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Routinization and the Labour Market: Evidence from European Countries

Federico Biagi, Paolo Naticchioni, Giuseppe Ragusa and Claudia Vittori

4.1 Introduction

The impact of technological change on the labour market is an evergreen topic in economics, due to an endless list of contributions started with David Ricardo, Karl Marx, John Maynard Keynes, and Wallise Leontief, among others. In this chapter, we take into account a recent debate about a specific dimension of the technological change, concerning the routinization process that is taking place in most of the developed and developing countries, and its impact on the labour markets of European countries.

This interesting issue has been introduced at the core of the recent economic and policy debate by some recent best seller books, such as Brynjolfsson and McAfee (2011, 2014), which have provided some forecasts on how technological progress will impact ordinary life of individuals, in particular on the labour market. According to Brynjolfsson and McAfee (2011, 2014),

F. Biagi
University of Padova, Padova, Italy

P. Naticchioni (✉)
Roma Tre University, Rome, Italy

G. Ragusa
Luiss Business School, Rome, Italy

C. Vittori
Sapienza University of Rome, Rome, Italy

L. Pupillo et al. (eds.), *Digitized Labor*, https://doi.org/10.1007/978-3-319-78420-5_4

the technological progress is entering into a new historical phase that will completely change the existing standards for individuals and firms. Also, Brynjolfsson and McAfee (2011, 2014) stress the importance of the routinization trends as a new shape of the technological change, and its impact on the labour market.

Even if this is a recent phenomenon, there is already a robust literature on routinization, which has often been associated to the polarization trends in the labour market.

Autor et al. (2006) have shown that the US labor market has become increasingly polarized both in terms of occupations and wage distributions. The routinization hypothesis has been advocated for explaining this empirical evidence (Autor et al. 2003). Goos et al. (2009) show similar findings for Europe, where the fall in the middling occupations, the ones mostly routinized, has driven the job polarization processes.

So far, most of the literature has investigated these issues making comparisons between cross-sectional data over time, analysing changes in employment share in each occupation (manual/service, routine, and abstract), without analysing the flows, i.e. individual longitudinal careers. Cortes (2016) and Cortes et al. (2016) analyse job polarization using a dynamic approach for the United States, highlighting the importance of using longitudinal data: Flows are crucial to understand the mechanisms behind routinization and job polarization.

In this chapter, we focus on the routinization processes in Europe, using the Survey on Income and Living Conditions (SILC) data. The main reason for using these data is their longitudinal dimension, which allows us to follow individual careers over time. Using longitudinal data, we focus on the following issues. First, we investigate whether routinization processes are confirmed. Second, we study the determinants of routinization, using the rich EU-SILC set of available socio-economic variables. Third, we analyse the relation between routinization and unemployment inflows, to investigate whether routinization can be considered as a driver of unemployment.

We consider several routinization variables, in line with the literature. In such a way, we aim at testing whether using different measures may lead to different outcomes, from both a qualitative and quantitative point of view. Furthermore, apart from studying the sample with all available European countries, we also focus on five different groups of countries (Southern, Continental, Anglo-Saxon, Nordic, and Eastern), which are characterized by different institutions, cultural settings, business cycles, and so on, in order to detect any heterogeneity in the routinization process.

4.2 The EU-SILC Database

We make use of European data, the SILC, from 2004 to 2012. We do not use data for the following years (2013 and 2014) since the classification of occupation ISCO has substantially changed in the SILC data in 2012, from the ISCO88 classification to the ISCO08. This means we can use the ISCO88 classification until 2011, while we use the year 2012 only to compute some employment status that will be used in the analysis.

The SILC data have been introduced in 2004, in order to replace the European Community Household Panel that has been in place from 1994 to 2001. The SILC data are very rich in terms of information. The primary focus of SILC is the collection of information on the income and living conditions of different types of households in order to derive indicators on poverty, deprivation, and social exclusion. It is a voluntary survey (for potential respondents) of private households and is carried out under EU legislation (Council Regulation No. 1177/2003). The income reference period for SILC is the 12 months prior to date of interview. SILC is currently being conducted on an annual basis in order to monitor changes in income and living conditions over time. The target population is the representative sample of households in the different countries, and the sample size is different across countries.

The EU-SILC panel is a rotational panel which is comparable in its structure to the Current Population Survey. In a rotational panel, the same individuals are interviewed for a certain time period (four years) and each year one-quarter of all respondents are replaced by new respondents. The integrated design consists in selecting four panels at the first wave. Each subsequent year, a panel is dropped and replaced by a new replication. For a given year, the respective longitudinal file available from Eurostat only contains those respondents that were interviewed both in the respective year and in the preceding years. In this work, we follow Engel and Schaffner (2012), merging different panel data sets provided by Eurostat. Hence, we derive a panel over the whole period 2004–2012.

In addition to the structure of the data, the cross-sectional data and the longitudinal data also differ to some extent in the covered variables. There are some variables in the cross-sectional data file that are also of interest for the analysis of labour market transitions and mobility, but they are not included in the longitudinal data sets. For our analysis, the main limitation of using the longitudinal data is related to the fact that while the occupation variable is available, the industry classification variable is missing.

