Low-skill jobs and Routine tasks specialization:

New insights from Italian provinces

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Abstract

We combine U.S. occupational-tasks information with Italian labor-market data to assess whether in Italy recent employment dynamics are consistent with the "routinization hypothesis" (Autor et al., 2003). We first describe occupational major-groups variations in both wages and employment shares over 2004-2016, and document a clear labor market polarization pattern. We further investigate on the topic by adopting the empirical strategy proposed by Autor and Dorn (2013) and test whether the relationship between provinces' specialization in routine-tasks and the within-province growth of elementary-jobs is statistically significant. By also addressing possible estimation bias by using 2SLS models, we recover a highly significant impact of routine specialization on the growth of elementary occupations - even when taking into account time-invariant characteristics by including provinces' fixed effects. After breaking down the response variable in three different educational-attainment groups , we find that employment growth is highly significant for low-educated workers, non-significant for high-school ones and – in stark contrast with generally-common assumptions - slightly significant for those with a university degree.

1. Introduction

Since the early 90's, the composition of European employment is following a job-polarization pattern - i.e. medium-paid occupations are losing employment shares in favor of low-paid and high-paid occupations. Such a U-shaped trend in employment growth by skill/income levels has been detected both in the U.S (Acemoglu and Autor, 2011; Autor and Dorn, 2013) and European countries (Spitz-Oener, 2006; Goos and Manning, 2007; Dustmann et al., 2009; Goos et al., 2014), even in light of the important between-country differences in occupational wages and employment dynamics observable in Europe (Fernandez-Macias, 2012).

As the empirical evidence is increasingly confirming the plausibility of the *routine-replacing technical change* (RRTC) explanation, this theory has drawn notable attention among both academics and the general public. The underlying idea is that computer capital (robots, software technology and, more in general, ICTs) substitutes for *routine tasks*, mainly performed by workers employed in occupations located towards the center of the skill/wage distribution. At the same time, new technologies are more likely to complement for non-routine tasks - both at the bottom (*non-routine manual*) and at the top end (*non-routine cognitive*) of the distribution (see Autor et al. 2003). If - for what concerns high-skilled labor – the mechanisms for such a complementarity effect are theoretically straightforward, in the case of low-skilled occupations the complementarity effect is supposed to be lower or somehow ambiguous. Nevertheless, we still would have increasing proportions in the employment shares of both the worse and the best paid occupations in the labor market facing the contraction of medium-paid occupations (Harrigan et al., 2016; Bock, 2016).

Employment polarization has been also related to spatial dynamics reflecting economic, social and institutional specificities (Moretti 2013; Charnoz and Orand 2017; Ciarli et al. 2018; Consoli and Sanchez-Barrioluengo 2019). 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 labor markets. In addition, economic geographers studying the impact of local occupation structure on economic performance in regions or municipalities started to take into account the task-based approach (Bacolod et al., 2010; Scott, 2010; Kok and Ter Weel, 2014). Indeed, given the co-localization of supply and demand for employment, local labor markets represent a relevant dimension for the analysis of occupational changes. Hence, not taking into account the spatial dimension of the labor market increases the risk to miss relevant aspects of mechanisms at play (Moretti, 2008; Autor et al. 2013).

This paper contributes to the task approach literature in three main aspects. First, it focuses for the first time on the Italian case, which has been so far considered as part of the wider European labor market only. Second, it takes into account the spatial dimension of the labor market. This approach, rather than focusing on the negative correlation between occupational-tasks measures and subsequent changes in occupations employment shares, addresses the relationship between RRTC and employment polarization in a local perspective. Third, it takes into account the educational-attainment composition of low-skill occupations and, therefore, further characterizes the main findings.

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

2. Literature review

No study has previously focused on the topic of job tasks and *routinization* in Italy, though several studies adopt the task-based framework to study the relationship between technological progress and labor markets dynamics for other countries (see, i.e., Goos and Manning, 2007 for U.K.; Spitz-Oener, 2006 and Dustmann et al., 2009 for Germany; and Acemoglu and Autor, 2011 or Autor and Dorn, 2013 for the U.S. and Europe). Focusing on the phenomenon of labor market polarization, this literature provides very valuable evidences on the topic both for U.S. and Europe. Although the empirical literature does somehow reach some consensus with reference to the presence of polarization patterns in the growth of both employment and wages, there is a variety of explanations that may explain these phenomena. Digital technologies (Autor et al., 2003; Acemoglu and Autor, 2011; Goos et al. 2009, 2014), consumption spillovers (Manning, 2004; Mazzolari and Ragusa 2012), offshoring of tasks (Thoenig and Verdier, 2003; Feenstra and Hanson, 2003; Grosmann and Rossi-Hansberg, 2012), labour markets and institutions (Di Nardo et al., 1996; Firpo et al, 2011; Mishel et al., 2013).

