routine-jobs employment shares kept stable over-time within each sector. What if, for instance, routine employment shares contracted within the service to persons and businesses industry, while the employment share of the industry itself increased? The negative or positive contribution to the total contraction of routine employment would depend on the interaction between the relative growth of that industry and changes in the routine employment share *within* that industry. Hence, at this point we believe it is appropriate to complete the picture by reporting how routine-jobs employment shares have changed over-time within broad economic sectors. At this aim, in figure 3 we plot the employment share of routine occupations by broad economic activity branch over 2004-2019, while in table 3 we report the corresponding changes.

Figure 3. The decline of routine employment in Italian industries (2004-2019)



Note: routine occupations employment shares of national industry employment.
Source: our calculations on RCFL data

Table 3. Routine-jobs employment shares changes by broad industry branch

	Share of industry employment			Change		
	2004	**2012**	**2019**	**2004-2012**	**2012-2019**	**2004-2019**
Manufacturing	.544	.469	.430	-.075	-.039	-.114
Construction	.141	.151	.110	.010	-.041	-.031
Trade	.283	.240	.143	-.043	-.097	-.140
Restaurants and Accommodation	.066	.048	.042	-.018	-.006	-.024
Transport and Communications	.313	.282	.219	-.031	-.063	-.094
Financial activities	.307	.235	.171	-.072	-.064	-.136
Services to persons/businesses	.405	.331	.231	-.074	-.100	-.174
Other personal services	.124	.103	.080	-.021	-.023	-.044

Source: our calculations on RCFL data

The trend displayed in figure 3 and described in table 3 is rather impressive. Indeed, the negative slopes of the graphs reported in figure 3 indicate that the disappearance of routine-jobs in Italy is a generalized phenomenon that transversally occurred across all branches of economic activity. Moreover, in most of the cases the magnitude of the contraction is far from being negligible. As table 3 shows, over 2004-2019 the importance of routine employment has declined dramatically in sectors such as manufacturing (11.4 p.p.), trade (14 p.p.), transport and communication (9.4 p.p.), the financial sector (13.6 p.p.) and – above all – the services to persons and businesses industry (-17.4 p.p.). Further, figure 3 points out that – with the exception of the construction sector – the contraction of routine employment is generally smooth and continuous, up to the point that in those industries registering higher contractions the declining trend appears as substantially monotonic (see in particular manufacturing, trade, transport and communication, finance).

The descriptive evidences provided so far point out that though the structural change pattern of Italian employment is characterized by the pronounced contraction of the most routine-intensive sector of the economy – i.e. the manufacturing sector – the disappearance of routine employment is a generalized phenomenon that is affecting transversally all sectors of economic activity.

At this point, we may argue with a certain confidence that structural change may only partially explain the polarization of Italian employment. However, the simple comparison of statistics just presented cannot be of much information if we are concerned in quantifying the contribution of structural change on the contraction of routine employment in Italy. Indeed, we also rely on a shift-share decomposition in order to disentangle the contribution of the relative growth of broad industry branches displayed in figure 2 from the contribution of the within-industry dimension described in figure 3 (please see Spitz-Oener 2006, and Goos *et al.* 2014 for other applications of the shift-share method within this literature).

The total contraction of routine-jobs is decomposed into a between and within-industry components with the aim of disentangling the contribution of the relative growth of broad industry branches displayed. Formally, the standard shift-share decomposition method we perform here can be described in two nested equations, as follows:

$$\Delta RSH = \overbrace{\textstyle\sum_j \Delta RSH_j \times ESH_j}^{Within-Provinces} + \overbrace{\textstyle\sum_j \Delta ESH_j \times RSH_j}^{Between-Provinces} + \overbrace{\textstyle\sum_j \Delta ESH_j \times \Delta RSH_j}^{Interaction\ Term}; \tag{2}$$

$$\overbrace{\textstyle\sum_j \left(\overbrace{\textstyle\sum_{j,i} \Delta RSH_{j,i} \times ESH_{j,i}}^{Within-Industries} + \overbrace{\textstyle\sum_{j,i} \Delta ESH_{j,i} \times RSH_{j,i}}^{Between-Industries} + \overbrace{\textstyle\sum_{j,i} \Delta ESH_{j,i} \times \Delta RSH_{j,i}}^{Interaction\ Term} \right) \times ESH_j}^{\boldsymbol{Within-Provinces}} \tag{3}$$