This is another disappointing choice made by Eurostat, that really represents a strong constraint in any analysis of the labour market. In addition, we do not consider the sample for Germany, since there is evidence that German EU-SILC data on income is plagued with problems (Hauser 2008; Frick and Krell 2010).

It is interesting to note that so far the literature on the impact of technological change on the labour market has mainly focused on comparisons between cross-sectional data over time, investigating changes in employment share in each occupation (manual/service, routine, and abstract), without analysing the flows, i.e. individual longitudinal careers. Cortes (2016) and Cortes et al. (2016) analyse job polarization using a dynamic approach for the United States, highlighting the importance of using longitudinal data: Flows are crucial to understand the mechanisms behind job polarization.

Cortes (2016) shows that workers in routine jobs have higher probability to separate from their job. Interestingly, he finds that: High skilled routine workers display higher probability to move to abstract jobs; low ability routine workers show higher probability to switch to manual jobs; the decrease in routines employment is primarily due to the change in propensity of young workers to enter the labour market in routine jobs.

Furthermore, in order to investigate the potential heterogeneity across European countries, we carry out our analysis at the European level as a whole, considering all countries in the data sample, as well as at the level of standard groups of countries for Europe, defined as follows: Southern (Italy, Spain, Portugal, Greece, and Cyprus); Continental (Austria, Belgium, France, Luxembourg, and the Netherlands); Anglo-Saxon (Great Britain, Ireland); Nordic (Denmark, Finland, Island, Norway, and Sweden); and Eastern (Bulgaria, Check Republic, Poland, Romania, Slovakia, Lithuania, Latvia, Slovenia, and Estonia).

4.2.1 Different Measures of Routinization

In the literature, several measures of routinization are available, but none of the measures can be so far considered as the standard, the best one to use. For this reason, in this work, we will make use of different measures of routinization, in order to provide a test of consistency across different measures. The first variable is the Routine Task Intensity (RTI) index, developed by Autor and Dorn (2013). At first, they measure routine task activities using the occupational composition of employment. Following Autor et al. (2003), they merge job task requirements from the fourth edition of the US Department of Labor's Dictionary of Occupational Titles (DOT) to

their corresponding Census occupation classifications to measure routine, abstract, and manual task content by occupation. These three variables measure intensity in the different type of task. They hence combine these measures to create a summary measure of RTI that varies at occupation classification ISCO 2-digits, standardized in the whole data set (zero mean and one standard deviation), as follows:

$$\text{RTI} = \ln(\text{Routine}) - \ln(\text{Manual}) - \ln(\text{Abstract})$$

This measure increases in the importance of routine tasks in each occupation and decreases in the importance of manual and abstract tasks.

As second measures, we use directly the three intensity measures in abstract, routine, and manual/service tasks, that have been aggregated to compute the RTI index, i.e. the task measures used in Autor et al. (2003).

4.2.2 Trends in Routinization in Europe

In the following we present routinization trends in Europe, and in the different groups of countries. The period of analysis provided by the EU-SILC data is 2004–2011. As mentioned earlier, we cannot consider years after 2011 since the occupation classification has completely changed from ISCO88 to ISCO08.

In Fig. 4.1, we show the trend over time of the RTI measure that will be the main variable used in the paper because of its synthetic nature. RTI displays a clear decreasing trend overtime, suggesting that the relative intensity

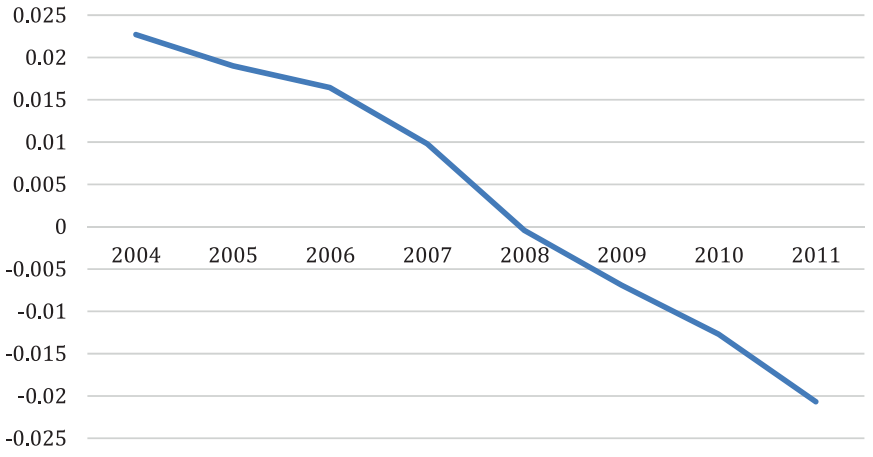

Fig. 4.1 Trends of the RTI index. All countries

of routine jobs are decreasing in the labour market, consistently with the intuition that routine jobs can be more easily replaced by technology. The magnitude of the change is relevant but not huge when considering that the RTI by definition is constrained to have zero mean and one standard deviation.

