TYÖPAPEREITA | WORKING PAPERS 314

Where do workers from declining routine jobs go and does migration matter?

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Financial support from the Palkansaajasäätiö and the Academy of Finland Strategic Research Council project Work, Inequality and Public Policy (number 293120) are gratefully acknowledged. All the data work of this paper was carried out at Statistics Finland, following its terms and conditions of confidentiality. We are grateful to Hannu Karhunen and Tuomas Kosonen, as well as the audience at the ERSA conference in Wien and at the 4th International TASKS Cinference in Mannheim.

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Työpapereita | Working Papers 314
ISBN 978-952-209-164-2 (pdf)
ISSN 1795-1801 (pdf)

Helsinki 2017

Tiivistelmä

Tässä artikkelissa tarkastellaan työmarkkinoiden rakennemuutosta ja sitä mihin supistuvissa ammateissa olevat työntekijät päätyvät hyödyntämällä suomalaista rekisteripohjaista kokonaisaineistoa. Tarkastelu tehdään myös alueellisen muuttoliikkeen näkökulmasta. Tulosten mukaan työntekijät näyttäisivät siirtyvän pois rutiininomaisista ammateista. 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 päätyvät puolestaan suuremmalla todennäköisyydellä työttömiksi tai tippuvat matalapalkka-aloille. Alueellinen keskittyminen vientivetoisiin ja teollistuneisiin maakuntiin näyttäisi lieventävän työmarkkinoiden rakennemuutoksesta aiheutuvia kustannuksia yksilötasolla.

Abstract

Using administrative panel data on the entire Finnish population, we study the occupational switching patterns of routine workers to different labor market states. We find that workers tend to move out from routine-intensive occupations. The direction of the shift is nevertheless different between routine cognitive and routine manual workers. Routine manual workers are more likely to end up in low-paying non-routine manual jobs or become unemployed, while routine cognitive workers are more likely to move upwards to non-routine cognitive jobs. Worker migration particularly to urban and highly industrialized regions seems to mitigate the negative labor market consequences of occupational polarization.

Keywords: job polarization, routine manual, routine cognitive, occupational mobility, migration

JEL Classification: J23, J62, R23

1. Introduction

What has happened to routine workers in middle-skilled occupations? Labor market polarization has been the subject of numerous studies 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 middle-skilled workers performing routine[1] tasks, while at the same time, the demands for both low-skilled non-routine manual and highly-skilled abstract tasks have increased. Although job polarization as a phenomenon has been well documented in the burgeoning literature (e.g., Goos and Manning 2007, Goos, Manning and Salomons 2014, Autor and Dorn 2013), we still know much less about the implications of job polarization at the individual level.

In this paper we study the occupational switching patterns of workers from declining middle-skilled routine occupations. From the individual and state perspectives, this is a highly relevant political issue and must be taken into account for the design of effective policy response. The empirical literature on this issue is still quite scarce. Autor et al. (2014) examined the effect of exposure to Chinese import competition on employment and movements across industries for US manufacturing workers. They found that employees adjust to import shocks by moving out from the manufacturing industry. An increase in imports also increases unemployment and decreases labor force participation in local labor markets (Autor, Dorn and Hanson 2013). Although very interesting, the results do not say much about the kind of occupations the workers shifted to.

The most relevant studies are from Cortes (2016) and Holmes (2011), who studied the occupational switching patterns of routine workers in the US and UK, respectively. The results showed that particularly low-ability routine workers have shifted to non-routine manual occupations (such as services), whereas high-ability routine workers were more likely to move to occupations that involve abstract tasks (such as managerial). Accordingly, workers with a high level of routine-specific experience were more likely to stay in routine occupations (Holmes 2011, Holmes and Tholen 2013).[2] We provide new descriptive evidence on the occupational transition patterns of routine workers to different labor market states. Using register-based data from the entire Finnish population, we follow the labor market status of people who were routine workers in 1995 up to 2009. In the main empirical analysis, we apply a multinomial logit model to

[1] A routine task refers to a task that can be specified as a series of instructions and can be executed by machine (Acemoglu and Autor 2011).

[2] See, also, a report by Asplund, Kauhanen and Vanhala (2015, in Finnish). They used the Finnish register panel data (as we do) and found that blue collar workers are more likely to end up in low-paying occupations or become non-workers (unemployed or out of the labor force), while office clerks are more likely to move upward within the skill distribution.

examine the occupational switching pattern of routine workers to re-employment (self-employed, non-routine manual, intermediate or higher non-routine cognitive) and non-employment (unemployed or out of labor force). In the analysis, we control for important observables, such as initial skill level, education, industry and demographic variables.

Our study also extends the previous literature in two important ways. First, we distinguish routine manual (such as production, craft and repair) and routine cognitive (such as office, sales and administrative) workers. Although routine occupations have the common trait of being increasingly performed by computers or machines, these occupations are heterogeneous in terms of their working tasks, as Autor et al. (2003) also point out. It is therefore likely that the occupational transitions from routine occupations differ between these two distinct categories.

Second, to gain deeper knowledge regarding mobility patterns of routine workers, we also investigate the role of within-country migration in re-employment and non-employment probabilities. This is partly inspired by the study of Autor et al. (2014), who examined the effect of import shocks on employment of manufacturing workers both within regional stayers and regional movers. Regional differences in wages and employment prospects are important drivers of within-country migration (e.g., Pissarides and McMaster 1990). The standard view thus suggests that individuals move out from high unemployment regions, making the migration decision one of the key mechanisms that facilitates the adjustment toward equilibrium in the labor market.[3] We therefore extend our analysis to include regional aspects by taking into consideration whether within-country migration is related to the re-employment probabilities of routine workers. Interestingly, Autor et al. (2014) showed that migration was not an important mechanism through which workers adjust to exogenous trade shocks, as measured by the cumulative employment in years.

Our findings show that workers tend to move out from routine occupations. However, there are different re-employment and non-employment transition patterns between routine cognitive and routine manual workers. We find that routine manual workers are more likely to end up in low-paying non-routine manual jobs or become unemployed, while routine cognitive workers are more likely to move upward within the skill distribution to non-routine cognitive jobs. The results provide inconclusive evidence on the relationship between within-country migration and re-employment probabilities of

[3] According to the previous literature, there are also other motives for migration decisions besides economic and job-related motives. Such non-economic motives include social reasons (family-related reasons), education, housing, and environment-related reasons. For example, the study by Lundholm et al. (2004), focusing on five Nordic countries shows that the main motives for long-distance migration are other than employment. See, also, the expository survey by Greenwood (1985) on the determinants of internal migration.

routine workers. The results show that workers are more likely to shift to some middle- or high-paying cognitive jobs if they move particularly to more urban areas. In turn, routine workers are more likely to become non-employed (unemployed or out of labor force) if they migrate to less urban areas. Interestingly, these regional movers typically moved to locations where their parents or siblings live. It might well be that regional migration mitigates the negative aspects of exogenous labor demand shocks if the migration decision is made based on economic incentives, such as better employment and wage prospects. On the contrary, people might migrate to less urban areas based on incentives outside economic ones, such as family ties. This could serve as one of the explanations for the finding by Autor et al. (2014) that a zero net effect of regional migration on employment existed in US labor markets.

The rest of this paper is organized as follows. Chapter 2 describes the register data and Chapter 3 presents aggregate level evidence on job market polarization and occupational transition patterns of routine manual and routine cognitive workers based on the total employee database. Chapters 4 and 5 present our empirical approaches and the results of our analyses. Chapter 6 concludes the paper.