where ΔRSH is the 2004-2019 change in the routine employment share nationally, RSH_j is the 2004 routine-jobs employment share in province *j*, ESH_j is the 2004 province *j* employment share of national employment, $RSH_{j,i}$ is the 2004 routine-jobs employment share in industry *i* in province *j,* and $ESH_{j,i}$ is the 2004 industry *i* employment share of province *j* employment. Please note that Δ stands for the 2004-2019 first difference of these variables. It is important to note that equation (3) is a decomposition of the first of the three products appearing in equation (2) – that is, the within-province component. The results of this simple shift-share computational exercise are reported in table 4.

Table 4. Shift-share decomposition of the national change in the employment share of routine occupations 2004-2019

Routine occupations employment shares						
Panel A	**Panel B: national-level variations**			**Panel C: average within-province variations**		
Total change	*Within provinces*	*Between provinces*	*Interaction term*	*Within industries*	*Between industries*	*Interaction term*
-.134	-.132	-.003	.001	-.105	-.025	-.002

Note: panel C statistics are weighted by provinces' share of national employment in 2004.
Source: our calculations on RCFL data

As panel A of table 4 makes clear, the raw change of the routine-jobs employment share nationally (i.e. ΔRSH) is of -13.4 percentage points, which is almost entirely attributable to the within province dimension (-13.2 p.p., see panel B)[10]. Moving to panel C, we display province-level average employment-weighted values instead of scalar terms as reported in Panels A and B. As we can see from panel C, the between industry dimension is of only -2.5 p.p. – i.e. about 19 per cent of the within-province variation reported in panel B. Accordingly, the within-industry component of -10.5 p.p. amounts instead to about 80 per cent of the -13.2 p.p. attributable to within-province variations.
This simple exercise does suggest that structural change plays indeed some role for what concerns the disappearance of routine-jobs in Italy. Nevertheless, the importance of the between-industry channel results to be rather marginal if compared to the within-industry one, which takes the lion share of the total contraction observed. To recap, the evidence provided in table 4 indicates that the contraction of industries highly endowed with routine employment and the simultaneous expansion of industries that are less intensive in routine-jobs may have determined about 1/5 of the total negative change of routine-jobs employment shares in Italy. Therefore, we can feel rather confident in claiming that employment polarization in Italy is only marginally driven by the structural change pattern and/or by the decline of the manufacturing sector. This, of course, leaves much room for the technological argument and the routinization hypothesis, which we will empirically address in the following section.

