I. Introduction

Workers' experiences over their lifetimes are varied: transitions between jobs can be voluntary or not, associated with an unemployment spell, or involve changes across sectors and/or occupations. Insights into how these transitions impact workers' earnings and are related to workers' demographic characteristics are essential to understanding current income inequality trends and formulating appropriate labor policies. Recent literature has documented that low-skilled workers are more likely to experience labor market transitions between sectors and occupations via unemployment and that these transitions usually carry earning losses (Huckfeldt, forthcoming). In contrast, high-skilled workers have a higher chance of experiencing job-to-job transitions associated with earnings gains. Most of these studies, however, focus on US labor market dynamics (Kambourov and Manovskii 2008, 2009), or consider only a few individual advanced economies (Carrillo-Tudela and others 2016).[2] Moreover, much less is known about how structural changes in routinization (automation) have impacted workers' transitions across sectors and occupations and the associated effects on earnings.

This paper studies the impact of workers' sectoral and occupational changes and their earnings' consequences in a large sample of European countries. We focus on three critical workers' characteristics: (i) educational attainment, (ii) gender, and (iii) age, and how these three aspects interact with the business cycle and structural trends in routinization. To study these features, we combine two different data sets—the European Union Labor Force Survey (EU-LFS) and the European Union Statistics on Income and Living Conditions (EU-SILC). The EU-SILC records annual income and hours worked in a panel structure that allows tracking of individuals across multiple years, which is crucial to construct earnings changes associated with occupational switches. However, the EU-SILC is available only starting in 2005 (till 2018). To overcome this limitation, we complement our analysis with the EU-LFS, which provides coverage from 1989 to 2019 and sector of employment, but lacks information on occupation and earnings.

Our rich set of stylized facts are categorized into three categories:

1. *Incidence of sectoral and occupational switches*: young workers are more likely to experience job-to-job sectoral and occupational switches. These switches decline during recessions. Women, older workers, and low-skilled workers are less likely to experience job-to-job sectoral and occupational switches, with no signs that the frequency varies over the business cycle. Young workers are also more prone to switch occupations after being non-employed, while older workers are generally less likely to switch occupations.

2. *Earnings consequences of occupational switches:* Differences in occupational switches are accompanied by differences in earnings consequences. We find that on-the-job (sometimes referred to as "job-to-job") occupational switches are on average associated with earnings gains, while an occupational switch via an unemployment spell is associated with a large earnings penalty. This average phenomenon, however, masks large heterogeneity across different demographic groups. Young workers are more likely to conduct job-to-job switches and receive larger earnings gains. Moreover, they face earnings penalties like others when switching occupations upon reemployment after an unemployment spell. In contrast, low-skilled workers are more likely to experience no gain

[2] The only exception is Bachmann, Bechara, and Vonnahme (2019) who consider 27 European countries.

from an on-the-job occupational switch. These workers also experience large earnings losses upon reemployment after unemployment but are not necessarily penalized by the occupational switch.

3. *Earnings consequences of occupational switches interact with routinization:* Differences in earnings impacts from job changes are also associated with trends in routinization. The aggregate declining trend in share of routine jobs, which accelerates during recessions, has significant distributional consequences at the individual level. Workers who previously worked in non-routine occupations are much less likely to lose jobs, much more likely to find jobs, and more likely to stay in non-routine occupations than those previously employed in routine occupations. Moreover, workers whose occupational switches are from non-routine to routine jobs do not enjoy the usual earnings gains associated with a job-to-job switch. They also tend to suffer a higher earnings penalty with occupational switches via unemployment, particularly if they are low-skilled or older workers.

The key contribution of our paper is to provide for a large set of European countries a broad set of stylized facts on (i) job transitions, particularly sectoral and occupational switches, (ii) the earnings consequences associated with such switches, and (iii) how they differ over business cycles and across different demographic groups and by routinization. These sets of facts can be particularly useful as stylized facts for both researchers in motivating and calibrating theoretical (search-and-matching) models and for policymakers in making well-informed policy decisions.

Our paper contributes to the literature that studies trends in occupational mobility and the associated earnings consequences at the country level (for instance, Kambourov and Manovskii 2008, 2009 for the US and by Carrillo-Tudela and others 2016 for the UK) by examining a large sample of European countries. Our paper also complements Bachmann, Bechara, and Vonnahme (2019), which documents occupational mobility in Europe using the EU-SILC data. Our main contributions compared to Bachmann, Bechara, and Vonnahme (2019) are twofold. First, we document the importance of the business cycle on workers' sectoral and occupational mobility. Second, we explore the importance of routinization in occupational switches, which is crucial to understand long-term labor markets trends.

Our paper also contributes to the literature that studies job polarization (Autor and others 2006, Goos and Manning 2007, Goos and others 2009, and Acemoglu and Autor 2011). It is closely related to Cortes and others (2020), which focuses on the individual-level implications of routinization in the United States. Similar to Cortes and others (2020)'s results for the US, we also find a lower inflow from non-participation and unemployment to routine jobs relative to the inflow to non-routine jobs in Europe. In addition, we provide new evidence about the earnings implications of these transitions. We find that the earnings losses associated with the transition from non-routine to routine occupations more than offset the average earnings gains associated with on-the-job occupational switches, helping to explain the low inflow to routine occupations.

The rest of the paper is organized as follows. Section 2 describes our data. Section 3 presents stylized facts about the incidence of sectoral and occupational switches and earnings consequences associated with occupational switches over business cycles. Section 4 studies the incidence and earning consequences of worker reallocation at the individual level and studies patterns across different demographic groups. Section 5 shows how the reallocation between routine and non-routine jobs across time has evolved and studies how being employed in routine jobs affects worker reallocation chances and the related earnings impacts. Section 6 concludes.