2. Data

We use the Finnish Longitudinal Employer-Employee Data (FLEED) of Statistics Finland. The data are based on various administrative registers that have been linked together using identification codes for individuals, firms and plants. The FLEED cover all working age persons with permanent residence in Finland for the period 1988-2012 (under the age of 70). The data include information on occupational status, employment and earnings along with a number of background characteristics.

Our occupation variable is based on the ISCO-88 (International Standard Classification of Occupation) classification, and it is reported for the years 1995, 2000 and 2004-2012. A new classification was introduced in 2010, but it is possible to compare data before and after 2010. In the main analysis, we examine persons who initially (1995) worked in jobs that are characterized by a declining employment share. The labor market status of those individuals is followed up to 2009. As the purpose of this paper is to examine the implications of job market polarization rather than cyclical fluctuations on re-employment and non-employment probabilities of routine workers, the period following financial crisis is excluded from the analysis.[4]

[4] During recessions, the structure of the labor market changes, as a higher share of low-skilled employees loses their jobs, and there are relatively more highly skilled employees in the labor

The data contain yearly recordings of the occupational status and individual's main activity, which allows us to uncover patterns in post-1995 trajectories in labor market status. Our measure for income is the annual taxable wage and salary earnings. The income is deflated to 2009 prices using the cost of living index. Information on region is based on the 19 NUTS 3-level (Nomenclature of Territorial Units for Statistics) classification. In the main analysis, we focus on persons that we observe in the data both in 1995 and 2009. Because the data include all Finnish persons, the attrition from the data is due to death, out-migration or ageing (more than 70 years old). In addition to private sector workers, we also include public sector workers in the analysis. Approximately one-third of Finnish wage earners are employed either in the local or central government. Therefore, the exclusion of the public sector would likely exacerbate the pattern of job market polarization as well as the re-employment and non-employment probabilities of routine workers in declining occupations.

3. Aggregate-level analysis

3.1. Job polarization and shrinking occupations

As in most industrialized countries, the 'hollowing out of the middle' is evident also in Finland (e.g., Asplund et al. 2011, Böckerman, Laaksonen and Vainiomäki 2014, Pekkala Kerr, Maczulskij and Maliranta 2016). We characterize job market polarization by ranking 2-digit occupations based on their initial wage and then looking at (smoothed) changes in employment shares across those occupations. We created the smoothed changes using the nonparametric LOWESS-method, i.e. locally weighted scatterplot smoothing. The conventional U-shape trend in the change in occupational shares between the years 1995 and 2009 is detected in Figure 1.[5]

[Figure 1 in here]

market. This trend is shown in Figure A1 (in the Appendix), in which we analyzed the data simply at the 1-digit occupational classification for the period 1995 and 2009/2012. The change in the job distribution between 1995 and 2012 shows more peaks among high-paying abstract occupations and more dips among plant operators and craft workers compared to the period 1995-2009. The most visible difference in job polarization patterns is the decrease in the share of service workers between 1995 and 2012. It is thus clear that service workers have also been heavily affected by the aftermath of the financial crisis. The period 2010-2012 was nevertheless included in the robustness tests, and the overall conclusions were consistent with those reported in this paper.

[5] In order to obtain a pattern of job polarization comparable to other countries, the sample used to create Figure 1 also includes persons that entry into the data after 1995 and/or exit from the data before 2009. This provides an estimate for the overall development of job market polarization in Finland.

We also examine the changes in occupational structure using a straightforward polarization measure that is estimated using the quadratic regression suggested by Dauth (2014):

$$\%\Delta \mathrm{Employment}_{j,2009-1995} = \beta_1 \mathrm{Skill}_{j,1995} + \beta_2 \mathrm{Skill}^2_{j,1995} \qquad (1)$$

where the dependent variable is the employment growth rate in occupation *j* and *Skill* is the rank of occupation *j* based on the 1995 average annual wage level in occupation *j*. The estimates are weighted by the initial share occupation *j* in total employment. The polarization measure is the *t*-value of parameter β_2. For the overall data, the regression line in (1) is U-shaped and fits the hypothesis of the job market polarization quite well, with the polarization measure being 2.18. We have further calculated the polarization measures for each 19 NUTS 3-level region. In four of these regions, the labor markets have been polarized statistically significantly at least at the 10% significance level. These regions are Uusimaa, Kanta-Häme, Pirkanmaa and Varsinais-Suomi and they are all located near the coast of Southern Finland, constituting approximately 50% of all inhabitants in Finland.[6] Three of these regions (Uusimaa, Pirkanmaa and Varsinais-Suomi) are classified as the most industrialized, export-oriented regions of Finland (Statistics Finland 2012). Similarly, Dauth (2014) found using data from Germany that job polarization most strongly occurs in regions with export-oriented manufacturing industries.

Table 1 shows the ISCO occupations at 2-digit level and their percentage point changes between 1995 and 2009. Occupations are ranked by their average annual earnings in 2009. We distinguished between high-paying, middle–paying and low-paying occupations, which are close to those adopted by Goos et al. (2014) and Asplund et al. (2011). The sample includes those individuals that we observe in the data both in 1995 and 2009. The largest increases are associated with managerial (12), professional (21 to 24), and associate professional (34) occupations, whereas the biggest dips represent craft and related trade workers (72), office clerks (41), and sales workers (52). The employment shares of plant and machine operators and assemblers (81 to 83) have also declined. Similar to patterns found by Goos et al. (2014) for 16 Western European countries, some low-paid service workers (51) and elementary workers (92) have also increased their occupation shares during 1995-2009.

[6] See Figure A2 in the Appendix for a map showing the distribution of the polarization measures across the NUTS 3-level regions. The description of different regions is reported in Table A1.

We have further distinguished routine manual (RM) and routine cognitive (RC) workers (e.g., Autor et al. 2003). Among the shrinking occupations, jobs that involve analytic and interactive tasks but are highly substitutable for computer capital are defined as routine cognitive jobs. These include ISCO classifications 31 (associate professionals), 41-42 (clerks) and 52 (models, salespersons and demonstrators). Another group of shrinking occupations involve picking, sorting or repetitive assembling tasks. These are included in the group of routine manual jobs, constituting ISCO classifications 72-74 (craft and related trade workers), 81-83 (plant and machine operators and assemblers) and 91 and 93 (sales and service elementary occupations and laborers).

To observe changes in the job distribution stemming from region (in)mobility, we decompose the overall changes in employment shares into a within and between region components. In a within region analysis we compare the changes in occupational shares for those individuals who stayed at the same region both in 1995 and 2009. The between region calculation, on the other hand, is done by comparing the 1995 versus 2009 occupational distribution among those individuals who have moved to other regions after 1995. The decompositions are shown in columns 3 and 4 in Table 1.

The phenomenon of overall job polarization is driven by polarization both within and between regions, although some differences exist between the two components. In particular, the increase in professional jobs and decline of plant operating and clerical jobs comes mostly through the dynamics of worker migration. Regional migration also contributes to most of the decline in sales workers' and some elementary-based cleaning jobs' shares. Unsurprisingly, the dominant role of between region dynamics is mostly explained by worker migration to polarized and more urban areas, rather than worker migration to less urban areas (not reported in Table 1).

