Employment polarization: evidence from regions in Greece

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25 September 2023

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This version: 25 September 2023

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Abstract

This study first provides evidence compatible with the idea of employment polarization in the Greek labour market since the early 1990s. Then, using an instrumental variables approach, it uncovers the potential role of routine biased technological change in explaining these developments in the employment structure. The empirical results consistently suggest that employment has polarized more into regions with a higher initial routine share. Overall, the impact of technology on the employment rate is negligible, implying that the expansion of non-routine manual employment fully compensates for the destruction of jobs in middling, routine occupations.

1 Introduction

Job polarization, that is, the growing number of jobs located at the extremes of the occupational spectrum, and the concurrent disappearance of the middling ones has been well-documented in many advanced economies since the early 1980s (Goos and Manning, 2007; Goos et al., 2009 and 2014; Autor and Dorn, 2013).[1] Routine biased technological change (RBTC) is widely shared among economists as the main

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[1] Some authors, however, dispute whether job polarization is prevalent in Western countries (see, e.g., Oesch and Piccitto, 2019; Hunt and Nunn, 2022)

explanation of these developments in the employment structure.[2] Specifically, individuals in cognitive occupations tend to benefit from complementarities with computers. On the other hand, the adverse effects of automation are mainly felt by medium-skilled workers in routine occupations who are more easily substitutable by technology. This, in turn, induces a reallocation of medium-skilled workers, mainly toward low-paid jobs, generating a polarized employment structure.[3] Previous studies have shown that job polarization is not only a mere stylized fact but also a key factor in understanding intergenerational occupational mobility, as well as the recent developments in the political landscape (see, e.g., Drinkwater, 2021; Guo, 2022; García-Peñalosa et al, 2023)

This article contributes to the literature further evidence from local labour markets in Greece using census data for the period 1981-2011. Although there is ample evidence concerning the importance of technology in shaping the employment structure in European regions (see, e.g., Montresor, 2019; Consoli, and Sánchez-Barrioluengo, 2019; Brunetti et al., 2020; Terzidis and Ortega-Argilés, 2021), we are not aware of any previous study focusing solely on employment dynamics in Greece and important driving factors. Apart from the advent of technology, we account for major changes in labour supply that have taken place over the period under consideration, including the expansion of university graduates and the mass entry of immigrants, mainly from contiguous Balkan countries. We also pay attention to the aging of population, which has previously been associated with increased demand for low-skilled services (see, e.g., Moreno-Galbis and Sopraseuth, 2014). This study also extends previous analyses, by examining the net impact of routine biased technology on regional employment rates.[4]

To motivate the empirical analysis, we first explore the incidence of polarization in the Greek labour market by plotting the decadal changes in the employment shares in three broad occupational categories. Specifically, on the basis of the task content within one-digit ISCO88

[2] The main difference between the RBTC and the so-called skill biased technological change (SBTC) is that the latter attributes the change in the structure of the labour market on the impact of technology on the demand for skills rather than tasks.

[3] The growth of low-skilled jobs could also be attributed to consumption spillovers or to the rise in the share of married women in paid employment (see, e.g., Leonardi, 2015; Lee et al., 2022).

[4] To the best of our knowledge, the only study having already considered such an empirical exercise is Maarek and Moiteaux (2021). Using a sample of fifteen European countries, these authors establish that the ability of the economy to create additional jobs in manual occupations in response to the destruction of routine jobs is inversely related to the level of the minimum wage.

occupations, we consider a broad division into manual, routine, and cognitive intensive ones.[5] The ensuing patterns by decade as well as the period averages are displayed in Figure 1. For completeness, we also report the evolution of employment in the pre-sample period (1971-1981). The descriptive evidence shown therein is suggestive of job polarization that seems to have been taking place mainly since the 1990s. On the contrary, the developments during the 1970s are compatible with the idea of occupational upgrading, as we observe a dramatic decline in low-skill manual occupations, whilst routine, and especially cognitive occupations expanded significantly. Taken together, we consider the descriptive evidence before 1981 as indicative that the identified change in the employment structure thereafter is not an artifact in the data.

[Insert Figure 1 about here]

To explore whether technology has contributed to these U-shaped patterns in employment, we use census data spanning the 30-year interval from 1981 to 2011. Our main explanatory variable is the share of routine employment at the beginning of each decade across 51 Greek prefectures. We consider the following outcomes: the share of non-routine employment, either at the top or the bottom end of the occupational distribution, and the share of employment in middling jobs. To mitigate endogeneity concerns, we use the 1971 industry mix, interacted with time dummies as an instrument. Overall, our preferred 2SLS estimates suggest that employment in non-routine occupations grew more into regions with a higher initial routine share. On the contrary, the share of middling occupations is negatively associated with the main independent variable of interest. Overall, we establish that the net impact of exposure to technology on the employment rate clusters around zero.