II. Data

This section describes the data and the construction of the outcomes used in the empirical analysis. We combine two main data sources: the European Labor Force Survey (EU-LFS) and the European Union Statistics on Income and Living Conditions (EU-SILC). The EU-LFS is a repeated cross-section with information about individual labor market status and other variables for the current and last year, while the EU-SILC has a panel structure which allows to track individuals over several periods. While we rely on the EU-LFS to construct the European countries' job-to-job switch and sectoral switch, we exploit the EU-SILC to compute occupational switch and the earnings-related outcomes. The clear advantage of the EU-SILC data is the recording of annual income and hours worked and the panel structure that allows tracking individuals for multiple years. This latter characteristic is crucial to construct earning changes associated with occupational switch within a three-year period, e.g. on-the-job occupational switches and via-unemployment switches (see Section 2.1 for the exact definitions). The limitation of the EU-SILC is that the data are available only starting in 2005 (till 2018) while EU-LFS is available from 1983 to 2019. On the contrary, the distinct advantage of the EU-LFS is the length of the sample (from the early 1990s to 2019 for most countries) which allows a more complete analysis of labor market sensitivity to the business cycle. Another key difference between the EU-LFS and EU-SILC is that, while worker's sectoral switches can be calculated only for workers who are employed for two consecutive years in EU-LFS, occupational switches can be calculated for workers in all three labor force statuses (employed, unemployed, and out-of-labor force) in the EU-SILC.

The EU-SILC data are aggregated as follows: first, to obtain a comprehensive dataset for each country-year, we merge four EU-SILC data files (household register, household data, personal register, personal data). Second, we append the resulting files to build a panel of individuals for each country. To avoid duplicate personal indicators (PIDs), the sample is restricted to individuals who appear for 4 years consecutively in the survey.[3] Following Nekarda (2009), we compute the matching validity for all PID, considering whether the sex is the same and the age difference between two consecutive years is within ±1/2 years for the same PIDs. Lastly, we eliminate the unmatched individuals from the panel, and weights are readjusted to have the same aggregate cross-sectional weights.

The industrial classification follows the International Standard Industrial Classification (ISIC) Revision 4 (Rev. 4). The occupation codes follow the one-digit ISCO-08 classification and the definition of "routine occupations" is taken from Carrillo-Tudela and others (2016). The business cycle phases are computed following the Hardin and Pagan (2002) algorithm for annual data. Recessions are defined as years with negative GDP growth.

2.1 Measuring the incidence and earnings consequences of worker reallocation

This section describes how we measure the incidence of worker reallocations and earning consequences associated with worker reallocation that we will consider throughout the empirical exercises. We consider worker reallocation related to changes in jobs, sectors, and occupations. Job-to-job transitions capture any incidence of worker switching jobs among those who were employed in two consecutive years (labeled as *EE_job*). Sector-to-sector transitions capture the incidence of a worker switching occupations conditional on being employed for two consecutive years. Similarly, to measure the extent of occupational switch we follow Carrillo-Tudela and others (2016) and consider occupational switches with and without unemployment spells.

[3] In the case of France, 4-year restrictions are not imposed since the survey is designed to be a 9-year panel.

The probability of occupational switching is defined by considering (i) employment to employment or "on-the-job" transitions (*EE_occ*), (ii) unemployment to employment or "via unemployment" transitions (*UE_occ*). When studying the changes in earnings among those who get reemployed after an unemployment spell (*UE)*, we compare the pre-displacement earning and the earning upon reemployment (*EUE*).[4] Outcomes that require job-to-job and sectoral information are constructed using EU-LFS data, while outcomes that require occupation information are based on the EU-SILC data. EU-SILC data are also used to construct the variables that require a panel structure (e.g. individual labor market status over a three-year period). Earnings related outcomes also rely on EU-SILC. Below we present details about the outcomes' definition.

Job-to-job and sectoral switches (EU-LFS): *EE_job* is a dummy equal to one if an individual, conditional on being employed this and last year, was hired within the last 12 months. *EE_sec* is a dummy equal to one if an individual, conditional on being employed this and last year, changed sector this year, and zero otherwise. One-digit industries are defined according to the ISIC Rev. 4 classification.

Occupational switches (EU-SILC). EE_occ is a dummy equal to one if an individual, conditional on being employed this and last year, changed occupations, and zero otherwise. Occupations are defined according to the one-digit International Standard Classification of Occupations (ISCO-08). *UE_occ* is a dummy equal to one if an individual, conditional on being unemployed last year and employed this year, changed occupation this year, and zero otherwise.

Earnings (EU-SILC): Earnings changes are defined as the log changes in real earnings (nominal earning deflated by the consumer price index) as follows:

$$\Delta lnEarning_t = 100 * (ln(Earning_t) - ln(Earning_{t-l}))$$

As previously explained, earnings changes are defined over a two-year period for "on-the-job" occupational switch (*EE*) among those who continue to be employed, and over three years (change of earnings between this year and two years ago) for "via unemployment" (*EUE*) for those who were employed two years ago, unemployed last year, and employed this year.[5]

III. The extent, consequences, and cyclicality of career changes

In this section, we first document the average probability of job-to-job, sectoral, and occupational switches across different labor market transitions and earnings losses associated with such occupational transitions (Table 1)

3.1 Long-run likelihoods and earnings consequences of career changes

We start the analysis by looking at the most aggregate labor market transitions to assess the average likelihood of changing either job or sector. The probability of a job-to-job switch is equal to 6 percent, whereas the

[4] We only observe earnings when workers are employed, therefore our baseline specification for comparing the earning changes for those who were employed two years ago, unemployed a year ago, and got reemployed in year *t*.

[5] Earning changes for "via non-participation" is similarly calculated over three years (OE).

probability of changing sector is about 3 percent. We then zoom into the outcomes that track different labor market history thanks to the panel structure of the data. Among those who are continuously employed over the past two years ("on-the-job"), the probability of occupational switch is only about 12 percent. On the other hand, the probability of an occupational switch for a worker reemployed after a one-year unemployment spell ("via-unemployment") is nearly four times higher, at 47 percent.[6] In other words, workers generally appear to prefer sticking with their current occupation, unless circumstances—such as an unemployment spell—force them to switch.