[Table 1 in here]

3.2. The subsequent labor market states

We follow the labor market status and occupational transition of individuals who work in declining routine occupations. These individuals may move between occupational categories or end up as non-workers. We have classified the main activity into seven non-overlapping categories (see Table 2). The first occupational group is Routine job, indicating that the routine worker stays in a shrinking occupation or has moved from an RM job to RC job (or vice versa). The second group is Non-routine manual, indicating that a routine worker has switched to a low-paying non-routine occupation (such as services and elementary).[7] The third and fourth occupational groups are Intermediate non-routine cognitive and Higher non-routine cognitive, indicating that the routine worker has moved to a middle-paying or high-paying non-routine abstract occupation. The fifth group is Unemployed, and the sixth group is Self-employed. The seventh group is other, which constitutes students, retired persons and those who are otherwise out of the labor force.

[Table 2 in here]

3.3. Worker transition from routine occupations

We show descriptive evidence of occupational churning in Figure 2 by plotting the smoothed outflow rate by initial occupation and inflow rate by target occupation between 1995 and 2009 (cf. Fedorets et al. 2014). The outflow (inflow) rate is calculated as the number of employees who exited occupation *j* by year 2009 (who entered occupation *j* by year 2009), divided by the total number of employees in occupation *j* in year 2009. The outflow and inflow rates also include individuals who enter or exit the labor markets after 1995, such as retired persons and former students.[8] Figure 2 shows a clear inverse U-shaped relationship between the outflow rate and individual's skill. The outflow rate thus increases with routine intensity. The inflow rate shows some evidence of a lower rate of entering into routine occupations compared to other occupations. The evidence is thus in accordance with the hypothesis that workers adjust to exogenous shocks in demand of occupations by moving out from routine occupations.

Next, we focus on those persons who were routine cognitive (RC) or routine manual (RM) workers in 1995. The distribution of main activities in 2009 for those workers is illustrated in Figure 3. There is a clear discrepancy in occupational transition between the two worker groups. Routine manual workers are more likely than routine cognitive workers to stay in a routine job also 14 years later (48% vs. 39%). Approximately 24% of those who were routine cognitive workers in 1995 have switched to intermediate or high-paying cognitive jobs by the end of 2009. The corresponding share for those who were routine manual workers in 1995 is only 6%. Routine manual workers are also more likely

[7] This non-routine manual category includes ISCO classification 71 (Extraction and building workers), although there may be a disagreement whether this occupation involves non-routine tasks. However, Goos et al. (2014) found that the Routine Task Intensity (RTI) index for ISCO code 71 was negative (Table 1, p. 2512), indicating less routineness of that occupation.

[8] Our calculations are not sensitive to the exclusion of persons who retired after 1995; the shapes of the outflow and inflow rates remained the same as presented in Figure 4. Accordingly, we calculated net outflow rates for three distinct periods: 1995-2000, 2000-2004 and 2004-2009. All the periods show net outflows from routine occupations, especially during 2000-2004. The figures are available from the authors upon request.

to end up unemployed compared to routine cognitive workers (6% vs. 9%). Approximately 90% of the observations in the group *Other* are retired persons, and this share is similar for both worker groups. We also took a closer look at the pathways from 1995 to 2009 and found that the gaps in distributions of main activities were already distinct in 2000, and the gaps remained quite stable from 2004 onwards (not shown in figures).

Figure 4 shows the distribution of main activities in 2009 separately for regional stayers and regional movers by routine worker group. It is likely that regional migration mitigates the negative labor market effects of polarization. As can be seen from the figure, occupational shift to some non-routine cognitive job is stronger among movers than among stayers (5% vs. 13% among RM workers and 23% vs. 31% among RC workers). However, persons are more likely to stay in declining routine occupations if they do not migrate.

In the analysis, it is important to distinguish occupational transitions that can be explained, e.g., by career progression and routinization-driven replacement of employees (e.g., Holmes 2011, Holmes and Tholen 2013).[9] However, career progression is accompanied by a voluntary occupational change and wage gain, as Gathmann and Schönberg (2010) and Fedorets et al. (2014) also point out. Therefore, it is not meaningful to assume that the occupational transition of routine workers to non-employment or to low-paid or other middle-paid occupations is explained by career progression. The occupational transition to high-paying occupations may instead be explained by career progression. We take this possibility into account in the empirical part of our analysis by controlling for a person's skill level, education and age in the models. Occupational transition is furthermore an important adjustment mechanism in the labor market. In contrast to career progression, occupational changes may be driven, for example, by exogenous shifts in demand for occupations, as Figure 2 suggests. [10]

[Figures 2-4 in here]

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[9] Holmes (2011) and Holmes and Tholen (2013) simply compared the occupational transitions using different cohorts of people who were either unaffected or affected by routinization. They found that routine workers among older cohorts (i.e., in the absence of job polarization) were more likely to stay in routine work and less likely to switch to non-routine jobs compared to younger cohorts.

[10] It is informative to compare the occupational transition patterns between each main occupation group: non-routine manual, routine, intermediate non-routine and higher non-routine cognitive. The results are reported in Table A2 in the Appendix. The results show that a higher share of routine workers than other workers have dropped into low-paying manual jobs or ended up unemployed or out of the labor force. Interestingly, the occupational transition upward to cognitive jobs is similar for both low-skilled non-routine manual and middle-skilled routine workers, although routine workers have typically attained more formal education.

4. Empirical analysis on occupational transition

4.1. Empirical models

We first look at the general occupational transition pattern over time by creating a panel data for the years 1995, 2000, 2004 and 2009. We apply a logit model to examine the probability that a worker switched occupation, as measured by the 2-digit ISCO classification, between the years *t-1* and *t*. The equation is the following:

$$\text{Occupational change}_{\text{it}} = \boldsymbol{\alpha}'\mathbf{Task}_{\text{it}-1} + \gamma\Delta \text{u}_{\text{t}} + \delta\text{Time}_{\text{t}} + \boldsymbol{\beta}'\mathbf{X}_{\text{it}-1/\text{t}} + \varepsilon_{\text{it}}\,, \qquad (2)$$

where $\mathbf{Task}_{\text{it}-1}$ is a categorical variable consisting of non-routine manual, routine, intermediate non-routine cognitive and higher non-routine cognitive workers *i* at year *t-1* (cf., Table 2). Time_{t} is time trend and $\Delta \text{u}_{\text{t}}$ is the change in unemployment rate between the years *t* and *t-1* that is added to condition out the cycle effect. Accordingly, matrix $\boldsymbol{\beta}'\mathbf{X}_{\text{it}-1\,/\,\text{t}}$ includes background characteristics that are associated with an individual's transition pattern (see, also, Holmes 2011, Asplund et al. 2015). The controls are measured in year *t-1* and include cohort dummies (four categories: Less than 25 years old, 25-34 years old, 35-44 years old, and Over 45 years old), gender (Female), working sector (Public sector = 1 if the individual works in the public sector), marital status (Married = 1 if the individual is married), having children (Children = 1 if the individual has underage children), native language (Finnish = 1 if individual speaks Finnish as native language), home ownership (Home ownership = 1 if the individual is homeowner) education level (three categories: Primary, Secondary, and Higher), field of study (nine categories: General, Teaching, Humanistic & arts, Business & social sciences, Natural sciences, Technology, Forestry & agriculture, Health & social work, and Services), and industry (six categories: Manufacturing, Construction, Sales & Accommodation & Food service, Transportation, Services & other industries, and Public administration & Education & Health). It is possible that persons have attained more education between the years *t* and *t-1,* which might explain some of the career paths together with the increased work experience. Therefore, we also add education level measured in year *t* to the model.

