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Occupational Mobility of Routine Workers*

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Abstract

This paper analyzes occupational polarization within and across workers, as well as the occupational mobility of routine workers, using comprehensive data from Finland. As in most industrialized countries, job markets have polarized over the last few decades. Decomposition analysis shows that the upper tail of occupational polarization is largely a with-workers phenomenon, indicating that workers have moved to abstracts tasks. In contrast, the share of low-level service tasks increases largely through entry dynamics. The direction of occupational mobility is nevertheless linked with the task content in origin jobs. Conditional on observed general and specific human capital, routine cognitive workers are more likely to move up in the hierarchy, while routine manual workers are more likely to move to low-skilled service occupations. Data on plant closures and mass lay-offs are also used to identify involuntary separations from routine occupations. These results demonstrate similar strong uneven adjustment pattern, with routine cognitive workers being more able to adjust with smaller employment disruptions and wage costs.

JEL: J23, J62

Keywords: job market polarization, routine manual, routine cognitive, occupational mobility, displacement

Tiivistelmä

Tutkimuksessa tarkastellaan ammattirakenteiden polarisaatiota sekä työntekijöiden ammatin vaihdon näkökulmasta että työntekijärakenteiden muutoksen välityksellä. Lisäksi tutkimuksessa tarkastellaan sitä mihin supistuvissa ja rutiininomaisissa ammateissa olevat työntekijät päätyvät. Aineistona käytetään Suomen yritys-työntekijäaineistoa vuosille 1990-2014, ja lisäksi väestölaskentatietoja vuosille 1970, 1975, 1980 ja 1985. Kokonaisuudessaan aineisto ulottuu pitkälle aikavälille ja kattaa kaikki Suomen työlliset 45-vuoden ajanjakson ajalta. Ammattirakenteiden polarisaatio on jatkunut Suomessa jo vuosikymmeniä. Keskitason tuotantotehtäviä ja toimistotehtäviä sisältävien ammattien osuus on pienentynyt. Samaan aikaan matalan osaamistason palveluammattien ja korkean osaamistason erityisasiantuntija-ammattien osuus on puolestaan ollut kasvussa. Ammattirakennemuutoksen kehityskulku on pääosin tapahtunut siten, että keskipalkkaiset työntekijät ovat nousseet urapolkuja pitkin asiantuntijatöihin. Viimeaikaista palveluammattien osuutta on puolestaan kasvattanut se, että nuoret siirtyvät työmarkkinoille palvelutöihin. Rutiininomaisia ja kognitiivisia taitoja vaativien ammattien työntekijöillä on kuitenkin suurempi todennäköisyys nousta korkeammille palkkaluokille rutiininomaista ja fyysistä työtä tekeviin työntekijöihin verrattuna. Rutiininomaista ja fyysistä työtä tekevät tippuvat puolestaan suuremmalla todennäköisyydellä matalapalkka-aloille, ja heidän ansiotason kehitys on myös heikompaa.

Avainsanat: työmarkkinoiden polarisaatio, rutiini, ammatillinen liikkuvuus, työttömyys

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1. Introduction

What has happened to mid-skilled production and clerical workers? 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 showed that computer technology advances have decreased the demand for mid-skilled workers performing routine tasks, while the demands 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 occupational mobility of mid-skilled 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 of 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 labor markets from routine occupations are replaced by workers who enter nonroutine occupations. If we assume that the within-worker explanation prevails and that workers performing routine tasks are plausibly involuntarily shifted to low-skilled service occupations, then public resources should be targeted to vulnerable groups by providing, e.g., effective re-education programs. Routine

[1] Some studies have linked the observed polarization of labor markets to other phenomena such as the introduction of ICT, globalization and population ageing (e.g, Van Reenen 2011, Michaels, Natraj and Van Reenen 2014, Autor et al. 2014, Moreno-Galbis and Sopraseuth 2014, Nillson Hakkala and Huttunen 2016, Keller and Utar 2016, Utar 2018, Böckerman, Laaksonen and Vainiomäki 2019).

workers might also move to abstract tasks, for example, through career progression. Forming a comprehensive picture of the specific worker skills that have helped 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 at an even higher scale (e.g., Brynjolfsson and McAfee 2012, Akst 2013).[2]

Let us then assume that the explanation of an extensive margin prevails. Then it would be important to analyze the mechanisms underlying the exit routes from employment to nonemployment. Training subsidies, apprenticeships and other measures of active labor market policies might be more or less effective depending on the sources of exit routes, whether influx to unemployment, labor force nonparticipation or (old age) pensions.

The empirical literature on worker-level adjustment is still quite scarce. The most relevant study to the setting of the current paper is from Cortes (2016), who found that particularly low-ability routine workers in the US have shifted to service occupations, whereas high-ability routine workers have been more likely to move to occupations that involve abstract tasks.[3] Recently, a few papers have focused on a more causal analysis, examining the trade impacts at the level of individual workers

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

[3] Vainiomäki (2018, in Finnish) found similarly that high-skilled routine workers have had a higher probability of moving to abstract tasks, and less-skilled routine workers have been more likely to move to service tasks. Fedorets et al. (2014) found, using data from Germany, that higher routine task input is associated with more occupational changes, and higher manual task input is associated with fewer occupational changes, compared to cognitive task inputs. Asplund, Kauhanen and Vanhala (2015, in Finnish) used the same Finnish register panel data and showed that blue collar workers were more likely to end up in low-paying occupations or become non-workers (unemployed or out of labor force), while office clerks were more likely to move upwards within the skill distribution.

(e.g., Donoso, Martin and Minondo 2010, Autor, Dorn, Hanson and Song 2014, Keller and Utar 2016, Utar 2018). These analyses have been tightly focused around manufacturing industries affected by import competition from China, i.e., the globalization explanation of job market polarization. Utar (2018) used matched employer-employee data from Denmark and found that low-wage competition from China has resulted in significant earnings and employment reductions for Danish manufacturing workers. Many employees have moved to the service sector, and workers' recovery from trade shocks has also grealty depended on their education relevant to the new work (see also, Keller and Utar 2016). Autor et al. (2014) likewise found that employees adjust to import shocks by moving out of the 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, these studies tell us little about the types of occupations or labor market states to which routine workers have shifted.

This paper provides several contributions. First, it examines in detail whether the overall occupational polarization pattern takes place within workers or due to changes in the composition of workers. This type of analysis has been absent from the literature.[4] The study establishes a matched employer-employee data for the 1988-2014 period. To these data I have linked total data from Population Censuses for the

[4] Böckerman, Laaksonen and Vainiomäki (2013, 2018), Cortes and Salvatori (2015), Heyman (2016), Harrigan, Reshef and Toubal (2016), and Pekkala Kerr, Maczulskij and Maliranta (2019) have examined occupational polarization with a focus on the extensive versus intensive margin at the firm level. Cortes, Jaimovich and Siu (2017) examined the changes in the share of routine and non-routine tasks in the US by decomposing the total change into components attributable to changes in the composition of demographic groups and changes in the propensity to enter the occupations, conditional on demographic characteristics.

years 1970, 1975, 1980 and 1985. Together the data create a unique opportunity to evaluate the occupational polarization and track the occupational trajectories of all routine workers over a 45-year inspection period.

While earlier studies have mainly focused on manufacturing workers or routine workers as one occupation group, I distinguish routine manual (such as production, craft and repair) and routine cognitive (such as office, sales and administrative) tasks (see also Cortes et al. 2017). Although routine occupations have 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 pointed out. We already know from the previous literature that origin task or skill composition is related to the direction of occupational movements (Gathman and Schönberg 2010, Robinson 2018). Since routine cognitive occupations involve more analytic and interactive tasks, and routine manual occupations involve more sorting and repetitive assembling tasks, it is reasonable to expect that the transitions from routine occupations differ between these two distinct categories. For example, the hypothesis is that routine cognitive workers are more likely to move to abstract occupations that have more similar (analytical) task requirements.

Overall occupational mobility includes both voluntary and involuntary shifts between jobs. I specifically contribute to the existing literature by also offering a more causal interpretation on the occupational movements of displaced routine task workers. Here, I utilize matched employer-employee data for the entire worker population for the 1995-2014 period. Displaced workers are those who have lost their jobs due to plant closures, mass lay-offs or other financial and production-related reasons.[5]

[5] Typically plant closures and mass lay-offs are used to identify exogenous job loss. The seminal contributions to the literature are Podgursky and Swaim (1987), Addison and Portugal (1989) and

Previous studies have mainly focused on the effects of China import shocks on the labor market outcomes of manufacturing workers. Using job displacement to identify involuntary separations from voluntary worker outflows enables a broader examination of occupational mobility of all routine workers from all industries.

Like most previous studies, I find evidence of U-shaped labor market polarization during the 1995-2014 period. However, job markets started to polarize as far as back as the 1970s, when there was a decrease in routine manual tasks and a similar increase in abstract tasks. The observed trend mostly stems from routine workers moving to abstract tasks, indicating that the "right-hand side" of employment polarization has largely occurred at the intensive margins, although a small fraction of the most recent decrease in routine manual jobs also occurred at the extensive margins. Here, some routine manual workers have exited employment to enter unemployment or labor force nonparticipation. The entry dynamics explains most of the increase in the share of service tasks, when people who have left the labor markets have been replaced by younger people who have entered low-skilled service occupations.