These worker preferences are also evident in the earnings changes associated with occupational switches, when comparing those who switched occupations with those that stayed in their original occupations while experiencing similar employment paths (Table 1). Among the employed, those who switched occupations saw an average earnings gain of about two percent on average, consistent with the theories with sequential bargaining in which the bargaining position is affected by a worker's recent employment history (e.g. Postel-Vinay and Robin 2002a,b, Cahuc and others 2006 and Jarosch, 2015). In contrast, among the unemployed workers who successfully found a new employment, those who switched occupations saw an average earnings penalty of about fifteen percent, consistent with empirical evidence for the US (Huckfeldt, forthcoming).

Table 1. Long-term average sectoral and occupational transitions: probability and earnings changes

Transition	Probability	95 Percent confidence bands	Earning change due to switch	95 Percent confidence bands
		Sectors		
Job-to-job (*EE_job*)	0.060	[0.059, 0.061]	-	-
Sector-to-sector (*EE_sec*)	0.033	[0.032,0.035]	-	-
		Occupations		
Employed workers (*EE_occ*)	0.123	[0.116,0.130]	0.019	[0.029, 0.009]
Unemployed workers (*UE_occ*)	0.466	[0.450,0.481]	-0.158	[-0.078, -0.238]

Note: The table reports the mean and the 95 percent confidence bands of the sectoral and occupation transitions outlined in Section 2.1. The mean is obtained running a linear probability model on a constant (see Section 2.1 for definition). The regression also includes country, year and sector in year t-1/occupation in year t-1 fixed effects. Standard errors are clustered at the country-year level.

3.2 Cyclical fluctuations

In this section, we study whether the stylized facts discussed in the previous section vary over the business cycle. The literature has been long debating whether the extent of reallocation is constant over the business cycle. On one hand, some view recessions as times in which the labor market is cleansed by accelerating the reallocation of workers (see for instance, Mortesen and Pissarides 1994, Groshen and Potter, Jaimovich and Siu 2014). On the other hand, some find that employment-to-employment transitions are more frequent during expansions rather than recessions (Barlevy 2002, Carrillo-Tudela and others 2016).

Table 4 shows (i) job-to-job (*EE_job*), (ii) on-the-job sectoral switch (*EE_sec*), (iii) on-the-job occupational switch (*EE_occ*), (iv) via unemployment occupational switch (*UE_occ*) during expansions, recessions, and recoveries. We also show the earning changes associated with on-the-job occupational switches (*EE_occ*), and via-unemployment occupational switches (*EUE_occ*).

[6] While it is not possible to precisely compare the magnitudes of this measure in the literature due to differences in the sample of countries and level of disaggregation of occupation categories, these results are broadly in line with the literature—see Huckfeldt (Forthcoming) and Gertler and others (2000). Furthermore, the earnings change is mainly due to changes in the hourly wage change and not changes in hours worked.

To assess if the business cycle affects the different transitions, we estimate the following linear probability model:

$$outcome_{ict} = \alpha + \lambda_c + \tau_t + \beta Recession_{ct} + \phi Recoveries_{ct} + \varepsilon_{ict} \qquad (1)$$

where the outcome variable is one of the labor market transitions for individual *i*, in country *c* and time *t*.[7] $Recession_{ct}$ and $Recoveries_{ct}$ are dummies for recession and recovery periods calculated following Hardin and Pagan (2002) and capture the deviation from expansion periods (see Section 2 for details on the calculation of the business cycle phases). Standard errors are clustered at the country-year level.

The state of the business cycle does not appear to impact the sectoral and occupational switch probabilities, as there is generally no statistically significant difference between their values during expansions versus recessions (Table 2).[8] Even so, the facts that unemployment rises in a recession and that the incidence of occupational switches are larger after unemployment spells indicates that mechanically there are likely to be more occupational switches and more workers suffering earnings penalties upon reemployment after recessions.

Table 2. Sectoral and occupation transition probabilities during the business cycle

Transition	Business cycle phase	Mean	95 Percent confidence bands
		Sectors	
Job-to-job			
(EE_job)	Expansion	0.062	[0.061, 0.064]
	Recession	0.055	[0.051, 0.059]
Sector-to-sector			
(EE_sec)	Expansion	0.035	[0.032, 0.038]
	Recession	0.029	[0.020, 0.037]
		Occupations	
All workers			
	Expansion	0.127	[0.114, 0.139]
	Recession	0.131	[0.110, 0.152]
Employed workers			
(EE_occ)	Expansion	0.119	[0.107,0.132]
	Recession	0.124	[0.103,0.145]
Unemployed workers			
(UE_occ)	Expansion	0.430	[0.384,0.477]
	Recession	0.444	[0.353,0.535]

Note: The table reports the mean and the 95 percent confidence bands of the sectoral and occupation transitions outlined in Section 2.1 and obtained estimated Equation (1). The mean is obtained running a linear probability model with a constant, and three dummies for recessions, recoveries, and expansions (see Section 2.1 for definition). The regression also includes country, year and sector in year t-1/occupation in year t-1 fixed effects. Standard errors are clustered at the country-year level.

Earning changes associated with occupational switches instead vary significantly over business cycle (Table 3). The business cycle has an impact on earnings gains, when considering “on-the-job” occupational switches

[7] The regression is also weighted using the individual level weights rescaled to sum to one for each country-year. In the case of the EU-SILC data the longitudinal sampling weights provided by the EU-SILC are used. This ensures that each country-year observation is equally weighted in the estimation.

[8] At 5% significance level, only occupational switch via non-participation (OE) is statistically higher during recession than expansion.