We control for individual's skill level, which is calculated as the worker's rank (1-100) in the gender-specific wage distribution within his or her occupation in year *t-1*. We used the most disaggregated definition of the occupational category (4-digit code). We control for the initial skill level because Groes, Kircher and Manovskii (2015) have shown that the occupational transition is U-shaped. This means that both low-ability and high-ability workers within an occupation are more likely to switch jobs compared to middleability workers. In particular, low-ability workers are more likely to switch to a new occupation with lower wages, whereas high-ability workers are more likely to switch to a new occupation with higher wages. Finally, ε_{it} is the error term.

We next focus on a sub-group of people who were either routine manual or routine cognitive workers in 1995. We apply a multinomial (polytomous) logit regression to examine the occupational transition patterns of these routine workers from 1995 to 2009. This discrete choice model is used because the response variable has m > 2 unordered categories. The response variable is $Activity_{i,2009}$, and it is equal to one if person *i´*s main activity in year 2009 has occurred, and it is zero otherwise. In particular, our (latent) outcome variable can be expressed as follows:

$$\mathrm{Activity}_{i,2009} = \alpha \mathrm{RM}_{i,1995} + \boldsymbol{\beta}'\mathbf{X}_{i,1995/2009} + \varepsilon_i \quad , \qquad (3)$$

where $RM_{i,1995}$ gets a value of one if person *i* worked in a routine manual occupation in 1995 and zero if person *i* worked in a routine cognitive occupation in 1995. Matrix $\boldsymbol{\beta}'\mathbf{X}_{i,1995/2009}$ is similar to that in equation (2). [11]

Finally, we examine whether within-country migration is associated with the re-employment and non-employment probabilities of routine workers. The multinomial logit model is as follows:

$$\mathrm{Activity}_{i,2009} = \alpha Migration_{i,2009-1995} + \boldsymbol{\beta}'\mathbf{X}_{i,1995} + \gamma House\ prices_{r,1995} + \delta Family\ location_{i,1995} + \varepsilon_i \quad , \qquad (4)$$

where $Migration_{i,\,2009\text{-}1995}$ gets a value of one if an individual *i* has moved from one region to another between 1995 and 2009 and zero if an individual *i* has stayed at the same region both in 1995 and 2009. The multinomial logit model (4) is estimated separately for routine cognitive and routine manual workers.

In the migration analysis, we acknowledge that within-country movers among the routine workers are not randomly drawn but are self-selected to migration (e.g., Borjas et al 1992). The estimates are essentially descriptive, and care must be taken when it comes to causal interpretations. For example, there might be omitted variables that affect both

[11] The results of our analysis are not sensitive to chosen base and end years (1995 vs. 2009). We created a similar panel data as in model (2) and included the years 2000 and 2004 in the analysis. We then re-ran the multinomial logit model to examine whether routine manual workers at year *t-1* were less/more likely to switch to another labor market state by the end of year *t* compared to routine cognitive workers. The results were in line with those reported in this paper (Table 4).

migration and occupational transition. A special emphasis in the literature has been the treatment of the migration decision using some form of Instrumental Variable (IV) method. If endogenous migration is properly accounted for, the results regarding the occupational transition may change. However, it is difficult to find instruments that meet the conditions of a strong first stage and the exclusion restriction. As we know, using weak instruments increases the risk that the estimates are even more biased (e.g., Angrist and Krueger 1999). Therefore, we interpret the results as magnitudes of associations rather than causal effects.

Local house prices have been used as an instrument for the migration decision (e.g., Pekkala and Tervo 2002). It is, however, likely that house prices are higher (lower) in more urban (rural) areas that have better (worse) employment prospects in general. We therefore use local house prices only as additional control variables. Huttunen, Møen and Salvanes (2016) examined the migration decision using information on parents' and siblings' home location. The results showed that social interaction with the family is a predictive factor for the regional mobility decision. However, family location is not necessarily exogenous, nor does it fit the assumption of exclusion restriction. For example, if a routine worker lives in another region than his/her family, it is likely that the worker has moved before. We also know that previous migration behavior is a predictive factor for a future migration decision. Accordingly, family location can be indirectly related to the regressors of interest if displaced routine workers use family ties to find a new job, for example, in the form of nepotism or good connections with the local firms. Both local house prices and the location of the family could serve as useful controls. We thus add local house prices in 1995 and whether a parent or a sibling lives in the same region as a routine worker in 1995 to the model (4). Approximately 18 % of the observations did not have information on a family member. This means that they have no siblings and/or their parents are over 70 years old or already passed way. We simply treated these observations as not having a family member living in the same region as the routine worker lives. In robustness tests, we also re-ran all the models for a sub-group of people for which we had information on the location of some family member. The results were nevertheless similar in both specifications.

4.2. Empirical results

The marginal effects of logit estimates of $\mathbf{Task}_{\mathrm{it-1}}$ from equation (2) are reported in Table 3. For simplicity, other control variables are not reported. The hypothesis is that routine workers are more likely to change occupations compared to other workers. Fedorets et al. (2014) found that a higher routine task input is associated with more occupational changes, and a higher manual task input is associated with less occupational changes compared to cognitive task inputs. The results are consistent with the routine-bias hypothesis. Routine workers are more likely to change occupations compared to other workers. Non-routine manual and intermediate cognitive workers are on the other hand less likely to switch occupations. The time trend exhibits a positive value, which indicates that occupational transition, particularly among younger cohorts, has increased over time.

[Table 3 in here]

Table 4 reports the marginal effects of our multinomial logit model in equation (3). Routine manual workers have a ~6%-points higher probability of working in a routine job also in 2009 compared to routine cognitive workers. Routine manual workers also have a higher probability of ending up in a low-paying non-routine manual occupation 14 years later. The labor market prospects are clearly better for routine cognitive workers. In particular, they have a ~5-7%-point higher probability of moving to an intermediate or high-paying non-routine cognitive occupation compared to routine manual workers. The probability of non-employment is also higher for routine manual workers (1-2 %-points).

The estimates of background characteristics correspond to the expectations well. More skilled workers (measured by education or initial wage level within an occupation) have a higher re-employment probability, particularly with respect to middle- and high-paying non-routine jobs. Older people are less likely to keep their routine job or switch to another occupation compared to younger people. Females also have weaker labor market prospects compared to males (see,, also Holmes 2011). For example, females are more likely to end up in low-paying non-routine manual occupations (~3%-points), and less likely to shift to high-paying non-routine cognitive occupations (~4%-points) compared to males. Married individuals and those who have children have a generally higher probability of staying employed, either as a wage earner or self-employed. Being married and parenting could increase incentives to search for better labor market prospects to provide living for the family.[12] Field of study and industry also contribute significantly to the individual transition pattern. All these results are in large part in line with Asplund et al. (2015).