As hypothesized, the regression results show that routine cognitive workers are more likely to move to abstract tasks, while routine manual workers are more likely to move to service tasks. The results remain robust to estimation on a smaller sample of individuals who must find new work for reasons unrelated to voluntary worker flows between jobs: those highly attached routine workers who have been displaced from their work. Routine cognitive workers tend to have a greater probability of re-employment in abstract occupations, and they are more able to adjust with smaller wage costs. Occupational mobility is also linked to both general and specific human

Jacobson, LaLonde and Sullivan (1993), among others, who examined the earnings losses of displaced workers.

capital of workers. More educated and skilled workers have a greater probability of moving to abstract tasks, while less-skilled workers have a greater probability of moving to manual occupations or ending up nonemployed. Accordingly, regardless of education level, workers educated in business, technical or natural science fields are more likely to move up the job hierarchy. In contrast, health education is positively related to both upward and downward mobility.

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 1970-2014 period, as well as the decomposition results related to the intensive and extensive margins of polarization. Section four presents the descriptive empirical evidence for the occupational mobility of routine workers, also based on more causal analysis. Finally, section five places the findings in a larger context and concludes the paper.

2. Data Description

2.1. Data Sources

The main data are the Finnish Longitudinal Employer-Employee Data (FLEED) of Statistics Finland. The data are based on various administrative registers linked together using identification codes for individuals, firms and plants. The FLEED cover all persons younger than 70 years old with permanent residence in Finland for the period of 1988-2014. The data include information on occupation, socioeconomic status, employment and earnings, along with a number of background characteristics. Accordingly, data from population censuses, which include all Finnish persons, for

1970, 1975, 1980 and 1985 are matched with the FLEED. These data are utilized to analyze the historical trends in occupational restructuring from the 1970s onwards.

Information on the occupation of individuals, a key variable for the current paper, is available in each population censuses (1970, 1975, 1980 and 1985) and in FLEED for 1990, 1995, 2000 and 2004-2014. The occupation variable for 1970-1990 is based on the ISCO-58 classification. A new classification was introduced in 1988 (ISCO-88), which is used for the occupation variable for the period of 1995-2009. Finally, the occupation variable for the period of 2000-2014 is based on the newest classification introduced in 2010 (ISCO-08). The occupation measures before 2010 are recoded to match the new classification introduced in 2010 utilizing crosswalk codes constructed by Statistics Finland. The different occupation classifications are thus harmonized across time and should be suitable for long-term analysis. Comparing occupations at a very detailed level could be problematic for historical analysis but less so when more aggregated occupation categories are used.

2.2. Occupation Measures

The ISCO occupations are first classified into three main task groups following Acemoglu and Autor (2011): nonroutine cognitive (abstract), routine and nonroutine manual (service) tasks. The abstract group mostly includes managers, professionals and technical workers; the routine group includes sales, clerical, production and operator work; and services include e.g., cleaning, elementary work, personal care and services (cf. Böckerman et al. 2019).[6] I have further manually distinguished routine

[6] I thank Jari Vainiomäki for the codes in converting Finnish ISCO 2010 classification into groups based on routine content.

manual and routine cognitive tasks (e.g., Autor et al. 2003). Routine occupations that involve analytic and interactive tasks are defined as routine cognitive occupations (such as clerical work). Another group involves picking, sorting or repetitive assembling tasks, and these tasks are included in the group of routine manual occupations (such as craft workers and plant and machine operators).

Identifying and measuring occupation groups appropriately can be difficult for historical analysis for two main reasons. First, there has been revisions in occupation classifications during the 1970-2014 period, so mapping ISCO-58 and ISCO-88 with ISCO-08 might affect the results even when we use the crosswalk codes constructed by Statistics Finland. To this end, I have examined how well the mapping works by examining the employment shares across the four main occupation task groups from 1970 to 2014. The results indicate that the harmonized occupation variable works reasonably well, except that there is a comparability problem with the 1990 occupation variable. According to the data, there were some (illogical) shifts from some abstract tasks to service tasks between 1985 and 1990, and these shifts account together for approximately 160,000 employees, corresponding to 7% of the total employed work force. For example, most of the workers who were defined as social workers and counseling professionals in 1985 were defined as childcare workers or helpers in offices in 1990. The data are comparable again in 1995. In what follows, several sensitivity checks are also performed by excluding 1990 (and 1995) from the analyses.

The second potential challenge is that the tasks within a specific occupation might have changed over the 45-year inspection period. However, Cortes et al. (2017) examined the disappearing routine jobs using data for the 1979-2014 period and categorized similarly the occupations based on task content (Acemoglu and Autor 2011). Although using task measures might not be problematic for historical analysis, I have evaluated the robustness of the various results presented in this paper using alternative measure for occupation groups. The alternative occupation category is defined in the same way as in Goos et al. (2014, Table 1). To be more specific, ISCO 2-digit occupations are first ranked by their mean earnings (in terms of Finnish wages) and then divided into three wage groups (*Low*, *Middle* and *High*). The middle-pay occupation group is then manually distinguished between workers performing cognitive (mostly clerical occupations) and manual (mostly craft and plant operators) tasks. These results are presented and discussed below.

3. Aggregate-level Evidence

3.1. Job Market Polarization

It is interesting to first examine the aggregate level trends in job polarization using descriptive analysis and techniques prevalent in the literature. To begin with, Figure 1 shows the occupational restructuring separately for the periods of 1970-1995 and 1995-2014. Here, the 2-digit occupations are first ranked based on their initial mean wage (annual earnings in 1970 or 1995) and examining the smoothed changes in employment shares (in %-points) across those occupations. The smoothed changes are created using the nonparametric LOWESS method, i.e., locally weighted scatterplot smoothing (see also, Mitrunen 2013). The analysis is performed using all employees (and self-employed people) that have occupation codes in the data, and they could work in the private or public sector. The figure shows an increased trend in employment shares along the skill distribution between 1970 and 1995, resembling the skill-biased technological change (SBTC) hypothesis. The changes in employment shares by the initial earnings level between 1995 and 2014 resembles the U-shaped curve found in many other studies.[7]

An alternative way to characterize the polarization of job distribution is to depict the employment shares across the three main occupation groups (abstract, routine, service) and to examine the changes in employment shares for the entire inspection period from 1970 to 2014. Figure 2 shows a clear, decreasing trend in the share of employees in the mid-skilled routine group, while at the same time, the share of high-skilled abstract group workers increased over time.[8] The share of abstract task workers was 15% in 1970, and it increased to 34% by the end of 2014. In contrast, the share of routine task workers was 62% in 1970 and it decreased to 43% in 2014. The decrease in the employment share of routine workers is mostly explained by the decrease in the employment share of routine manual, rather than routine cognitive, workers. The share of nonroutine manual tasks started to increase slowly after 1985. 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. The increased demand for service jobs might also be due to an economic upturn that occurred during the late 1980s in Finland and might also reflect the expansion of local government. A similar trend in employment shares is also detected in Figure A2 in the Appendix, in which an alternative measure for occupation group is used (Goos et al. 2014). These results confirm that the share of high-wage occupations

[7] See, also, studies by Asplund, Barth and Lundborg (2011), Böckerman et al. (2019) and Pekkala Kerr et al. (2019) from Finland.

[8] The year 1990 was excluded from Figure 2 because it is difficult to compare occupation data in 1990 with those from other years, as discussed above.

has increased, and the share of middle-wage occupations has decreased steadily since the 1970s. In contrast, the share of low-wage occupations started to increase after 1985.

[Figures 1-2 in here]

3.2. Transition Matrix of Occupational Mobility

Table 1 illustrates the dynamic occupational movements with a matrix cross-classifying the occupations and other labor market states at two points at times *t* and *t+5*. People may move between four main occupation groups (abstract, routine cognitive, routine manual and service) and shift to nonemployment (unemployment or labor force nonparticipation). In these calculations, retired people are excluded. The average occupational movements are reported separately for the periods of 1970-1995 (Panel A), 1970-1985 (Panel B) and 1995-2014 (Panel C).[9] In what follows, three important findings stand out. First, the diagonal elements of the matrices reveal that the total movements have not varied a great deal over the 45-year inspection period, although they might have been slightly affected by the economic cycles, for example, during the 1990s. Some of the recent increases in mobility occurred between routine

[9] The sensitivity analysis is performed by excluding 1990 and 1995 from the data, mainly because the occupation variable in 1990 is problematic in terms of comparability. Since the workers' occupational status is examined according to their origin occupation five years earlier, then it is reasonable also to exclude 1995 from the analysis. Another reason to exclude the period of 1990-1995 is that the late 1980s was characterized by overheating of the Finnish economy, followed by a severe recession in 1991-1994, when the unemployment rate increased to a historically high level.

and abstract tasks, when a large share of routine cognitive workers in particular moved to abstract tasks.

