Occupational Mobility of Routine Workers

Abstract

This paper analyzes whether occupational polarization takes place within workers or due to changes in the composition of workers by using comprehensive panel data from Finland. The decomposition analysis shows that the decrease in mid-level routine occupations and the simultaneous increase in high-level abstract occupations is largely a within-worker phenomenon. In contrast, the share of low-skilled nonroutine manual tasks has largely increased through entry dynamics. Data on plant closures are used to identify involuntary separations from routine occupations. These results demonstrate a strong, uneven adjustment pattern, with routine cognitive workers being more able to move to abstract tasks and adjust with smaller wage costs than routine manual workers.

Terhi Maczulskij
ETLA Economic Research, Finland and
IZA Institute of Labor Economics, Germany
terhi.maczulskij@etla.fi

Suggested citation:
Maczulskij, Terhi (9.4.2021). "Occupational Mobility of Routine Workers".

ETLA Working Papers No 87.
http://pub.etla.fi/ETLA-Working-Papers-87.pdf

Tiivistelmä

Rutiinityötä tekevien ammatillinen liikkuvuus

Tutkimuksessa tarkastellaan ammattirakenteiden muutosta sekä sitä, että mihin supistuvissa ja rutiininomaisissa ammateissa olevat työntekijät päätyvät hyödyntämällä kokonaisaineistoa vuosille 1970–2015.

Ammattirakenteiden polarisaatio on jatkunut Suomessa jo vuosikymmeniä. Ammattirakennemuutoksen kehityskulku on pääosin tapahtunut siten, että keskitason tuotanto- ja toimistotyöntekijät ovat nousseet urapolkuja pitkin asiantuntijatöihin. Viimeaikaista palveluammattien osuutta on puolestaan kasvattanut se, että nuoret siirtyvät työmarkkinoille palvelutöihin. Kun malleissa vakioidaan erot työntekijöiden taustaominaisuuksissa, kuten koulutuksessa, niin kognitiivista rutiinityötä (kuten toimistotyö) tekevillä on suurempi todennäköisyys nousta korkeammille palkkaluokille ja siirtyä uudelleenkoulutukseen fyysistä rutiinityötä (kuten tuotantotyö) tekeviin työntekijöihin verrattuna.

Perinteistä tuotanto- ja kokoonpanotyötä tekevät tippuvat puolestaan suuremmalla todennäköisyydellä matalapalkka-aloille, vaikkakin heidän työttömyystodennäköisyytensä on pienempi. Rutiinityötä tekevien ryhmät eroavat siis merkittävästi sen mukaan, mihin ammattiin tai työmarkkina-asemaan he siirtyvät. Tulokset pysyvät samankaltaisina, kun analyysi tehdään pienemmälle joukolle henkilöitä, jotka joutuvat etsimään uuden työn toimipaikan sulkemisen seurauksena.

Tutkimustulokset myös osoittavat, että työntekijästä riippumaton työpaikan menetys johtaa keskipitkällä aikavälillä jopa 15 prosenttia heikompaan ansiokehitykseen tuotantotyöntekijöillä kuin toimistotyöntekijöillä.

DSc (Economics) **Terhi Maczulskij** is a Chief Research Scientist at ETLA Economic Research, Research Director at Yrjö Jahnsson Foundation and IZA Research Fellow.

KTT **Terhi Maczulskij** on Elinkeinoelämän tutkimuslaitoksen tutkimuspäällikkö, Yrjö Jahnssonin säätiön tutkimusjohtaja ja IZA Research Fellow.

Acknowledgements: Financial support from the Palkansaajasäätiö and the Academy of Finland Strategic Research Council project (number 293120) are gratefully acknowledged. All the data work in this paper was carried out at Statistics Finland, following its terms and conditions for confidentiality. I wish to thank the following people for helpful comments on and suggestions for this paper: Jari Vainiomäki, Petri Böckerman and Stijn Broecke; the Finnish Economic Association seminar audiences; and the participants in the virtual SOLE/EALE 2020 conference, the EEA/ESEM 2018 conference in Cologne and the OECD seminar in Paris in 2018.

The previous version of this paper has been published in Labour Institute for Economic Research WP series (327/2019).

Kiitokset: Tutkimusta ovat rahoittaneet Palkansaajasäätiö ja Suomen Akatemia (numero 293120). Kiitän Jari Vainiomäkeä, Petri Böckermania, Stijn Broeckea sekä seuraavien konferenssien ja kokousten yleisöä hyvistä kommenteista: Kansantaloustieteen päivät, virtuaalinen SOLE/EALE konferenssi vuonna 2020, EEA/ESEM konferenssi vuonna 2018 ja OECD seminaari vuonna 2018.

Tutkimuksen aiempi versio on julkaistu Palkansaajien tutkimuslaitoksen työpapereissa (327/2019).

Keywords: Job market polarization, Routine manual, Routine cognitive, Decomposition, Occupational mobility, Displacement

Asiasanat: Työmarkkinoiden rakennemuutos, Fyysinen ja rutiininomainen, Kognitiivinen ja rutiininomainen, Hajotelmamenetelmä, Ammatillinen liikkuvuus, Työpaikan menetys

JEL: J23, J62

1. Introduction

Where have all the mid-skilled routine workers gone? Job market polarization has become one of the defining issues in labor economics over the last two decades. A classic example is Autor, Levy and Murnane (2003), who show that advances in computer technology have decreased demand for mid-skilled workers performing routine tasks, while demand for low-skilled service occupations and high-skilled specialist occupations have increased.[1] Notwithstanding a growing body of research in this area (e.g., Goos and Manning, 2007; Acemoglu and Autor, 2011; Autor and Dorn, 2013; Goos, Manning and Salomons, 2014), we still know little about the implications of occupational polarization at the worker level.

This paper analyzes the occupational mobility of routine workers. From the individual and labor market perspectives, this issue is highly relevant and must be considered when designing effective policy responses to the decline in mid-skilled jobs. Employment polarization can occur at the intensive margin, when routine workers move up or down in the job hierarchy, or at the extensive margin, when workers who leave the labor market from routine occupations are replaced by workers who enter into nonroutine occupations. If the within-worker explanation prevails and routine workers are plausibly involuntarily shifted to low-skilled nonroutine manual occupations, then public resources should be directed toward vulnerable groups by providing, e.g., effective re-education programs. Routine workers might also move to

[1] Other factors, such as offshoring and import competition, have also been linked to observed polarization of the labor markets (e.g., Autor et al., 2014; Nillson Hakkala and Huttunen, 2016; Keller and Utar, 2016; Utar, 2018; Kerr, Maczulskij and Maliranta, 2020). According to Moreno-Galbis and Sopraseuth (2014), population aging is behind the increased demand for personal services and thus the rise of employment in low-skilled occupations.

abstract tasks, for example, through career progression. Forming a comprehensive picture of the specific worker skills that allow routine workers to move up the career ladder would then be important because the accelerating automation of tasks has raised concerns that new technologies will replace labor on an even greater scale (e.g., Brynjolfsson and McAfee, 2012; Akst, 2013).[2] If the extensive margin explanation prevails, then it is important to analyze the mechanisms underlying the exit routes from routine jobs to nonemployment. Training subsidies, apprenticeships and other measures of active labor market policies might be more or less effective depending on the exit routes, whether an influx to unemployment, to further education or to retirement.

The empirical literature on worker-level adjustment is still somewhat scarce. scant. The study most relevant to the setting of the current paper is from Cortes (2016), who finds that particularly low-skilled routine workers in the US have shifted to service occupations, whereas high-skilled routine workers have been more likely to move to occupations that involve abstract tasks. Recently, a few papers have examined trade impacts at the level of individual workers (e.g., Donoso, Martin and Minondo, 2010; Autor et al., 2014; Keller and Utar, 2016; Utar, 2018). These analyses are tightly focused on the manufacturing industries affected by import competition from China, i.e., the globalization aspect of job market polarization. Utar (2018) finds that low-wage competition from China has resulted in significant employment reductions for Danish manufacturing workers. Many employees have moved to the service sector, and workers' recovery from trade shocks has also been greatly dependent on their education relevant to their new work (see also Keller and Utar, 2016). Autor et al. (2014) likewise find that employees adjust to import shocks by moving out of the

[2] Autor (2015) argues that employment polarization is unlikely to continue indefinitely.

manufacturing industry in the US. Exposure to trade shocks has also increased the risks of unemployment and labor force nonparticipation (Autor, Dorn and Hanson, 2013; Donoso et al., 2010). In all, although very interesting, we still lack a comprehensive picture of which occupations or labor market statuses routine workers have moved to.