(*EE_occ*), but this is not the case when workers experience occupational switches "via-unemployment" (*EUE_occ*). Those who switch occupation "on-the-job" do not gain as much during recessions as during expansions.

Table 3. Earning consequences of occupation transitions during the business cycle

Transition all workers	**Business cycle phase**	Mean	95 Percent confidence bands
	Expansion	0.018	[-0.004, 0.041]
	Recession	0.021	[-0.011, 0.052]
Employed workers			
(EE_job)	Expansion	0.029	[0.014, 0.043]
	Recession	0.001	[-0.019, 0.020]
Unemployed workers			
(EUE_occ)	Expansion	-0.172	[-0.305, -0.038]
	Recession	-0.150	[-0.304, 0.005]

Note: The table reports the mean and the 95 percent confidence bands of the earning changes as defined in Section 2.1 and obtained estimating Equation (1). The mean is obtained running a linear probability model with a constant, and three dummies for recessions, recoveries, and expansions (see Section 2.1 for definition). The regression also includes country, year and occupation in year t-1 fixed effects. Standard errors are clustered at the country-year level.

IV. Career changes: why, who, where, and at what wage gains?

4.1 Who changes careers?

We now zoom into how sectoral and occupational switches differ across individual level demographic characteristics. To study how the likelihood of these switches vary with individual level characteristics we estimate the following linear probability model:

$$outcome_{ict} = \alpha + \lambda_c + \tau_t + \phi_{st-1} + \beta X_{ict} + \gamma Recession_{ct} + \theta X_{ict} * Recession_{ct} + \varepsilon_{ict}$$

(2)

Where X_{ict} is a vector of individual level and socioeconomic characteristics including age, gender, and skill level. More specifically, the following dummy variables are defined: $youth_{ict}$ is equal to one for individuals between 15 and 29 years of age, old_{ict} is equal to one for those aged 55-64 and above, $lowskill_{ict}$ is equal to one for those with secondary education and below, $female_{ict}$ is equal to one for women.[9] The base category is prime-age high-skilled men. ϕ_{st-1} are sector or occupation (depending on the outcome) fixed effects.

Table 4 reports the results focusing on sectoral transitions. The results suggest that women, old and the low skilled tend to have lower chances of switching jobs (Column 1). Whereas only old and low skilled have a significantly lower probability of switching sectors (Column 3). Youth have higher chances of switching both jobs and sectors (Column 1 and 3). There is no statistically significant evidence of cyclicality of job-to-job and sectoral switches during recessions. However, we do observe some heterogenous behavior across groups of

[9] In the EUSILC data youth is a dummy equal to one for those aged 16 to 29.

individuals during recessions. Women have higher chances to switch job during a typical recession, whereas young workers have worse prospects in terms of job switches during recessions (Column 2). When focusing on the sectoral switches (Column 4), young again appear at a disadvantage, while old workers have marginally higher chances of changing sector of occupation. It is important to note that the regressions account for sector specific employment structure by controlling for sector in *t-1* fixed effects. This is important to control, for instance, for the fact that women tend to be employed in certain sectors, such as services and education.

Table 4. Impact of recessions and heterogeneity by individual level characteristics for sectoral outcomes

	(1)	(2)	(3)	(4)
Dep. Var.: Transitions	EE_job	EE_job	EE_sec	EE_sec
Female	-0.00360***	-0.00393***	-0.000312	-0.000275
	(0.000337)	(0.000370)	(0.000500)	(0.000520)
Youth	0.0651***	0.0659***	0.0273***	0.0280***
	(0.00135)	(0.00143)	(0.000794)	(0.000840)
Old	-0.0326***	-0.0329***	-0.0124***	-0.0129***
	(0.000673)	(0.000722)	(0.000661)	(0.000641)
Low skilled	-0.00480***	-0.00500***	-0.00175***	-0.00206***
	(0.000513)	(0.000569)	(0.000511)	(0.000587)
Recession	-0.000576	-0.00200	-0.00468	-0.00584
	(0.00284)	(0.00328)	(0.00875)	(0.00746)
Recession X Female		0.00283***		-0.000277
		(0.00108)		(0.00105)
Recession X Young		-0.00736**		-0.00601***
		(0.00358)		(0.00227)
Recession X Old		0.00269		0.00426*
		(0.00192)		(0.00243)
Recession x Low skilled		0.00181		0.00274
		(0.00178)		(0.00501)
Constant	0.0643***	0.0644***	0.0383***	0.0384***
	(0.000821)	(0.000848)	(0.00175)	(0.00163)
N	29,684,842	29,684,842	29,684,842	29,684,842
R2	0.039	0.039	0.056	0.056
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Sector FE in t-1	Yes	Yes	Yes	Yes

Note: The table reports the results obtained from Equation (2). The regression includes country, year and sector in year t-1 fixed effects. Standard errors are clustered at the country-year level.

When focusing on the incidence of occupational switches across demographic groups, we also observe some notable differences (Table 5). Even after accounting for skills and occupations fixed effects, women are less likely than men to switch occupations independently of their labor force transition history (either “on-the-job” or via an unemployment spell). On the other hand, young (older) workers are more (less) likely to switch occupations than prime-aged workers regardless of their labor force history. Lastly, low-skilled workers are less likely to switch via-employment. There is not a statistically significant difference in switching probability for low-skilled workers via-unemployment.