The remainder of the paper is structured as follows. Section 2 describes the data and the 2SLS empirical strategy. Section 3 discusses our main findings. Section 4 concludes the paper.

2 Data and Empirical Framework

The main analysis is carried out using four Census samples for the years 1981, 1991, 2001, and 2011, downloaded from the Public Use Microdata

[5] See section 2 for more details on the classification of occupations, which is based on O*NET data.

Series International (IPUMS-I).[6] We also use the 1971 wave to construct our instrumental variable. The sample is restricted to persons aged between 15 and 64 years, aggregated at the NUTS 3 level. Broad occupations are classified into manual, routine, or cognitive categories on the basis of their task content, in the spirit of pioneering studies by Autor et al. (2003) and Acemoglu and Autor (2011). Specifically, we use data on the task content of occupations from the 2006 O*NET database, scaled from 1 to 5.[7] We, first collapse this information at the three-digit ISCO88 occupation level.[8] Our routine, manual, and cognitive measures are then further aggregated at the one-digit ISCO88 level and standardized to mean zero and standard deviation one.[9] The final step involves calculating the routine task intensity indicator as follows:[10]

$$RTI_k = \ln(T_k^R) - \ln(T_k^M) - \ln(T_k^C) \tag{1}$$

where T_k^R, T_k^M, and T_k^C stand for routine, manual, and cognitive importance obtained in the previous step. As is standard in the literature we classify occupations as routine intensive if they fall into the upper routine task intensity tercile. As can be seen in Table 1, these occupations are "Clerical support workers", "Craft and related trade workers", "Plant and machine operators and assemblers". Hence, our main regressor of interest, the share of routine employment, is given by the following formula:

$$RSH_{rt} = \left(\sum_{k=1}^{K} L_{rkt} \cdot 1[RTI_k > RTI^{p66}]\right)\left(\sum_{k=1}^{K} L_{rkt}\right)^{-1} \tag{2}$$

where L_{rkt} is the number of employees in occupation k and in region r. Employment in cognitive occupations is the sum of "Managers", "Professionals", "Technicians and associate professionals". Lastly,

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[6] Minnesota Population Center. Integrated Public Use Microdata Series, International: Version 7.3 [dataset]. Minneapolis, MN: IPUMS, 2020. https://doi.org/10.18128/-D020.V7.3

[7] The task measures used to calculate manual, routine and cognitive importance are listed in the Appendix.

[8] The translation of the SOC-00 occupation classification into the ISCO88 one was based on the crosswalks constructed by Hardy et al. (2003).

[9] Following common practice in previous related literature, we discard from the sample employees in armed forces and in agricultural occupations.

[10] Unfortunately, with the data in our disposal, it is not possible to compute the task content of occupations at a lower level of aggregation (i.e., two-digit or three- digit occupations).

“Elementary occupations” and “Service and sales workers” constitute the group of low-skilled manual employment.[11]

[Insert Table 1 about here]

The previous section has shown that employment expanded in manual and cognitive occupations, whilst it declined in routine occupations, at least since the early 1990s. To understand whether “routinization” explains these patterns in the structure of the labour market, we estimate the following empirical model, as in Autor and Dorn (2013); Montresor (2019); Consoli, and Sánchez-Barrioluengo (2019).

$$\Delta EMP_{rt} = \alpha + \beta_1 RSH_{rt-10} + \beta_3 X_{rt-10} + \varphi_t + \varphi_r + \epsilon_{rt} \tag{3}$$

where ΔEMP_{rt} stands for the decadal change in the employment shares in manual, routine, and cognitive occupations, respectively, across 51 NUTS3 regions r; RSH_{rt-10} is the local share of routine employment at the beginning of each decade, capturing exposure to technology; $\boldsymbol{X}$ is a vector of regional controls, including the unemployment rate, the share of pensioners (i.e., persons 65 years and older), the share of immigrants (foreign-born persons/total population), and the ratio of university to no university graduates; φ_t and $\boldsymbol{\varphi_r}$ are period and NUTS1 fixed effects,[12] respectively; and ϵ_{rt} is the error term. Equation (1) is estimated using autocorrelation and heteroskedasticity robust standard errors, clustered at the NUTS3 level.[13]

[Insert Table 2 about here]

However, the main identification challenge concerns the possibility of unobserved confounding that might be associated with both the routine share in local employment and each of the dependent variables considered in the current study. Following existing studies (e.g., Autor and Dorn, 2013), we recur to a 2SLS strategy which uses past industry mix as an instrumental variable. Specifically, our instrument is obtained by

[11] A visualization of the main variables is shown in Appendix figure A1. Darker colours indicate, larger routine shares in 1981, larger increases in the share of manual and cognitive occupations, and larger declines in the share of routine occupations over the period 1981-2011.