The focus of this paper is twofold. The first objective is to present for the first time whether occupational polarization takes place within workers or due to changes in the composition of workers. The analysis is done by modifying a decomposition method that has previously been used in analyses that have examined occupational polarization with a focus on the extensive versus intensive margin at the firm level.[3] The recent literature has thus paid attention to the role of firm-level restructuring involving entries, exits and the reallocation of labor but not to the role of individual worker mobility. This is the novel contribution of this paper. The study utilizes total administrative data for the 1970-2015 period. The data create a unique opportunity to evaluate occupational polarization and track the occupational trajectories of all mid-skilled routine workers over a 45-year period. While earlier studies have mainly focused on manufacturing workers or routine workers as one occupation group, we also distinguish between routine manual and routine cognitive tasks (see also Cortes et al., 2017).

[3] See, Böckerman, Laaksonen and Vainiomäki (2013, 2018), Cortes and Salvatori (2015), Heyman (2016), Harrigan, Reshef and Toubal (2016), and Kerr et al. (2020). Cortes, Jaimovich and Siu (2017) also examine the changes in the share of routine and nonroutine tasks in the US by decomposing the total change into components that are attributable to changes in the composition of demographic groups and those attributable to changes in the propensity to enter the occupations, conditional on demographic characteristics.

The second objective is to complete the analysis provided by the decomposition analysis by comparing the occupational trajectories of routine manual and routine cognitive workers. We carry that comparison out by estimating a multinomial logit model in which routine workers may choose between seven mutually exclusive occupation and nonemployment categories. In this part of the analysis, we also look at which types of characteristics are related to movements across the job hierarchy and to nonemployment. Overall occupational mobility includes both voluntary and involuntary shifts between jobs. This paper also adds to the literature by offering a causal interpretation of the occupational movements of routine workers who need to find new work after an exogenous job loss. This analysis utilizes matched employer-employee data for the entire worker population for the 1995-2015 period. Previous studies have mainly focused on the causal effects of Chinese import competition on the labor market outcomes of manufacturing workers (e.g., Keller and Utar, 2016).[4] Using job displacement to identify involuntary separations from voluntary worker outflows also enables a broad examination of the occupational mobility of all routine workers from all industries.

Like most previous international studies, we find evidence of occupational restructuring in the Finnish labor market. The observed aggregate trend mostly stems from routine workers moving to abstract tasks, although one-fifth of the recent decrease in the share of routine manual jobs can be attributed to exit dynamics to weak labor

[4] Keller and Utar (2016) use a plausibly exogenous source of occupational mobility (an import competition shock) to derive causal interpretations and evaluate the technical change, offshoring and import competition factors of job polarization side-by-side in terms of their worker-level consequences. They find that import competition is quantitatively comparable to technical change as an explanation for the hollowing out of middle-class jobs.

market attachment. The entry-exit dynamics explain most of the increase in the share of nonroutine manual jobs, when people who have left the labor markets have been replaced by younger people who have entered into nonroutine manual occupations. Routine cognitive workers tend to have a greater probability of moving to abstract occupations, and they are more able to adjust with smaller wage costs than routine manual workers. Routine manual workers are, in turn, more likely to move to nonroutine manual jobs. The results remain robust to estimations that use a smaller sample of displaced workers who must find new work for reasons unrelated to voluntary worker flows between jobs. Occupational mobility is also strongly linked to both the general (education level) and specific (education field) human capital of workers.

The rest of this paper is organized as follows. The second section presents the data sources, and section three presents the aggregate-level evidence for employment polarization during the 1970-2015 period, as well as the decomposition results related to the intensive and extensive margins of polarization. Section four presents the estimation results for the occupational mobility of routine manual and routine cognitive workers, along with some extended analyses of the costs of job loss. Finally, section five places the findings in a broader context and concludes the paper.

2. Data Description

2.1. Data Sources

The main data used are the Finnish Longitudinal Employer-Employee Data (FLEED) from Statistics Finland. The data are based on various administrative registers linked together using identification codes for individuals, firms and plants. The FLEED cover all individuals younger than 70 years old with a permanent residence in Finland for the years 1988-2015. The data include information on occupation, socioeconomic status, employment and earnings, along with a number of background characteristics. To these data we matched the total population censuses for 1970, 1975, 1980 and 1985. All wage-earners over 15 years old are included in the analysis.

Occupation variables are available in each population census and in FLEED for 1990, 1995, 2000 and 2004-2015. The ISCO-58 classification is used for the period 1970-1990, and ISCO-88 is used for the period 1995-2009. The occupation variable for the 2010-2015 period is based on the newest classification (ISCO-08). The occupation measures before 2010 are recoded to match the newest classification utilizing the crosswalk codes constructed by Statistics Finland. The same ISCO-08 classification is therefore used throughout the whole time frame of 1970-2015.

2.2. Occupation Measures

The ISCO-08 classification (mainly the 3-digit and 4-digit occupation categories) is converted into four aggregated groups based on routine content, which resembles Acemoglu and Author's (2011) suggestions: abstract, routine cognitive, routine manual and nonroutine manual occupations. The abstract group includes 68 occupation categories that are mostly from major groups 1, 2 and 3 (managers, professionals and technical occupations). The routine cognitive group is constructed by including 32 occupation categories that are mostly from major group 4 but also includes occupations from major groups 3 and 5 (sales, clerical and administrative support occupations). The routine manual group involves picking, sorting or repetitive assembly tasks. This group includes 39 occupation categories mostly from major groups 7 and 8 (e.g., production, craft, repair, and operative occupations). The nonroutine manual group includes 28 occupation categories mostly from major groups 5 and 9, such as cleaning, elementary work and services. This classification has been used previously (Böckerman, Laaksonen and Vainiomäki, 2019; Kerr et al., 2020).[5] A detailed list of the occupations in each group is available from the author. Self-employed individuals and workers in the armed forces and agricultural sector are excluded from the sample.

Although routine occupations share the common trait of being increasingly performed by computers or machines, these occupations are heterogeneous in terms of their task composition, as Autor et al. (2003) also point out. Therefore, we distinguish cognitive tasks from manual tasks. Workers are more likely to move between occupations that are more similar in terms of tasks and skills (Gathman and Schönberg, 2010; Robinson, 2018). Since routine cognitive occupations involve more analytical and interactive tasks and routine manual occupations involve more sorting and repetitive assembly tasks, it is reasonable to expect that the transitions from routine occupations differ between these two distinct categories.

Identifying and measuring occupation groups appropriately for historical analysis can be difficult for two main reasons. First, there have been revisions in occupational classifications during the 1970-2015 period, so mapping earlier versions to the ISCO-08 might affect the results even when we use the crosswalk codes constructed by Statistics Finland. A further examination of how well the mapping works is therefore performed by analyzing the trends in occupation shares over time. The results show that the harmonized occupation variable works well, apart from some comparability problems that arise for 1990.[6] In what follows, several sensitivity

[5] A small exception to the original classification is the inclusion of teachers in the sample. This is meaningful, as our paper considers all wage-earners from both the private and public sector. The results nevertheless remain the same when the initial occupation group classification is used.

[6] According to the data, some occupations were defined as abstract jobs in 1985 but as service jobs in 1990. For example, most of the workers who were defined as social workers and counseling

checks are performed by excluding the problematic year from the analyses. All the conclusions drawn from the analyses nevertheless remain the same. The second potential challenge is that the tasks within a specific occupation might have changed over the 45-year period. However, Cortes et al. (2017) examine disappearing routine jobs using data from five decades, as we do in this paper, and similarly categorized the occupations based on task content (cf. Acemoglu and Autor 2011). We thus argue that using these task measures might not be problematic for historical analysis, especially when broadly defined occupation categories are used in the analysis.

3. Aggregate-Level Evidence

3.1.Job Market Polarization

Figure 1 shows the aggregate-level trend in occupational restructuring between 1970 and 2015. The 3-digit occupations are first ranked based on their 1970 mean annual earnings, and smoothed changes in employment shares are examined across those occupations. The smoothed changes are created using the nonparametric LOWESS method, i.e., locally weighted scatterplot smoothing. The analysis is performed using all wage earners who have an occupation code in the data and positive annual earnings, and they could work in the private or public sector. The changes in employment shares by initial earnings levels between 1970 and 2015 resemble the U-shaped curve documented in many other countries and in Finland (e.g., Böckerman et al. 2019, Kerr et al. 2020).