Table 5. Impact of recessions and heterogeneity by individual level characteristics for occupational outcomes

	(5)	(6)	(7)	(8)
Dep. Var: Transitions	EE_occ	EE_occ	UE_occ	UE_occ
Female	-0.0174***	-0.0181***	-0.0189	-0.0172
	(0.00237)	(0.00273)	(0.0186)	(0.0190)
Youth	0.0399***	0.0428***	0.0562**	0.0584**
	(0.00316)	(0.00364)	(0.0223)	(0.0235)
Old	-0.0195***	-0.0186***	-0.0757***	-0.0718***
	(0.00185)	(0.00214)	(0.0225)	(0.0234)
Low skilled	-0.00668**	-0.00737**	0.0125	0.00345
	(0.00268)	(0.00287)	(0.0217)	(0.0221)
Recession	-0.00124	-0.00253	-0.0598	-0.126**
	(0.0126)	(0.0140)	(0.0440)	(0.0603)
Recession X Female		0.00328		-0.0301
		(0.00499)		(0.0614)
Recession X Young		-0.0130*		-0.0234
		(0.00748)		(0.0682)
Recession X Old		-0.00421		-0.0590
		(0.00469)		(0.0865)
Recession x Low skilled		0.00341		0.128**
		(0.00629)		(0.0556)
Constant	0.134***	0.134***	0.467***	0.472***
	(0.00537)	(0.00551)	(0.0216)	(0.0223)
N	439,004	439,004	8,189	8,189
R2	0.084	0.084	0.064	0.065
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Occupation FE in t-1	Yes	Yes	Yes	Yes

Note: The table reports the results obtained from Equation (2). The regression includes country, year and occupation in year t-1 fixed effects. Standard errors are clustered at the country-year level.

Differences in the occupation switching probability across demographic groups do not generally vary over the business cycle with few exceptions. Young workers are less likely to switch via “on-the-job” during recessions than during expansions. More importantly, low-skilled workers have a higher chance of switching occupation via-unemployment during recessions than during expansions, suggesting a potential distributional impact of recessions.

Table 6. Earning consequences of occupational switches and heterogeneity during the business cycle

	(1)	(2)
Dep. Var: Change in earnings	EE	EUE
Switch	0.0186**	-0.366***
	(0.00875)	(0.117)
Female	0.0176***	-0.00889
	(0.00293)	(0.0611)
Young	0.180***	0.265***
	(0.00616)	(0.0756)
Old	-0.0331***	-0.0879
	(0.00251)	(0.0911)
Low skill	-0.0145***	-0.227**
	(0.00337)	(0.0885)
Female x Switch	0.00366	0.0438
	(0.00764)	(0.0857)
Young x Switch	0.0273*	0.165
	(0.0144)	(0.114)
Old x Switch	-0.0132	-0.124
	(0.00827)	(0.120)
Low skill x Switch	-0.0194**	0.200*
	(0.00868)	(0.117)
Constant	0.0513***	-0.233***
	(0.00407)	(0.0860)
N	369,381	4,616
Country FE	Yes	Yes
Year FE	Yes	Yes
Occupation FE in t-1	Yes	Yes
R2	0.027	0.096

Note: The table reports the results from Equation (2). The regression includes country, year and occupation in year t-1 fixed effects. Standard errors are clustered at the country-year level.

4.2 Who experiences earnings gains and losses?

In this section, we study how earning consequences of occupational switches vary across demographic groups. Table 6 presents the results for the earning consequences “on-the-job” (Columns 1) and “via-unemployment” (Columns 2).

The sum of the coefficients on the constant and the demographic group dummy provides the average earning change for workers of a specific demographic group, who are continuously employed (*EE*) (Column 1), and who get reemployed after one-year of unemployment spell (*EUE*) (Column 2). All demographic groups considered in this section experience an average earning gain while being continuously employed, however the magnitude of the earnings gain vary across demographic groups. While being continuously employed, female and young experience larger earning gains while old workers and low-skilled workers experience smaller earning gains (Column 1).

Young workers who switch occupations “on-the-job” tend to gain more, while low-skilled workers tend to earn less than others. This suggests that earnings growth is higher for young and lower for low-skilled among those who continued to be employed (EE). With regards to comparing recessions and expansions, we do not observe

a statistically significant difference in earning gains when considering “on-the-job” occupational switches across different demographic groups (results not reported).

We now turn to the “via-unemployment” transitions in Column (2). Workers who continue to be employed for two consecutive years enjoy earning gains on average, and those who lose their job, even if they get reemployed after an unemployment spell (*EUE*), instead suffer from an earning loss. This corresponds to the sum of the coefficients on the constant and the demographic group dummy in Column 2. With the exception of young workers (-0.233+0.265=0.035), every demographic group suffers earning losses compared to their pre-displacement earnings level, but this earning loss is particularly severe for low-skilled workers (-0.233-0.227=-0.46). Moreover, a further earning loss of –0.37 is experienced on average if the worker also switches occupation upon reemployment (*EUE_occ*).

In summary, this section finds that:

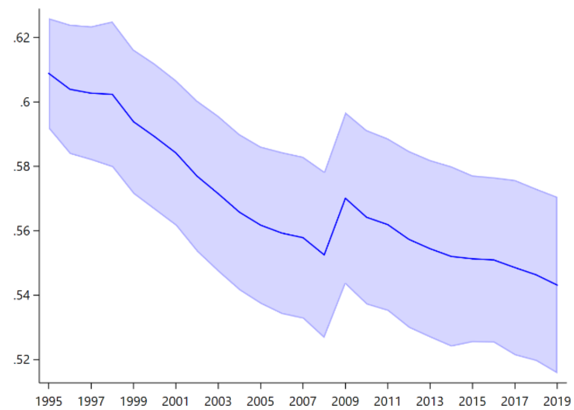
- Workers who continue to be employed for two consecutive years (*EE*) experience earning gains while those who lose their job tend to earn less upon reemployment (*EUE*) with respect to their pre-unemployment earnings.
- “On-the-job” occupational switches (*EE_occ*) are associated with earning gains while “via-unemployment” occupational switches (*EUE_occ*) are associated with an earning loss.
- Low-skilled workers experience smaller earning gains while continuously being employed (*EE*) and larger earning losses upon reemployment after going through an unemployment spell (*EUE*).
- Low-skilled workers also do not experience substantial earning gains when experiencing “on-the-job” occupational switches (EE_occ) like other workers categories do, but also do not suffer as much when changing occupation via unemployment (EUE_occ).
- Young workers seem to experience larger earning gains in the case of “employment-to-employment” transitions *(EE),* and smaller earning penalties when they get reemployed after an unemployment spell (*EUE*). Their earnings also increase disproportionately more when changing occupation “on-the-job” (*EE_occ*) and they suffer less significant losses from a switch “via-unemployment” (*EUE_occ*).
- Women experience larger gains while continuously employed *(EE)* and they were less likely to switch occupation (*EUE_occ*).
- On average, during recessions, young workers experience smaller earning gains than other demographic groups when they switch occupation and remain employed, and their earning losses are more substantial when they go through an unemployment spell.