3. Econometric analysis

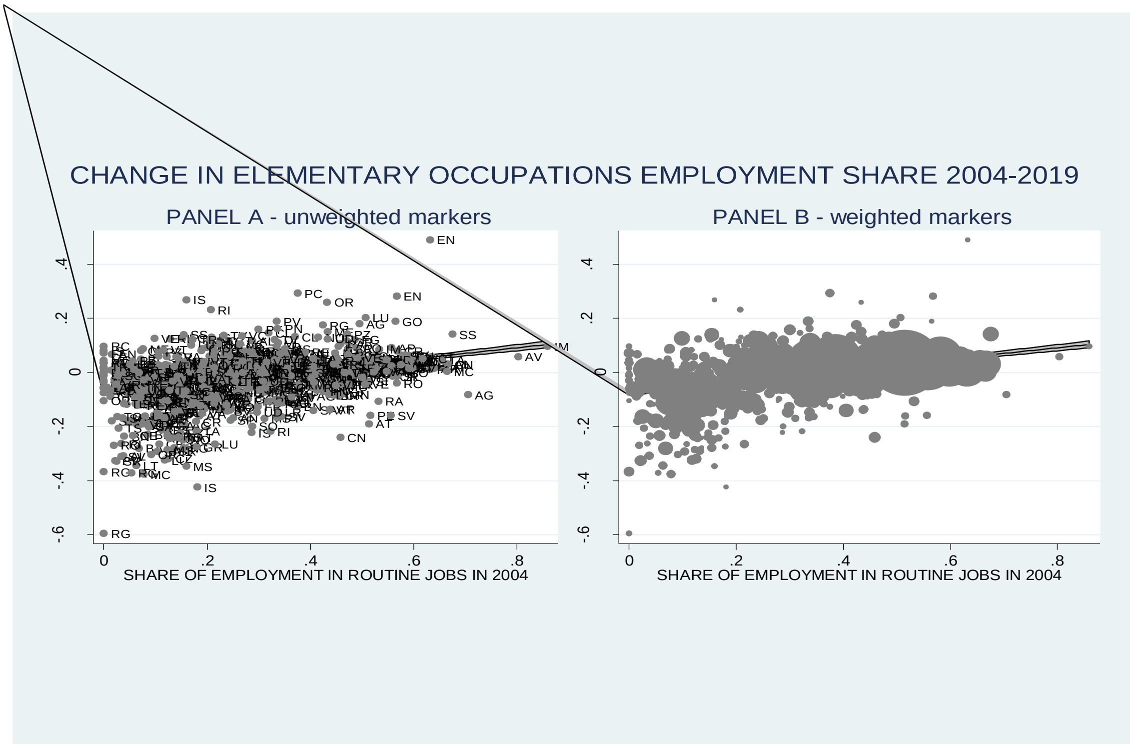
We now move on to a regression analysis in order to recover empirical evidences in favor of the technological argument for job-polarization in Italy by taking into account – together with the regional dimension – the structural dimension. As far as we are aware, we are the first to employ Autor and Dorn (2013) empirical framework to investigate employment polarization in local-level industries. More specifically, we observe occupational composition changes within 760 province-industry cells (8 industries x 95 provinces) in order to check whether it is possible to provide empirical evidences in favor of the routinization hypothesis by means of our measure of local industries specialization in routine-tasks (see section 2.2). Our response variable is the change in the employment share of

[10] This result is not surprising, since provinces' employment shares of national employment are plausibly almost fixed over-time.

elementary occupations in province-level industries. This is our proxy of employment polarization and captures changes in low-skill/low-wage employment shares (*professioni non qualificate*), for the least paid and the least educated broad occupational category in the Italian classification of occupations (see Brunetti *et al.* 2020, for more details).

Figure 4 provides some first insight on the relationship of interest by showing the regression estimate of the bivariate relationship between routine-tasks specialization and the growth of elementary occupations (pooling 760 unit of analysis) over the 2004-2019 period.

Figure 4. Routine-tasks specialization and growth of elementary occupations in Italian industries by province (2004-2019)



Note: N=760, our calculations on RCFL data. Parameters weighted by province-industry cell share of national employment in 2004. The OLS regression in figure 4 can be described as follows: $\Delta ELM_{i,j,2004-2019} = -0.075 + 0.208 \times RSH_{i,j,2004} + e_{ijt}$ $R^2 = 0.27$, where $\Delta ELM_{i,j,2004-2019}$ is the 2004-2019 change in the employment share of elementary occupations in industry *i* of province *j* and $RSH_{i,j,2004}$ is our measure of routine-tasks specialization summarized in table 1. The relationship identified is strong and significant (t=15.06), while the beta of 0.208 predicts a 3.4 p.p. larger expansion of elementary-jobs employment shares in a province-industry cell scoring at the (employment-weighted) 75th percentile of $RSH_{i,j,2004}$ relative to a province-industry cell scoring at the median.

Source: our calculations on RCFL data

The interesting preliminary evidence offered in figure 4 encourages a more accurate analysis of the industry-level database used in our study. First of all, we may wonder whether the coefficient of interest is still positive and significant when running separate regressions for each broad industry branch. At this aim, we estimate the same relationship for each of the 8 industry separately and additionally include a series of demographic and labor market controls.