Figure 4.2 instead includes the trends of the three separate task measures described above: Abstract, routine, and manual (used to compute the RTI index). Actually using these measures, the routinization trends are even more pronounced. As expected, the abstract intensity increases sharply overtime, the routine one decreases, and the manual intensity has a non-monotonic trend, increasing until 2008 and then decreasing. Hence, only a part of the routinization story applies, since routine intensity decreases but this is not associated to a monotonic increase in manual intensity tasks.

Let us now move to the evidence concerning different set of countries. In Fig. 4.3, we include the trends of the RTI intensity in the five set of countries defined above. First of all, it is worth noting that the RTI variable is standardized in the sample of all European countries in all years. This means that differences across lines in Fig. 4.4 indicate differences in intensity levels across groups. In such a framework, it emerges that trends for all groups display a similar decreasing trend across groups. However, the Nordic group line is always much below the other groups, suggesting that the relative intensity in routine jobs is much lower in this group with respect to the others, probably because the routinization process started earlier in the Nordic group.

When moving to the three separate task intensities, it is worth noting that the abstract one increases in basically all groups of countries, except in the Eastern group where it displays a non-monotonic trend. Further, differences in levels across groups emerge, suggesting that in Nordic and Anglo-Saxon

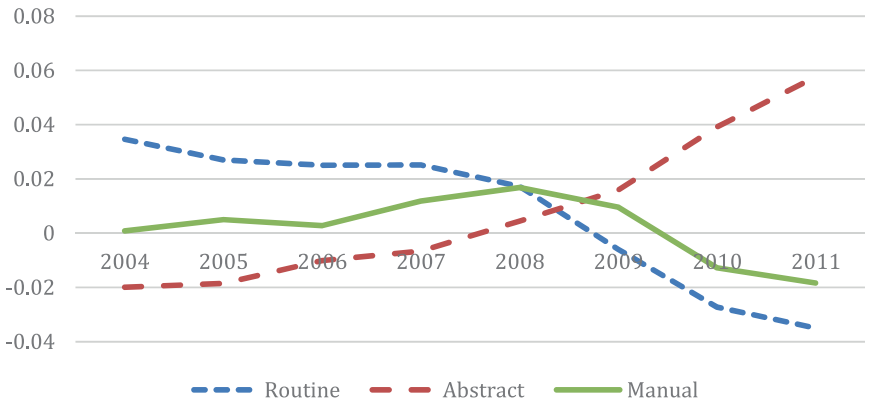

Fig. 4.2 Trends of the task intensity measures. All countries

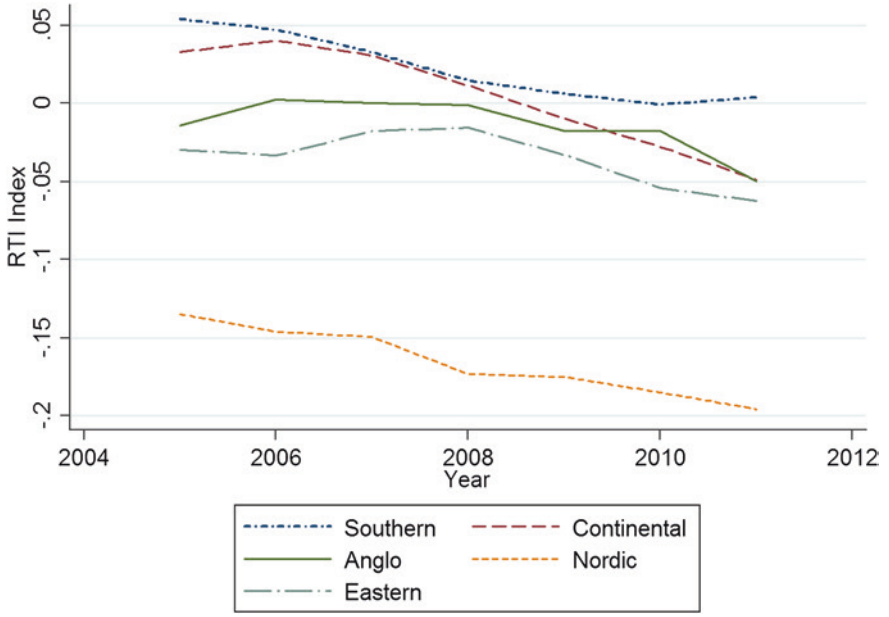

Fig. 4.3 RTI index in the country groups

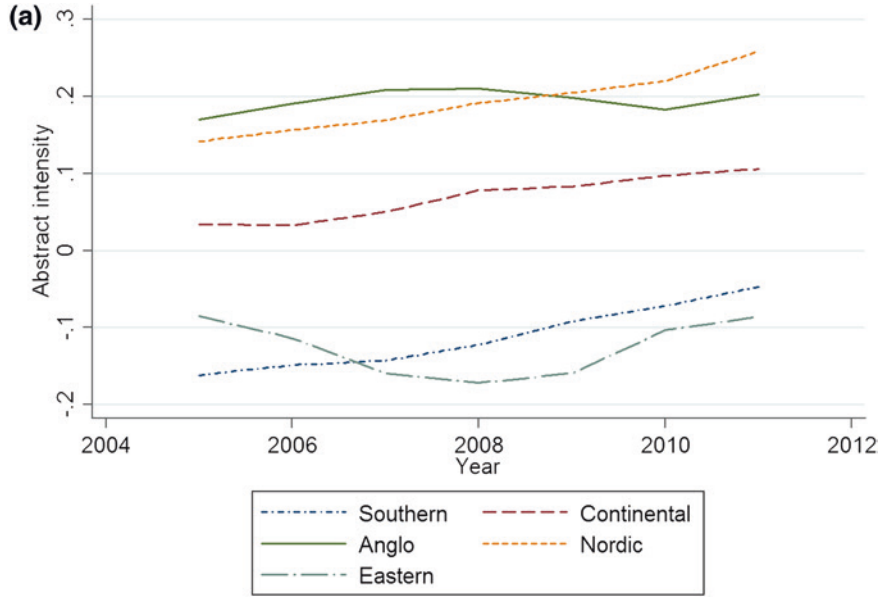

Fig. 4.4 Abstract (**a**), routine (**b**), and manual (**c**) intensities in the country groups

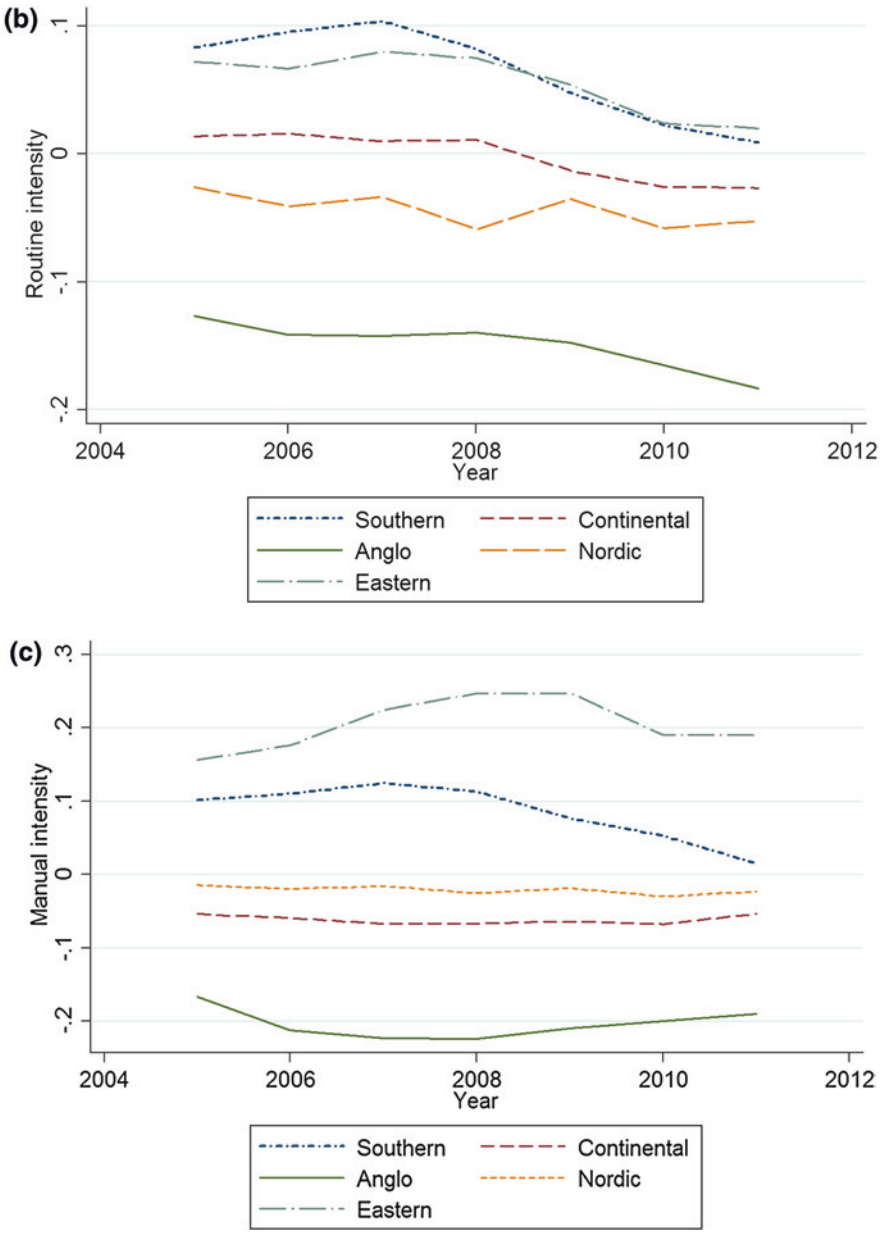

Fig. 4.4 (continued)

countries, the intensity of abstract jobs is higher, while it is lower in the Southern and the Eastern groups, with the Continental group being in the middle. As for the routine intensity, the trend is still the same (decreasing) in all groups. However, also in this case, differences in levels emerge, with Southern and Eastern having the highest intensity in routine jobs, and Nordic and Anglo-Saxon with the lowest.

More mixed is the evidence concerning the manual intensity. A stable trend is observed for the Continental and the Nordic groups, a decreasing trend for the Southern and for the Anglo-Saxon ones, and an increasing trend for the Eastern group.