V. The role of routinization

The literature has documented that over the last several decades jobs that require “routine tasks” have declined (Goos and others, 2009, Autor, 2003, Acemoglu and Autor, 2011, and Autor and Dorn, 2013) and some argue that this decline in routine jobs occur particularly during recessions (Jaimovich and Siu, 2020, Gaggle and Kauman, 2020, and Furukawa and Toyoda, 2013). In this section, we therefore first study whether the phenomenon of declining routine jobs has been observed in our sample of European countries and whether

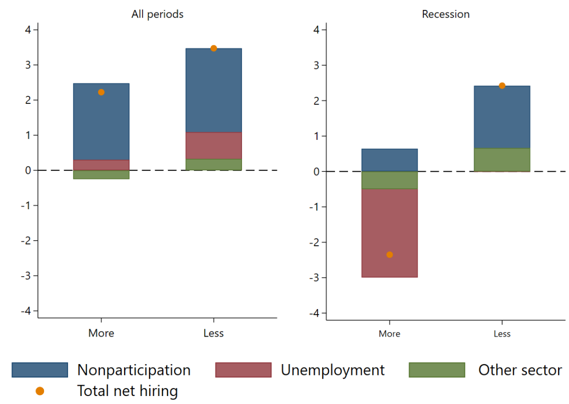
the decline in routine jobs happened disproportionately more during recessions. We then study the individual consequences of switching jobs and their earning consequences focusing on routine jobs

Figure 1: Average Employment Share of Routine Jobs (percent)



Note: The figure shows averaged employment in routine occupations as classified by (Carrillo-Tudela and others, 2016). The average is unweighted across all countries in our sample. To account for sample coverage changes, the average share of employment in working-age population across selected economies over time is calculated from the normalized, time fixed effects from a regression of the indicated variable on country and time fixed effects (Karabarbounis and Neiman 2014). The light-shaded bands show the 90 percent confidence interval.

Figure 2: Average Net Hiring Rates Across the Business Cycle (average economy-wide rate, percent)



Note: Hiring and separation rates and components are calculated as annual hires/separations divided by the average employment over the current and previous year. More (less) vulnerable sectors are defined as sectors where the share of employment classified as vulnerable to routinization is more (less) than 50 percent of employment. For details see Carrillo-Tudela and others (2015).

Figure 2 shows how the shift away from sectors dominated by routine jobs accelerates during recessions. The figure shows the net hiring rate for all periods and recession periods for sectors classified as routine, respectively. Sectors are classified as routine if more than half of their employment are in occupations classified as routine tasks (Carrillo-Tudela and others, 2016). We break down net hiring into net hiring from (i) other sectors, (ii) non-participation, and (iii) unemployment. Across all periods, net-hiring into routine jobs is on average positive (Figure 2). However, net hiring is relatively higher for non-routine sectors; predominantly through hiring from unemployment and non-participation, but also through direct hiring from sectors that are predominantly routine. During recessions, however, net-hiring into routine sectors turns negative, led by net movements into unemployment. On the other hand, net hiring into non-routine sectors remains positive.

5.1 Aggregate Level of Trend and Cyclicality of Routine Jobs

We start by looking at aggregate trends of routinization over time to understand the evolution of different labor market margins and their exposure to routinization in our sample of countries. Figure 1 shows how the share of jobs in occupations characterized as "routine" has declined steadily since 1995. The figure depicts the average share of employment in occupations characterized as routine, as defined by Carrillo-Tudela and others (2016)

across countries in our sample.[10] The figure shows how the average share of routine jobs has fallen from around 61 percent in 1995 to 55 percent in 2019.

5.2 Transitions between Routine and Non-Routine Jobs

After having established aggregate labor markets trend in relation to routinization, we now unpack these patterns by focusing on the transition probability between routine and non-routine occupations at the individual level (Table 7). The transition matrix in Table 7 reinforces the general reallocation patterns observed in the previous subsection. We first find that workers who were previously employed in non-routine occupations are much less likely to lose jobs, much more likely to find jobs, and more likely to stay in non-routine occupations than those who were previously employed in routine occupations.

Table 7. Transition matrix for occupational switches

Origin Occ	Origin LFS	**Non-Routine**	**Routine**	**Non-Employment**	**Share of Routine vs Non-Routine**
Non-Routine	**Total**	0.86	0.05	0.09	0.42
	E	0.92	0.05	0.02	0.43
	U	0.23	0.11	0.66	0.21
Routine	**Total**	0.04	0.77	0.19	0.58
	E	0.04	0.91	0.04	0.57
	U	0.02	0.25	0.72	0.79

The level of disaggregation allows us to investigate how these patterns vary across demographic groups. Table 8 shows that working in a routine sector increases the probability of switching jobs (Columns 1-3) and sectors (Columns 4-6). While young workers in routine jobs have a higher chance of changing jobs and sectors, women and older workers have a lower likelihood to find a different job (Column 2) and these trends remain true in recessions (Column 3). When switching sectors female and youth have a higher chance of switching (Column 5), and this is also the case during recessions (Column 6).

[10] To account for sample coverage changes, the average share of employment in working-age population across selected economies over time is calculated from the normalized, time fixed effects from a regression of the indicated variable on country and time fixed-effects (Karabarbounis and Neiman 2014).