Table 5 reports the output of a set of 8 different regressions run by pooling elementary jobs employment shares changes over 4 different time periods (2004-2008/2008-2012/2012-2016/2016-2019) according to the following equation:

$$\Delta ELM_{j,\,t_0-\,t_1} = \delta_t + \beta_1 RSH_{j,\,t_0} + \beta_2 \mathbf{X'}_{j,\,t_0} + \eta_j + e_{jt} \tag{5}$$

where $\Delta ELM_{j\,t_0-\,t_1}$ is the change in the employment share of elementary jobs in province *j* between t_0 and t_1, $RSH_{j,\,t_0}$ is the routine-jobs employment share in province *j* at t_0 and $\mathbf{X'}_{j,\,t_0}$ is a vector of socio-demographic and labor-market control variables in province *j* at t_0[11]. Since each of the 8 equations estimates the relationship of interest in a different industry, each model is weighted by the start-of-period province share of total national employment in the reference industry.

Table 5. Growth of elementary jobs and routine-tasks specialization within province by broad industry branch (2004-2019)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Manufacturing	Construction	Trade	Restaurants & Accommodation	Transport & Comm.	Finance	Services to Pers. & Bus.	Other Pers. Services
RSH	0.130**	0.192**	0.154***	-0.038	0.214***	0.024	0.514***	0.526***
	(0.053)	(0.084)	(0.051)	(0.139)	(0.075)	(0.018)	(0.074)	(0.138)
Constant	0.014	-0.072	-0.037	0.006	-0.107	-0.020	-0.147*	0.044
	(0.050)	(0.057)	(0.056)	(0.066)	(0.072)	(0.035)	(0.080)	(0.134)
N	380	380	380	380	380	378	380	380
R^2	0.300	0.162	0.158	0.175	0.241	0.327	0.756	0.301

Note: pooled OLS regressions, N=380 (95 provinces x 4 time periods, 2004-2008/2008-2012/2012-2016/2016-2019). Dep. Var: industry-level stacked first differences of changes in employment shares of elementary occupations by province. All regressions are weighted by start-of-period province-industry cell share of national industry employment and include a vector of control variables (graduate/non-graduate ratio, female employment share, temporary-contract workers share, part-time workers share and immigrant/native workers' ratio), time period dummies and province fixed effects. Standard errors are clustered by period and province.
Source: our calculations on RCFL data

As clearly shown in table 5, in 6 out of 8 cases coefficients are both significant and show the expected sign. Please note that – since the distribution of $RSH_{j,t0}$ varies according to the structure of the different 8 broad industry branches analyzed – coefficient reported in table 5 cannot be directly compared. Our calculations reveal that the largest impact is recovered in the case of the services to persons and businesses industry (column 7) – in which the predicted change in the employment share of elementary jobs in provinces scoring at the 75th percentile of $RSH_{j,\,t_0}$ is on average 3.8 p.p. larger than that in provinces scoring at the median. In the case of other personal services (column 8) this differential is instead of 1.7 percentage points. Differently, in the other cases in which the coefficient on $RSH_{j,\,t_0}$ is also positive and significant (manufacturing, construction, trade, transport and communication), the predicted differential scores below 1 percentage point[12]. As for the restaurant and accommodation sector and the financial sector, conversely, the effect of routine-tasks

[11] More specifically, the vector $\mathbf{X'}_{j,\,t_0}$ includes, for each observation, the start-of-period graduate/non-graduate ratio, the female employment share, the temporary-contract workers share, the part-time workers share and the immigrant/native workers ratio.

[12] In particular, the predicted differential is of 0.6 p.p. in the case of manufacturing, 0.8 p.p. in both the construction industry and the trade sector, while in the case of the transport and communications branch amounts to 0.5 p.p.

specialization on the relative growth of employment in low-wage/low-skilled elementary jobs is statistically non-significant (see column 4 and column 6).

Estimations provided in table 5 clearly indicate that the routinization hypothesis may be a plausible explanation for employment polarization in most of the broad industry branches analyzed in this study. Further, it is worth noting, as shown in table 2, that the employment shares of the restaurant and accommodation industry and of the financial sector together is between 10 and 12 per cent of total employment observed over the reference period. Accordingly, we feel rather confident in claiming that – by transversally occurring across the majority of sectors – the routinization process has involved around 90 per cent of the non-farm private employment.