A cornerstone empirical contribution in the task-literature is certainly Autor and Dorn (2013) – see also Autor et al. (2015). In this analysis, local-level employment shares variations are used in order to analyze the effects of RRTC on the U.S. labor market. The idea is that the higher the specialization of a province in routine tasks, the higher the extent of labor-saving technologies 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. In particular, they develop a spatial equilibrium model in which 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 polarization in the U.S over the period 1980-2005. Confirming this hypothesis, Consoli and Sanchez-Barrioluengo (2019) focus on the long-term transformations of the occupational structure of Spanish provinces, providing evidences of a higher increase if low–paid occupations in provinces with initial high level of routine occupations.

From a spatial point of view, theory from economic geography shows that those areas where innovations are prevalent may bring a wage and employment premium, attracting jobs, investment and firms (Hornbeck and Moretti, 2018). Starting from the concept of Marshallian externalities, the theory is based on agglomeration economies (Mion and Naticchioni, 2009; Feldman and Kogler, 2010; Meliciani and Savona, 2014). The evidence tends to focus on high tech sectors and productivity growth as indicators of innovation. Moretti and Thulin (2013), building on the job multiplier theory, highlight that jobs created in a local labour market specialized in a high-tech sector, once controlling for local prices, wages and services, create up to six additional jobs in services. Educated workers gain most. Lee and Clarke (2017) find a smaller, but still positive, multiplier for UK local labour markets. In their case, those who gain most are the unskilled workers. Gagliardi (2014) takes a different approach and indicator. She studies the impact of innovation on local labour markets exploiting the local industry specialization finding that innovation is negatively correlated with employment (reduces employment), and that the effect is stronger for workers with intermediate skills and in those areas with mature industries. Finally, she shows that areas that attract more skilled workers also attract less skilled workers, as the former generate employment in low skill

Finally, another strand of the literature looks at the spatial component of wage inequality and its interactions with workers' skills. Lindley and Machin (2014) and Moretti (2013) suggest that a spatial concentration of high‑skilled workers occurred, and related it to a skill‑biased spatial shift in labour demand. Charnoz and Orand (2017) have documented similar patterns for France. A potential explanation for this spatial shift in labour demand could be due to the fact that initial local industrial mix made some local labour markets more exposed to skill-biased technical change, offshoring or import competition.

On this ground, this work aims at exploring the existence of a significant relationship between initial specialization in routine tasks and the emergence of a pattern of job polarization possibly related to the adoption of labor-saving technologies. 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 we obtain document that also in Italy – similarly to others advanced economies - it is possible to observe a clear relationship between the local-level specialization in routine-tasks and changes in the employment composition. In particular, we analyze the relation between specialization in routine-tasks and the growth of employment in low-skilled/low-wage occupations among 95 Italian provinces over the period 2004-2017.

3. Data and Descriptive Statistics

3.1 Data

Our empirical analysis is based on different data sources. First of all, we measure Italian provinces' specialization in routine tasks by using the *Occupational Information Network* (O*NET) database, publicly provided by the U.S. Department of labor (previous versions of this database are known as the *Dictionary of Occupational Titles* – DOT – see for instance Goos and Mannig, 2007). To the best of our knowledge, we are the first to use O*NET data to elaborate Autor and Dorn's *routine tasks index* (*RTI*) for Italian occupations. We do so because the tasks literature has so far addressed the Italian case only as part of Europe (Goos et al. 2009, 2014) and in these papers the *RTI* is computed at the 2-digits level of the International Standard Classification of Occupations (ISCO). Of course, there are many reasons to prefer a less aggregated measure, and this is probably even more opportune when dealing with a single country. Hence - similarly to what done with DOT data in Goos and Manning (2007) for UK - we elaborate our own set of task indicators by mapping O*NET data into the 121 3-digit occupations of the Italian *Classificazione delle Professioni* (CP2001 - see subsection 3.3 for further details).