Table 8. Sectoral switches and routine jobs

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var. Transition	EE_job	EE_job	EE_job	EE_sec	EE_sec	EE_sec
Recession	-0.00513*			-0.00785		
	(0.00261)			(0.00892)		
Routine t-1	0.0436***	0.0211***	0.0188***	0.0246***	0.0209***	0.0188***
	(0.00104)	(0.00110)	(0.00217)	(0.00115)	(0.000899)	(0.00256)
Female X Routine t-1		-0.00431***	-0.00242		0.00972***	0.00961***
		(0.000705)	(0.00178)		(0.000940)	(0.00248)
Young X Routine t-1		0.0598***	0.0497***		0.0300***	0.0254***
		(0.00168)	(0.00408)		(0.000848)	(0.00209)
Old X Routine t-1		-0.0152***	-0.0149***		-0.00559***	-0.000904
		(0.000894)	(0.00208)		(0.00108)	(0.00531)
Low skill X Routine t-1		0.0176***	0.0136***		-0.00942***	-0.00377
		(0.00101)	(0.00226)		(0.00163)	(0.00627)
Constant	0.0489***	0.0560***	0.0516***	0.0310***	0.0333***	0.0371***
	(0.000987)	(0.00105)	(0.00189)	(0.00166)	(0.000981)	(0.00214)
Observations	29,684,842	29,684,842	4,138,623	29,684,842	29,684,842	4,138,623
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	No	No	No	No	No	No
Sample	Full	Full	Recession	Full	Full	Recession

Note: The table reports the results of a linear probability model like Equation (2). The regression includes country and year fixed effects. Standard errors are clustered at the country-year level.

Table 9. Occupational switches and routine jobs

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var. Transition	EE_occ	EE_occ	EE_occ	UE_occ	UE_occ	UE_occ
Recession	-0.00102			-0.0620		
	(0.0128)			(0.0446)		
Routine t-1	-0.0181***	0.0509***	0.0464***	-0.0480**	0.0955**	0.352**
	(0.00367)	(0.00496)	(0.00822)	(0.0207)	(0.0408)	(0.134)
Female X Routine t-1		0.000864	0.0138*		-0.0525	-0.196
		(0.00425)	(0.00766)		(0.0418)	(0.114)
Young X Routine t-1		0.0109*	-0.00188		0.165***	0.155
		(0.00625)	(0.0153)		(0.0495)	(0.132)
Old X Routine t-1		0.00204	0.00651		-0.0409	-0.263
		(0.00338)	(0.00702)		(0.0613)	(0.203)
Low skill X Routine t-1		-0.119***	-0.119***		-0.271***	-0.503**
		(0.00820)	(0.0176)		(0.0470)	(0.170)
Constant	0.131***	0.115***	0.111***	0.502***	0.424***	0.157
	(0.00532)	(0.00423)	(0.00683)	(0.0210)	(0.0302)	(0.0884)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE	No	No	No	No	No	No
N	438,971	438,971	84,418	8,189	8,189	498
R2	0.073	0.079	0.084	0.040	0.052	0.119
Sample	Full	Full	Recession	Full	Full	Recession

Note: The table reports the results of a linear probability model like Equation (2). The regression includes country and year fixed effects. Standard errors are clustered at the country-year level.

Looking at occupational switches, those who previously worked in routine jobs are on average less likely to switch occupations both "on-the-job" (EE_occ) and via-unemployment (UE_occ) (Table 9). When considering demographic groups instead, young workers who previously worked in routine-jobs have a higher chance of switching occupations than young workers who previously worked in non-routine jobs both "on-the-job" (EE_occ) and via-unemployment (UE_occ). Finally, low-skilled workers who previously worked in routine occupations have less chances of switching occupations than low-skilled workers who did not, regardless of the type of transition.

5.3 Earning Consequences in relation to Routine Jobs

In Section 3, we have shown that "on-the-job" occupational switches (EE_occ) are on average associated with earning gains, while occupational switches via-unemployment (EUE_occ) are on average correlated with an earning penalty. In this section, we zoom into the heterogeneity of earning changes within these two labor market transitions, EE and EUE in relation to routine occupations. First, we study how earning gains/penalties differ for those who move from non-routine to routine jobs. In a similar spirit and focusing on U.S. data, Huckfeldt (Forthcoming) documents that the wage loss associated with occupational switches after an unemployment spell is fully accounted for by the occupation downgrading—switching from an occupation with a higher average wage to an occupation with a lower average wage.

Table 10. Earning Changes and Routine Occupations

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var. Change in Earning	EE_occ			EUE_occ		
Switch	0.0107**	0.0200***	0.00697	-0.187***	-0.150***	-0.135
	(0.00485)	(0.00512)	(0.00826)	(0.0407)	(0.0413)	(0.0861)
Switch Non2Routine		-0.0502***	-0.0884***		-0.242***	-0.137
		(0.0101)	(0.0191)		(0.0890)	(0.124)
Constant	0.0431***	0.0429***	0.0390***	-0.415***	-0.409***	-0.371***
	(0.00385)	(0.00385)	(0.00608)	(0.0557)	(0.0555)	(0.123)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
N	369381	369348	71289	4616	4616	910
R-sq	0.026	0.026	0.041	0.081	0.083	0.144
Sample	All	All	Recession	All	All	Recession

Note: The table reports the results of a linear probability model like Equation (2). The regression includes country and year fixed effects. Standard errors are clustered at the country-year level.