[12] The NUTS1 regions are Northern Greece, Central Greece, Attica, Aegean Islands and Crete.

[13] Descriptive statistics of the covariates included in the empirical model are shown in Table 1.

multiplying the 1971 employment share of industry i in prefecture r ($E_{i,r,1971}$) by the 1971 share of routine employment in industry i at the national level ($R_{i-r,1971}$). To further strengthen the identification process, the second multiplicative term excludes each region's contribution to the national share. The predicted share of routine employment in 1971 in each region is then obtained by aggregating across industries:

$$\widetilde{RSH} = \sum_{I} E_{i,r,1971} \times R_{i-r,1971} \tag{4}$$

The instrument described in eq. (4) is interacted with time dummies in order to generate exogenous variation over the period considered in this study. Before we proceed with the main findings, it is worth discussing the scatterplots shown in Figure 2, which verify the relevance of our instrument. In particular, this figure displays the unconditional correlations in the base year 1971, and for each year considered in the empirical analysis. As one would expect, the regression line in 1971 is almost identical to the 45-degree line. Of course, the slight discrepancy stems from the fact that the second component of our predictor is the average proportion of routine occupations in Greece within each industry, without considering the contribution of each particular region. Reassuringly, the correlation turns out to be positive and significant for the remaining years, though the magnitude of the estimated coefficients declines from 0.508 in 1991 to 0.094 in 2011. These findings are further validated by the first stage, cluster-robust Kleibergen-Paap weak identification tests, which are shown at the bottom part of Tables 3, 4, and 5. Through specifications, the F-statistics range between 16.93 and 28.09, well-exceeding the generally accepted threshold value of ten.

Considering the second necessary condition on instrument validity, the so-called exclusion restriction, though it cannot be tested directly, it is reasonable to assume that it is more likely to be satisfied than in previous settings, considering the fact that Greece is among the technology-lagging countries, as well as the major structural changes that took place after 1971, including, among others, the transition to democracy in 1974, and Greece's accession to the European Community in 1979.

3 Results

This section presents the empirical evidence pertaining to the potential role of technology in explaining the polarization patterns in the Greek labour market we described above. To go beyond correlations, we instrument the main independent variable of interest by the industry mix in 1971, interacted with dummy indicators for each period considered, as in Autor and Dorn (2013).

Table 3 compares the OLS and the 2SLS estimates when the dependent variable is the decadal change in the share of non-routine manual employment. Each of the specifications reported therein includes NUTS1 and census year effects, whilst we add further controls sequentially. Inference is based on robust standard errors clustered at the prefecture level. It is apparent from this table that both methods suggest a significant positive impact of the initial routine share variable on the growth in the employment share of manual occupations. Notice, however, that the OLS findings are about two times as high as their 2SLS counterparts through specifications. Considering first the OLS results, point estimates of the main independent variable of interest, range between 0.57 and 0.63. On the other hand, the 2LS coefficients in columns (1) through (6) suggests that a ten percent rise in routine share employment causes the share of manual employment to increase between 3.4 and 3.6 percentage points.

We have also estimated whether the impact of routine share differs between skilled and unskilled workers. The results we obtain suggest that the findings reported in Table 2 are entirely driven by the unskilled group. As one should expect, the coefficient on the routine share variable turned out to be a weak and insignificant at conventional levels. On balance, the expansion of non-routine manual employment concerns those workers with at most a post-secondary, non-tertiary education.

[Insert Table 3 about here]

Considering the remaining controls, the estimated coefficients are broadly consistent with our expectations from economic theory.[14] Focusing on the specification with the full set of explanatory variables, we observe that the share of population above the age 65, and the local unemployment rate display a negative but insignificant association with the growth in the share of unskilled manual jobs, thereby indicating that local labour demand and population aging do not stimulate the reallocation of employment toward manual occupations. The relative share of university graduates appears to be positively associated with the share of manual employment at the ten percent level in the OLS specifications. On the other hand, the immigrant share enters with a negative but weak

[14] We have also run regressions including changes in the covariates instead of their initial levels. The results, not shown for brevity, remain robust to these modifications.

coefficient, which suggests that the supply shock does not explain the rise in unskilled employment.