Second, we analyze the Italian labor market by using survey microdata as reported in the Italian Labor Force Survey (*Rilevazione Continua sulle Forze di Lavoro* – RCFL) which is provided by the Italian National Statistical Institute (ISTAT). The RCFL database provide us with key information about recent developments in the Italian labor market, reporting data concerning workers' employment status, occupational category, economic activity branch, spatial location, as well as several other individual socio-demographic characteristics (such as age, gender and education). Further, the database is endowed with observations frequency weights, allowing us for the reconstruction of the whole Italian population in each of the periods observed. In particular, we analyze the period 2004-2016, and focus on all employees belonging to marketed sectors (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). The narrowest territorial unit available is the Italian province (i.e. administrative divisions corresponding to NUTS 3 regions), dividing the peninsula in 95 different spatial repartitions. Finally, we recover to balance-sheet information from the AIDA archives on the population of limited liability firms in order to link information concerning the evolution of labor market and the routinization contents of occupations to indicators of the productive system, i.e. the median wage per employee and density of firms measured in each local markets.

3.2. Labor market polarization in Italy: broad descriptive evidences

In this section, we exploit wage and employment information by broad occupational categories (i.e. 1 digit) in order to assess whether (and to which extent) between 2004 and 2016 it is possible to observe – on aggregate - a labor market polarization trend in Italy. More specifically, we wonder whether the least paid occupational group experienced - relatively to medium paid ones – a higher increase in wages growth rates (wage polarization) and/or a higher expansion in employment shares (job polarization). Note that, in this section, 1-digit occupations are classified according to both ISCO and CP occupational major groups.[1] As for wage polarization, Table 1 reports the 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. [2] 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

[1] Note that at the 1-digit level the Italian classification of occupations is substantially the same compared to the International Standard Classification of Occupations (ISCO), as the only difference is that ISCO major groups 6 and 7 are clustered in a single major group (CP major group 6 – "Craft, agricultural, forestry and fishery workers").

[2] We select the 2006 and 2014 waves because they are the waves immediately after and before the period considered for the analysis.

traditionally low-skilled jobs such as agricultural workers and elementary occupations. Consistently with the RRTC theory, middling/routine-intensive broad occupational clusters (such as clerical support workers and plant and machine operators and assemblers), are placed towards the center.

As clearly illustrated by columns 3 and 6 of Table 1, over 2006-2014 occupational-wage growth rates in Italy did follow a wage polarization pattern with high-wage and low-wage occupational groups experiencing - compared to medium-wage occupations - a higher/lower relative increase/decrease in both mean and median retributions. This result is even more striking when looking at the relative increase of wages for elementary occupations – i.e. the least paid occupational category. Indeed, for this group the average hourly wage only slightly contracted by 1.9 per cent (above this figure we only have managers and professional – see column 3) while it is worth noting that is the only one to show a positive sign in the case of median retributions (column 6).

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%

Notes: 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).

Moving to Table 2, we describe the educational attainment composition of these occupational clusters in Italy. Not surprisingly, 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-educated workers. Though contracting over time, indeed, we observe that low educated individuals hold the highest share among workers employed in these occupations - i.e. 72.6 per cent in 2004 and 62.4 per cent in 2016 – always slightly more than the share held among craft and agricultural occupations (69.2 and 58.3 per cent, respectively).

Table 2. *Share of employees by educational attainment in each occupational group (2004-2016).*

Italian occupations ordered by Italian 2006 mean wage rank	Educ. group	Educ. group share 2004	Educ. group share 2016	Change
Managers	*low*	.095	.213	.118
	med	.526	.457	-.069
	high	.379	.330	-.049
Professionals	*low*	.036	.010	-.026
	med	.326	.185	-.140
	high	.638	.805	.166
Technicians and associate professionals	*low*	.113	.081	-.032
	med	.744	.622	-.122
	high	.144	.297	.154
Clerical support workers	*low*	.227	.145	-.082
	med	.694	.693	-.002
	high	.079	.162	.084
Plant and machine operators and assemblers	*low*	.692	.589	-.125
	med	.302	.400	.12
	high	.006	.012	.005
Service and sales workers	*low*	.514	.393	-.120
	med	.461	.539	.078
	high	.025	.068	.043
Craft, agricultural, forestry and fishery workers	*low*	.692	.583	-.109
	med	.302	.401	.099
	high	.006	.015	.010
Elementary occupations	*low*	.726	.624	-.102
	med	.259	.342	.083
	high	.014	.034	.019

Notes: 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 across different occupational groups is following a job-polarization pattern, in Table 3 we report the employment shares of 1-digit 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 percent 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). Moreover, 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 relatively to the southern part of the country.