Table 10 presents the earning changes for "on-the-job" occupational switchers (Column 1-3) and "via-unemployment" occupational switchers (Columns 4-6). Column 1 presents the baseline result considering an average switch, while Column 2 includes a dummy if the switch is associated with a movement from non-routine to routine jobs (Switch Non2Routine).11 The sum of coefficients on SwitchNon2Routine and Switch is negative and statistically significant. In other words, we find that the occupational switch associated with

[11] The difference between the results in this table and the overall historical average of earning changes due to occupational switch in Section 4 is due to control for individual characteristics. We include female, young, old, and low-skilled dummies to control for individual characteristics.

moving from non-routine to routine occupations can more than offset the earnings gains from the "on-the-job" occupational switch. Therefore, on average, the additional earning gains due to an occupational switch on-the-job are not witnessed by workers who experience a downgrading from a non-routine occupation to a routine occupation. We also find some evidence that this earning loss is associated with a downgrading from non-routine to routine occupation is particularly strong during a recession (Column 3).

Similarly, when we look at the earning penalty due to the fact that workers have to go through an unemployment spell (EUE_occ), we find that those who move from a non-routine to a routine occupation suffer more. When an occupational switch "via-unemployment" (EUE_occ) is associated with transitioning from a non-routine to a routine occupation, the additional earning loss is at around 24 percent (Column 5). However, the business cycle does not seem to affect the earning penalty due to the downgrading.

In summary, we find that workers, whose switch is associated with movement from non-routine to routine jobs, do not enjoy the earning gain due to "on-the- job" switches and suffer a higher earning penalty due to occupational switch via-unemployment. Thus, our individual level analysis highlights significant distributional impacts of an economy-wide general declining trend of routine jobs on workers. Workers suffer significantly from both a lower job finding probability and worse earning consequences from occupational switches (both via EE and EUE).

5.4 Earning Consequences Across Demographic Groups in relation to Routine Jobs

We now study whether such differences in the earning loss associated with switching from non-routine jobs to routine jobs differ across demographic groups. Table 11 presents the earning changes due to occupational transitions from non-routine to routine occupations across different demographic groups over business cycle.

Among those who experience on-the-job occupational switches (EE_occ), we find that the earning penalties of switching from non-routine to routine occupations are worse for women and the young (Column 1 and 3). During recessions, the earning penalty due to switching from non-routine to routine occupations generates a more substantial earning loss for women (-12.4 percentage points during the recession relative to -5.4 percentage points for the whole sample), older workers (-6.4 percentage points during recession relative to -3.8 percentage points for the whole sample), and low-skilled (-6.7 percentage during recession relative to -3.5 percentage point loss for the whole sample) (Column 7). Young workers' earning losses due to switching from non-routine to routine jobs do not vary as much over the business cycles (Column 3-4).

Looking at workers who are going through EUE transitions, we find a large penalty due to switching from non-routine to routine occupations for older (Column 5) and low-skilled workers (Column 7), but we do not find the same pattern for women and young workers (Column 1 and 3). We do not observe a statistically significant difference in the additional earning loss due to switching from non-routine to routine occupations during the entire sample and recession periods.

Table 11. Earning Changes and Routine Occupations: Demographics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var Changes in Earning			On-the-job occupational switch (EE_occ)					
	Women		Young		Old		Low skill	
Switch	0.0305***	0.0235*	0.0508***	0.0299	0.00244	-0.000204	0.0169***	-0.000261
	(0.00754)	(0.0138)	(0.0152)	(0.0254)	(0.00719)	(0.0146)	(0.00599)	(0.0111)
Switch Non2Routine	-0.0544***	-0.124***	-0.0620*	-0.0699	-0.0387**	-0.0635***	-0.0351***	-0.0673***
	(0.0143)	(0.0341)	(0.0334)	(0.0462)	(0.0166)	(0.0226)	(0.0125)	(0.0206)
Constant	0.0772***	0.0731***	0.229***	0.206***	0.0202***	0.0147***	0.0669***	0.0595***
	(0.00345)	(0.00474)	(0.00683)	(0.0105)	(0.00354)	(0.00347)	(0.00347)	(0.00505)
N	180415	34344	39896	8017	71787	12820	229429	44836
			Via-unemployment occupational switch (EUE_occ)					
	Women		Young		Old		Low skill	
Switch	-0.134**	-0.219**	-0.00846	0.0615	-0.246**	-0.195	-0.0604	-0.0474
	(0.0572)	(0.100)	(0.0948)	(0.255)	(0.109)	(0.210)	(0.0478)	(0.0885)
SwitchNon2Routine	-0.199	0.0143	-0.0348	0.137	-0.358**	-0.139	-0.454***	-0.253
	(0.145)	(0.151)	(0.253)	(0.382)	(0.166)	(0.274)	(0.106)	(0.179)
Constant	-0.337***	-0.236***	-0.167***	-0.322***	-0.442***	-0.488***	-0.371***	-0.338***
	(0.0346)	(0.0487)	(0.0643)	(0.0985)	(0.0679)	(0.0978)	(0.0317)	(0.0457)
N	2,096	426	1,024	169	536	101	3,449	697
Sample	All	Recession	All	Recession	All	Recession	All	Recession

Note: The table reports the results of a linear probability model like Equation (2). The regression includes country and year fixed effects. Standard errors are clustered at the country-year level.

In summary, we find that the earning losses due to switching from non-routine to routine occupations are larger for young and women in general among those going through EE labor market transitions, but get worse during recessions for women, older and low-skilled. Among the workers going through EUE transitions, older and low-skilled workers suffer a large earning penalty due to switching from non-routine to routine occupations.

VI. Conclusion

Using individual level data from 30 European countries between 1983 and 2019, we studied the distributional consequence of labor market transitions. We documented the extent and earning consequences of workers' reallocation across occupations and industries and how these outcomes vary with individual-level characteristics, including education, gender, and age.

We find that while young workers are more likely to experience job-to-job sectoral and occupational switches with earning gains associated with on-the job transitions, low-skilled workers tend to suffer from earning losses upon reemployment after an unemployment spell. These differences in earning gains and losses also mask a high degree of heterogeneity associated with trends in routinization. We find that workers, particularly low-skilled and old workers during recession, experience severe earning penalty when occupational switch associated with moving from non-routine to routine occupations.

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