Finally, the estimate for the public sector dummy confirms known facts that public sector workplaces are more stable than private sector workplaces. We examined the role of the public sector in more detail (not reported in tables). We found that the occupational

[12] 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 especially were more likely to make occupational choices that sorted them into safer jobs.

transition from routine jobs to low-paying manual jobs (middle- or high-paying cognitive jobs) was often combined with exit from the private (public) sector and entry into the public (private) sector. [13]

Table 5 reports the results of our migration analysis from equation (4) separately for routine manual and routine cognitive workers. For simplicity, other covariates are not reported, but we comment on some of the interesting results here briefly. House prices and family location were related to the re-employment and non-employment probabilities of routine workers. As hypothesized, higher house prices were positively related to the occupational transition to cognitive jobs and negatively related to non-employment. Family closeness, as measured by location, was negatively associated in particular with the probability of ending up out of the labor force.[14]

The estimates for the migration dummy indicate that there is both a positive and negative association between migration and future labor market states (Table 5, Panels A). On the one hand, routine workers who migrate are less likely (~9-10%-points) to keep their shrinking occupation and more likely (~2-5%-points) to become non-workers 14 years later, but on the other hand, they are more likely (~1%-point) to move upward within the skill distribution. There is thus inconclusive evidence on the association between regional mobility and future labor market status, and this discrepancy is explained by the worker flows to different areas. As an additional test, we run the multinomial logit model for the sub-group of regional movers. We created a dummy variable indicating whether an individual has moved to an urban and polarizing region (=1) or to a less urban, non-polarizing region (=0). [15] The results are reported in Table 5, Panels B. As expected, the occupational shift to cognitive jobs is clearly stronger for those former routine workers who migrate to more urban and polarizing regions. For example, regional movers have a 2-3 %-point higher probability of shifting to high-paying cognitive jobs if they move to more urban regions compared to less urban regions. The re-employment probabilities are also more profound for former routine cognitive workers. Inter-country migration to more urban regions is also negatively associated with

[13] Approximately 20% of routine workers in our sample switched working sectors between the years 1995 and 2009, as calculated conditional on being a wage earner also in 2009. The direction of the shift was more common from the public sector to the private sector (33%) than from the private sector to the public sector (14%).

[14] Family location was an important predictor for the migration decision (cf. Huttunen et al. 2016). In particular, workers were less likely to migrate from their initial location if they had a parent and/or a sibling living in the same location. Higher house prices were negatively associated with the migration decision.

[15] We also considered four ´home location-target location´ combinations: migration from polarizing region to non-polarizing region; migration from non-polarizing region to polarizing region; internal migration between polarizing regions; and internal migration between non-polarizing regions. The results were basically intact.

unemployment and being out of the labor force. The results thus suggest that routine workers who move to less urban regions are clearly worse off when examined based on their labor market status. Interestingly, these regional movers moved often to locations where their family lives. We calculated the *t*-test for equal means of the same family member location by movers who moved to more urban regions and movers who moved to less urban regions. For approximately 30% of 'urban' movers, some family member was already living in the target region in 2009. The corresponding share for 'less urban' movers was approximately 40%, and this difference in group means was statistically significant at least at the 1% significance level. Overall, the results suggest that routine workers might improve their labor market prospects by moving to more urban regions with lower unemployment. People might also migrate based on incentives other than economical ones, such as family ties. These movers are nevertheless less likely to find a new job after displacement from routine work.

5. 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 extensive Finnish linked employee-employer data (FLEED), we investigated the impact of job polarization on the labor market position and labor market transition of workers from declining routine occupations into different labor market states (non-routine manual, intermediate non-routine cognitive, higher non-routine cognitive, unemployed, outside the labor market). In the analysis of the switching patterns of workers in declining routine jobs, we classified routine occupations into manual and cognitive categories (Autor et al. 2003). We also investigated the role of within-country migration in re-employment (and non-employment) probabilities.

Our results are consistent with a mechanism of occupational transition out of routine occupations that is related to routinization-driven shocks in the labor market. Nilsson Hakkala and Huttunen (2016) have used the same register data as we do to examine the causal effect of Chinese import competition and offshoring on employment in Finland. They instrumented Chinese imports by changes in China's share of world exports to other EU countries and found that both types of importing increase the risk of job loss particularly among production workers (see also Autor et al. 2014). Autor et al. (2013) also showed that importing decreases the shares of both routine manual and routine cognitive workers in the US. Our descriptive result that workers tend to move out (either voluntarily or involuntarily) from routine occupations is thus in line with previous studies that rely on identification of causal effects.

However, the consequences of job polarization and occupational transition patterns are not similar to all routine workers, but there are distinct differences between routine manual and routine cognitive worker groups. Routine manual workers are more likely to end up in low-paying non-routine manual jobs or become unemployed, while routine cognitive workers are more likely to move upwards to non-routine cognitive jobs. The upward occupational transition may well be explained by a career progression, but we have taken this into account by controlling for the individual's skill level and other important background characteristics in the models. Interestingly, the role of public vs. private sector in these occupational transitions is quite important. In general, jobs in the public sector are less threatened by displacement due to routinization shocks. Many former routine workers have also combined the occupational move with the shift between private and public sectors as well. Those routine workers who ended up in low-paying manual occupations often exited the private sector to enter the public sector. This is reasonable, as the public sector pays more at the lower-end of the wage distribution (e.g., Lucifora and Meurs 2006, Cai and Liu 2011). On the contrary, former routine workers who moved to middle- or high-paying cognitive occupations often switched from the public sector to the private sector, which generally pays more at the high-end of the wage distribution. [16]

Further, we find that migration to more urban and industrialized regions mitigates the negative labor market effects of polarization. The results show that the re-employment probabilities are clearly better, and non-employment probabilities are clearly lower for those former routine workers who migrate particularly to more urban and polarizing areas. It thus seems that people respond to economic incentives by moving out from high unemployment areas, as also found in a previous study from Finland (Böckerman et al. 2017). However, the migration decision can also be based on motives other than economic ones, such as close family ties. We find that routine workers who migrated to less urban areas often moved to regions where some of their family members lived. Those former routine workers had a higher probability of becoming unemployed or moving outside the labor force.

[16] Workers also respond to these wage differences along the distribution by moving out from the public sector to enter the private sector at higher wage levels (Borjas 2002, Maczulskij 2017). Workers also tend to exit the private sector to enter the public sector at lower wage levels (Maczulskij 2017). Our findings are thus in line with the previous literature on public sector labor markets.

One key goal for public labor market policy should be to support routine manual workers in particular to obtain training and other active labor market policy measures that would improve their future employment prospects. One way to deal with occupational transition problems is also to link (former) routine workers more closely to good non-routine jobs, for example, through apprenticeships or other education programs with firms. The role of firms is important in explaining the current process of job polarization, as occupational restructuring has been shown to happen both via within and between firm dynamics (e.g., Heyman 2016, Pekkala Kerr et al. 2016). However, the increase in non-routine cognitive jobs is more profound within continuing firms, whereas new firms are showing a much higher job concentration in non-routine manual occupations relative to existing or exiting firms (Pekkala Kerr et al. 2016). This indicates that such work-to-work training in firms would not necessarily be beneficial if the direction of the shift is aimed at elementary or service occupations because such jobs are not necessarily available in those firms. The work-to-work training in firms should therefore be concentrated on upward mobility, which is not easy as many non-routine cognitive jobs need some formal higher education. Therefore, the role of public labor market policy is more important.

Our results also suggest that migration in particular to more urban and polarizing regions mitigates the negative labor market effects of job polarization. Therefore, it would also be important to promote more affordable housing options in areas with more job opportunities, thereby also making migration a more feasible option for routine workers.