Table 3. *Employment shares changes by broad occupational group in Italy (2004-2016).*

Macro region	Italian occupations ordered by 2006 mean wage rank	2004	2016	Change
Northern Italy	Managers	.017	.028	.011
	Professionals	.039	.101	.062
	Technicians and associate professionals	.186	.216	.030
	Clerical support workers	.169	.123	-.046
	Plant and machine operators and assemblers	.175	.100	-.075
	Service and sales workers	.122	.189	.067
	Craft, agricultural, forestry, fishery workers	.200	.148	-.052
	Elementary occupations	.092	.096	.004
Central Italy	Managers	.017	.029	.012
	Professionals	.048	.119	.071
	Technicians and associate professionals	.171	.183	.013
	Clerical support workers	.163	.135	-.028
	Plant and machine operators and assemblers	.121	.071	-.051
	Service and sales workers	.153	.222	.068
	Craft, agricultural, forestry, fishery workers	.210	.139	-.072
	Elementary occupations	.116	.103	-.014
Southern Italy	Managers	.013	.026	.014
	Professionals	.034	.099	.066
	Technicians and associate professionals	.122	.158	.035
	Clerical support workers	.123	.112	-.011
	Plant and machine operators and assemblers	.133	.079	-.054
	Service and sales workers	.171	.258	.087
	Craft, agricultural, forestry, fishery workers	.259	.153	-.106
	Elementary occupations	.145	.115	-.030

Notes: 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.

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.

3.3 Measuring Italian provinces' specialization in routine tasks

For what concerns the Italian labor market, several previous empirical studies analyzed employment characteristics in a local perspective. Basile et al. (2012), for instance, assess the effects of sectoral shifts and industry specialization patterns on regional unemployment in Italy over the years 2004–2008 by using employment data at the Local Labor System level (LLS - i.e. clusters of Italian municipalities). In a similar perspective, Basile (2004) addresses the topic of the determinants of FDIs location in Italy.

Our main contribution is to exploit Italian provinces' employment data in order to link the local-level specialization in routine-tasks to local-level changes in the employment shares of elementary occupations – which is the strategy we use to detect the existence of a link between RRTC and job polarization in Italy. More specifically, firstly we compute a Routine Task Index (RTI) for each occupation, and in order to do so, we map a set of 16 O*NET tasks indicators into the Italian classification of occupations (see, Acemoglu and Autor, 2011).[3] Two are the main steps. As a first step, we average the set of indicators (computed for each SOC-00 5-digits occupation) by ISCO-88 3 digits 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 CP2001 3 digits occupations. 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 six task domains considered by Acemoglu and Autor (2011) into three main task-categories - i.e. T_k^R, T_k^C and T_k^M, respectively, the aggregate indicators of occupation k intensity in routine, non-routine cognitive and non-routine manual tasks.[4]

The indexes are rescale to positive values (adding one) to allow the log-transformation required by the RTI formula: $RTI_k = \ln\left(T_{k,o*net}^R\right) - \ln\left(T_{k,o*net}^C\right) - \ln\left(T_{k,o*net}^M\right)$, where the measure is standardized to have mean 0 and standard deviation 1 by using RCFL occupational weights in 2004.

Table 4 reports the nomenclature of those occupations identified as "routine-intensive" by following the outlined procedure. Occupations identified as *routine-intensive* result to be semantically consistent with the concept of "routine occupation" developed in the literature. Moreover, none of these occupations result to appreciably expand its overall employment shares, as the trend is negative or

[3] The 16 O*NET indicators used in Acemoglu and Autor (2011, p. 1163) scores from 1 to 5 for each SOC-00 occupation.