Apart from the manual intensity, trends are rather similar across groups of countries, although differences in levels across groups seem to emerge, suggesting that the routinization process is at a different stage across groups.

4.3 The Determinants of Routinization

In this section, we focus on the identification of the determinants of routinization, in a 'descriptive' regression framework. In other words, we use as dependent variables our routinization measures, and we regress them, one at a time, on a set of socio-economic individual covariates (gender, age, education, whether single/married/no more married), some labour market covariates (permanent vs temporary job, full-time vs part-time job, hours worked). Since we make use of categorical variables, it is worth noting that the omitted group refers to individuals in the age class 55–64, single, with primary education). Moreover, all estimates include country dummies, to take into account time-invariant unobservable at the country level, and time dummies, to capture the business cycle.

Let us start by using the RTI index as dependent variable. In the first column of Table 4.1, the sample of all European countries is considered, while from column 2 to column 6, the regressions are carried out separately for the different country groups. The following findings emerge:

- Female workers display a higher incidence of RTI, in all columns.
- With respect to the omitted category (age 55–64), young individuals are characterized by the highest incidence of RTI. This correlation holds in all columns apart for the Anglo-Saxon group. In general, it emerges that RTI decreases along the career of the worker, and this is somehow unexpected, since one might believe that the new generations of workers are the ones with the highest level of education and more used, and more complement, to new technologies.

Table 4.1 Determinants of the RTI variable

	(1)	(2)	(3)	(4)	(5)	(6)
	All countries	Southern	Continental	Anglo	Nordic	Eastern
Female	0.210***	0.205***	0.260***	0.273***	0.098***	0.219***
	(0.002)	(0.005)	(0.005)	(0.013)	(0.006)	(0.004)
Age 15–24	0.134***	0.186***	0.098***	0.032	0.079***	0.141***
	(0.005)	(0.011)	(0.012)	(0.027)	(0.014)	(0.009)
Age 25–34	0.104***	0.175***	0.059***	0.020	0.028***	0.114***
	(0.004)	(0.008)	(0.008)	(0.021)	(0.010)	(0.006)
Age 35–44	0.055***	0.121***	0.062***	−0.009	0.016*	0.018***
	(0.004)	(0.007)	(0.008)	(0.018)	(0.009)	(0.006)
Age 45–54	0.031***	0.091***	0.031***	−0.004	−0.001	0.007
	(0.003)	(0.007)	(0.008)	(0.018)	(0.009)	(0.006)
Upper secondary	0.052***	0.105***	0.060***	0.157***	−0.038***	−0.055***
	(0.003)	(0.005)	(0.006)	(0.017)	(0.009)	(0.006)
Tertiary	−0.578***	−0.508***	−0.571***	−0.425***	−0.637***	−0.700***
	(0.003)	(0.005)	(0.006)	(0.017)	(0.009)	(0.006)
Temporary	−0.073***	−0.143***	−0.103***	−0.070**	−0.087***	0.055***
	(0.003)	(0.005)	(0.007)	(0.029)	(0.010)	(0.006)
Part time	−0.012***	0.120***	−0.094***	−0.133***	−0.116***	−0.067***
	(0.004)	(0.009)	(0.008)	(0.021)	(0.011)	(0.010)
Married	−0.049***	−0.043***	−0.041***	−0.094***	−0.051***	−0.047***
	(0.003)	(0.006)	(0.006)	(0.015)	(0.007)	(0.005)
Divorced/separ/ widowed	−0.038***	−0.062***	−0.030***	−0.093***	−0.043***	−0.027***
	(0.004)	(0.010)	(0.009)	(0.022)	(0.010)	(0.007)
Hours worked	−0.002***	0.008***	−0.006***	−0.012***	−0.008***	−0.004***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Constant	0.232***	−0.286***	0.426***	0.508***	0.330***	0.259***
	(0.010)	(0.019)	(0.018)	(0.046)	(0.024)	(0.023)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	817,775	239,803	202,476	32,135	90,239	253,122
R-squared	0.099	0.067	0.102	0.108	0.121	0.109

Robust standard errors in parentheses
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 4.2 Determinants of the routine intensity variable