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Figures and tables

Figure 1. Smoothed job polarization graph ranked by initial wage, 2-digit level (1995 vs. 2009)

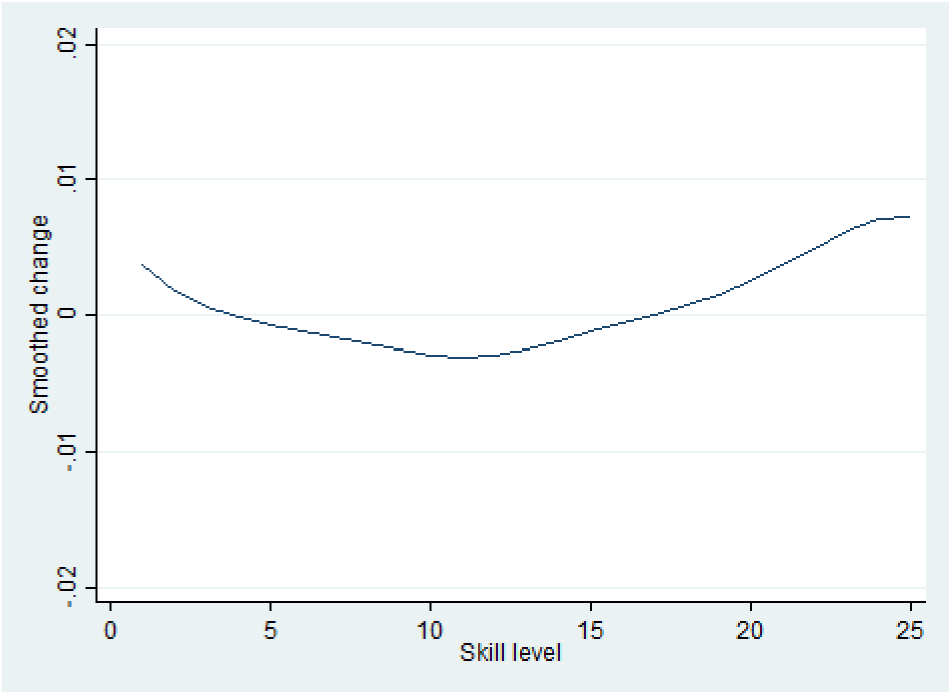

Figure 2. Smoothed outflow and inflow rates by 2-digit occupation level ranked by initial wage (1995 vs. 2009)

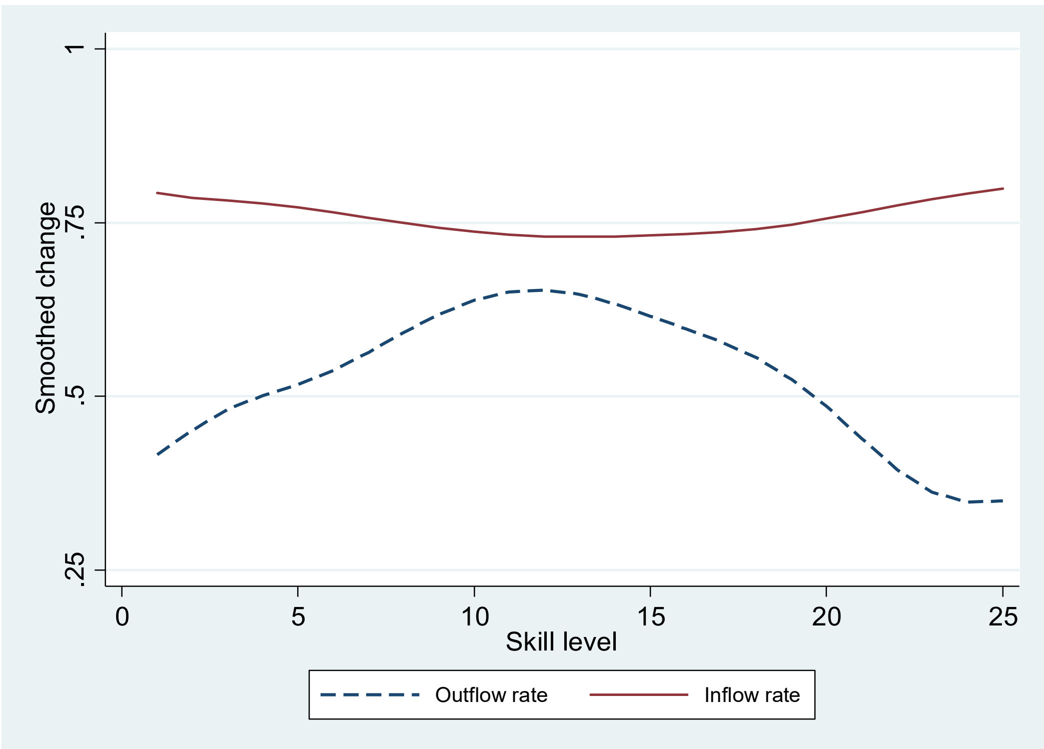

Figure 3. Distribution of main activities in 2009 for individuals who were RM or RC workers in 1995

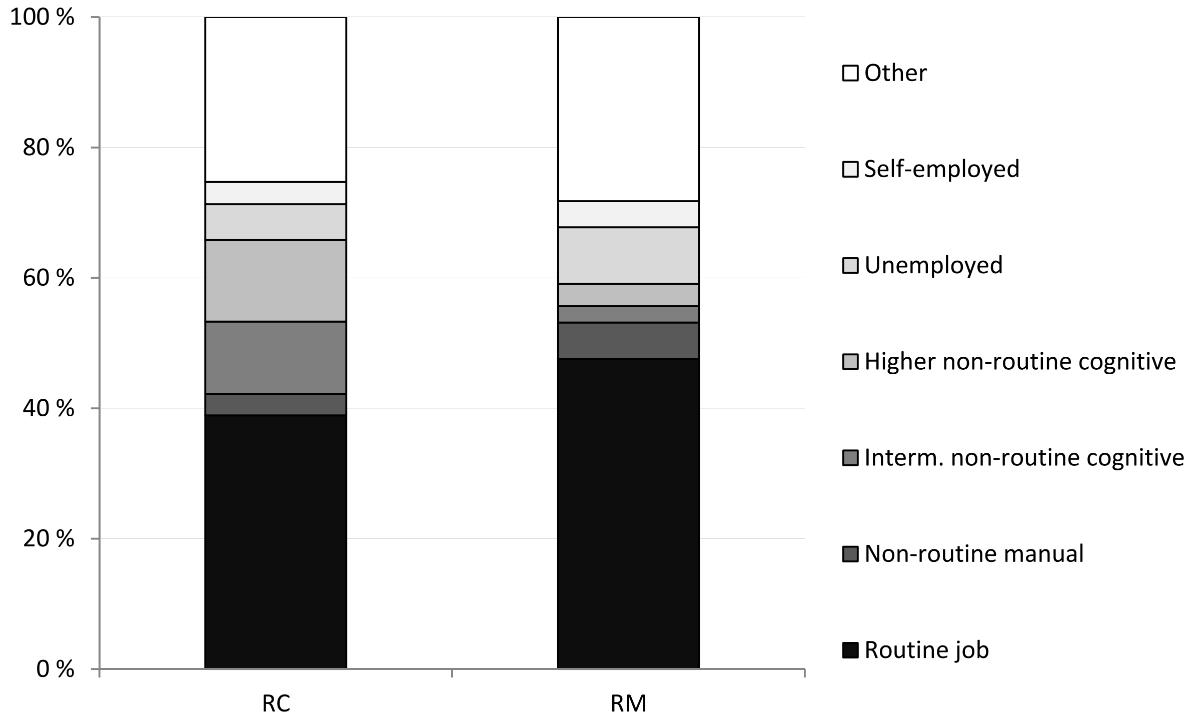

Figure 4. Distribution of main activities in 2009 for individuals who were RM or RC workers in 1995: movers and stayers