[4] 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.

very close to zero in all cases. Further, we can see that routine occupations do not exclusively belong to the broad "clerks" (typically routine-cognitive) or "machine operators" (routine-manual) 1-digit groups, but also include several 3-digits occupations that are classified within different 1-digit occupational clusters. For instance, "administrative associate professionals" (occupation 331) represents a typical routine-cognitive clerical job, though not included in the "clerks" group (CP 4). Similarly, a number of "craft" occupations (CP 6) are identified as routine-intensive, as well as for some occupation classified in the "elementary" and "service and sales" major groups (respectively, occupations 863 and 513).

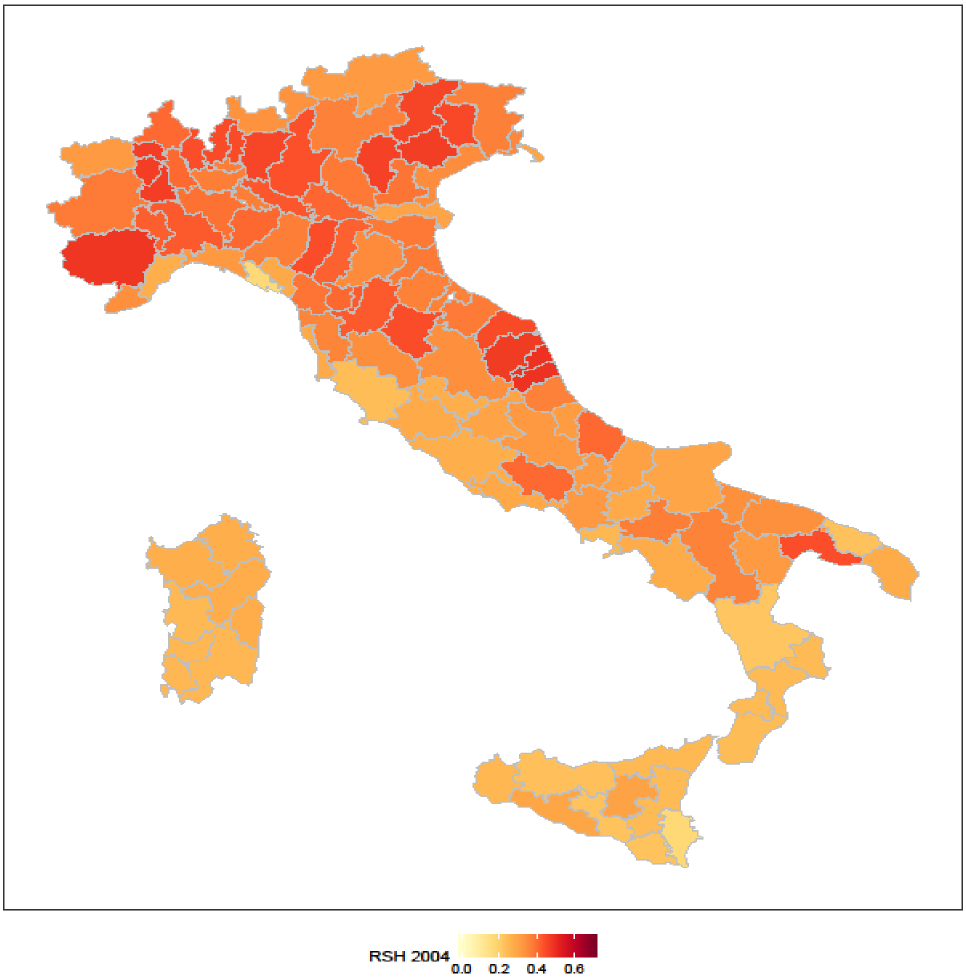
Table 4. *Routine-intensive occupations and routine-tasks-index.*

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
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

Notes: Our calculations on RCFL data. By construction, routine occupations capture 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 – though showing a relatively low *RTI* – score in the top third of the *RTI* measure in spite of the fact that 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 negligible drawback may be plausibly attributable to some little inconsistency in the O*NET-to-CP mapping procedure. See the appendix for more details.

The geographical distribution of the *RSH* variable described in equation (2) are described by Figure 1, while the basic statistics of provinces' specialization in routine-tasks are reported in Table 5. Figure 1 makes clear that routine employment in 2004 is predominantly located in the north. Of course, this concentration has to be attributed to the well-known north-south divide of manufacturing activities in Italy, since southern regions are mainly specialized in industries less intensive in routine jobs (such as construction, trade and transport). Figure 1 shows that the routine share tends to be higher in provinces located in Northern Italy, though at the top end of the *RSH* distribution there are a number of provinces that, differently, are located in central part of the country (for instance, 49.1 per cent of employment in Ascoli Piceno and 47.4 in Macerata).