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	All countries	Southern	Continental	Anglo	Nordic	Eastern
Female	−0.431***	−0.393***	−0.409***	−0.216***	−0.408***	−0.504***
	(0.002)	(0.004)	(0.005)	(0.012)	(0.007)	(0.004)
Age 15–24	0.140***	0.279***	0.252***	−0.007	0.002	0.023**
	(0.006)	(0.011)	(0.011)	(0.026)	(0.017)	(0.010)
Age 25–34	0.135***	0.246***	0.159***	0.067***	0.108***	0.052***
	(0.004)	(0.008)	(0.008)	(0.020)	(0.011)	(0.007)
Age 35–44	0.086***	0.155***	0.125***	0.040**	0.077***	0.010
	(0.004)	(0.007)	(0.007)	(0.017)	(0.009)	(0.007)
Age 45–54	0.055***	0.099***	0.083***	0.019	0.050***	0.015**
	(0.004)	(0.007)	(0.007)	(0.016)	(0.009)	(0.006)
Upper secondary	0.036***	−0.074***	0.108***	0.128***	0.040***	0.027***
	(0.003)	(0.005)	(0.006)	(0.016)	(0.010)	(0.007)
Tertiary	−0.379***	−0.301***	−0.316***	−0.154***	−0.295***	−0.556***
	(0.003)	(0.005)	(0.006)	(0.017)	(0.010)	(0.008)
Temporary	−0.080***	−0.110***	−0.109***	−0.029	−0.128***	−0.023***
	(0.003)	(0.005)	(0.007)	(0.024)	(0.011)	(0.006)
Part time	−0.145***	−0.080***	−0.161***	−0.248***	−0.256***	−0.297***
	(0.004)	(0.008)	(0.007)	(0.018)	(0.011)	(0.011)
Married	−0.015***	0.024***	−0.009*	−0.068***	−0.083***	−0.019***
	(0.003)	(0.005)	(0.005)	(0.015)	(0.008)	(0.006)
Divorced/separ/ widowed	−0.040***	−0.048***	−0.023***	−0.072***	−0.079***	−0.027***
	(0.004)	(0.008)	(0.008)	(0.020)	(0.011)	(0.008)
Hours worked	−0.001***	0.010***	−0.005***	−0.007***	−0.010***	−0.003***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Constant	0.307***	−0.170***	0.361***	0.288***	0.529***	0.715***
	(0.010)	(0.019)	(0.017)	(0.045)	(0.027)	(0.028)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	817,775	239,803	202,476	32,135	90,239	253,122
R-squared	0.106	0.097	0.098	0.041	0.091	0.140

Robust standard errors in parentheses
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

- With respect to the omitted category of primary education, workers with tertiary education display a lower incidence of RTI. Workers with upper secondary education display an intermediate value. These correlations apply to all groups of country, and are very robust from a statistical point of view.
- Permanent workers are associated to lower level of routinization, and this relation holds in all groups of countries. The same evidence applies for part-time workers.
- There is a positive correlation between hours worked and RTI, in all groups of countries.
- With respect to the omitted category (single), married and divorced/separated/widowed individuals have lower levels of RTI. Also, these relations apply to all groups of countries.

In Tables 4.2, we report as robustness check the same estimates with the routine intensity. It is actually reassuring that determinants have basically the same correlations as the ones detected in Table 4.1.

We do believe the most interesting evidence emerging from the analysis of the determinants concerns the fact that whatever routinization measure is used the young individuals display a higher level or routine jobs. In the following we will present some graphs showing the levels and trends of the RTI index for young individuals (15–34) and adults (over 34), for all groups of countries. It emerges clearly that for all groups, young individuals have a much higher level of RTI, and that for both groups, there is a decreasing trend. In particular, for the Southern group, the fall of the RTI index seems to be steeper than the one of the over 34, even if the difference between the two lines remain substantial even at the end of the period.

4.4 Is Routinization a Driver of Unemployment Inflows?

Another very debated issue in recent years is whether technological change fosters the destruction of jobs. There is an endless debate, with optimistic and pessimistic positions, started with David Ricardo (1817), and debated by well-known economists like John Maynard Keynes (1930) and Wassily Leontief (1983). Recently, the two bestseller books by Brynjolfsson and McAfee (2011, 2014), among others, have reintroduced this classic economic issue at the centre of the debate. Actually, there is little empirical evidence in recent years about the unemployment effect of technology

(while more evidence is available for the composition issue), and the few existing papers provide mixed results.

The (scarce) existing literature generally uses aggregate data, at the country-industry level, in order to test whether some proxies of technological change affects the employment and unemployment variations. We do something different and somehow original in the literature for several reasons. First, we use as a proxy of technological change the routinization of an individual occupation. This represents a novelty that allows considering individual data instead of aggregate data, since for each individual in EU-SILC, it is possible to recover the occupation and then the associated measure of routinization. Second, since we make use of longitudinal data, we can follow individual careers over time, at least in the four years provided by the short EU-SILC panel. So far, the focus in the literature has been on changes of stocks, i.e., changes in employment share in each occupation (manual/service, routine, and abstract), without analysing the flows, i.e. individual longitudinal careers. Cortes (2016) and Cortes et al. (2016) point out that using longitudinal data matters: Flows are crucial to understand the mechanisms behind job polarization. In particular, Cortes (2016) shows for the United States that workers in routine jobs have higher probability to separate from their job. Interestingly, he finds that high skilled routine workers display higher probability to move to abstract jobs, while low ability routine workers are associated to higher probability to switch to manual jobs. Further, he shows that the decrease in routine employment is primarily due to the change in propensity of young workers to enter the labour market in routine jobs.

In such a framework, we follow individual careers over time in order to investigate the determinants for employed individuals to get into unemployment between time t and time $t+1$. In particular, we want to test whether this event is correlated to the routinization of the occupation before the job change. In the regressions, we introduce all the control variables that have been used in the analysis of the determinants of routinization (female, age classes, education, hours worked, permanent job, part time job, being married or no more married) as well as country dummies and year dummies.

We will consider two dependent variables. The first dependent variable is a dummy equal to one when an employed individual becomes unemployed the following year. The second dependent variable is equal to one when an employed individual become not employed (either unemployed or inactive) the following year. In this latter case, the dependent variable might be equal to one for individuals that exit voluntarily from the labour market,

and for this reason, it might be considered as less reliable. Hence, the most reliable variable of interest concerns the transition from employment to unemployment.