An alternative way to characterize the polarization of job distribution is to depict the employment shares across the four main occupation groups and to examine the

professionals in 1985 were defined as childcare workers or helpers in offices in 1990.

changes in employment shares from 1970 to 2015.[7] Figure 2 shows a clear and increasing share of employees in the high-skilled abstract group, while at the same time, the share of mid-skilled routine manual group has decreased over time. The share of abstract workers was 17 % in 1970, and it increased to 39 % by the end of 2015. In contrast, the share of routine manual workers was 47 % in 1970, but it decreased to 21 % in 2015. The share of routine manual workers was quite stable between 1995-2000, which was the period of recovery after the deep recession that hit the Finnish labor market in the early 1990s.[8] Employment increased rapidly after 1994, especially in the electronics and construction industries. The employment share of routine cognitive workers was approximately 23 % during 1970-1990, after which it decreased steadily to 18 % in 2015. The overall decrease in the employment share of routine workers is thus mostly explained by the reduction in manual, rather than cognitive, tasks. The share of nonroutine manual occupations increased after 1985, showing a clear jump during and after the recession in the early 1990s. Approximately 55 % of nonroutine manual jobs are in the public sector, and the ratio of public sector employment to private sector employment typically increases during recessions. There was also rapid recovery in the entire service sector after the recession.

[Figures 1 and 2 in here]

[7] The values for abstract and nonroutine occupations are replaced by their trend values for 1990 because of the difficulties in comparing the occupation data for abstract and nonroutine occupations in 1990 with those from other years, as discussed above.

[8] The unemployment rate increased from 3 % in 1990 to 17 % in 1994, and the growth rate declined dramatically by 6 % in 1991.

3.2.Transition Matrix for Occupational Mobility

Table 1 illustrates the dynamic occupational movements with a matrix that cross-classifies occupations and other labor market statuses at times *t* and *t+5*. Individuals may move between the four main occupation groups (abstract, routine cognitive, routine manual and nonroutine manual) or move to three stages of nonemployment (unemployment or labor force nonparticipation, being a student and retirement). The average occupational movements are reported separately for the periods 1970-1995 (Panel A), 1970-1985 (Panel B), and 1995-2015 (Panel C). In what follows, four important findings stand out. First, total movement has not varied a great deal over the 45-year period. Second, there has consistently been more upward than downward mobility, and this trend has increased over time, especially among routine cognitive workers. Third, the numbers do not reveal any increase in the shifts from routine jobs to lower-paid nonroutine manual jobs, nor to weak labor market attachment. The movements from employment to nonemployment have been quite stable over time in each occupation group. One of the notable exceptions is that a higher share of nonroutine manual workers shifted to weak labor market attachment during the recession years.

Fourth, the pattern of occupational mobility is nevertheless different between routine manual and routine cognitive workers. During the period 1995-2015, routine cognitive workers were more likely to move to abstract occupations than routine manual workers (15 % versus 6 %), whereas routine manual workers were more likely to move to unemployment or out of labor force than routine cognitive workers (11 % versus 8 %).

[Table 1 in here]

3.3.Decomposing the Aggregate Changes

The changes in occupation shares are decomposed into changes that occurred at the intensive margin and those that occurred at the extensive margin. If the transformation from routine to nonroutine occupations occurred at the intensive margin, it means that workers changed their jobs. Conversely, if the transformation occurs at the extensive margin, then routine workers who left the labor market were replaced by workers who entered the labor market into nonroutine occupations. Specifically, a formula proposed by Vainiomäki (1999) is adopted and modified to decompose the aggregate change in occupation share *j* (*j* = abstract, routine cognitive, routine manual, nonroutine manual), ΔS_j, into three components:

$$\Delta S_j = \Delta S_j^C + \frac{L_t^N}{L_t}\left(S_{jt}^N - S_{jt}^C\right) + \frac{L_{t-1}^D}{L_{t-1}}\left(S_{j,t-1}^C - S_{j,t-1}^D\right) \tag{1}$$

Superscript *C* denotes individuals appearing (those who are employed) in both *t-1* and *t*; *N* denotes entrants, i.e., individuals not in the labor market in *t-1* but who entered the labor market by *t*; and *D* denotes exiting persons, i.e., those in the labor market in *t-1* but not in *t*. ΔS_j^C is the change in the employment share of occupation *j* from year *t-1* to *t* within group *C*. $\left(S_{jt}^N - S_{jt}^C\right)$ is the difference in the employment shares of occupation *j* in year *t* between groups *N* and *C*. $\left(S_{j,t-1}^C - S_{j,t-1}^D\right)$ is the difference in employment shares of occupation *j* in year *t-1* between groups *C* and *D*. $\frac{L_t^N}{L_t}$ is the employment share of entrants in year t, and $\frac{L_{t-1}^D}{L_{t-1}}$ is the employment share of exiting individuals in year *t-1*. The first term on the right-hand side of Equation (1) measures the change in the aggregate employment share of occupation *j* that is explained by the intensive margin (within workers). The sum of the second and third terms measures the change in the aggregate employment share of occupation *j* that is explained by the extensive margin (between workers), with the total contribution being decomposed into entry and exit dynamics.

The contribution of the extensive margin can be explained either by aging or weak labor market attachment. The total contribution of the entry dynamics, $\frac{L_t^N}{L_t}\left(S_{jt}^N - S_{jt}^C\right)$, can be further decomposed into two parts: $\frac{L_t^{N,Y}}{L_t}\left(S_{jt}^{N,Y} - S_{jt}^C\right) + \frac{L_t^{N,U_1}}{L_t}\left(S_{jt}^{N,U_1} - S_{jt}^C\right)$. The superscript *Y* denotes individualswho were children (or not even born yet), students or in military service in *t-1* and workers in *t*. U_1 denotes entrants who were unemployed or labor force nonparticipants (excluding retired people and students) in *t-1* but employed in *t.* This term thus captures the inflow from unemployment (or labor force nonparticipation) to employment. Similar reasoning applies to the exit dynamics, $\frac{L_{t-1}^D}{L_{t-1}}\left(S_{j,t-1}^C - S_{j,t-1}^D\right) = \frac{L_{t-1}^{D,O}}{L_{t-1}}\left(S_{j,t-1}^C - S_{j,t-1}^{D,O}\right) + \frac{L_{t-1}^{D,U_2}}{L_{t-1}}\left(S_{j,t-1}^C - S_{j,t-1}^{D,U_2}\right)$. The superscript *O* denotes individuals who were employed in *t-1* but were retired, more than 70 years old or already deceased in *t*.[9] U_2 denotes individuals who were employed in *t-1* but unemployed or out of the labor force in *t*. This term can be considered as capturing the outflow from employment to weak labor market attachment.

The results of the decomposition analysis are presented in Table 2. The results show that both the periods 1970-1995 and 1995-2015 were characterized by occupational polarization. The shares of abstract and nonroutine manual tasks increased, while at the same time, the shares of routine tasks decreased (Panels A and C). These

[9] This group also includes out-migrants, whom we do not observe in the data. According to Statistics Finland, the share of out-migrants in the total employed work force in Finland is approximately 0.5 % annually.

changes were high for abstract (15.8 percentage points) and routine manual (-20.5 percentage points) occupations during 1970-1995. However, the aggregate-level trend in occupational restructuring was much weaker during 1970-1985, which was the period preceding a severe recession in the early 1990s (Panel B). This result is reasonable since during recessions, labor markets typically experience faster polarization (Foote and Ryan 2014).

The decomposition results show that the decrease in mid-level routine occupations with a simultaneous increase in high-level abstract occupations is largely a within-worker phenomenon. This indicates that many routine workers have moved to abstract tasks, while the downward movement of routine workers is weaker, as already illustrated in Table 1. This type of occupational mobility has not varied a great deal over time, except that before 1995, the decrease in the share of routine manual tasks was also explained by the lower entry of those workers into the labor market. We note that occupations with heavy influxes of workers also tend to have many workers moving out. These occupations are typically those that require less formal education, such as service and sales jobs. Therefore, it is possible that some routine workers have also moved to nonroutine manual tasks, and some former nonroutine manual workers have moved to abstract tasks (cf. Table 1).