Second, the numbers show that routine workers today do not seem to fare worse in the labor market than routine workers yesterday. In fact, there has consistently been more upward than downward mobility, and this trend has increased over time. For example, during the period of 1970-1985/95, approximately 10% of routine cognitive workers moved to abstract tasks between the years t and $t+5$. During the period of 1995-2014, this share had already increased to 15%. The numbers do not reveal any increased shifts from routine to less-skilled service tasks either: the share of routine workers who have moved to service tasks within five years has been ~4% over time. Accordingly, the movements from employment to unemployment or labor force nonparticipation have been quite stable over time as well as when examining the trends across occupation groups. The only exception is that a few more routine manual workers have shifted to unemployment (or labor force nonparticipation) after 1995.

Third, the pattern of occupational mobility is nevertheless different between routine manual and routine cognitive workers. Movement is more likely to occur between occupations that are closely related to task composition and social status. During the inspection period of 1995-2014, routine cognitive workers were more likely to move to abstract occupations than routine manual workers (15% versus 7%), whereas routine manual workers were more likely to end up nonemployed compared to routine cognitive workers (11% versus 9%). The hypothesis of equal group means is rejected for these cells. Overall, the figures reveal quite stable long-term occupational mobility patterns, with an increase in the occupational mobility from routine to abstract tasks.[10]

[Table 1 in here]

3.3. Decomposing Aggregate Changes

One main goal of this study is to decompose the changes in occupation shares to changes that occur at the intensive margin and at the extensive margin. If the transformation from routine to nonroutine occupations occur at the intensive margin, it means that workers have changed their jobs. Conversely, if the transformation occurs at the extensive margin, then workers who have left the labor markets from routine occupations have been replaced by workers who enter nonroutine occupations. Specifically, I adopt and modify a formula proposed by Vainiomäki (1999) and decompose the aggregate change of occupation share *j* (*j* = abstract, routine cognitive, routine manual, service), ΔS_j, into three components:

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

[10] Table A1 of the Appendix shows the transition matrices using alternative occupation categories that ares based on Goos et al. (2014): High-paying, Middle-paying cognitive, Middle-paying manual and Low-paying occupations. For these broad wage groups, I find similar trens in increased occupational mobility from middle-paying occupations to high-paying occupations as well as greater shifts to unemployment.

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

The contribution of the extensive margin can be explained either by ageing or weak labor market attachment. The total contribution of entry dynamics, $\frac{L_t^N}{L_t}\left(S_{jt}^N - S_{jt}^C\right)$, can be further decomposed into two parts: $\frac{L_t^{N,Y}}{L_t}\left(S_{jt}^{N,Y} - S_{jt}^C\right) + \frac{L_t^{N,U1}}{L_t}\left(S_{jt}^{N,U_1} - S_{jt}^C\right)$. The superscript *Y* denotes persons who were children (or not even born yet), students or in military service at *t-1* and employed at *t*. U_1 denotes entrants who were unemployed or labor force nonparticipants (excluding retired persons and students) at *t-1* but employed at *t.* This term is thus an inflow from unemployment (or labor force nonparticipation) to employment. Similar reasoning applies to exit dynamics, $\frac{L_{t-1}^D}{L_{t-1}}\left(S_{j,t-1}^C - S_{j,t-1}^D\right) = \frac{L_{t-1}^{D,O}}{L_{t-1}}\left(S_{j,t-1}^C - S_{j,t-1}^{D,O}\right) + \frac{L_{t-1}^{D,U2}}{L_{t-1}}\left(S_{j,t-1}^C - S_{j,t-1}^{D,U_2}\right)$. The superscript *O* denotes persons who were employed at *t-1* but were retired, older than 70 years old or already deceased in *t*. [11] U_2 denotes persons who were employed in *t-1* but unemployed or out of the labor force in *t*. This term can be considered as an outflow from employment to weak labor market attachment.

The results of the decomposition analysis are presented in Table 2. The results show that the period of 1970-1995 was characterized by occupational restructuring. The share of abstract tasks increased, while at the same time, the share of routine manual tasks decreased (Panel A). These changes were high, at ~14%-points. Approximately one-half of the decrease in the employment share of routine manual occupations occurred during the period of 1985-1995, which included 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). Overall, the results suggest that labor markets had started to polarize already in the 1970s, or even earlier. The share of routine cognitive tasks decreased, and the share of non-routine manual tasks increased during 1995-2014 (Panel C).

The decomposition results show that the decrease in mid-level routine occupations and increase in high-level abstract occupations are largely within-worker phenomena, indicating that many routine workers have moved to high-wage abstract tasks, while the downward movement of routine workers is weaker, as illustrated in Table 1. This type of occupational mobility has not varied a great deal over time. However, occupations with heavy influxes of workers also tend to have many workers moving out. These occupations are typically those that require less formal education,

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

such as service and sales jobs. Therefore, it is possible that some routine workers have moved to low-skilled nonroutine manual tasks, and some former service workers have moved to abstract tasks (cf. Table 1).

Interestingly, approximately one-fourth of the recent decrease in the share of routine manual tasks can be explained by the exit dynamics (1.4% -points). An increase in the recent employment share of service tasks can be attributed to entries, indicating that the employment share of these tasks is typically larger among those who enter the labor markets than among those who exit them.[12] It seems that most of the changes in occupational restructuring can be explained by typical career progression, with the combination of exit-entry dynamics, when some routine manual workers who have exited the labor markets are being replaced by workers who have entered low-skilled occupations.[13]

Table 3 reports the detailed decomposition results of the contribution of the extensive margin. The results for the period of 1995-2014 reveal that the increase in the employment share of service tasks is mainly explained by young people entering the labor market (2.6% -points out of 3.4% -points). Population ageing also explains a significant part of the decrease in the share of routine manual occupations at the extensive margin, although the largest fraction of this decrease can be attributed to the worker flows from employment to unemployment or to labor force nonparticipation (-

[12] The change in the share of abstract workers exhibits a negative coefficient for entry dynamics for the 1995-2014 period but a positive sign for the earlier periods. Although people are more 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) showed that the traditional upward, linear career paths are being replaced by a mixture of upward, lateral and downward moves.

[13] Table A2 of the Appendix reports the decomposition results using GMS-type wage groups, and these results are largele in line with those reported in Table 2 using AA-type task measures.

0.9% -points out of -1.4% -points). Evidently, the outflow from employment to unemployment (or labor force nonparticipation) is more profound among routine manual workers than among routine cognitive workers. The detailed decomposition results for the earlier periods show different entry-exit dynamics at the extensive margin. For example, the earlier decrease in routine manual tasks at the extensive margin was mostly explained by the smaller share of young people entering the labor market who perform routine manual work.

[Tables 2 and 3 in here]

4. Empirical Analysis

4.1. Descriptive Evidence on Occupational Mobility

The first part of the empirical analysis is conducted utilizing panel data for the periods of 1970-1985/95 and 1995-2014. The purpose of the empirical examination is first to compare the occupational mobility of routine cognitive and routine manual workers to different labor market states between years t and $t+5$.[14] The setting resembles Cortes (2016), who examined the occupational mobility of routine workers at different skill levels. In our setting, a routine worker in t can belong to no more than one of category

[14] The Population Censuses are available for 1970, 1975, 1980 and 1985, and the occupation variable in FLEED is reported for 1990, 1995, 2000, and 2004-2014. Therefore, the occupational movements are examined using five-year gaps (except for the period of 2010-2014, there will be a four-year gap). I also examined the sensitivity of the results by including the entire period from 2004 onwards in the analysis. The results were in line with those reported in this paper.

in year $t+5$ from the set {Abstract, Routine cognitive, Routine manual, Service, Unemployed or labor force nonparticipant}. Labor force nonparticipants exclude students and retired persons. The dependent variable, occupational mobility, is denoted by $\mathrm{OM}_{\mathrm{it}}$. A multinomial logit model is applied to study whether routine manual workers in *t* are less/more likely to switch to another occupation or nonemployment by the end of *t+5,* compared to routine cognitive workers. The equation can be expressed as follows:

$$OM_{it+5} = \alpha RM_{it} + \boldsymbol{\beta}'\boldsymbol{X}_{it} + \delta Time \quad + \varepsilon_{it} \tag{2}$$

The model controls for year dummies and a variety of individual characteristics measured in *t*: age dummies (four categories: Less than 25 years old, 25-34 years old, 35-44 years old, and Older than 45 years old), gender (1 = Female), working sector (1 = Public sector), marital status (1 = Married), having children (1 = Underage children), native language (1 = Finnish), home ownership (1 = Home owner) education level (three categories: Primary, Secondary, Higher), field of study (six categories: General, Business and social sciences, Technical and natural sciences, Health, Service, and Other fields), and industry (six categories: Manufacturing, Construction, Services, Finance, reals estate and professional services, Public sector services, and Other)[15]. The model accordingly controls for individual's pre-existing skill level. It is calculated as the gender-specific rank order (1-100) of wage distribution within worker's

[15] Service industries include wholesale and retail trade, accommodation and food services, transportation, storage and information communication. Other industries include forestry, mining, electricity and water supply and other personal services.

occupation in t. I used the most disaggregated definition of the occupational category (4-digit code). The variable describes how well an individual fares relative to other individuals who work in similar occupations. Pre-existing skill level is included in the model because the occupational transition is found to be U-shaped (Groes, Kircher and Manovskii 2015), meaning that both low-ability and high-ability workers within an occupation are more likely to switch jobs, compared to mid-ability workers. Cortes (2016) found that, among routine workers, less-skilled workers are more likely to end up in service occupations, and more-skilled workers are more likely to move to abstract tasks.