To provide a national-level aggregate estimate, in table 6 we pool all observations used to obtain estimations reported in table 5 within a single integrated pooled-OLS model. Accordingly, we weight observations with the province-industry cell share of total national employment and include a set of industry dummies, as formally illustrated by the following equation:

$$\Delta ELM_{i,j,\,t_0-t_1} = \delta_t + \beta_1 RSH_{i,j,\,t_0} + \beta_2 \mathbf{X}'_{i,j,\,t_0} + \eta_j + \sigma_i + e_{ijt} \tag{6}$$

where $\Delta ELM_{i,j,t0-t1}$ is the change in the employment share of elementary jobs of industry *i* in province *j* between t_0 and t_1, $RSH_{i,j,\,t_0}$, is the routine-jobs employment share of industry *i* in province *j* at t_0 and $\mathbf{X}'_{i,j,\,t_0}$ is a vector of socio-demographic and labor-market control variables of industry *i* in province *j* at t_0.

Table 6. Growth of elementary jobs and routine-tasks specialization within province-industry cells (2004-2019)

	(1)	(2)	(3)	(4)	(5)
	OLS				2SLS
RSH	0.149***	0.170***	0.149***	0.161***	0.321***
	(0.023)	(0.021)	(0.022)	(0.021)	(0.097)
Grad/non-grad		0.077***		0.064***	0.081***
		(0.018)		(0.017)	(0.022)
Female share		-0.082***		-0.039	-0.018
		(0.025)		(0.025)	(0.024)
Immigrants/native		-0.003*		-0.142***	-0.136***
		(0.001)		(0.028)	(0.030)
Temp contr. share			-0.035	-0.022	-0.043
			(0.025)	(0.024)	(0.032)
Part-time share			-0.167***	-0.003*	-0.002
			(0.028)	(0.001)	(0.001)
Constant	-0.082**	-0.084**	-0.067*	-0.073**	-0.135***
	(0.033)	(0.034)	(0.037)	(0.037)	(0.051)
N	3,038	3,038	3,038	3,038	3,038
R^2	0.132	0.159	0.141	0.161	

Notes: pooled OLS regressions. N=3040 (95 provinces x 8 industries x 4 time periods, 2004-2008/2008-2012/2012-2016/2016-2019) Dep. Var: stacked first differences of changes in employment shares of elementary occupations by province-industry cell. Al regressions are weighted by start-of-period province-industry cell share of national employment and include time period dummies, industry dummies and province fixed effects. Standard errors are clustered by period and province. In 2SLS models, we drop time-period dummies and instrument RSH with interactions between time-period dummies and province-industry cell subsectors intensity in routine-jobs in 1993 in all Italian provinces except those belonging to the NUTS2 region in which the reference province-industry cell is located.

Source: our calculations on RCFL data

First column of table 6 shows the raw model when only the routine share is included. In column (2) we add a set of control variables accounting for province-industry cells socio-demographic characteristics (i.e. the graduate/non-graduate workers' ratio, the employment share of females and the ratio between immigrant and native workers), while in column (3) we control instead for labor market characteristics such as the share of temporary workers and the share of part-time workers. Finally, the full model is displayed in column (4). The relationship of interest is positive and highly significant across all specifications reported. According to the coefficient on the routine share in column (1) (β_1=0.149), when excluding all variables of vector $\mathbf{X}'_{i,j,\,t_0}$the model predicts a 2.2 p.p. larger expansion of elementary jobs employment shares in province-industry cells scoring at the 75th percentile of $RSH_{i,j,\,t_0}$ relative to those at the median. Compared to our estimate in column (1), the inclusion of our set of socio-demographic control variables in column (2) only slightly increases our estimate (2.2 p.p. vs. 2.5 p.p.) – while we can see that the model predicts that the increase of elementary jobs has been larger within province-industry cells with higher graduate/non-graduate ratios and lower within cells with higher female workers employment shares. Analogously negative is also the coefficient on the immigrants/native ratio, though relatively small and barely significant. As for coefficients on labor-market controls included in column (3), we can see that elementary jobs increased significantly less in province-industry cells with higher part-time employment shares, whereas the negative estimate on the employment share of temporary-contract workers is relatively small and non-significant. Finally, in column (4) we report the full-fledged OLS model, showing that the significance of β_1 is robust to the inclusion of all covariates of vector $\mathbf{X}'_{i,j,\,t_0}$. In particular, the model predicts a 2.3 p.p. larger expansion of elementary jobs employment shares in province-industry cells scoring at the 75th percentile of $RSH_{i,j,\,t_0}$ relative to those at the median.