Next, we proceed by estimating the potential association between technology and the decline in routine occupations. Hence, we re-estimate eq. (1) by using the change in the routine employment share as the dependent variable. As the estimated effects on university graduates are not statistically significant, we focus on the sample of persons without a bachelor's degree. Our preferred 2SLS specifications yield quite consistent results, indicating that the change in routine employment is negatively associated with the initial routine intensity across the Greek prefectures. The estimates are always significant and economically important. Column (6), which corresponds to full specification, implies that a ten percent rise in the initial routine share reduces employment in middling occupations by about 3.9 percent. More interestingly, the absolute value of the estimated coefficient of interest is almost equal to the one we found in Table 3, possibly indicating the capacity of the economy to compensate for lost jobs in the middle of the occupational distribution.

[Insert Table 4 about here]

We then explore whether routine intensity is associated with the expansion of employment in non-routine cognitive occupations. The estimates for university graduates are shown in Table 5.[15] In line with our expectations, the effects experienced by high-skilled employees are positive and significant. The coefficients on the main independent variable are precisely estimated, implying that in regions where the routine share is ten percent higher, cognitive employment increases by about 0.4 percent.

[Insert Table 5 about here]

Apart from endogeneity, there is yet another identification concern that stems from the fact that workers can freely move between regions in response to technology (see, e.g., Montresor, 2019). Internal mobility could, then, disperse the effects of technology into the least affected regions, thereby rendering the estimates reported above unreliable. To gain insights whether this is an issue in the current study, we regress percentage changes in the working-age population on the initial routine shares and the usual set of the additional covariates. We carry out the analysis for the entire population, as well as by level of educational attainment.

[15] The results for the group of the less-skilled workers (not shown for brevity) are insignificant.

Reassuringly, the 2SLS results, shown in the top part of Table 6, suggest that the working age population is not significantly affected by the share of routine employment. We, therefore, exclude the possibility that our main findings are driven by changes in the workforce.

Summarizing the results we obtained so far, there is substantial heterogeneity across different parts of the occupational distribution, consistent with the idea of routine biased technological change. Specifically, the share of employees in middling, routine occupations declined dramatically in prefectures with a higher initial routine share. On the contrary, the share of high-skill cognitive employment, and, especially, the share of unskilled manual employment grew more into more intensively exposed regions. With these issues in mind, it would be informative to estimate whether the overall employment rate has eventually been affected by the advent of technology. To do so, we re-estimate our model substituting the dependent variable by the employment to population ratio. As can be seen in panel B of Table 6, the association between the employment rate and the routine share variable is negligible. This is also verified when considering skilled and unskilled workers separately. Overall, we interpret these findings as suggestive of the capacity of the Greek economy to compensate for the destruction of middling jobs by creating more non-routine manual jobs.

[Insert Table 6 about here]

Lastly, in Table 7, we investigate whether the effects of technology are age and gender specific. Comparing first the estimates between young workers and their older counterparts, we observe that the technology induced reduction in the share of routine employment is somewhat stronger among the group 35—64 years old. This appears also to be the case when considering the impact on nor-routine manual employment. Interestingly, those in the age group 15-34 experience the larger gains from automation, as their share in cognitive jobs increases substantially. On the contrary, the share of the high-skilled old workers appears to be largely unaffected by technology. Turning to the estimates by gender, two points are worth noting. First, the negative effects of automation are mainly felt by female workers in routine occupations. Second, only male workers experience a rise in their share in cognitive jobs. Notice, however, that caution is needed when interpreting female regressions, as the first-stage cluster-robust F-test for weak instrumentation declines significantly. It is also important to emphasize that the magnitudes of the opposing effects appear, once again, to cancel each other out.

[Insert Table 7 about here]

4 Conclusion

This article documents that the incidence of employment polarization is prevalent in the Greek labour market, using data from four consecutive decennial census samples for the years 1981, 1991, 2001, and 2001. We compute regional exposure to technology by the share of routine employment. This is formally defined according to the task content of broad occupations, drawing the relevant information from the O*NET database. Relying on an instrumental variables approach, which uses the 1971 industry mix as a source of exogenous variation, we provide robust empirical evidence that the expansion of non-routine skilled and unskilled occupations and the decline in the share of routine employment is mostly driven by task-biased technological changes. Our findings are largely consistent with previous related studies and specifically to those from other Southern European countries (e.g., Consoli and Sánchez-Barrioluengo, 2019; Brunetti et al., 2020).

The analysis also suggests that the heterogeneous effects across broad occupations do not translate in changes on the overall employment rate. This implies that the expansion of the unskilled occupations fully absorbed workers previously being employed in routine intensive jobs. Lastly, there is substantial heterogeneity between different demographic groups. The groups of workers experiencing the larger gains from automation are men and those in the age group 15-24 years old. This finding stands in contrast with the evidence reported in Terzidis and Ortega-Argilés (2021) for Netherlands.