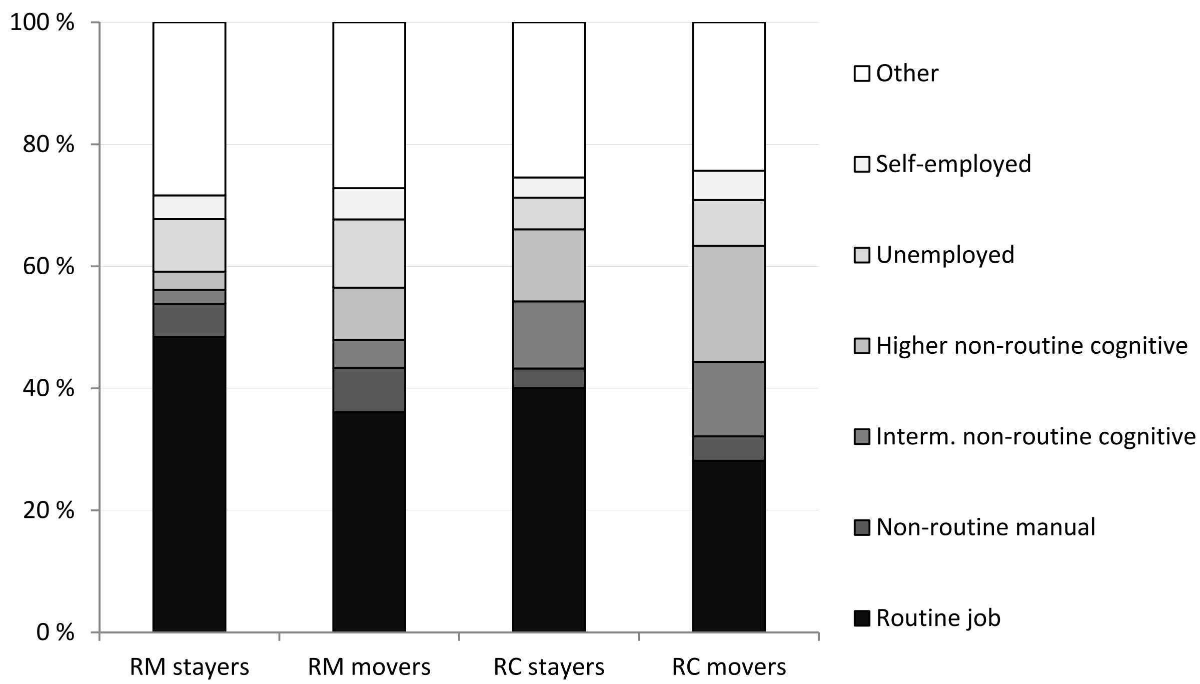

Table 1. Changes in the shares of occupations 1995-2009

Occupations ranked by 2009 occupational mean wage	ISCO code (1)	%-point change 1995-2009 (2)	Within regions (3)	Between regions (4)
High-paying occupations				
Corporate managers	12	1.91	1.77	2.51
Legislators and senior officials	11	0.11	0.11	0.12
Life science and health professionals	22	0.19	0.10	0.42
Physical, mathematical and engineering professionals	21	1.63	1.20	3.97
General managers	13	0.86	0.88	0.65
Other professionals	24	1.69	1.25	4.02
Physical and engineering associate professionals	31	-0.81 (RC)	-1.00	0.54
Middle-paying occupations				
Teaching professionals	23	1.23	0.92	2.38
Stationary plant and machine operators	81	-0.08 (RM)	0.02	-0.47
Other associate professionals	34	2.43	2.39	2.42
Metal, machinery and related trades workers	72	-2.77 (RM)	-2.64	-2.89
Life science and health associate professionals	32	0.66	0.51	1.50
Extraction and building trade workers	71	0.73	0.83	0.35
Labourers in mining, construction, manufacturing and transport	93	-0.32 (RM)	-0.24	-0.67
Customer services clerks	42	-0.74 (RC)	-0.71	-0.71
Handicraft and printing workers	73	-0.51 (RM)	-0.51	-0.45
Machine operators and assemblers	82	-0.85 (RM)	-0.68	-1.76
Drivers and mobile plant operators	83	-0.52 (RM)	-0.36	-0.98
Teaching associate professionals	33	0.02	0.003	-0.004
Office clerks	41	-2.54 (RC)	-2.35	-3.38
Low-paying occupations				
Personal and protective service workers	51	0.17	0.54	-2.23
Other craft and related trades workers	74	-0.51 (RM)	-0.46	-0.82
Models, salesperson and demonstrators	52	-1.60 (RC)	-1.46	-2.75
Sales and service elementary occupations	91	-0.40 (RM)	-0.13	-1.79
Agricultural, forestry and fishery labourers	92	0.02	0.02	0.01

Notes: Occupations are ranked by their mean annual earnings in 2009. The rank order is in some cases different in column (3) and (4). RM = routine manual; RC = routine cognitive.

Table 2. Main activity groups

Group	Definition
(a) Routine job	Stay in shrinking routine cognitive or routine manual job. ISCO classifications 31, 41-42, 52, 72-74, 81-83, 91, 93
(b) Non-routine manual	Move to non-routine manual job. These jobs are typically located at the bottom-half of the wage distribution. ISCO classifications 51, 71, 92
(c) Intermediate non-routine cognitive	Move to intermediate non-routine job that involves abstract tasks. These jobs are typically located at the middle of the wage distribution. ISCO classifications 32-34
(d) Higher non-routine cognitive	Move to higher (managerial or professional) non-routine cognitive job that involves abstract tasks. These jobs are located at the top of the wage distribution. ISCO classifications 11-13, 21-24
(e) Unemployed	Individual becomes unemployed
(f) Self-employed	Individual becomes self-employed
(g) Other	Individual becomes other non-worker. This group includes students, retired persons and those who are otherwise out of labor force.

Table 3. Logit estimates (marginal effects) of occupational change

	Occupational change
Non-routine manual	-0.049***
	(0.0010)
Routine	0.031 ***
	(0.0010)
Intermediate non-routine cognitive	-0.007 ***
	(0.0009)
Higher non-routine cognitive	(Ref.)
Time	0.086 ***
	(0.0006)
Other controls	Yes
Number of obs.	3,900,603

Notes: Other controls include skill level, change in unemployment rate, age, female dummy, public sector dummy, marital status, having children, native language, home ownership, education level, field of study and industry. *** is statistically significant at least at the 1% significance level