As a final robustness, column (5) reports the instrumental variable regressions (IV) for the full-fledged model, estimated by elaborating a 2-stage least squares (2SLS) framework *a la* Autor and Dorn (2013) for equation (6). The instrumental variable for $RSH_{i,j,\,t_0}$we use for this purpose can be thought as an industry-level extension of the IV strategy proposed by Autor and Dorn (2013) and also used in Brunetti *et al.* (2020). In particular, we predict $RSH_{i,j,\,t_0}$by interacting – for each province-industry cell *i,j* – the share of province-level employment in 1993 with the industry *i* 1993 routine-jobs employment share in all Italian provinces excluding those within the region in which province *j* is located, as follows:

$$\widetilde{RSH_{\imath\jmath}} = \sum_{s=1}^{S} E_{s,i,j,1993} \times R_{s,i,-j,1993} \tag{7}$$

where $E_{s,i,j,1993}$ is the 1993 industry *i* subsector *s* share of province *j* employment and $R_{s,i,-j,1993}$ is the 1993 routine share in subsector *s* of industry *i* within all Italian provinces except those belonging to the NUTS2 region in which province *j* is located. The idea behind this IV strategy is to extend the concept elaborated in Autor and Dorn (2013) – and used in Brunetti *et al.* (2020) – to our industry-province cell setting by exploiting variations within local industries at the sub-sector level rather than variations within LLMs at the industry level. Before commenting our 2SLS estimates, we first test for the correlation of the response variable with our instrumental variable by running the reduced-form version of equation (6), as follows:

$$\Delta ELM_{i,j,\,t_0-t_1} = \delta_t + \beta_1(\widetilde{RSH_{\imath\jmath}} \times t_1) + \beta_2(\widetilde{RSH_{\imath\jmath}} \times t_2) + \beta_3(\widetilde{RSH_{\imath\jmath}} \times t_3) + \beta_4\mathbf{X}'_{ij,\,t_0} + \eta_j + \sigma_i + e_{ijt} \tag{8}$$

where we allow for over-time variation in $\widetilde{RSH}_{ij}$ by interacting it with time-period dummies and estimating three different coefficients – i.e. β_1, β_2 and β_3[13].
Table 7 reports both reduced-form regression and first stage estimates of our 2SLS model in column (5) of table 6. Column (1) of table 7 shows that our instrument is indeed highly correlated with our dependent variable, whereas first stage estimates in column (2) confirm that our instrumental variable strategy is not affected by weak identification issues.

Table 7. Instrumental variable reduced-form and first-stage estimates for growth of elementary jobs and routine-tasks specialization within province-industry cells (2004-2019)

	(1)	(2)
RSH	-	0.321***
		(0.097)
	reduced form	1^{st} Stage
$\widetilde{RSH}_{ij} \times t_1$	0.102***	0.419***
	(0.030)	(0.036)
$\widetilde{RSH}_{ij} \times t_2$	0.477***	0.270***
	(0.033)	(0.030)
$\widetilde{RSH}_{ij} \times t_3$	0.229***	0.060**
	(0.032)	(0.030)
Kleibergen-Paap Wald F		53.732
N	3,038	3,038
R^2	0.205	

Note: IV reduced-form regression and first stage estimates of the two-stage regression of equation (6). N=3040 (95 provinces x 8 industries x 4 time periods, 2004-2008/2008-2012/2012-2016/2016-2019) Dep. Var: stacked first differences of changes in employment shares of elementary occupations by province-industry cell. All regressions are weighted by start-of-period province-industry cell share of national employment and include industry dummies and province fixed effects.
Source: our calculations on RCFL data

As we can see in column (5) of table 6, the parameter estimated on the routine share in our 2SLS model doubles its magnitude, in line to results obtained in a regional setting both in Autor and Dorn (2013) for the U.S. and in Brunetti *et al* (2020) for Italy. In particular, the model predicts a 4.7 p.p. larger expansion of elementary jobs employment shares in province-industry cells at the 75th percentile of RSH_{i,j,t_0} relative to those at the median. In other words, we find that – when accounting for endogeneity issues – the effective impact of local industries routine-tasks specialization on the growth of low-skilled/low-paid jobs results to be substantially twice the one estimated in a simple OLS setting – a result that is very similar to that obtained in Autor and Dorn (2013) in a regional setting for the U.S.