Interestingly, approximately one-third of the recent decrease in the share of routine manual tasks can be explained by exit dynamics (1.6 percentage points). An increase in the recent employment share of nonroutine manual tasks can be attributed to entries, indicating that the employment share of nonroutine manual occupations is larger among those who enter the labor markets than among people who were already in the labor market in those occupations. The results suggest that most of the changes in occupational restructuring can be explained by typical career progression, along with the combination of exit-entry dynamics, in which some routine manual workers who have left the labor market are replaced by workers who have entered into low-skilled occupations.

Table 3 reports the detailed decomposition results for the contribution of the extensive margin. The results reveal that the increase in the employment share of nonroutine manual occupations is mainly explained by young people entering the labor market (on average, 60 % of the total change at the extensive margin). Population aging explains a substantial part of the overall decrease in the share of routine manual occupations at the extensive margin, although the largest portion of this decrease can be attributed to worker flows from employment to weak labor market attachment for the 1995-2015 period. Evidently, the outflow from employment to unemployment or out of the labor force is more profound among routine manual workers than among routine cognitive workers. The results for abstract workers show important differences in their entry-exit dynamics at the extensive margin over time. The change in the share of abstract workers has a negative coefficient for entry dynamics for the 1995-2014 period but a positive coefficient for the earlier periods. Although people are more highly educated today, the career mobility patterns of young people entering the labor market might have changed over time. In fact, Lyons, Schweitzer and Ng (2015) show that traditional upward, linear career paths are being replaced by a mixture of upward, lateral and downward moves.

[Tables 2 and 3 in here]

4. Regression Analysis and Results

4.1. Empirical Models of Occupational Mobility

To gain deeper insights into the evolution of the occupational mobility of routine workers, a multinomial logit model is applied to study whether routine manual workers in *t* are more or less likely to move between occupations and nonemployment by the end of $t+5$ than routine cognitive workers. In our setting, a routine worker in t can belong to one category from the set {Abstract, Routine cognitive, Routine manual, Nonroutine manual, Unemployed or labor force nonparticipant, Student, Retired} in year $t+5$. The dependent variable, occupational mobility, is denoted by OM_{it+5}. The equation is the following:

$$OM_{it+5} = \alpha RM_{it} + \boldsymbol{\beta}'\boldsymbol{X}_{it} + r_{it} + \tau_t + \varepsilon_{it} \quad (2)$$

where RM_{it} equals one if the person is a routine manual worker in t and zero if the person is a routine cognitive worker. X_{it} is a vector of control variables measured in year t, including indicators for gender, marital status, having underage children, native language, level of education, field of education, age and the square term of age, skill level and the square term of skill level, and indicators for industry (6 categories). Information on the field and level of education is based on the ISCED (International Standard Classification of Education) classification. The level and field of education are measured using 3 and 7 indicators, respectively. Skill level is measured as the worker's gender-specific rank order (1-100) within the wage distribution of his/her most disaggregated occupation category in t. The variable describes how well a person fares relative to other people who work in similar occupations. Skill level is included in the model because occupational mobility is found to be U-shaped (Groes, Kircher and Manovskii 2015). This indicates that both low-ability and high-ability workers within an occupation are more likely to switch jobs than mid-ability workers. The model is accordingly augmented with year indicators and 19 region indicators. The region indicators are based on the NUTS 3-level classification (Nomenclature of Territorial Units for Statistics). The individual-level clustered standard errors are used to take into account the within-correlation over time in the panel.

Workers change occupations for numerous reasons. Some workers are attracted to better pay, better job security or more interesting job tasks. In contrast, other workers need to change jobs because of a lack of employment opportunities in their original field or their job of interest. As the overall pattern of occupational mobility includes both voluntary and involuntary job changes, the results from Equation (1) should be interpreted only as descriptive evidence. The next step is to use involuntary job losses to examine the occupational mobility of routine manual and routine cognitive workers after displacement using linked employer-employee data covering the 1995-2015 period. Plant closures are used to identify exogenous and involuntary separations from voluntary worker outflows. Aside from providing data on all workers and their employers from all industries for three decades, the data offer another advantage since they report the main reason for a person's most recent unemployment spell. This register-based variable is available for 1995-2004, and it includes information about whether a worker lost his/her job involuntarily for financial or production-related reasons.

Building on the earlier literature, displaced workers are defined as those who were separated from their routine jobs after a plant closure (e.g., Addison and Portugal 1989) or for other financial or production-related reasons. We use plants instead of firms to distinguish true plant closures and mass layoffs from firm mergers, outsourcing and other related organizational changes.

The year of displacement is denoted by *b* (the base year). Workers must have also worked in the same private sector plant in the previous year. The pretreatment sample is restricted to full-year (12 employment months) wage-earners who have worked in plants having at least 10 employees. Our subsample of displaced routine workers is thus different from the total sample of all routine workers.

Information on workers' occupations is measured during *b-1*. The first potential base year is 1996, and subsequent labor market status is measured in 2000, when the occupation is observed in the data. As in previous analyses, occupational mobility is examined using 5-year gaps. The next potential base years are 2001 and 2005-2011; the initial occupations are thus measured in 2000 and 2004-2010, and subsequent labor market statuses are measured in 2005 and 2009-2015, respectively. The empirical analysis examines the occupational mobility of routine workers after displacement using the following empirical specification:

$$OM_{ib+4} = \alpha RM_{ib-1} + \boldsymbol{\beta}'\boldsymbol{X}_{ib-1} + r_{ib-1} + \tau_{b+4} + \varepsilon_{ib+4} \qquad (3)$$

The model resembles Equation (2), with the exception that it is estimated for the smaller sample of workers with strong labor market attachment who were separated from their private sector routine occupations.

4.2.Results for Occupational Mobility

The marginal effects of the *RM* indicator from Equation (2) are reported in Table 4. The results are presented separately for the periods 1970-1995 (Panel A), 1970-1985 (Panel B) and 1995-2015 (Panel C). These results should be treated as descriptive, and no causal interpretation should be placed on the estimates. In addition, Panel D reports the results from Equation (3), which includes the subsample of individuals who were separated from their routine jobs due to plant closures or other financial or production-related issues.

The results for the most recent inspection period are discussed first. Consistent with our hypothesis, routine cognitive workers have a higher probability of moving to abstract occupations than routine manual workers, whereas routine manual workers have a higher probability of moving to nonroutine manual occupations (Panel C). Conditional on observed characteristics, routine cognitive workers also have a 0.3 percentage-point higher probability of acquiring further education. Although routine cognitive workers have a higher probability of moving up the job hierarchy, they are also more likely to become unemployed or labor force nonparticipants than routine manual workers. When these marginal effects are compared to those obtained using earlier time periods, one important finding stands out. The occupational mobility between routine manual and routine cognitive workers was quite similar across the entire period from 1970 to 2015. The only difference is that routine manual workers were less likely to move to nonroutine manual occupations than routine cognitive workers during 1970-1985 (Panel B). Finally, the results in Panel D offer a causal interpretation of the occupational trajectories of workers who had lost their routine jobs due to plausibly involuntary reasons. Even for this smaller subsample, the results provide similar trajectories into different occupation groups or into nonemployment statuses for routine manual and routine cognitive workers.

The marginal effects for the background variables are provided in Table A1 of the Appendix. The results are highly similar for each time period and specification, although not all the estimates are statistically significant due to the smaller sample size in Panel D. Therefore, only the results for the sample of all routine workers for the most recent period of 1995-2015 are presented. Overall, the estimates correspond to our expectations well. Both general and specific human capital are related to occupational movements. More highly educated individuals have a higher probability of moving to abstract occupations. Less-skilled individuals have, in turn, a higher probability of moving to nonroutine manual occupations or ending up unemployed or out of the labor force. The direction of occupational mobility is also strongly related to workers' education fields. Routine task workers who have educations in the general, technical or natural sciences have a higher probability of moving up the job hierarchy. Worker education in services is, in contrast, related to downward mobility toward nonroutine manual tasks. Health education is related to both the upward (such as nursing professionals) and downward (such as health care assistants) movements of routine workers. These results are in line with the findings for the subsample that includes involuntary job changes.