The marginal effects of the RM_{it} dummy and pre-existing skill level from Equation (2) are reported in Table 4. I first comment on the results for the most recent inspection period of 1995-2014 (Panel C). Although no causal interpretation should be placed on these estimates, the results prove both interesting and intuitive. According to the hypothesis, routine cognitive workers have a higher probability of moving up the skill distribution to abstract tasks compared to routine manual workers, while routine manual workers have a higher probability of moving down the skill distribution to service tasks. Conditional on observed characteristics, routine manual workers also have a 3.6% -points lower probability of becoming nonworkers. When I compare the marginal effects between different time periods, one important finding stands out. The occupational mobility of routine manual and routine cognitive workers was quite similar across the entire period from 1970 to 2014. The only difference is that routine manual workers were less likely to move to low-skilled nonroutine manual tasks before 1995.

The marginal effects for the background characteristics for the 1995-2014 period are provided in Table A3 of the Appendix. Overall, the estimates correspond to the expectations well. Both general human capital and specific human capital are related to the occupational mobility of routine workers. More skilled workers, as measured by education level or wage rank order within origin jobs, have a higher probability of moving to abstract tasks (e.g., Cortes 2016). Less-skilled workers have, in turn, a higher probability of moving to manual occupations or ending up nonemployed. With regard to the education field, I find that workers educated in business, technical or natural science fields are more likely (less likely) to move up (down) the job hierarchy. In contrast, health education is positively related to both upward and downward mobility.

Interestingly, occupational polarization is also linked to the age polarization of employees. Younger individuals have a higher probability of moving both up and down the job hierarchy, while older workers are more likely to remain within routine jobs or end up nonworkers. Women also have weaker labor market prospects in general, compared to men. For example, women are less likely to move to abstract tasks than men, but they are more likely to end up in low-paying service tasks or become nonworkers. Married individuals and those who have children generally have a higher probability of remaining employed. Being married and parenting could increase incentives to search for better labor market prospects to provide a living for the 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 were specifically more likely to make occupational choices that sorted them into safer jobs. Those whose routine work was initially situated in the public sector are more likely to remain in routine tasks, and they are also less likely to become nonworkers. This result is in line with the view that public sector jobs are less sensitive to labor market disruptions (e.g., Pagani 2003, Sanz-de-Galdeano and Turunen 2008).

Manufacturing and construction routine workers have a higher probability of becoming nonworkers, while routine workers in high-paying service industries or public sector activity industries (e.g., health and education) are more likely to move to abstract tasks.

4.2. Job Loss and Occupational Mobility

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 are forced to change jobs because of lack of employment opportunities in their origin field or job of interest. As the overall pattern of occupational mobility includes both voluntary and involuntary job changes, the previous results should only be interpreted as descriptive evidence. The next step is to use involuntary job losses to examine occupational mobility after displacement between routine cognitive and routine manual workers using linked employer-employee panel data covering the period of 1995-2014. I use plant closures and/or mass lay-offs to identify involuntary separations from voluntary worker outflows. Aside from data on all workers and their employers for 2 decades from all industries, the data offer another advantage since they report the main reason for a person's most recent unemployment spell. The variable is available for 1995-2004, and it includes information about whether an individual lost his/her job involuntarily on financial and production-related grounds.

Building on the earlier literature, I define displaced workers as those who lose their routine cognitive or routine manual jobs after a plant closure or mass lay-off or for other financial and production-related reason. Mass lay-offs occur when the plants downsize their workforce by 30% or more (cf. Huttunen et al. 2018). The treatment group also includes early leavers, defined as workers who leave a plant that downsizes or closes within a one-year window before the closure (Schwerdt 2011). Displaced workers and early leavers are defined as persons who ultimately enter unemployment from employment and experience at least one unemployment month in *b*. This restriction indicates, for example, that early leavers do not move (potentially voluntarily) from plant to plant and remain employed.

The year of displacement is denoted by *b* (the base year). Workers must have worked in the same plant (with at least 10 employees) also at *b-1*. The information on worker's occupation is measured in *b-1*. The first potential base year is 1996, and the subsequent labor market status is measured in 2000, when I observe occupations in the FLEED. The next potential base years are 2001 and 2005-2010, and the subsequent labor market statuses are measured in 2005 and 2009-2014, respectively. The empirical analysis examines the occupational mobility of routine workers after displacement using a similar empirical specification as in Equation (2), with the exception that it is estimated for the (smaller) sample of displaced workers.

The results, presented in Table 5, are well in line with the descriptive evidence. Routine manual workers have a 7.5% -points lower probability of moving up the career ladder after a job loss, compared to routine cognitive workers. They have, in contrast, a 2.3% -points higher probability of moving to service tasks. Finally, routine cognitive workers have a greater propensity to become nonworkers after displacement. To examine potential heterogeneity in the effects of job loss on occupational mobility between routine manual and routine cognitive workers, the model is stratified based on gender, and people can also select between unemployment and labor force participation (i.e., the outcome variable includes six categories). These results are reported in Table A5 in the Appendix. The results are robust for upward and lateral moves, but not for downward moves. For example, the results show that women routine manual workers have a higher unemployment probability after displacement, compared to routine cognitive workers. Overall, the results offer a more causal interpretation of the occupational trajectories of routine task workers and provide even stronger uneven adjustment patterns, with the greatest costs of adjustment being borne by routine manual workers.[16]

Workers' recovery from displacement is also highly dependent on their education relevant to the new work (cf. Keller and Utar 2016, Utar 2018). As expected, routine workers who are more skilled and more educated have a higher probability of finding new abstract occupations after displacement compared to less skilled and less educated routine workers. They are also less likely to move to low-paying service occupations or to end up nonworkers. The direction of occupational mobility after displacement is also highly related to workers' education fields. Routine task workers who have educations in business or technical or natural sciences have a higher probability of moving up the job hierarchy after a job loss. Workers' education in services is, on the contrary, related to downward mobility to service tasks after displacement. Health education is related to both upward (such as nursing professionals) and downward movements (such as health care assistants) of displaced routine workers. These results are largely in line with the findings for the total sample, which includes both voluntary and involuntary job changes.

[Table 5 in here]

[16] Table A6 of the Appendix reports the results using GMS-type wage groups, and these results are largely in line with those reported in Table 4 using AA-type task measures.

4.3. Costs of Job Loss

Finally, I examine the effects on the earnings of workers after displacement. The origin job in *b-1* is either routine cognitive or routine manual. The base year is *b*, when a worker is potentially displaced, and I examine workers' earnings in *b+5*, conditional on employment. The empirical specification is the following:

$$log(earnings)_{ib+5} = \alpha D_{ib} + \gamma RM_{i(b-1)} + (\delta D_{ib} \times RM_{i(b-1)}) + \boldsymbol{\beta}'\boldsymbol{X}_{i(b-1)} + \epsilon_{ib+5} \quad (3)$$

where earnings are annual wage and salary earnings in *b+5*, D_{ib} is a dummy indicating whether worker i was displaced in year *b*, and $RM_{i(b-1)}$ is a dummy indicating whether the origin job of worker *i* was routine manual (= 1) or routine cognitive (= 0). As before, $X_{i(b-1)}$ is a vector of other control variables measured in *b-1*. I investigate the wage costs of involuntary job loss between routine manual and routine cognitive workers by including an interaction term ($D_{ib} \times RM_{i(b-1)}$) in the model. The direct wage cost analysis is also linked with occupational mobility by analyzing the earnings conditional on switching occupation and distinguishing the direction of the occupational moves (see also Robinson 2018). To emphasize, I have therefore estimated Equation (3) separately for the subgroups of workers, who 1) have remained within similar routine tasks; 2) have switched to another routine task (for example, from routine manual jobs to routine cognitive jobs); 3) have moved to low-skilled nonroutine manual jobs; or 4) have moved to high-skilled abstract jobs. The models are estimated by ordinary least squares (OLS).

The estimates of D_{ib} and $(D_{ib} \times RM_{i(b-1)})$ are presented in Table 5. Column 1 presents the wage effect of job loss for all workers whose origin jobs were either routine manual or routine cognitive. Columns 2-5 present the wage effects of displacement separately to occupational stayers and occupational switchers. The results show that involuntary job loss affects future wages negatively by ~15%. The magnitude of this wage cost is in line with other recent studies that similarly used plant closures and mass lay-offs for identification of job displacement (e.g., Korkeamäki and Kyyrä 2014). However, the results demonstrate an uneven wage adjustment pattern, with the greatest costs of adjustment being borne by routine manual workers. In particular, workers displaced from their routine manual jobs earn approximately 12% less five years later than their displaced routine cognitive counterparts. This difference in wage costs, which is disadvantageous for routine manual workers, remains high for occupational stayers (~15%) and for those who find other routine work with differing tasks (~11%). However, I find that the wage costs of job losses are not statistically significantly different between the groups of routine manual and routine cognitive workers, who have switched to service tasks after displacement. Finally, the uneven adjustment pattern is also linked with upward occupational mobility after displacement. Routine manual workers earn approximately 17% less than routine cognitive workers five years after displacement, even when they have moved up the career ladder to abstract tasks.