Table 4.3 includes the related estimates when using the RTI index as routinization index. In column 1, we consider Europe as a whole. It emerges that the coefficient of RTI is positive and statistically significant, i.e., having a high RTI is positively associated to the probability to become unemployed the following year, even after controlling for observable differences in individual characteristics (mainly education and age), effort in the labour market (hours worked), selection into a permanent and a part time job, and marital status, as well as after controlling for unobservable differences across countries and time periods. The magnitude of the impact is not negligible: An increase of one standard deviation in RTI increases the baseline probability to become unemployed (2%) of 0.2%, i.e. of around 10%. This suggests that a new weak segment in the labour market can be identified. While in the last decades, the standard weak segment was always considered the one of unskilled labour in manual jobs, in recent years also individuals employed in routine occupations might be more likely to be exposed to higher risk of unemployment, even if they might not be necessarily unskilled workers.

When investigating this relation across different groups of countries, the positive coefficient of RTI holds in all groups except in the Anglo-Saxon one, suggesting that RTI is a driver on unemployment inflows, although groups of countries are characterized by very different institutional and industrial settings.

Table 4.4 refers to the same estimates when using as task variables the three task intensities (abstract, routine, and manual) that were collapsed in a synthetic measure when using the RTI index. The positive impact of routine intensity is now statistically significant only in two groups of countries, Southern and Continental, while it is not statistically different from zero (and actually very small in magnitude in the other groups). Interestingly, having high abstract intensity strongly reduces the probability to become unemployed, and this holds in all groups of countries. It is also worth noting that having high manual intensity is associated to a positive effect on the probability to become unemployed only in Europe as a whole and in the Southern group. This is on the one hand something unexpected, since manual tasks are usually associated to unskilled jobs, which are usually considered as the standard weak segment in the labour market. On the other, it is consistent with the polarization explanations, i.e. unskilled and manual jobs are increasingly demanded in the labour market.

Table 4.3 The impact of RTI on unemployment probabilities

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	All countries	Southern	Continental	Anglo	Nordic	Eastern
RTI	0.002***	0.001***	0.001***	0.001	0.002***	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Female	−0.003***	−0.000	−0.003***	−0.006***	−0.005***	−0.004***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age 15–24	0.012***	0.022***	0.008***	0.010***	−0.005*	0.012***
	(0.001)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)
Age 25–34	0.004***	0.008***	0.005***	0.000	−0.006***	0.004***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Age 35–44	0.002***	0.002*	0.002**	−0.001	−0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Age 45–54	0.001	−0.002	−0.001	−0.001	−0.002*	0.005***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Upper secondary	−0.015***	−0.017***	−0.012***	−0.008***	−0.006***	−0.026***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
Tertiary	−0.026***	−0.029***	−0.018***	−0.010***	−0.012***	−0.041***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Temporary	0.054***	0.062***	0.056***	0.014***	0.041***	0.046***
	(0.001)	(0.001)	(0.002)	(0.004)	(0.003)	(0.002)
Part time	0.009***	0.014***	0.005***	0.002	0.007***	0.006**
	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
Married	−0.006***	−0.007***	−0.005***	−0.003**	−0.009***	−0.005***
	(0.000)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Divorced/separ/ widowed	0.001*	−0.002	0.005***	−0.000	−0.001	0.002
	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
Hours worked	0.000***	0.000***	−0.000**	−0.000**	0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.025***	0.021***	0.032***	0.025***	0.034***	0.061***
	(0.002)	(0.003)	(0.003)	(0.005)	(0.004)	(0.004)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	817,775	239,803	202,476	32,135	90,239	253,122
R-squared	0.027	0.035	0.024	0.007	0.016	0.022

Robust standard errors in parentheses
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 4.4 The impact of task intensities on unemployment probabilities

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	All countries	Southern	Continental	Anglo	Nordic	Eastern
Routine intensity	0.000	0.001**	−0.002***	−0.001	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Abstract intensity	−0.006***	−0.006***	−0.005***	−0.002***	−0.004***	−0.008***
	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)
Manual intensity	0.001***	0.003***	0.001	−0.001	−0.000	0.001
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)
Female	−0.002***	0.002**	−0.003***	−0.007***	−0.005***	−0.002***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age 15–24	0.011***	0.021***	0.007***	0.010***	−0.006**	0.012***
	(0.001)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)
Age 25–34	0.004***	0.006***	0.004***	0.000	−0.006***	0.004***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Age 35–44	0.001**	0.001	0.002*	−0.001	−0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Age 45–54	0.000	−0.002*	−0.001	−0.001	−0.002*	0.005***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Upper secondary	−0.013***	−0.013***	−0.009***	−0.007***	−0.006***	−0.023***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
Tertiary	−0.017***	−0.018***	−0.012***	−0.009***	−0.009***	−0.028***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Temporary	0.053***	0.060***	0.056***	0.014***	0.041***	0.044***
	(0.001)	(0.001)	(0.002)	(0.004)	(0.003)	(0.002)
Part time	0.007***	0.013***	0.005***	0.002	0.007***	0.003
	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
Married	−0.006***	−0.007***	−0.005***	−0.003**	−0.008***	−0.005***
	(0.000)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)