Younger individuals have a higher probability of moving up the job hierarchy, and women have weaker labor market prospects than men in general. Married individuals and those who have children generally have a higher probability of remaining employed. Being married and a parent could increase incentives to search for better labor market prospects to provide a living for one's family. For example, DeLeire and Levy (2004) and Grazier and Sloane (2008) used family structure as a proxy variable for preferences for risky jobs and found that parents specifically were more likely to make occupational choices that sorted them into safer jobs. Routine manufacturing and construction workers have a higher probability of becoming nonworkers, while routine workers in high-paying service industries or public-sector industries (e.g., health and education) are more likely to move to abstract tasks.

4.3.Extensions: Adjustments at the Intensive Margin

The results suggest that routine cognitive workers are more likely to move to abstract tasks and acquire further education than routine manual workers. On the other hand, they also have a higher probability of becoming unemployed. The net effect of the labor market adjustments of routine manual and routine cognitive workers is thus unclear. As an extension, we look at employment recovery from external shocks at the intensive margin. To this end, the effect of an exogenous job loss on the subsequent earnings of routine workers is examined by utilizing the information on job separation from the previous section. The original job in *b-1* is either routine cognitive or routine manual. The base year is *b*, when a worker is potentially displaced, and workers' subsequent earnings are measured five years after predisplacement year. We use full-year routine workers who are attached to plants with at least 10 employees as the control group, and workers must have worked in these same plants one year before the base year and must not have been displaced from their work in *b*. The empirical specification is as follows:

$$\log(w)_{ib+4} = \alpha D_{ib} + \gamma RM_{ib-1} + (\delta D_{ib} \text{ x } RM_{ib-1}) + \boldsymbol{\beta}'\boldsymbol{X}_{ib-1} + r_{ib-1} + \tau_{b+4} + \varepsilon_{ib+4}$$

(4)

where the outcome is the log of annual earnings in *b+4*, and D_{ib} is an indicator variable that gets a value of one if person *i* was displaced in year *b* and zero otherwise. RM_{ib-1} is an indicator variable indicating whether the predisplacement job was routine manual and is set to zero for routine cognitive jobs. As before, X_{ib-1} is a vector of predisplacement control variables. The wage costs of involuntary job loss for routine manual and routine cognitive workers are compared by including an interaction term between D_{ib} and RM_{ib-1} in the model. The wage equation accordingly includes predisplacement region indicators and time indicators. The model is estimated by ordinary least squares, and standard errors are clustered at the individual level. Earnings are deflated to 2015 prices using the cost-of-living index. A value of one is added to the earnings data before taking the logarithms; thus, zero earnings are included. The treatment is considered to be independent of potential earnings, conditional on the observed covariates.

Table A2 in the Appendix reports the covariate balance test results for the pretreatment variables, along with the t-tests highlighting the significant differences between the two groups. We find that workers who worked in plants that closed down within one year earned approximately 220 euros (or 0.7 %) less annually than their nondisplaced counterparts. Individuals had completed approximately the same level of education in both groups, and they were 40-41 years old on average. The table provides evidence for the validity of the research design by showing that the differences between the displaced and nondisplaced workers are small in terms of key individual characteristics and that the significant t-values are driven by the large sample sizes rather than large absolute differences between the groups.

Table 5 provides the results. The results show that involuntary job loss affects earnings negatively four years after displacement. The average effect is -28 %. The magnitude of this wage cost is in line with the results of other studies reported in Finland (Korkeamäki and Kyyrä, 2014; Verho, 2020). For example, Korkeamäki and Kyyrä (2014) analyze the effect of plant closures on the earnings distribution and find that at the 5th and 6th deciles, the negative effect four years later is 1-25 % for males and 10-36 % for females. Workers displaced during a recession period are subject to larger earnings losses (cf. Verho, 2020). Our results further demonstrate an uneven adjustment pattern, with the greatest costs of adjustment being borne by routine manual workers. In particular, workers separated from their routine manual jobs earn approximately 15 % less four years later than their otherwise similar displaced routine cognitive counterparts.

5. Summary and Conclusions

Although job polarization of the labor market has been well documented in the burgeoning literature, we still know very little about the implications of job polarization at the individual level. Using employer-employee data matched with population censuses that include all wage earners from all industries, this paper has the advantage of studying occupational polarization and the occupational mobility of workers from declining routine occupations over a 45-year period. According to the data, the Finnish labor market has experienced a long-lasting change in its occupational distribution, characterized by an increase in the shares of high-skilled and low-skilled nonroutine tasks and a decrease in the share of routine tasks. Long-term evidence of polarization has also been reported for the US labor market (Cortes et al. 2017, Bárány and Siegel 2018).

Using a decomposition analysis, we find that the "right-hand side" of job market polarization is largely a within-worker phenomenon, indicating that routine workers have moved to abstract tasks. A small proportion of the most recent decline in routine manual occupations has also occurred at the extensive margin, with some routine manual workers exiting the labor market and becoming weakly attached to the labor market. Conversely, the "left-hand side" of job market polarization is explained by entry-exit dynamics, in which people who have exited the labor market have been replaced by younger people who have mainly entered into low-skilled service occupations.

Although there has been more upward than downward mobility, distinct differences between routine manual and routine cognitive worker groups remain. Based on descriptive empirical evidence, the direction of the occupational mobility is linked to the specific skill and task compositions of workers. As hypothesized, routine cognitive workers are more likely to move up the job hierarchy, while routine manual workers are more likely to move to low-skilled nonroutine manual occupations. However, routine cognitive workers are more likely to become unemployed or to exit the labor force. These results are robust to the use of a smaller sample of displaced workers who need to find new work for plausibly exogenous reasons. Our additional analyses reveal that routine cognitive workers are generally more able to adjust with smaller employment disruptions at the intensive margin, as the wage costs of their job losses are 15 % lower a few years after displacement than those of routine manual workers.

Loosely related to this study, Nilsson Hakkala and Huttunen (2016) examine the effects of Chinese import competition and offshoring on employment by utilizing the same matched employer-employee panel data as used in the current paper. They find that importing increases the risk of unemployment, particularly among production workers (see also Autor et al. 2014), in the manufacturing industry. Autor et al. (2013) show that importing decreases the demand for both routine manual and routine cognitive workers in the US. Our results can also be contrasted with those of Gathmann and Schönberg (2010), who propose the concept of task-specific human capital to analyze the mobility of skills across occupations. They find that workers typically move to occupations with task requirements similar to those of their original job. Related to this finding, upward occupational mobility is largely related to the specific skills of a worker, such as having an education in the technical and natural sciences or health fields (cf. Keller and Utar 2016, Utar 2018).

The policy lessons from this exercise are threefold. First, the increase in the share of high-level abstract tasks ("good jobs") is largely explained by former routine workers being able to move up the job hierarchy. This upward mobility is closely linked to better general human capital, as well as to having specific skills relevant to the new work.

Conversely, low-level service tasks ("bad jobs") are created by young people who enter the labor market. Given that new technologies and globalization could replace labor on a greater scale, education policy could more readily respond to these changes by, for example, increasing available places for fields that will be in higher demand in the future. Second, the results from the decomposition analysis show that routine task workers in Finland have been able to adjust with relatively small employment disruptions. More work is still needed to fully understand whether this pattern in the occupational mobility of routine workers is explained by a relatively high education level in Finland, or a well-functioning active labor market or education policies and whether we could find similar decomposition results for other Nordic countries or countries with more distinct labor market institutions.

Third, the focus of our concern should be routine manual workers who are generally more injured by polarization. Public labor market policies could support routine manual workers in obtaining training, or other labor market policy measures that would improve their re-employment opportunities could be implemented. Comparing worker-level and firm-level decomposition analyses provides some interesting details. Kerr et al. (2020) and Böckerman et al. (2019) use the matched employer-employee data from Finland and find that the increase in abstract occupations with a decrease in routine occupations is mainly a within-firm phenomenon. In contrast, low-skill service occupations have largely increased due to entry dynamics, indicating that entering firms have a much higher concentration of service jobs than existing firms. Therefore, one way to manage occupational mobility is to more closely link former routine manual workers to good abstract occupations, for example, through apprenticeships within existing firms. Such work-to-work training within firms would not necessarily be beneficial if the direction of the shift were aimed at service occupations because such jobs are not necessarily available in these firms. Work-to-work training within firms should therefore target upward mobility, which could be challenging since the original task composition of routine manual workers' jobs does not necessarily match the skills required in new abstract jobs.

References

Acemoglu, D. and Autor, D. 2011. Chapter 12 – Skills, tasks and technologies: implications for employment and earnings. Volume 4, pp. 1043-1171. Elsevier.