5. Summary and Conclusions

Although job polarization of the labor market has been well documented in the burgeoning literature, we still know much less about the implications of job polarization at the individual level. Using matched employer-employee data (FLEED) linked with population censuses from the 1970s, including all workers from all industries, this paper has the advantage of studying the occupational polarization and occupational mobility of workers from declining routine tasks over a 45-year period.

According to the data, the Finnish labor market has experienced a rapid and long-lasting change in the occupational distribution, characterized by an increase in the share of high-skilled abstract 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 decomposition analysis, I find that the right-hand side of job market polarization is largely a within-worker phenomenon, indicating that workers have moved from routine tasks 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 markets to enter unemployment or labor force nonparticipation. Conversely, the left-hand side of job market polarization is explained by the entry-exit dynamics, when people who have exited the labor markets have been replaced by younger people who have mainly entered low-skilled service occupations.

Although there has been more upward than downward mobility, there remain distinct differences between routine manual and routine cognitive worker groups. Based on descriptive empirical evidence, the direction of the occupational mobility is linked to 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 service occupations. The paper also attempts to provide a more causal interpretation for the findings of the occupational mobility of routine workers. Plant closures, mass lay-offs and register-based information about the causes of the most recent unemployment spell available in the FLEED were used as measures of involuntary job loss. These results confirm that routine cognitive workers are generally more able to adjust with smaller employment disruptions, and their wage costs of job loss were found to be 10-17% smaller, compared to routine manual workers. Loosely related to my study, Nilsson Hakkala and Huttunen (2016) examined the effects of Chinese import competition and offshoring on employment utilizing the same matched employer-employee panel data as used in the current paper. They found that importing increases the risk of unemployment, particularly among production, i.e., routine manual workers (see also Autor et al. 2014), in the manufacturing industry. Autor et al. (2013) showed that importing decreases the demand for both routine manual and routine cognitive workers in the US.

My results can also be contrasted with those of Gathmann and Schönberg (2010), who proposed a concept of task-specific human capital to analyze the mobility of skills across occupations. They found that workers typically move to occupations with similar task requirements as the origin job. Accordingly, workers who move to occupations with distant task requirements after a job loss suffer a 10-percentage point larger wage loss than workers who can find new employment with similar task requirements (see also Robinson 2018). The results of my paper also showed that the relative magnitude of wage losses was particularly high among routine workers who moved to abstract tasks after displacement. This finding could be explained by routine manual workers having less specific task requirements relevant to new abstract work that is well rewarded in the labor market.[17] Related to this finding, upward occupational mobility was largely related to the specific skills of a worker, such as an education in business, the technical and natural sciences or health fields (cf. Keller and Utar 2016, Utar 2018).

The policy lessons from this exercise are interesting. First, an 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 specific skills relevant to 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 at higher levels of the scale, education policy could more readily respond to these changes by, for example, increasing the available places in 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 required to fully understand whether this pattern of occupational mobility of routine workers is explained by high education level in Finland, or a well-functioning active labor market or education policies and whether we could find similar decomposition results from other Nordic countries or countries with more decentralized labor markets.

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[17] In their ongoing work, Kauhanen and Riukula (2019) studied the impact of job loss on task usage. Their preliminary results showed that the costs of job loss are smaller when the origin and current jobs have similar task structures.

Third, the focus of our concern could be routine manual workers who are generally more injured by polarization. Public labor market policy could support routine manual workers in obtaining training or other labor market policy measures that would improve their re-employment opportunities. Comparing worker-level and firm-level decomposition analyses provides some interesting observations. Pekkala Kerr et al. (2019) and Böckerman et al. (2019) used the matched employer-employee data from Finland and found that the increase in abstract occupations and decrease in the routine occupations were mainly within firm phenomena. On the contrary, low-skill service occupations have largely increased through entry dynamics, indicating that entering firms are showing a much higher concentration in service jobs than exiting firms. Therefore, one way to manage occupational mobility is to link former routine manual workers more closely to good abstract occupations, for example, through apprenticeships within existing firms. Such work-to-work training in firms would not necessarily be beneficial were the direction of the shift aimed at service occupations because such jobs are not necessarily available in these firms. The work-to-work training in firms should therefore be concentrated on upward mobility, which could be challenging since the origin task composition of routine manual workers 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.

Asplund, R., Barth, E. and Lundborg, P. 2011. “Polarization of the Nordic Labor Markets.” *Finnish Economic Papers*, 24, 87-110.

Asplund, R., Kauhanen, A. and Vanhala, P. 2015. Ammattirakenteet murtuvat. Mihin työntekijät päätyvät ja miksi? (in Finnish). Helsinki: Taloustieto Oy.

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.

Bárány, Z. and Siegel, C. 20018. "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.

Fedorets, A., Fitzenberger, B., Schulze, U. and Spitz-Oener, A. 2014. "Routine Bias, Changing Tasks, and Occupational Mobility. Mimeo.

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.

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: Routine-biased 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.

Huttunen. K., Møen. J., and Salvanes. K. 2018. "Job Loss and Regional Mobility." *Journal of Labor Economics* (forthcoming).

Jacobson, L., LaLonde, R., and Sullivan, D. 1993. "Earnings Losses of Displaced Workers." *American Economic Review,* 83, 685-709.

Kauhanen, A. and Riukula, K. (2019). "The Costs of Job Loss, Occupational Mobility and Task usage". Mimeo.

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

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.

Michaels, G., Natraj, A. and Van reenen, J. 2014. “Has ICT Polarized Skill Demand? Evidence from Eleven Countries Over 25 Years”. *Review of Economics and Statistics* 96, 60-77.

Mitrunen M. 2013. Työmarkkinoiden polarisaatio Suomessa (in Finnish). Government Institute for Economic Research Memorandum 33.

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.

Pagani, L. (2003), “Why Do People from Southern Italy Seek Jobs in the Public Sector?”, *Labour* 17, 63-91.

Pekkala Kerr, S., Maczulskij, T., and Maliranta, M. 2019. “Within and Between Firm Trends in Job Polarization: The Role of Globalization and Technology”. Mimeo.

Podgursky, M. and Swaim, P. 1987. “Job Displacement and Earnings Loss: Evidence from the Displaced Worker Survey.” *Industrial and Labor Relations Review* 40, 17-29.

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

Sanz-de-Galdeano, A. and Turunen, J. (2006). “The Euro Area Wage Curve.” *Economics Letters* 92, 93-98.

Schwerdt, G. 2011. “Labor Turnover Before Plant Closure: “Leaving the Sinking Ship” vs. “Captain Throwing Ballast Overboard”.” *Labour Economics* 18, 93-101.

Utar, H. 2018. “Workers Beneath the Floodgates: The Impact of Low-Wage Import Competition and Workers' Adjustment.” *Review of Economics and Statistics* (forthcoming).

Vainiomäki, J. 1999. Technology and Skill Upgrading: Results from Linked Worker-plant 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.

Vainiomäki, J. (2018). Ketkä poistuvat rutiiniammateista ja kuinka se vaikuttaa tulevaan palkkakehitykseen? Yhteiskuntapolitiikka 83, 272-286 (English summary available: ”Who leave routine occupations and how does it affect their future wages?”).

Van Reenen, J. 2011. “Wage Inequality, technology and Trade: 21st Century Evidence.” *Labour Economics* 18, 730-741.

Figures

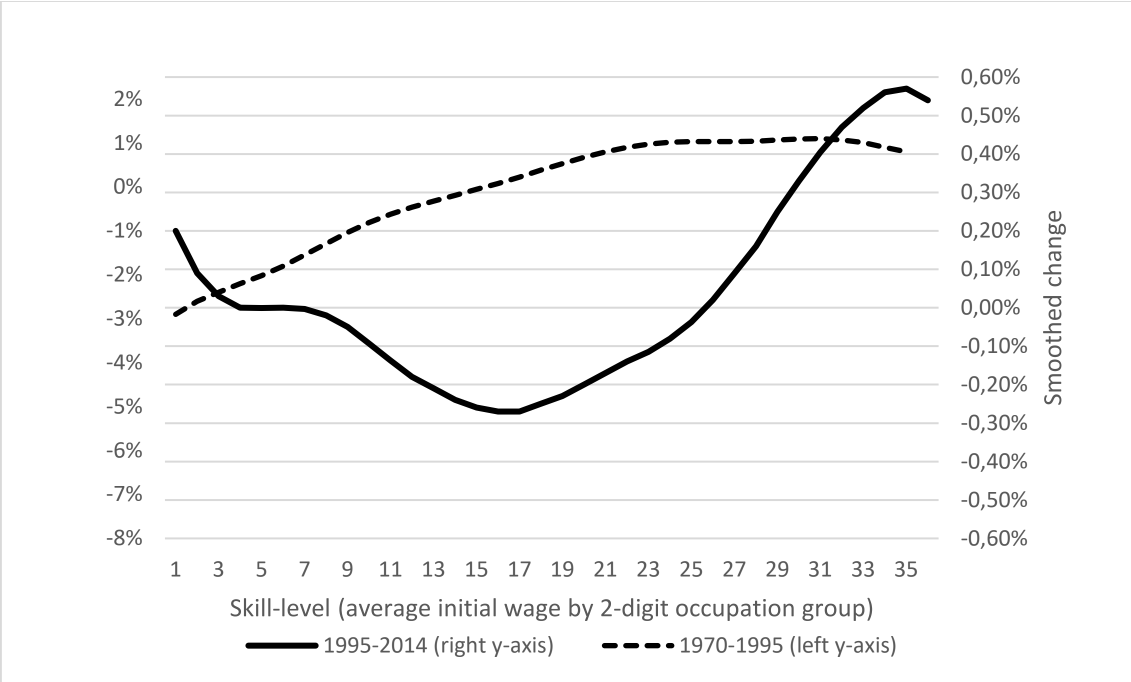

Figure 1: Smoothed changes in shares of 2-digit occupations by initial skill level (average annual earnings) for the periods of 1970-1995 and 1995-2014