Figure 1. *Provinces' specialization in routine-tasks. Geographical distribution.*



Notes: 95 Italian provinces.

Table 5. *Provinces' specialization in routine-tasks: descriptive statistics (2004-2016).*

Variable	Min.	Max.	Mean	Median	Std.	Italy
$RSH_{j,2004}$	.173	.491	.343	.354	.076	.327
$RSH_{j,2016}$	.144	.442	.267	.261	.056	.260
ΔRSH_j	-.159	.048	-.078	-.079	.036	-.067

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

After having built our measure of provincial specialization in routine tasks, we verify 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. In addition, we study the correlation between the start of period *RSH* and the relative growth of low-wage/low-skilled elementary occupations employment shares. 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.[5] The population-weighted correlation between this variable and the start of period *RSH* computed at the provincial level is of 0.57, and is statistically 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. In Table 6 are reported the results of the estimate of 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 $_{-1}$	-0.218***	-1.206***
	(0.024)	(0.088)
Province FE	no	yes
R^2	0.220	0.702

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.

In order to address point 3, finally, we run the simple univariate regression described in equation (3), where $\Delta ELM_{j,2004-2016}$ is the change in elementary occupations employment shares in province j over the period 2004-2016, $RSH_{j,2004}$ is province j routine occupations employment share in 2004, and

[5] 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.

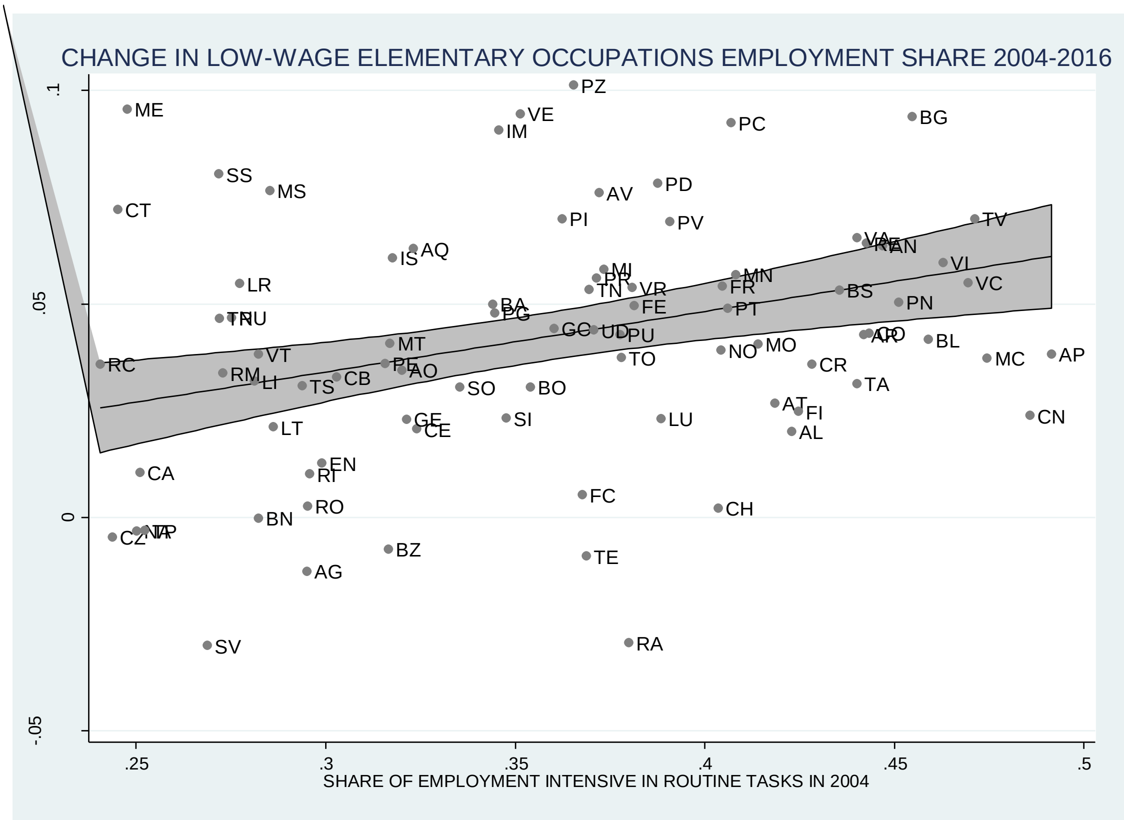
weights are equal to the start of period province j share of national population.[6] We obtain the following results:

$$\Delta ELM_{j,2004-2016} = -0.023 + 0.169 \times RSH_{j,2004} + e_{jt}, \quad (3)$$
$$(t=4.00) \qquad N=95,\ R^2=0.175$$