Addison, J.T. and Portugal, P. 1989. "Job Displacement, Relative Wage Changes, and Duration of Unemployment." Journal of Labor Economics 7, 281-302.

Akst, D. 2013. What Can We Learn from Past Anxiety over Automation? The Wilson Quarterly, Summer.

Autor, D. 2015. "Why Are There Still So Many Jobs? The History and Future of Workplace Automation." Journal of Economic Perspectives 29, 3-30.

Autor, D. and Dorn, D. 2013. "The Growth of Low-skill Service Jobs and the Polarization of the US Labor Market." American Economic Review 103, 1553-1597.

Autor, D., Dorn, D., and Hanson, G. 2013. "The China Syndrome: Local Labor Market Effects of Import Competition in the United States." American Economic Review, 103, 2121-2168.

Autor, D., Dorn, D., Hanson, G., and Song, J. 2014. "Trade Adjustment: Worker-level Evidence." The Quartely Journal of Economics, 129, 1799-1860.

Autor, D., Levy, F., Murnane, R.J. 2003. "The Skill Content of Recent Technological Change: An Empirical Exploration." The Quartely Journal of Economics, 118, 1279-1333. 32

Bárány, Z. and Siegel, C. 2018. "Job polarization and Structural Change". American Economic Journal: Macroeconomics 10, 57-89.

Brynjolfsson, E. and McAfee, A. 2014. The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies. W. W. Norton & Company.

Böckerman P, Laaksonen S. and Vainionmäki J. 2013. “Is There Job Polarization at the Firm level?” Tampere Economic Working Papers 91.

Böckerman P, Laaksonen S. and Vainionmäki J. 2019. “Does ICT Usage Erode Routine Occupations at the Firm Level?” Labour 33, 26-47.

Cortes, G. 2016. “Where Have the Middle-wage Workers Gone? A Study of Polarization Using Panel Data.” Journal of Labor Economics, 34, 63-105.

Cortes, G., Jaimovich, N. and Siu, H. (2017). “Disappearing Routine Jobs: Who, How, and Why?” Journal of Monetary Economics 91, 69-87.

Cortes G.M. and A. Salvatori. 2015. Task Specialization within Establishments and the Decline of Routine Employment. Mimeo.

DeLeire, T. and Levy, H. 2004. “Worker Sorting and the Risk of Death on the Job.” Journal of Labor Economics, Vol. 22 No. 4, pp. 210-217.

Donoso, Vicente, Victor Martin, and Asier Minondo. 2015. “Does Competition from China Raise the Probability of Becoming Unemployed? An Analysis Using Spanish Workers’ Micro-Data.” Social Indicators Research 120(2): 373–394. F

Foote, C. and Ryan, R. (2014). “Labor-Market Polarization over the Business Cycle.” NBER Macroeconomics annual 29, 371-413.

Gathmann, C. and Schönberg, U. 2010. “How General is Human Capital? A Task based Approach.” Journal of Labor Economics 28, 1-49. 33

Goos, M. and Manning, A. 2007. “Lousy and Lovely Jobs: The Rising Polarization of Work in Britain.” Review of Economics and Statistics, 89, 118-133.

Goos, M., Manning, A. and Salomons, A. 2014. “Explaining Job Polarization: Routinebiased Technological Change and Offshoring." American Economic Review, 104, 2509-2526.

Grazier, S. and Sloane, P. 2008. "Accident Risk, Gender, Family Status and Occupational Choice in the UK." Labour Economics, Vol. 15 No. 5, pp. 938- 957.

Groes, F., Kircher, P., and Manovskii, I. 2015. "The U-shapes of Occupational Mobility." Review of Economic Studies 82, 659-692.

Harrigan J., A. Reshef and F. Toubal 2016. "The March of the Techies: Technology, Trade, and Job Polarization in France, 1994-2007." NBER Working Paper 22110.

Heyman, H. 2016. "Job Polarization, Job Tasks and the Role of Firms." Economic Letters 145, 246-251.

Keller, W., and Utar, H. 2016. "International Trade and Job Polarization: Evidence at the Worker Level." NBER Working Paper 22315.

Kerr, S., Maczulskij, T., and Maliranta, M. 2019. "Within and Between Firm Trends in Job Polarization: The Roles of Globalization and Technology". Journal of Economic Geography 20, 1003-1039.

Korkeamäki, O. and Kyyrä, T. 2014. "A Distributional Analysis of Earnings Losses of Displaced Workers in an Economic Depression and Recovery." Oxford Bulletin of Economics and Statistics 76, 565-588.

Lyons, S., Schweitzer, L. and Ng, E. (2015). "How Have Careers Changed? An Investigation of Changing Career Patterns Across Four Generations." Journal of Managerial Psychology 30, 8-21.

Moreno-Galbis, E. and Sopraseuth, T. 2014. "Job Polarization in Aging Economies." Labour Economics 27, 44-55.

Nilsson Hakkala, K., and Huttunen, K. 2016. "Worker-level Consequences of Import Shocks." IZA discussion papers No. 10033.

Robinson, C. 2018. "Occupational Mobility, Occupation Distance, and Specific Human Capital." Journal of Human resources 53, 513-551.

Utar, H. 2018. "Workers Beneath the Floodgates: Low-Wage Import Competition and Workers' Adjustment." Review of Economics and Statistics 100.

Vainiomäki, J. 1999. Technology and Skill Upgrading: Results from Linked Workerplant Data for Finnish Manufacturing. In: Haltiwanger, J., Lane, J., Spletzer, J.R., Theuwes, J.J.M., and Troske, K.R (Eds.). The creation and analysis of employer-employee matched data. Elsevier Science, North-Holland, Amsterdam; New York and Oxford, pp. 115-145.

Verho, J. 2020. "Economic Crises and Unemployment Persistence: Analysis of Job Losses During the Finnish Recession of the 1990s." Economica 87, 190-216.

Tables and figures

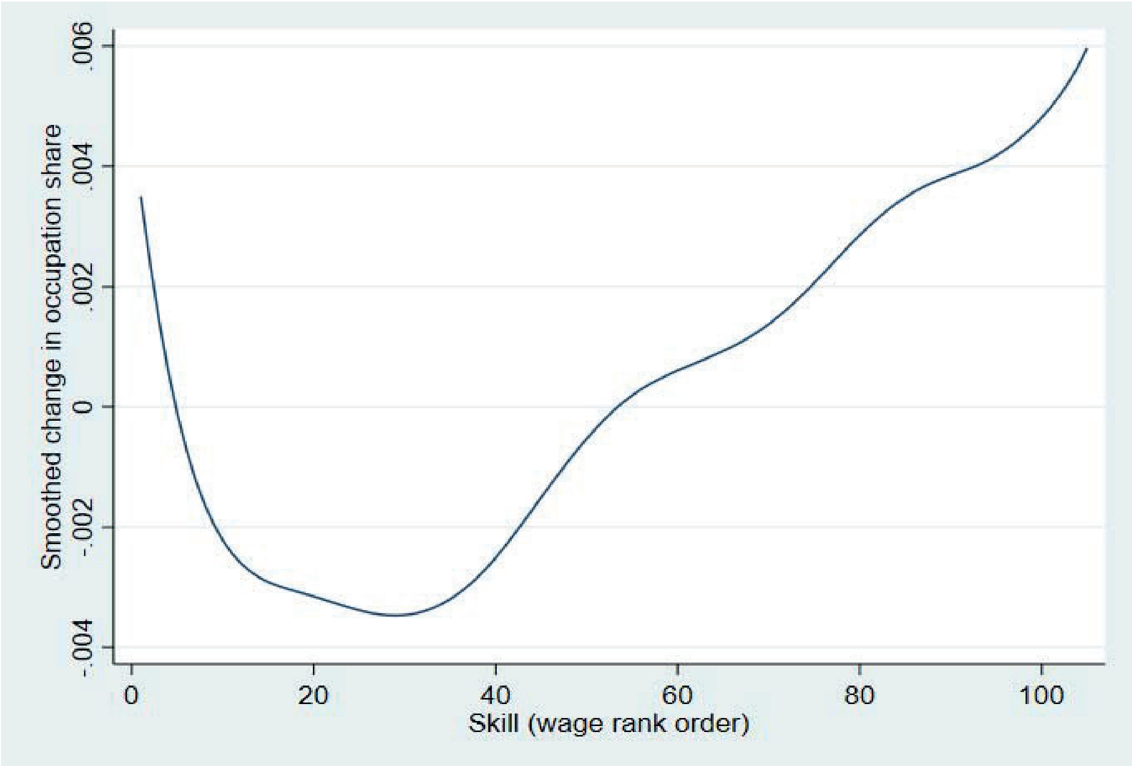

Figure 1: Smoothed change in employment share across the skill distribution between 1970 and 2015