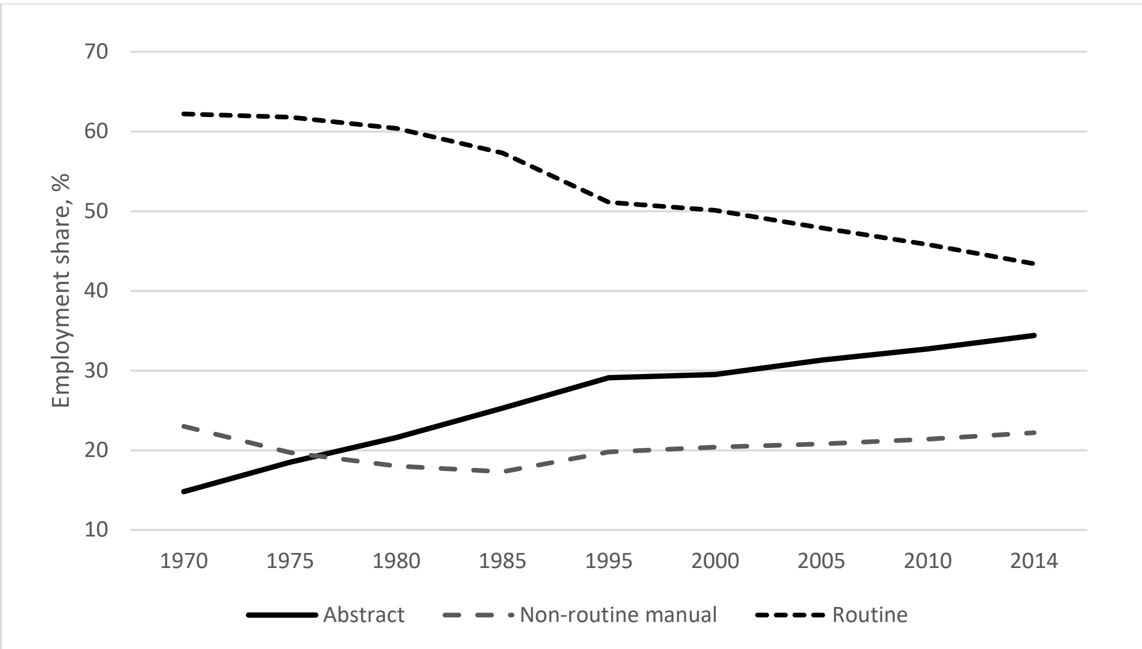

Figure 2: Employment share by task group in Finland over the period 1970-2014

Tables

Table 1: Transition matrix of average occupational mobility between 5-year gaps

		Year t+5				
		Abstract	RC	RM	Services	Unemp/LFN
Panel A: 1970-1995						
Year t	Abstract	78%	8%	4%	4%	6%
	RC	10%	72%	5%	4%	9%
	RM	5%	3%	78%	4%	10%
	Services	4%	6%	8%	69%	13%
		Abstract	RC	RM	Services	Unemp/LFN
Panel B: 1970-1985						
Year t	Abstract	82%	7%	4%	2%	5%
	RC	9%	73%	6%	4%	8%
	RM	5%	3%	80%	4%	7%
	Services	4%	6%	9%	71%	10%
		Abstract	RC	RM	Services	Unemp/LFN
Panel C: 1995-2014[a]						
Year t	Abstract	82%	6%	4%	2%	6%
	RC	15%	67%	4%	5%	9%
	RM	7%	4%	75%	3%	11%
	Services	7%	6%	4%	73%	10%

Note: [a]: 4-year gap is used in calculating the occupational mobility between 2010 and 2014

Table 2: Decomposition of employment share change by occupation group (% -points)

Panel A: 1970-1995	Δ emp. share	Intensive margin	Extensive margin	Entry	Exit
Abstract	14.0	10.8	3.2	2.5	0.7
Routine cognitive	2.1	-3.7	5.8	-1.3	7.1
Routine manual	-13.0	-9.0	-4.0	-4.7	0.7
Services	-3.1	1.9	-5.0	3.5	-8.5
Panel B: 1970-1985					
Abstract	10.6	6.7	3.9	1.0	2.9
Routine cognitive	2.2	-1.2	3.4	0.2	3.2
Routine manual	-7.1	-4.8	-2.2	-2.4	0.2
Services	-5.7	-0.7	-5.1	1.2	-6.3
Panel B: 1995-2014					
Abstract	5.3	8.1	-2.8	-3.6	0.8
Routine cognitive	-2.6	-3.4	0.8	0.2	0.6
Routine manual	-5.1	-3.7	-1.4	0.0	-1.4
Services	2.4	-1.0	3.4	3.4	0.0

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

Table 3: Decomposition of the contribution of 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	3.2	3.3	-0.7	0.2	0.5
Routine cognitive	5.8	-1.4	0.1	6.8	0.3
Routine manual	-4.0	-4.0	-0.7	1.4	-0.7
Service	-5.0	2.1	1.4	-8.4	-0.1
Panel A: 1970-1985					
Abstract	3.9	1.4	-0.5	2.9	0.1
Routine cognitive	3.4	-0.3	0.5	3.1	0.1
Routine manual	-2.2	-1.5	-0.8	0.0	0.1
Service	-5.1	0.4	0.8	-6.0	-0.3
Panel B: 1995-2014					
Abstract	-2.8	-2.5	-1.1	0.2	0.5
Routine cognitive	0.8	0.4	-0.2	0.5	0.1
Routine manual	-1.4	-0.5	0.5	-0.5	-0.9
Service	3.4	2.6	0.8	-0.2	0.3

Notes: Total extensive margin component is divided into entry components (young people enter employment, or unemployed (or LFN) enter 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	Services	Unemp/ LFN
Panel A: 1970-1995					
Routine manual	-0.037 ***	-0.283 ***	0.342 ***	-0.007 ***	-0.015 ***
	(0.0003)	(0.0003)	(0.0004)	(0.0002)	(0.0003)
Skill	0.0005 ***	0.0005 ***	0.0007 ***	-0.0004 ***	-0.0014 ***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Number of obs.	4,644,206				
Panel A: 1970-1985					
Routine manual	-0.043 ***	-0.279 ***	0.344 ***	-0.014 ***	-0.009 ***
	(0.0003)	(0.0004)	(0.0005)	(0.0003)	(0.0004)
Skill	0.0005 ***	0.0004 ***	0.0005 ***	-0.0004 ***	-0.0011 ***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Number of obs.	2,771,753				
Panel B: 1995-2014					
Routine manual	-0.029 ***	-0.258 ***	0.316 ***	0.007 ***	-0.036 ***
	(0.0004)	(0.0005)	(0.0005)	(0.0003)	(0.0005)
Skill	0.0007 ***	0.0002 ***	0.0008 ***	-0.0004 ***	-0.0014 ***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Number of obs.	2,904,533				

Notes: Reference category is routine cognitive workers. Other controls include age cohort, gender, education level, education field, marital status, having underage children, home ownership, native language, public sector dummy, industry dummies and year dummies. *** is statistically significant at least at the 1% significance level.