Table 4.4 (Continued)

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	All countries	Southern	Continental	Anglo	Nordic	Eastern
Divorced/separ/ widowed	0.001*	−0.002	0.005***	−0.000	−0.001	0.002
	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
Hours worked	0.000**	0.000***	−0.000	−0.000**	0.000	−0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.021***	0.018***	0.028***	0.024***	0.033***	0.057***
	(0.002)	(0.003)	(0.003)	(0.005)	(0.004)	(0.004)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	817,775	239,803	202,476	32,135	90,239	253,122
R-squared	0.028	0.036	0.024	0.007	0.016	0.023

Robust standard errors in parentheses
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

4.5 Conclusion

In this chapter, we provide evidence on the ongoing routinization processes in Europe. We derive the following evidence: Routinization processes do not depend on the type of variable considered; groups of countries characterized by very different institutions, cultures, and labour market conditions, share similar routinization trends; routinization levels are different across groups, suggesting that groups of countries can be placed at different stage in the technological/routinization process; routinization seems to represent a driver, among others, of unemployment inflows: Individuals in routine jobs display, ceteris paribus, an higher probability to become unemployed. Further, the magnitude of the effect is not negligible: A one standard deviation increase in the RTI index entails a 10% increase of getting into unemployment. This evidence challenges the view that only unskilled workers represent the weak segment in the labour market, as it was in the last decades. This evidence applies also to routine workers, that are not necessarily unskilled. If confirmed, this issue would represent an important new dimension of the policy debate in the next years, to think about some new targeting dimensions of the active and passive labour market policies, with two main objectives. On the one hand, to ease the reallocation of routine workers towards other types of jobs, and on the other hand to provide some sort of additional institutional insurance for workers more exposed to unemployment risks.

Furthermore, future research is needed to investigate in more details what there is behind these findings. In particular, on the one hand, this result might be due to a casual effect of having a routine job on unemployment inflows. On the other hand, this effect might be due to a self-selection effect into routine jobs. In other words, it might be the case that unskilled individuals self-select into routine jobs, and hence the effect on unemployment inflows might be actually driven by this self-selection and not by a causal impact of performing a routine task. These issues should be analysed by using a counterfactual analysis, controlling for unobserved heterogeneity and exploiting some form of exogenous variation in order to identify from an econometric point of view the causal effect of having a routine job.

References

Autor, David H., and David Dorn. 2013. "The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market." *American Economic Review* 103 (5): 1553–1597.

Autor, David, Frank Levy, and Richard Murnane. 2003. "The Skill Content of Recent Technological Change: An Empirical Exploration." *The Quarterly Journal of Economics* 118 (4): 1279–1333.

Autor, David, Lawrence Katz, and Melissa Kearney. 2006. "The Polarization of U.S. Labor Market." *American Economic Review* 96 (2): 184–194.

Brynjolfsson, Erik, and Andrew McAfee. 2011. *Race Against the Machine: How the Digital Revolution is Accelerating Innovation, Driving Productivity, and Irreversibly Transforming Employment and the Economy*. Lexington, MA: Digital Frontier Press.

Brynjolfsson, Erik, and Andrew McAfee. 2014. *The Second Machine Age: Work, Progress and Prosperity in a Time of Brilliant Technologies*. New York: W. W. Norton.

Cortes, Mathias. 2016. "Where Have the Middle-Wage Workers Gone? A Study of Polarization Using Panel Data." *Journal Of Labour Economics* 34 (1): 63–105.

Cortes, Mathias, Nir Jaimovich, Christopher Nekarda, and Henry Siu. 2016. *The Micro and Macro of Disappearing Routine Jobs: A Flows Approach*. New York: Mimeo.

Engel, Melissa, and Sandra Schaffner. 2012. "How to Use the EU-SILC Panel to Analyse Monthly and Hourly Wages." Ruhr Economic Paper 336, Rheinisch-Westfälisches Institut für Wirtschaftsforschung.

Frick, Joachim R., and Kristina Krell. 2010. "Measuring Income in Household Panel Surveys for Germany: A Comparison of EU-SILC and SOEP." SOEP papers on Multidisciplinary Panel Data Research 265.

Goos, Maarten, Alan Manning, and Anna Salomons. 2009. "Job Polarization in Europe." *American Economic Review* 99 (2): 58–63.

Hauser, Richard. 2008. "Problems of the German Contribution to EU-SILC: A Research Perspective, Comparing EU-SILC, Microcensus and SOEP." German Council for Social and Economic Data (RatSWD) 80.

Keynes, John Maynard. 1930. *Economic Possibilities for Our Grandchildren*. New York: MIT Press.

Leontief, Wassily. 1983. National Perspective: The Definition of Problems and Opportunities. In *National Academy of Engineering Symposium, The Long-Term Impact of Technology on Employment and Unemployment*. Washington, DC: National Academy Press.

Ricardo, David. 1817. *On the Principles of Political Economy and Taxation*. London: Dent & Sons.