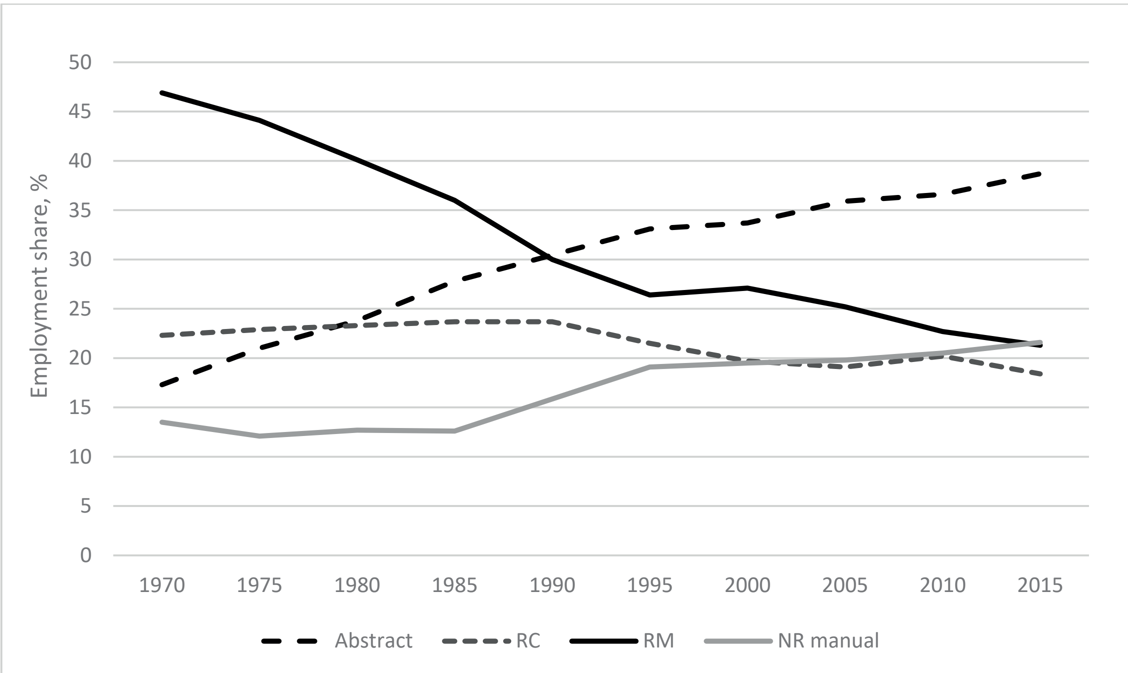

Figure 2: Employment share by occupation group over the period 1970-2015

Table 1: Transition matrix for average occupational mobility with 5-year gaps

		Year t+5						
		Abstract	RC	RM	NR manual	Unemp/LFN	Student	Retired
Panel A: 1970-1995								
	Abstract	72 %	7 %	3 %	3 %	6 %	1 %	8 %
Year t	RC	9 %	66 %	4 %	3 %	9 %	2 %	7 %
	RM	4 %	3 %	68 %	3 %	10 %	1 %	10 %
	NR manual	5 %	7 %	7 %	53 %	14 %	3 %	11 %
		Abstract	RC	RM	NR manual	Unemp/LFN	Student	Retired
Panel B: 1970-1985								
	Abstract	76 %	7 %	3 %	2 %	4 %	1 %	7 %
Year t	RC	8 %	68 %	5 %	3 %	8 %	1 %	7 %
	RM	4 %	3 %	71 %	3 %	8 %	1 %	10 %
	NR manual	5 %	8 %	10 %	52 %	11 %	2 %	12 %
		Abstract	RC	RM	NR manual	Unemp/LFN	Student	Retired
Panel C: 1995-2015								
	Abstract	77 %	5 %	2 %	2 %	5 %	1 %	8 %
Year t	RC	15 %	59 %	3 %	4 %	8 %	2 %	9 %
	RM	6 %	3 %	66 %	3 %	11 %	2 %	9 %
	NR manual	7 %	5 %	3 %	63 %	9 %	3 %	10 %

Notes: RC = routine cognitive; RM = routine manual; NR manual = nonroutine manual

Table 2: Decomposition of change in employment shares by occupation group (percentage points)

Panel A: 1970-1995	Δ Emp. share	Intensive margin	Extensive margin	Entry	Exit
Abstract	15.8	10.8	5.0	2.9	2.1
Routine cognitive	-0.8	-4.1	3.3	-1.6	4.9
Routine manual	-20.5	-9.3	-11.2	-4.3	-6.9
NR manual	5.5	2.6	2.9	3.0	-0.1
Panel B: 1970-1985					
Abstract	10.5	7.6	2.9	0.2	2.7
Routine cognitive	1.3	-1.5	2.8	0.0	2.8
Routine manual	-10.9	-5.1	-5.8	-2.6	-3.2
NR manual	-0.9	-1.0	0.1	2.4	-2.3
Panel B: 1995-2015					
Abstract	5.3	8.7	-3.4	-3.8	0.4
Routine cognitive	-3.0	-3.7	0.7	-0.4	1.1
Routine manual	-5.2	-4.2	-0.9	0.7	-1.6
NR manual	2.9	-0.8	3.6	3.5	0.1

Notes: Total change in employment share = Intensive margin + Extensive margin. Extensive margin = Entry + Exit. NR manual = nonroutine manual.

Table 3: Decomposition of the contribution of the extensive margin

Occupation group	Total extensive margin	Entry: Young people enter emp.	Entry: From UE/LFN to emp.	Exit: From emp. to retirement	Exit: From emp. to UE/LFN
Panel A: 1970-1995					
Abstract	5.0	3.7	-0.8	1.2	0.9
Routine cognitive	3.3	-1.7	0.1	4.6	0.3
Routine manual	-11.2	-3.8	-0.5	-5.7	-1.2
NR manual	2.9	1.8	1.2	-0.1	0.0
Panel B: 1970-1985					
Abstract	2.9	0.8	-0.6	2.1	0.6
Routine cognitive	2.8	-0.3	0.3	2.7	0.1
Routine manual	-5.8	-2.1	-0.5	-2.9	-0.3
NR manual	0.1	1.6	0.8	-1.9	-0.4
Panel C: 1995-2015					
Abstract	-3.4	-2.2	-1.6	-0.3	0.7
Routine cognitive	0.7	-0.3	-0.1	1.0	0.1
Routine manual	-0.9	0.4	0.3	-0.6	-1.0
NR manual	3.6	2.1	1.4	-0.1	0.2

Notes: The total extensive margin component is divided into entry components (young people entering employment or unemployed people (or LFN) entering employment) and exit components (exit to retirement or exit to unemployment (or LFN)).

Table 4: Multilevel logit estimates (marginal effects) of main activity in year *t* +5

	Abstract	RC	RM	Nonroutine manual	Unemp/ LFN	Student	Retired
Panel A: 1970-1995							
Routine manual	-0.026 ***	-0.282 ***	0.328 ***	0.000	-0.011 ***	-0.003 ***	-0.006 ***
	(0.0003)	(0.0003)	(0.0005)	(0.0002)	(0.0003)	(0.0001)	(0.0003)
Panel B: 1970-1985							
Routine manual	-0.031 ***	-0.276 ***	0.330 ***	-0.005 ***	-0.006 ***	-0.004 ***	-0.008 ***
	(0.0003)	(0.0004)	(0.0006)	(0.0002)	(0.0004)	(0.0002)	(0.0004)
Panel C: 1995-2015							
Routine manual	-0.021 ***	-0.256 ***	0.303 ***	0.007 ***	-0.027 ***	-0.002 ***	-0.003 ***
	(0.0004)	(0.0006)	(0.0006)	(0.0002)	(0.0004)	(0.0002)	(0.0003)
Panel D: 1995-2015, displaced workers							
Routine manual	-0.054 ***	-0.194 ***	0.293 ***	0.006 **	-0.037 ***	-0.005 ***	-0.008 ***
	(0.0037)	(0.0041)	(0.0055)	(0.0022)	(0.0043)	(0.0017)	(0.0024)

Notes: Reference category is routine cognitive workers. Other controls include age squared, skill-level squared, gender, education level, education field, marital status, an indicator for having underage children, native language, and industry, region and year indicators. *** $p < 0.01$, and ** $p < 0.05$. N = 4,585,519 (Panel A), N = 2,691,580 (Panel B), N = 3,079,939 (Panel C), and N = 52,107 (Panel D).