Table 5: Multilevel logit estimates (marginal effects) of main activity in *d+5* for displaced workers

	Abstract	RC	RM	Services	Unemp/LFN
Routine manual	-0.075 ***	-0.139 ***	0.234 ***	0.023 ***	-0.042 ***
	(0.0057)	(0.0057)	(0.0088)	(0.0044)	(0.0076)
Skill	0.0006 ***	-0.0003 ***	0.0009 ***	-0.0002 ***	-0.0010 ***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Age					
25-34	-0.013 *	-0.006	-0.001	-0.014 **	0.033 ***
	(0.0069)	(0.0082)	(0.0103)	(0.0061)	(0.0098)
35-44	-0.045 ***	-0.009	-0.010	-0.010	0.074 ***
	(0.0084)	(0.0095)	(0.0112)	(0.0069)	(0.0104)
≥45	-0.093 ***	-0.010	-0.018	-0.015 **	0.136 ***
	(0.0093)	(0.0098)	(0.0112)	(0.0069)	(0.0101)
Female	-0.016 ***	0.148 ***	-0.223 ***	0.048 ***	0.042 ***
	(0.0050)	(0.0053)	(0.0071)	(0.0042)	(0.0062)
Public sector	0.002	0.036 ***	0.013	-0.010	-0.041 ***
	(0.0078)	(0.0080)	(0.0127)	(0.0059)	(0.0108)
Married	0.009	0.019 ***	-0.003	0.004	-0.029 ***
	(0.0056)	(0.0060)	(0.0067)	(0.0045)	(0.0059)
Children	-0.010 **	0.008	0.019 ***	-0.001	-0.017 ***
	(0.0050)	(0.0056)	(0.0064)	(0.0042)	(0.0056)
Finnish	0.019 *	-0.001	-0.018	-0.008	0.009
	(0.0105)	(0.0114)	(0.0140)	(0.0085)	(0.0124)
Home ownership	-0.005	0.006	0.028 ***	-0.003	-0.025 ***
	(0.0050)	(0.0056)	(0.0064)	(0.0042)	(0.0057)
Education level					
Secondary	0.169 ***	0.052 ***	-0.144 ***	-0.027 ***	-0.050 ***
	(0.0089)	(0.0092)	(0.0133)	(0.0069)	(0.0122)
Higher	0.355 ***	0.115 ***	-0.408 ***	-0.075 ***	0.012
	(0.0113)	(0.0132)	(0.0236)	(0.0119)	(0.0182)
Education field					
General	0.056 ***	0.137 ***	-0.198 ***	-0.035 ***	0.040 ***
	(0.0111)	(0.0123)	(0.0182)	(0.0114)	(0.0145)
Business	0.027 **	-0.062 ***	0.002	0.024 **	0.009
	(0.0114)	(0.0137)	(0.0152)	(0.0109)	(0.0132)
Technical and natural sciences	0.003 ***	-0.010 ***	0.011 ***	-0.002 ***	-0.002 **
	(0.0009)	(0.0011)	(0.0010)	(0.0006)	(0.0009)
Health	0.091 ***	-0.019	-0.149 ***	0.094 ***	-0.017
	(0.0168)	(0.0197)	(0.0360)	(0.0127)	(0.0278)
Services	-0.031 **	-0.001	-0.027	0.072 ***	-0.014
	(0.0144)	(0.0146)	(0.0182)	(0.0112)	(0.0160)

Table 5 Cont.: Multilevel logit estimates (marginal effects) of main activity in *d + 5* for displaced workers

	Abstract	RC	RM	Services	Unemp/LFN
Industry					
Manufacturing	0.004	-0.086 ***	0.166 ***	-0.075 ***	-0.009
	(0.0105)	(0.0130)	(0.0121)	(0.0088)	(0.0105)
Construction	-0.025 **	-0.086 ***	0.151 ***	-0.072 ***	0.033 ***
	(0.0122)	(0.0169)	(0.0125)	(0.0105)	(0.0108)
Services	-0.023 **	0.109 ***	0.030 **	-0.049 ***	-0.066 ***
	(0.0093)	(0.0101)	(0.0117)	(0.0070)	(0.0103)
Finance, real estate and	0.055 ***	0.071 ***	-0.097 ***	-0.005	-0.024 *
professional services	(0.0099)	(0.0113)	(0.0151)	(0.0078)	(0.0126)
Public sector activities	0.036 ***	0.049 ***	-0.202 ***	0.065 ***	0.053 ***
	(0.0111)	(0.0120)	(0.0197)	(0.0076)	(0.0144)
Year dummies	Yes				
Number of observations	17,623				

Notes: Dependent variable is measured in *d+5,* and independent variables are measured in *d*. Reference categories for categorical variables are: 18-24 years old; Primary education; Other education fields (educational, humanities, arts, forestry); Other industries (mining, electricity, water supply, agriculture, personal activities). ***, ** and * are statistically significant at least at the 1%, 5% and 10% significance levels.

Table 6: The effect of job loss on earnings in *b+5*

	All RM and RC workers	Same routine task	Another routine task	Service task	Abstract task
	(1)	(2)	(3)	(4)	(5)
Displacement	-0.164 ***	-0.131 ***	-0.153 ***	-0.170 ***	-0.103 ***
	(0.0097)	(0.0114)	(0.0544)	(0.0568)	(0.0365)
Displacement x RM	-0.129 ***	-0.153 ***	-0.110 (*)	-0.015	-0.176 ***
	(0.0121)	(0.0136)	(0.0673)	(0.0736)	(0.0224)
Other controls	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.10	0.11	0.06	0.05	0.10
Number of obs.	2,884,142	2,396,496	98,379	90,203	299,064

Notes: The initial sample consists of routine cognitive (RC) and routine manual (RM) workers. Other controls include age cohort, gender, education level, education field, marital status, having underage children, home ownership, native language, public sector dummy, industry dummies and year dummies. *** is statistically significant at least at the 1% significance level. (*) is marginally significant at the 10% significance level.

Appendix

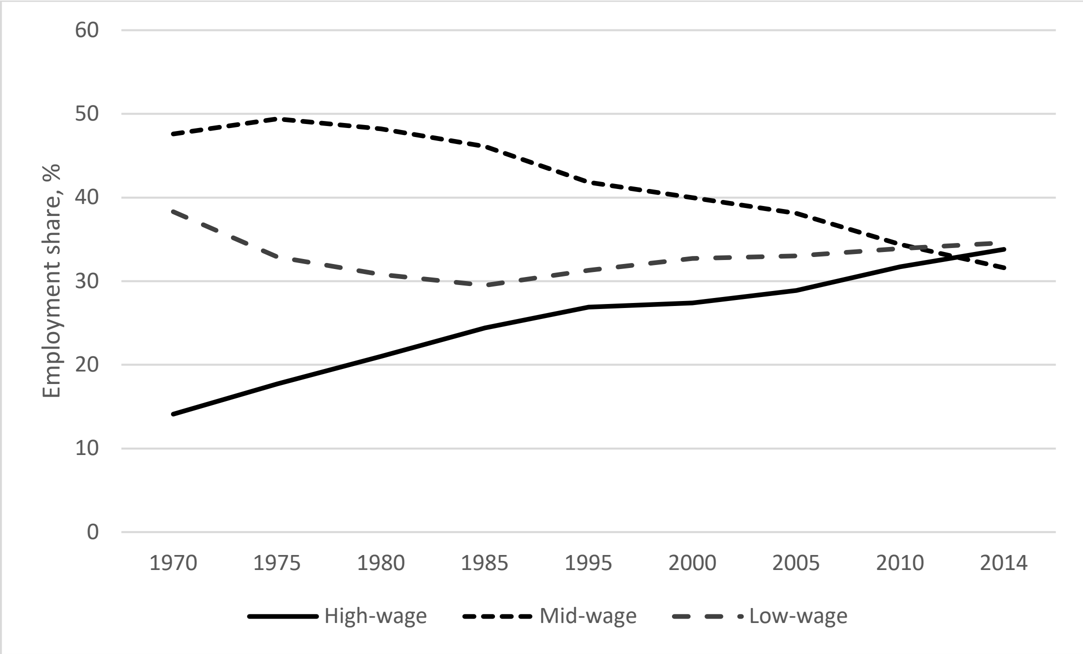

Figure A1: Job polarization in Finland, 1970-2014: the share of high-wage, mid-wage and low-wage worker groups

Table A1: Transition matrix of average occupational mobility between 5-year gaps

		Year t+5				
		High-wage	Mid-wage (cognitive)	Mid-wage (manual)	Low-wage	Unemp / LFN
Panel A: 1970-1995						
Year t	High-wage	71%	4%	7%	10%	8%
	Mid-wage (cognitive)	7%	68%	5%	9%	11%
	Mid-wage (manual)	5%	2%	73%	10%	10%
	Low-wage	5%	9%	11%	65%	14%
		High-wage	Mid-wage (cognitive)	Mid-wage (manual)	Low-wage	Unemp / LFN
Panel B: 1970-1985						
Year t	High-wage	68%	4%	10%	10%	8%
	Mid-wage (cognitive)	8%	66%	7%	10%	9%
	Mid-wage (manual)	6%	2%	72%	11%	9%
	Low-wage	5%	5%	14%	64%	12%
		High-wage	Mid-wage (cognitive)	Mid-wage (manual)	Low-wage	Unemp / LFN
Panel C: 1995-2014[a]						
Year t	High-wage	74%	3%	6%	7%	10%
	Mid-wage (cognitive)	13%	58%	5%	11%	13%
	Mid-wage (manual)	7%	2%	68%	9%	14%
	Low-wage	9%	4%	8%	65%	14%

Note: [a]: 4-year gap is used in calculating the occupational mobility between 2010 and 2014.