An important extension would be to further consider how the recent fiscal crisis and the coronavirus pandemic have shaped the employment structure across Greek regions.

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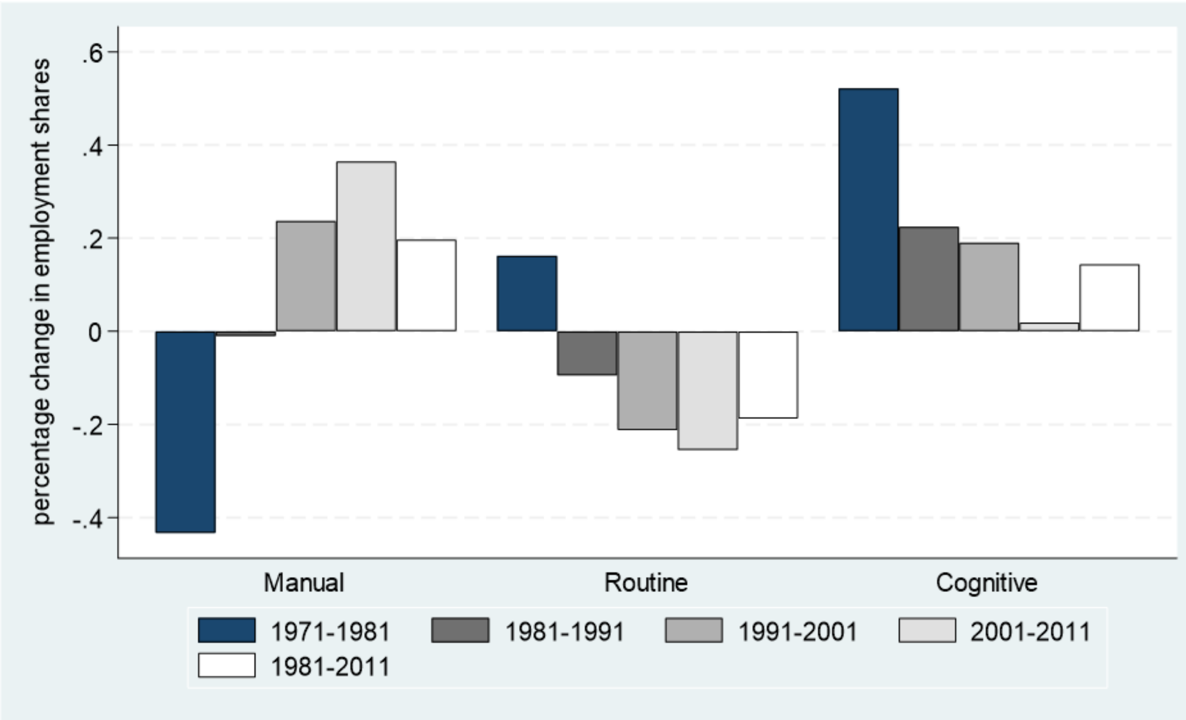

Figure 1 Evolution of the employment structure over the period 1971-2011. Decadal changes in manual, routine, and cognitive occupations. Own calculations on IPUMS and O*NET.