Table 5: The effect of job loss on earnings in *b+4*

	Log(annual earnings)
Displacement	-0.232 ***
	(0.0209)
RM	-0.107 ***
	(0.0066)
RM # Displacement	-0.151 ***
	(0.0278)
Main effect of Displacement	-28.3 %
Other controls	Yes
Adj. R^2	0.21
Number of obs.	2,256,294

Notes: The initial sample consists of routine cognitive and routine manual workers. Other controls include age and age squared, skill and skill squared, gender, education level, education field, marital status, an indicator for having underage children, native language and industry, region and year indicators. *** $p < 0.01$.

Appendix

Table A1: Multilevel logit estimates (marginal effects) of main activity in *b*+5

	Abstract	RC	RM	NR manual	Unemp/LFN	Student	Retired
Routine manual	-0.021 ***	-0.256 ***	0.302 ***	0.007 ***	-0.027 ***	-0.002 ***	-0.003 ***
	(0.0004)	(0.0006)	(0.0006)	(0.0002)	(0.0004)	(0.0002)	(0.0003)
Skill	-0.002 ***	0.003 ***	0.004 ***	-0.0005 ***	-0.003 ***	-0.001 ***	-0.001 ***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$Skill^2/100$	0.003 ***	-0.003 ***	-0.003 ***	0.000 ***	0.001 ***	0.000 ***	0.001 ***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Age	-0.003 ***	0.013 ***	0.011 ***	-0.001 ***	0.004 ***	-0.003 ***	-0.021 ***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$Age^2/100$	-0.000 ***	-0.017 ***	-0.017 ***	0.000 ***	-0.002 ***	0.002 ***	0.034 ***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Female	-0.027 ***	0.065 ***	-0.095 ***	0.025 ***	0.029 ***	0.008 ***	-0.005 ***
	(0.0004)	(0.0005)	(0.0005)	(0.0003)	(0.0004)	(0.0002)	(0.0003)
Married	0.012 ***	0.009 ***	0.006 ***	0.001 ***	-0.027 ***	-0.003 ***	0.001 ***
	(0.0004)	(0.0004)	(0.0004)	(0.0002)	(0.0004)	(0.0002)	(0.0003)
Children	-0.005 ***	0.005 ***	0.001 **	0.004 ***	-0.009 ***	0.004 ***	-0.000
	(0.0003)	(0.0004)	(0.0004)	(0.0002)	(0.0004)	(0.0002)	(0.0003)
Finnish	0.006 ***	0.005 ***	-0.010 ***	-0.004 ***	-0.012 ***	0.001 ***	0.013 ***
	(0.0007)	(0.0008)	(0.0009)	(0.0004)	(0.0008)	(0.0004)	(0.0005)
Education level							
Secondary	0.032 ***	-0.025 ***	0.018 ***	-0.002 ***	-0.013 ***	-0.002 ***	-0.008 ***
	(0.0013)	(0.0018)	(0.0013)	(0.0008)	(0.0012)	(0.0007)	(0.0009)
Higher	0.135 ***	-0.024 ***	-0.076 ***	-0.017 ***	-0.013 ***	-0.0003	-0.004 ***
	(0.0014)	(0.0018)	(0.0015)	(0.0009)	(0.0013)	(0.0007)	(0.0010)
Education field							
General	0.077 ***	0.025 ***	-0.097 ***	-0.003 ***	-0.015 ***	0.012 ***	-0.0004
	(0.0013)	(0.0018)	(0.0015)	(0.0008)	(0.0013)	(0.0007)	(0.0011)
Educ., hum. and arts	0.026 ***	-0.018 ***	-0.030 ***	0.001	0.021 ***	0.005 ***	-0.005 ***
	(0.0016)	(0.0022)	(0.0022)	(0.0011)	(0.0017)	(0.0008)	(0.0016)

Table A1: Continued. Multilevel logit estimates (marginal effects) of main activity in *b+5*

	Abstract	RC	RM	NR manual	Unemp/LFN	Student	Retired
Business and soc. sciences	-0.027 ***	0.068 ***	-0.039 ***	-0.013 ***	0.005 ***	-0.002 ***	0.008 ***
	(0.0013)	(0.0018)	(0.0015)	(0.0009)	(0.0013)	(0.0007)	(0.0010)
Technical and nat. sciences	0.012 ***	-0.012 ***	0.001	-0.002 ***	-0.002	-0.002 **	0.004 ***
	(0.0013)	(0.0018)	(0.0013)	(0.0008)	(0.0012)	(0.0007)	(0.0009)
Health	0.020 ***	-0.004 *	-0.046 ***	0.038 ***	-0.012 ***	-0.002 **	0.005 ***
	(0.0017)	(0.0021)	(0.0025)	(0.0009)	(0.0020)	(0.0010)	(0.0014)
Services	-0.044 ***	0.026 ***	-0.005 ***	0.020 ***	-0.009 ***	-0.001 *	0.013 ***
	(0.0015)	(0.0018)	(0.0015)	(0.0008)	(0.0013)	(0.007)	(0.0011)
Industry							
Manufacturing	0.006 ***	-0.053 ***	0.043 ***	-0.020 ***	0.010 ***	0.004 ***	0.009 ***
	(0.0008)	(0.0010)	(0.0009)	(0.0005)	(0.0007)	(0.0004)	(0.0005)
Construction	-0.006 **	-0.043 ***	0.013 ***	-0.017 ***	0.038 ***	0.002 ***	0.012 ***
	(0.0010)	(0.0014)	(0.0010)	(0.0006)	(0.0108)	(0.0004)	(0.0006)
Services	-0.014 ***	0.020 ***	0.015 ***	-0.008 ***	-0.012 ***	-0.003 ***	0.002 ***
	(0.0007)	(0.0008)	(0.0009)	(0.0004)	(0.0007)	(0.0003)	(0.0005)
Finance, real estate and professional services	0.022 ***	0.022 ***	-0.056 ***	-0.005 ***	0.003 ***	-0.001	0.015 ***
	(0.0008)	(0.0009)	(0.0013)	(0.0005)	(0.0009)	(0.0004)	(0.0006)
Education, health and public sector activities	0.003 ***	0.070 ***	-0.059 ***	0.001	-0.029 ***	-0.003 ***	0.017 ***
	(0.0009)	(0.0009)	(0.0014)	(0.0005)	(0.0010)	(0.0004)	(0.0005)
Region indicators	Yes						
Year indicators	Yes						
Number of observations	3,079,939						

Notes: The outcome variable is measured in *b+5,* and the independent variables are measured in *b*. Reference categories for the categorical variables are Primary education, Other education fields (forestry, unknown or no education field), and Other industries (mining, electricity, water supply, agriculture, personal activities). *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

Table A2: Balance check for the pretreatment variables of routine workers

	Displaced workers	Nondisplaced workers	t-test
Annual wages (b-1)	€33,626	€33,840	2.81 ***
Wage rank order (b-1)	60.0	61.1	7.31 ***
Age (b-1)	39.2	40.7	23.66 ***
Primary education (b-1)	0.21	0.23	5.34 ***
Secondary education (b-1)	0.58	0.59	5.45 ***
Tertiary education (b-1)	0.21	0.18	12.06 ***
Female (b-1)	0.37	0.37	3.33 ***
N of obs.	32,326	2,223,968	

Notes: t-test statistics are for equal sample means between displaced and nondisplaced workers. *** $p < 0.01$.

ETLA

Elinkeinoelämän tutkimuslaitos

ETLA Economic Research

ISSN-L 2323-2420
ISSN 2323-2420 (print)
ISSN 2323-2439 (pdf)

Publisher: Taloustieto Oy

Tel. +358-9-609 900
www.etla.fi
firstname.lastname@etla.fi

Arkadiankatu 23 B
FIN-00100 Helsinki