Table A2: Decomposition of employment share change by occupation group based on initial wage level (% -points)

Panel A: 1970-1995	Δ emp. share	Intensive margin	Extensive margin	Entry	Exit
High-wage	12.8	9.2	3.6	2.8	0.8
Mid-wage (cognitive)	2.2	0.0	2.2	-0.4	2.6
Mid-wage (manual)	-8.0	-6.4	-1.6	-5.3	3.7
Low-wage	-7.0	-2.8	-4.2	2.9	-7.1
Panel B: 1970-1985					
High-wage	10.3	6.5	3.8	1.1	2.7
Mid-wage (cognitive)	3.1	0.3	2.8	0.9	1.9
Mid-wage (manual)	-4.6	-3.3	-1.3	-3.1	1.8
Low-wage	-8.8	-3.5	-5.4	1.1	-6.4
Panel B: 1995-2014					
High-wage	7.0	8.5	-1.5	-2.1	0.6
Mid-wage (cognitive)	-4.6	-2.5	-2.1	-0.6	-1.5
Mid-wage (manual)	-5.6	-3.7	-1.9	-2.4	0.5
Low-wage	3.2	-2.3	5.5	5.1	0.5

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

Table A3: Multilevel logit estimates (marginal effects) of main activity in *t+5* (1995-2014)

	Abstract	RC	RM	Services	Unemp/LFN
Routine manual	-0.029 ***	-0.258 ***	0.316 ***	0.007 ***	-0.036 ***
	(0.0004)	(0.0005)	(0.0005)	(0.0003)	(0.0005)
Skill	0.0007 ***	0.0002 ***	0.0008 ***	-0.0004 ***	-0.0014 ***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Age					
25-34	-0.029 ***	0.010 ***	0.004 ***	-0.014 ***	0.029 ***
	(0.0006)	(0.0007)	(0.0007)	(0.0003)	(0.0006)
35-44	-0.058 ***	0.032 ***	0.010 ***	-0.018 ***	0.034 ***
	(0.0006)	(0.0008)	(0.0007)	(0.0004)	(0.0007)
≥45	-0.086 ***	0.038 ***	-0.009 ***	-0.024 ***	0.082 ***
	(0.0007)	(0.0008)	(0.0007)	(0.0004)	(0.0006)
Female	-0.033 ***	0.068 ***	-0.098 ***	0.028 ***	0.035 ***
	(0.0004)	(0.0004)	(0.0005)	(0.0003)	(0.0004)
Public sector	-0.024 ***	0.039 ***	0.014 ***	0.000	-0.029 ***
	(0.0005)	(0.0006)	(0.0007)	(0.0003)	(0.0006)
Married	0.014 ***	0.006 ***	0.003 ***	0.000	-0.022 ***
	(0.0004)	(0.0004)	(0.0004)	(0.0003)	(0.0004)
Children	0.001 **	0.006 ***	0.003 ***	0.003 ***	-0.013 ***
	(0.0004)	(0.0004)	(0.0004)	(0.0002)	(0.0004)
Finnish	0.001	0.001	-0.005 ***	-0.006 ***	0.010 ***
	(0.0007)	(0.0007)	(0.0008)	(0.0004)	(0.0007)
Home ownership	-0.004 ***	0.019 ***	0.019 ***	-0.006 ***	-0.028 ***
	(0.0004)	(0.0004)	(0.0004)	(0.0002)	(0.0003)
Education level					
Secondary	0.124 ***	-0.001	-0.086 ***	-0.005 ***	-0.032 ***
	(0.0006)	(0.0007)	(0.0009)	(0.0004)	(0.0008)
Higher	0.255 ***	-0.008 ***	-0.223 ***	-0.017 ***	-0.007 ***
	(0.0009)	(0.0011)	(0.0017)	(0.0008)	(0.0013)
Education field					
General	0.081 ***	0.028 ***	-0.091 ***	-0.000	-0.018 ***
	(0.0009)	(0.0012)	(0.0013)	(0.0007)	(0.0011)
Business	0.018 ***	0.074 ***	-0.072 ***	-0.020 ***	0.000
	(0.0009)	(0.0010)	(0.0012)	(0.0007)	(0.0010)
Technical and natural sciences	0.003 ***	-0.010 ***	0.011 ***	-0.002 ***	-0.002 **
	(0.0009)	(0.0011)	(0.0010)	(0.0006)	(0.0009)
Health	0.042 ***	-0.006 ***	-0.055 ***	0.041 ***	-0.023 ***
	(0.0014)	(0.0016)	(0.0022)	(0.0008)	(0.0018)
Services	-0.046 ***	0.032 **	0.005	0.022	-0.013 ***
	(0.0011)	(0.0012)	(0.0013)	(0.0006)	(0.0011)

Table A3 Cont.: Multilevel logit estimates (marginal effects) of main activity in *t+5* (1995-2014)

	Abstract	RC	RM	Services	Unemp/LFN
Industry					
Manufacturing	0.001	-0.038 ***	0.053 ***	-0.021 ***	0.004 ***
	(0.0008)	(0.0010)	(0.0009)	(0.0005)	(0.0008)
Construction	0.002	-0.037 ***	0.025 ***	-0.018 ***	0.029 ***
	(0.0010)	(0.0013)	(0.0010)	(0.0006)	(0.0009)
Services	-0.019 ***	0.033 ***	0.025 ***	-0.010 ***	-0.029 ***
	(0.0007)	(0.0008)	(0.0009)	(0.0004)	(0.0008)
Finance, real estate and professional services	0.028 ***	0.040 ***	-0.060 ***	-0.006 ***	-0.002 **
	(0.0008)	(0.0009)	(0.0012)	(0.0005)	(0.0009)
Public sector activities	0.004 ***	0.071 ***	-0.067 ***	-0.000	-0.008 ***
	(0.0009)	(0.0009)	(0.0014)	(0.0005)	(0.0011)
Year dummies	Yes				
Number of observations	2,904,533				

Notes: Dependent variable is measured in *t+5,* and independent variables are measured in *t*. Reference category for Routine manual -variable is Routine cognitive workers. Reference categories for categorical variables are: 18-24 years old; Primary education; Other education fields (educational, humanities, arts, forestry); Other industries (mining, electricity, water supply, agriculture, personal activities). *** and ** are statistically significant at least at the 1% and 5% significance levels, respectively.

Table A4: Multilevel logit estimates (marginal effects) of main activity in year t+5

	High-wage	Mid-wage (cognitive)	Mid-wage (manual)	Low-wage	Unemp/ LFN
Panel A: 1970-1995					
Mid-wage, manual	-0.052 ***	-0.223 ***	0.390 ***	-0.068 ***	-0.047 ***
	(0.0004)	(0.0003)	(0.0008)	(0.0004)	(0.0005)
Skill	0.0004 ***	0.0005 ***	0.0011 ***	-0.0006 ***	-0.0014 ***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Number of obs.	3,526,338				
Panel B: 1970-1985					
Mid-wage, manual	-0.065 ***	-0.204 ***	0.402 ***	-0.090 ***	-0.042 ***
	(0.0005)	(0.0004)	(0.0011)	(0.0006)	(0.0005)
Skill	0.0005 ***	0.0004 ***	0.0008 ***	-0.0007 ***	-0.0011 ***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Number of obs.	2,131,486				
Panel C: 1995-2014					
Mid-wage (manual)	-0.045 ***	-0.205 ***	0.386 ***	-0.035 ***	-0.101 ***
	(0.0005)	(0.0005)	(0.0011)	(0.0005)	(0.0008)
Skill	0.0005 ***	0.0004 ***	0.0012 ***	-0.0006 ***	-0.0015 ***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Number of obs.	1,967,211				

Notes: Reference category is mid-wage cognitive workers. Other controls include age cohort, gender, education level, education field, marital status, having underage children, home ownership, native language, public sector dummy, industry dummies and year dummies. *** is statistically significant at least at the 1% significance level.

Table A5: Multilevel logit estimates (marginal effects) of main activity in *d+5* for displaced workers, by gender

	Abstract	Routine cognitive	Routine manual	Service	Unemployed	Out of labor force
Panel A: Men						
Routine manual	-0.101 ***	-0.088 ***	0.266 ***	-0.020***	-0.048 ***	-0.009 **
	(0.0066)	(0.0050)	(0.0149)	(0.0047)	(0.0120)	(0.0041)
Skill	0.0005 ***	-0.0003 ***	0.0013 ***	-0.0004 ***	-0.0009 ***	-0.0003 ***
	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0001)
Number of obs.	11,121					
Panel B: Women						
Routine manual	-0.028 **	-0.224 ***	0.125 ***	0.092***	0.027 ***	0.008
	(0.0115)	(0.0137)	(0.0077)	(0.0084)	(0.0082)	(0.0051)
Skill	0.0007 ***	-0.0002	0.0002 *	-0.0000	-0.0003 **	-0.0005 ***
	(0.0002)	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0001)
Number of obs.	6,502					

Notes: Reference category is routine cognitive workers. Other controls include age cohort, gender, education level, education field, marital status, having underage children, home ownership, native language, public sector dummy, industry dummies and year dummies. ***, ** and * are statistically significant at least at the 1%, 5% and 10% significance levels, respectively.

Table A6: Multilevel logit estimates (marginal effects) of main activity in year *d*+5 for displaced workers

	High-wage	Mid-wage (cognitive)	Mid-wage (manual)	Low-wage	Unemp/ LFN
Mid-wage, manual	-0.059 ***	-0.117 ***	0.238 ***	0.021 ***	-0.083 ***
	(0.0061)	(0.0057)	(0.0146)	(0.0058)	(0.0118)
Skill	0.0003 ***	-0.0002 **	0.0013 ***	-0.0003 ***	-0.0011 ***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Number of obs.	12,851				

Notes: Reference category is mid-wage cognitive workers. Other controls include age, gender, education level, education field, marital status, having underage children, home ownership, native language, public sector dummy, industry dummies and year dummies. *** and ** are statistically significant at least at the 1% and 5% significance levels, respectively.