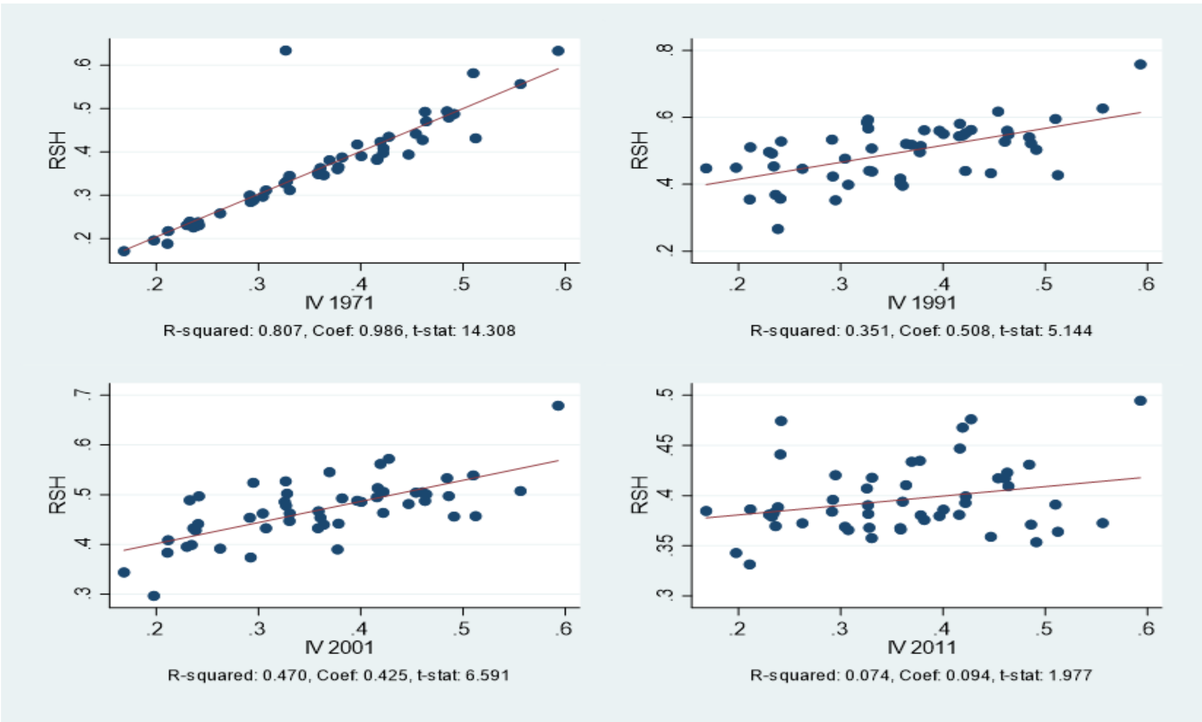

Figure 2 First-stage unconditional regressions between the RSH variable and the instrument in 1971, 1991, 2001, and 2011. Own calculations on IPUMS.

Table 1 Summary statistics

	mean	sd	min	max
Change in the share of manual employment	0.0308	0.0853	-0.256	0.209
Change in the share of routine employment	-0.0601	0.0560	-0.184	0.172
Change in the share of cognitive employment	0.0293	0.0458	-0.0788	0.138
Routine share	0.454	0.0773	0.266	0.759
Unemployment rate	0.0520	0.0253	0.00681	0.152
Pensioners share	0.169	0.0398	0.0917	0.259
University/no University	0.0947	0.0480	0.0364	0.288
Immigrant share	0.0352	0.0366	0.00171	0.170

Table 2 Task importance of one-digit ISCO88 occupations

Occupation (ISCO88)	Cognitive importance	Routine importance	Manual importance	Routine task intensity
Managers	1.549	-0.959	-1.403	-0.873
Professionals	1.109	-1.002	-0.986	-1.030
Technicians …	0.575	-0.333	-0.318	-0.431
Clerical support workers	-0.061	0.654	-0.474	**0.752**
Service and sales workers	-0.199	-1.049	-0.141	-1.089
Craft and related trades …	-1.060	0.860	0.997	**1.050**
Plant and machine operators	-1.095	1.630	1.259	**1.453**
Elementary occupations	-0.816	0.198	1.066	0.167

Notes: The table displays task intensities and a composite routine task intensity indicator calculated as described in eq (1) in the main text: Own elaborations on O*NET and IPUMS

Table 3 Effects on non-routine manual employment, OLS and 2SLS estimates

	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A. OLS estimates			
Routine share t-10	0.578***	0.576***	0.605***	0.587***	0.578***	0.634***
	(0.060)	(0.062)	(0.066)	(0.061)	(0.061)	(0.070)
Unemployment t-10		0.062				0.358
		(0.292)				(0.406)
Pensioners share t-10			0.155			0.274
			(0.130)			(0.183)
University/no University t-10				0.095		0.263*
				(0.080)		(0.141)
Immigrant share t-10					-0.036	-0.000
					(0.166)	(0.198)
NUTS1 FE	✓	✓	✓	✓	✓	✓
Period FE	✓	✓	✓	✓	✓	✓
Observations	153	153	153	153	153	153
R-squared	0.572	0.572	0.574	0.573	0.572	0.581
			Panel B. 2SLS estimates			
Routine share t-10	0.349***	0.339***	0.345***	0.358***	0.358***	0.362***
	(0.079)	(0.077)	(0.081)	(0.071)	(0.079)	(0.074)
Unemployment t-10		0.291				0.396
		(0.327)				(0.422)
Pensioners share t-10			-0.005			0.051
			(0.115)			(0.146)
University/no University t-10				0.023		0.123
				(0.107)		(0.140)
Immigrant share t-10					-0.081	-0.065
					(0.171)	(0.184)
NUTS1 FE	✓	✓	✓	✓	✓	✓
Period FE	✓	✓	✓	✓	✓	✓
Observations	153	153	153	153	153	153
Kleibergen-Paap F-Test	23.72	28.04	16.93	29.39	25.46	28.09