According to our results, we detect a substantially significant positive correlation between RSH and $\Delta ELM_{j,2004-2016}$. More specifically, for a province with a start-of-period routine share of 0.33 (i.e. $RSH_{j,2004} = 0.33$), the model predicts a 3.3 p.p. increase in the employment shares of elementary occupations. To provide a graphical insight about the relationship under analysis, in Figure 2 we describe the output of the regression model in equation (3) by displaying the bivariate scatter-plot and the corresponding estimated regression line.

Figure 2 adds further details about the north-south geographical pattern of job-polarization detected in Table 3 in two aspects: 1) it adds the routine share variable to the whole picture; 2) it reveals a certain degree of variability in the main trend.

Figure 2. *Change in elementary occupations employment share by province (2004-2016).*



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

[6] 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.

On the one hand, indeed, we can see that not all southern provinces experienced a contraction in elementary/low-wage occupations – though almost all provinces in the north exhibit an increase in the shares of this group. On the other hand, we can observe that even if routine labor results to be predominantly concentrated in the north, not all high *RSH* provinces are located in northern Italy (e.g. Rovigo and Massa Carrara). Instead, some locations in central Italy and southern Italy result to be relatively more endowed with routine employment than several other northern provinces (compare with Figure 1). 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.[7]

4. Econometric analysis

In this section we assess whether it is possible to recover a significant impact of provinces' specialization in routine tasks on the job-polarization pattern documented above. Our main response variable is the growth in the employment shares of the least-paid and least-skilled jobs in the labor market - in Autor and Dorn (2013) "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.[8] In 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.

Formally, we stack elementary occupations employment shares first differences over three different periods (2004-2008, 2008-2012, 2012-2016) and estimate the following equation:

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

where $\Delta ELM_{j,t}$ is the change in elementary occupations employment shares in province j between t1 and t0, $RSH_{j,t}$ is province j routine occupations employment share in t0 , $\mathrm{X'}_{j,t}$ is a vector of socio-demographic control variables in t0 derived from RCFL data, while the vector $\mathbf{F'}_{j,t}$ controls for the median wages per employee and the mean density of firms calculated from AIDA archive in each province j in t0. We also include a full set of time-period dummies and province fixed effects (η_j) and weight models by start of period province share of national population.

To begin with, we perform pooled OLS regressions to estimate different specifications of equation (4). However, endogeneity issues may be at play in our framework, making pooled OLS estimates potentially biased. This would happen if, for example, the routine share variable were correlated with

[7] 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.

[8] 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.

some cyclical unobservable simultaneously affecting changes in elementary occupations employment shares.

Then, we address possible endogeneity concerns that may bias OLS estimations by again following the identification strategy proposed in Autor and Dorn (2013). More specifically, we use province-level 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:

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

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.9 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.

4.1 Main results

I this subsection, we report the empirical results obtained (Table 7). As already mentioned, we are 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.

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. 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, we focus on high school 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.

9 More specifically, calculations are elaborated on 20 regions and 53 NACE economic sectors.

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 that 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.

Table 7. *Growth of low-skilled jobs employment share within province*

	OLS			2SLS-IV		
	[1]	[2]	[3]	[4]	[5]	[6]
RSH	0.255***	0.299***	0.299***	0.290*	0.490**	0.514**
	(0.088)	(0.090)	(0.090)	(0.174)	(0.225)	(0.228)
tertiary ed		0.326	0.303		0.335**	0.312**
		(0.198)	(0.197)		(0.139)	(0.141)
upper secondary ed		0.173*	0.176**		0.183**	0.186***
		(0.089)	(0.089)		(0.072)	(0.072)
Workforce characteristics.	no	yes	yes	no	yes	yes
Firms characteristics	no	no	yes	no	no	yes
Period FE	yes	yes	yes	yes	yes	yes
Province FE	yes	yes	yes	yes	yes	yes
Kleibergen Paap F				14.728	9.401	9.051
N of Observations	285	285	285	285	285	285
R-squared	0.356	0.416	0.419	0.046	0.400	0.399