[13] Since the interaction of our instrumental variable with time-period dummies t_1, t_2 and t_3 makes $\widetilde{RSH}_{ij}$ a linear combination of parameter δ_t, in our 2SLS setting collinearity issues affect the predictive power of $\widetilde{RSH}_{ij}$. For this reason we decide drop parameter δ_t from our 2SLS model. Results including parameter δ_t are indeed highly significant and show the expected sign but are characterized by a huge increase in coefficient magnitude and by first-stage Kleibergen-Paap Wald F statistics barley above the value of 10 (results available upon request).

4. Conclusions

In this paper we offer an integrated framework to analyze whether it is within-sector routine replacing technological change or, structural change (intended as employment shifts between sectors) to be mostly responsible for employment polarization in Italy.
In this effort, we have found that the decline in manufacturing and, more in general, the structural change pattern in Italy, tend to marginally explain the polarization of the labor market. By means of a standard shift-share decomposition method, we in fact observe that employment polarization in Italy turns out to be only marginally driven by the structural change pattern, with only a negligible 20 percent of the total contraction attributable to the between-industry dimension.
Robust evidences in favor of routine replacing technological change is found instead for at least 6 out of 8 broad industries showing a significant increase in the employment shares of the least skilled and least paid jobs of the occupational spectrum. Interestingly, we also find that - although manufacturing has the highest share in routine employment – the sector in which both the importance of routine-jobs has declined more and in which the estimated effect of RRTC is larger is the services to persons and business industry. Differently from the manufacturing sector – highly intensive in routine-manual jobs – the services to persons and business sector is mostly characterized by a high concentration of clerical and administrative occupations: the so-called routine-cognitive jobs. Furthermore, in stark contrast with the manufacturing sector (which contracted more relative to other industries), this industry registered the largest growth over the fifteen-year period analyzed.
As far as employment polarization is concerned, this finding helps to better understand the relationship between structural change patterns and technological change. More precisely, it is easy to see that the decline in middle-class jobs it is not only a matter of the decline in craft and production occupations along with the contraction of the manufacturing sector (say, because of technology, international trade or import competition from China), but is also related with the disappearing of administrative and clerical occupations within industries that are experiencing employment polarization and that – contrary to manufacturing – are increasing their relative size compared to other industries.

Appendix

Appendix A.

Table A1. Routine occupations

CP2001 code	Nomenclature	*RTI*	2004-2016 employment share change
723	Wood-products machine operators	.515	-.003
732	Food and related products machine operators	.587	-.000
741	Locomotive engine drivers and related workers	.597	-.001
728	Other machine operators not elsewhere classified	.624	.000
633	Handicraft workers in wood, textile, leather and related	.636	-.007
727	Assemblers	.636	-.004
731	Agricultural and other mobile plant operators	.658	-.000
721	Metal- and mineral-products machine operators	.699	-.009
331	Administrative associate professionals	.740	-.023
634	Craft printing and related trades workers	.761	-.004
400	Office and numerical clerks	.766	.002
712	Metal-processing plant operators	.798	-.008
714	Wood-processing- and papermaking-plant operators	.805	-.001
863	Manufacturing laborers	.833	-.008
632	Potters, glass-makers and related trades workers	.837	-.001
725	Printing-, binding- and paper-products machine operators	.907	-.001
724	Other wood-products machine operators	.922	-.001
726	Textile-, fur- and leather-products machine operators	.929	-.006
645	Fishery workers, hunters and trappers	.948	-.000
611	Miners, shot-firers, stone cutters and carvers	.982	-.002
651	Food processing and related trades workers	1.147	-.002
743	Agricultural engine drivers	1.880	.000
744	Other engine drivers	1.880	-.004
513	Shop, stall and market salespersons and demonstrators	1.940	.002 .0018
615	Painters, building structure cleaners and related trades workers	2.057	-.006
654	Pelt, leather and shoemaking trades workers	2.215	-.005
631	Precision workers in metal and related materials	2.219	-.001

Source: Brunetti *et al.* (2020)

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