Notes: Regressions are weighted by the prefecture share in total population at the beginning of each period. 2SLS estimates obtained using the interaction between the 1971 industry mix and time dummies as instruments. Robust standard errors clustered at the NUTS3 level in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 4 Effects on routine employment, 2SLS estimates

Sample: No University	(1)	(2)	(3)	(4)	(5)	(6)
Routine share t-10	-0.418***	-0.407***	-0.401***	-0.401***	-0.423***	-0.398***
	(0.070)	(0.066)	(0.071)	(0.057)	(0.070)	(0.063)
Unemployment t-10		-0.055				-0.198
		(0.231)				(0.250)
Pensioners share t-10			0.037			-0.004
			(0.080)			(0.095)
University/no University t-10				-0.094		-0.147
				(0.089)		(0.090)
Immigrant share t-10					0.043	0.094
					(0.103)	(0.114)
NUTS1 FE	✓	✓	✓	✓	✓	✓
Period FE	✓	✓	✓	✓	✓	✓
Observations	153	153	153	153	153	153
Kleibergen-Paap F-Test	23.72	28.04	16.93	29.39	25.46	28.09

Notes: Regressions are weighted by the prefecture share in total population at the beginning of each period. 2SLS estimates obtained using the interaction between the 1971 industry mix and time dummies as instruments. Robust standard errors clustered at the NUTS3 level in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 5 Effects on non-routine cognitive employment, 2SLS estimates

Sample: University	(1)	(2)	(3)	(4)	(5)	(6)
Routine share t-10	0.041**	0.041**	0.040*	0.047**	0.050***	0.042*
	(0.019)	(0.019)	(0.024)	(0.019)	(0.018)	(0.023)
Unemployment t-10		-0.033				-0.116
		(0.093)				(0.102)
Pensioners share t-10			0.001			-0.030
			(0.038)			(0.035)
University/no University t-10				-0.020		-0.028
				(0.047)		(0.055)
Immigrant share t-10					-0.107**	-0.124**
					(0.053)	(0.060)
NUTS1 FE	✓	✓	✓	✓	✓	✓
Period FE	✓	✓	✓	✓	✓	✓
Observations	153	153	153	153	153	153
Kleibergen-Paap F-Test	23.72	28.04	16.93	29.39	25.46	28.09

Notes: Regressions are weighted by the prefecture share in total population at the beginning of each period. 2SLS estimates obtained using the interaction between the 1971 industry mix and time dummies as instruments. Robust standard errors clustered at the NUTS3 level in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 6 Effects on working age population and employment rate, 2SLS estimates

Dependent variable	(1) All	(2) University	(3) No University
A. Working age population	-0.083	-0.084	0.041
	(0.192)	(0.135)	(0.124)
B. Employment rate	0.031	-0.072	0.006
	(0.102)	(0.045)	(0.106)
Controls	✓	✓	✓
NUTS1 FE	✓	✓	✓
Period FE	✓	✓	✓
Observations	153	153	153
KP F-Test	28.09	28.09	28.09

Notes: 2SLS estimates obtained using the interaction between the 1971 industry mix and time dummies as instruments. The dependent variable in panel A is the change in the (logged) population aged between 15 and 64 years. The dependent variable in panel B is the employment to population ratio. Robust standard errors clustered at the NUTS3 level in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 7 Gender and age specific effects in manual, routine, and cognitive employment, 2SLS estimates

	(1) Manual (All)	(2) Routine (No University)	(3) Cognitive (University)
		Panel A. Age group 15-34	
Routine share $_{t-10}$	0.226*	-0.352***	0.122***
	(0.121)	(0.090)	(0.045)
KP F-Test	16.17	16.17	16.17
		Panel B. Age group 35-64	
Routine share $_{t-10}$	0.422***	-0.426***	0.012
	(0.073)	(0.069)	(0.025)
KP F-Test	32.94	32.94	32.94
		Panel C. Male employment	
Routine share $_{t-10}$	0.337***	-0.382***	0.035*
	(0.068)	(0.062)	(0.020)
KP F-Test	25.84	25.84	25.84
		Panel D. Female employment	
Routine share $_{t-10}$	0.515***	-0.500***	0.013
	(0.141)	(0.134)	(0.072)
KP F-Test	6.881	6.881	6.881
Observations	153	153	153

Notes: 2SLS estimates from the specification with the full set of controls obtained using the interaction between the 1971 industry mix and time dummies as instruments. Robust standard errors clustered at the NUTS3 level in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Appendix

Tasks from the O*NET database used in the computation of the manual, routine, and cognitive importance within occupations.