Source: our calculations on RCFL-ISTAT 2004-2016 and AIDA archive. **Notes**: N=285 (3 periods for 95 provinces). Dependent variable: change in share of employment in elementary occupations by provinces (2004-08/08-12/12-16). The vector of workforce characteristics controls for eight different provinces' start of period socio-demographic conditions: unemployment rate, share of population with age >65, shares of employment of immigrant, low-tech manufacturing, female, part-time, and temporary workers. All models include constant, period and province fixed effects and are weighted by start of period province share of national population. In 2SLS-IV estimates, the share of routine occupations is instrumented by interactions between the 1993 industry mix instrument and time dummies. Standard errors in parentheses are clustered by provinces and periods. *** p<0.01, ** p<0.05, * p<0.1.

In sum, the empirical evidences provided in this section documents 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. Moreover, we think that the finding of this phenomenon in the Italian labor market of the XXI century may be interpreted as a consequence of the well-known lag in innovation that affected the Italian economy over the last few 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 – in so, by addressing the relationship between RRTC, job polarization and wage polarization in Italy.

4.1 A look into the educational-attainment composition of elementary jobs

As the Italian labor market is traditionally characterized by well-known over-educational patterns, In this last subsection we try to assess whether the increase of low-skilled workers in elementary jobs is exclusively driving the phenomenon or whether workers with higher education are also involvedà Indeed, 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 8 *Growth of L-S jobs employment share within province by educational groups*

	Tertiary ed		upper secondary ed		Lower/Primary ed	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
RSH	0.044*	0.075*	0.076	0.033	0.207***	0.510***
	(0.024)	(0.039)	(0.047)	(0.094)	(0.077)	(0.188)
tertiary ed			0.148	0.149*	0.337**	0.351***
			(0.104)	(0.082)	(0.161)	(0.129)
upper secondary ed	-0.033	-0.046			0.282***	0.297***
	(0.052)	(0.040)			(0.079)	(0.064)
lower secondary/primary ed	-0.024	-0.041	0.098**	0.100***		
	(0.047)	(0.038)	(0.039)	(0.031)		
Workforce characteristics.	yes	yes	yes	yes	yes	yes
Firms characteristics	yes	yes	yes	yes	yes	yes
Period FE	yes	yes	yes	yes	yes	yes
Province FE	yes	yes	yes	yes	yes	yes
Kleibergen Paap F		6.067		9.949		10.011
N of Observations	171	171	283	283	285	285
R-squared	0.408	0.394	0.233	0.228	0.457	0.406

Source: our calculations on RCFL-ISTAT 2004-2016 and AIDA archive. **Notes**: Dependent variable: change in share of employment in elementary occupations by provinces (2004-08/08-12/12-16). The vector of workforce characteristics controls for eight different provinces' start of period socio-demographic conditions: unemployment rate, share of population with age >65, shares of employment of immigrant, low-tech manufacturing, female, part-time, and temporary workers. All models include constant, period and province fixed effects and are weighted by start of period province share of national population. In 2SLS-IV estimates, the share of routine occupations is instrumented by interactions between the 1993 industry mix instrument and time dummies. Standard errors in parentheses are clustered by provinces and periods. *** p<0.01, ** p<0.05, * p<0.1.

Moving from Column 3 to 6, we consider non-university educated workers only (respectively, high school and non-high school low skilled workers). Though positive for all educational attainment groups, only in the case of the less-educated the impact of the routine share is strongly significant - an outcome that is highly reasonable to expect. On the contrary, particularly surprising is the fact that - though losing several observations because of the absence of university degree workers in many province-occupation cells - coefficients on the routine are slightly significant.

These results seem to point out that the employment composition effects of routinization in Italy may be potentially detrimental also for the working careers of highly educated individuals, and our guess is that this outcome may due to younger workers undertaking elementary jobs in regions where more RRTC is at work.

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, consistently with the RRTC framework. 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 - hence, higher adoption of new technologies - tended to partly reallocate highly educated workers into low skill jobs, with potentially detrimental consequences for economic growth.

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