Manual

Spatial Orientation, Manual Dexterity, Operating Vehicles, Mechanized Devices, or Equipment, Spend Time Using Your Hands to Handle, Control, or Feel Objects, Tools, or Controls.

Routine

Importance of Being Exact or Accurate, Importance of Repeating Same Tasks, Structured versus Unstructured Work, Pace Determined by Speed of Equipment, Spend Time Making Repetitive Motions, Controlling Machines and Processes

Cognitive

Analyzing Data or Information, Thinking Creatively, Interpreting the Meaning of Information for Others, Coaching and Developing Others, Guiding, Directing, and Motivating Subordinates, Establishing and Maintaining Interpersonal Relationships

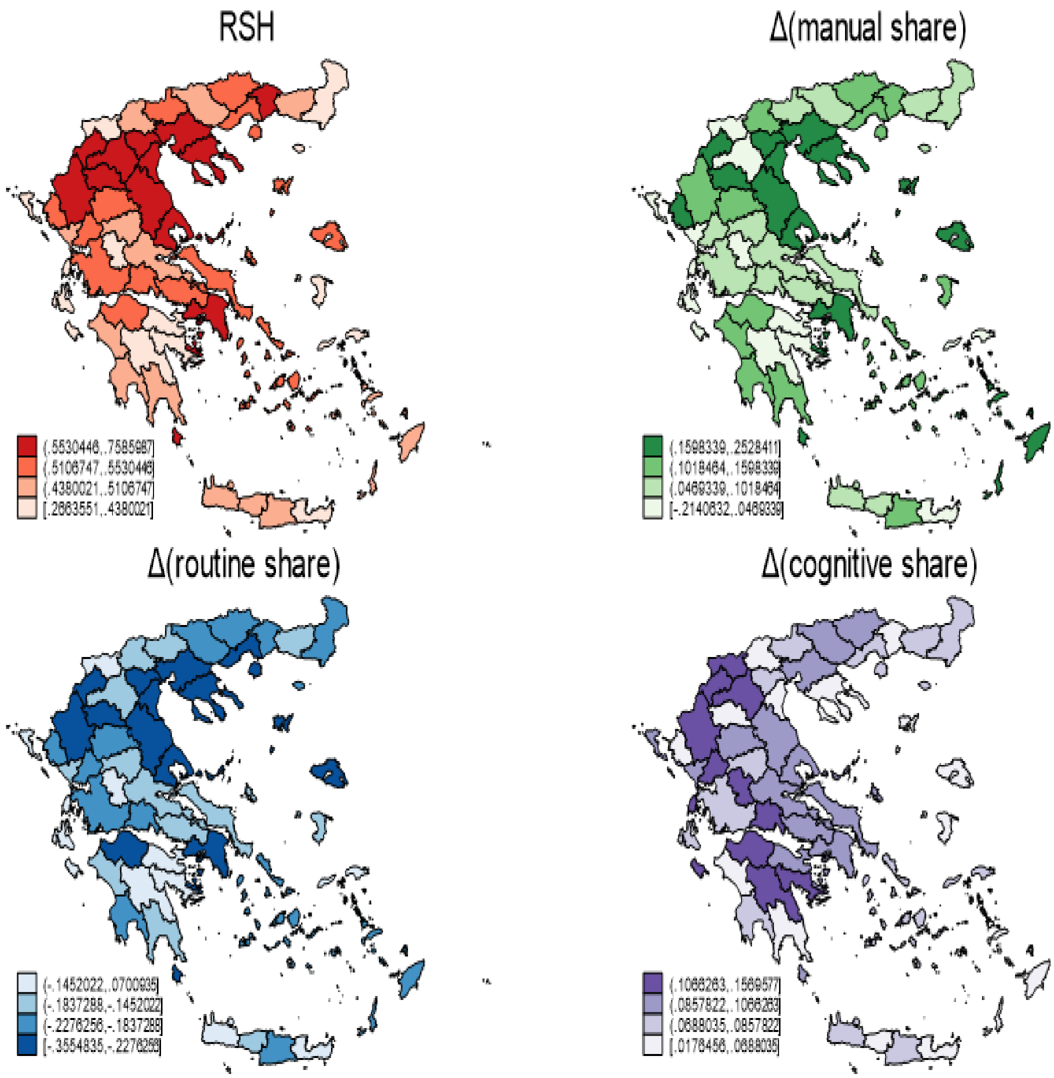

Figure A1 Spatial distribution of the routine share in 1981 and the 2011-1981 changes in the shares of manual, routine, and cognitive occupations