Table 4. Multilevel logit estimates (marginal effects) on main activity in 2009

	Stay in routine job	Non-routine manual job	Intermediate non-routine cognitive job	Higher non-routine cognitive job	Unemployed	Self-employed	Other
Routine manual	0.056 *** (0.001)	0.023 *** (0.001)	-0.047 *** (0.001)	-0.066 *** (0.001)	0.013 *** (0.001)	-0.0005 (0.001)	0.022 *** (0.001)
Skill	0.0008 *** (0.00002)	-0.0001 *** (0.00001)	0.0002 *** (0.00001)	0.0003 *** (0.00002)	-0.0005 *** (0.00001)	-0.0002 *** (0.00001)	-0.0004 *** (0.00002)
Age							
25-34	0.046 *** (0.002)	-0.011 *** (0.001)	-0.016 *** (0.001)	-0.016 *** (0.001)	0.022 *** (0.001)	-0.006 *** (0.001)	-0.019 *** (0.002)
35-44	0.027 *** (0.002)	-0.025 *** (0.001)	-0.033 *** (0.001)	-0.041 *** (0.001)	0.043 *** (0.001)	-0.026 *** (0.001)	0.056 *** (0.002)
45 >	-0.183 *** (0.002)	-0.046 *** (0.001)	-0.058 *** (0.001)	-0.068 *** (0.001)	0.034 *** (0.001)	-0.049 *** (0.001)	0.371 *** (0.002)
Female	-0.007 *** (0.001)	0.026 *** (0.001)	0.027 *** (0.001)	-0.040 *** (0.001)	-0.003 *** (0.001)	-0.024 *** (0.001)	0.021 *** (0.001)
Public sector	0.031 *** (0.001)	0.005 *** (0.001)	-0.001 (0.001)	-0.009 *** (0.001)	-0.015 *** (0.001)	-0.031 *** (0.001)	0.020 *** (0.001)
Married	0.007 *** (0.001)	0.004 *** (0.001)	0.006 *** (0.001)	0.011 *** (0.001)	-0.017 *** (0.001)	0.006 *** (0.001)	-0.017 *** (0.001)
Children	0.041 *** (0.001)	0.005 *** (0.001)	0.006 *** (0.001)	0.004 *** (0.001)	0.004 *** (0.001)	0.002 *** (0.0005)	-0.063 *** (0.001)
Finnish	-0.014 *** (0.002)	-0.006 *** (0.001)	-0.002 (0.001)	-0.001 (0.001)	0.019 *** (0.001)	-0.007 *** (0.001)	0.011 *** (0.002)
Home ownership	0.010 *** (0.001)	-0.003 *** (0.001)	-0.001 (0.001)	0.0001 (0.001)	-0.013 *** (0.001)	0.009 *** (0.0005)	-0.003 *** (0.001)
Education level in 1995							
Secondary	0.001 (0.004)	-0.032 *** (0.001)	-0.018 *** (0.002)	0.006 *** (0.002)	-0.007 *** (0.002)	0.001 (0.001)	0.049 *** (0.004)
Higher	-0.012 *** (0.004)	-0.039 *** (0.001)	0.0001 (0.001)	0.034 *** (0.001)	-0.018 *** (0.002)	0.002 *** (0.001)	0.032 *** (0.003)
Education level in 2009							
Secondary	-0.049 *** (0.003)	0.048 *** (0.001)	0.034 *** (0.001)	0.042 *** (0.002)	0.002 (0.002)	-0.003 *** (0.001)	-0.073 *** (0.003)
Higher	-0.210 *** (0.004)	0.002 (0.002)	0.071 *** (0.002)	0.155 *** (0.002)	0.010 *** (0.002)	-0.004 *** (0.001)	-0.024 *** (0.004)

Table 4 (Cont). Multilevel logit estimates (marginal effects) on main activity in 2009

	Stay in routine job	Non-routine manual job	Intermediate non-routine cognitive job	Higher non-routine cognitive job	Unemployed	Self-employed	Other
Field of education							
Teaching	-0.002	0.008 ***	-0.006 **	-0.023 ***	0.009 **	0.022 ***	-0.008
	(0.007)	(0.003)	(0.003)	(0.002)	(0.004)	(0.002)	(0.006)
Humanistic & arts	-0.088 ***	0.024 ***	0.007	0.037 ***	0.004	0.022 ***	-0.005
	(0.018)	(0.006)	(0.006)	(0.005)	(0.010)	(0.006)	(0.012)
Business & soc. sci	0.049 ***	-0.020 ***	0.019 ***	-0.021 ***	0.0004	-0.003 **	-0.025 ***
	(0.003)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
Natural sciences	0.078 ***	-0.005 ***	-0.029 ***	-0.019 ***	0.004 **	-0.003***	-0.027 ***
	(0.003)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
Technology	0.109 ***	-0.015 ***	-0.042 ***	-0.063 ***	-0.002	0.0000	0.014 ***
	(0.006)	(0.003)	(0.004)	(0.003)	(0.003)	(0.002)	(0.005)
Forestry & agriculture	-0.041 ***	0.048 ***	0.037 ***	-0.014 ***	-0.023 ***	0.023 ***	-0.029 ***
	(0.006)	(0.002)	(0.002)	(0.003)	(0.004)	(0.002)	(0.005)
Healt & social work	0.028 ***	-0.013 ***	0.014 ***	-0.037 ***	-0.009 ***	0.021 ***	-0.003
	(0.005)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.004)
Services	0.056 ***	0.018 ***	-0.018 ***	-0.039 ***	-0.003	0.001	-0.015 ***
	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.003)
Industry							
Construction	0.058 ***	0.016 ***	0.010 ***	0.010 ***	-0.070 ***	-0.008 ***	-0.016 ***
	(0.004)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)
Sales, acc. & food	-0.063 ***	0.047 ***	-0.001	0.019 ***	-0.018 ***	0.027 ***	-0.010 ***
	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Transportation	0.014 ***	0.015 ***	0.018 ***	-0.022 ***	-0.031 ***	0.019 ***	-0.013 ***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Services & other	0.024 ***	0.007 ***	0.005 ***	0.0002	-0.039 ***	0.018***	-0.015 ***
	(0.001)	(0.001)	(0.001)	(0.0001)	(0.001)	(0.001)	(0.001)
Public ad, educ & health	0.055 ***	0.038 ***	0.002 *	-0.012 ***	-0.061 ***	-0.006 ***	-0.017 ***
	(0.003)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Number of obs.	728,473	728,473	728,473	728,473	728,473	728,473	728,473

Notes: Reference categories for categorical independent variables: Less than 25 years old, primary education, general field of education, manufacturing. ***, ** are statistically significant at least at the 1% and 5% significance levels.

Table 5. Multilevel logit estimates (marginal effects) of region mobility and regional mobility to pol. region on main activity in 2009: RC and RM workers

	Stay in routine job	Non-routine manual job	Intermediate non-routine cognitive job	Higher non-routine cognitive job	Unemployed	Self-employed	Other
Routine manual workers:							
A: Entire sample							
Migration	-0.108 *** (0.003)	0.010 *** (0.001)	0.005 *** (0.001)	0.010 *** (0.001)	0.026 *** (0.002)	0.005 *** (0.001)	0.053 *** (0.002)
B: Sample of movers							
Migration to pol. region	0.041 *** (0.005)	0.008 *** (0.003)	0.006 *** (0.002)	0.019 *** (0.003)	-0.030 *** (0.004)	-0.004 (0.002)	0.040 *** (0.004)
Routine cognitive workers:							
A: Entire sample							
Migration	-0.098 *** (0.003)	0.004 *** (0.001)	0.001 (0.002)	0.014 *** (0.002)	0.021 *** (0.001)	0.008 *** (0.001)	0.051 *** (0.002)
B: Sample of movers							
Migration to pol. region	0.012 ** (0.005)	0.002 (0.002)	0.022 *** (0.004)	0.027 *** (0.004)	-0.019 *** (0.003)	-0.012 *** (0.003)	-0.031 *** (0.004)

Notes: Other controls include age, female dummy, public sector dummy, marital status, having children, native language, home ownership, education level, field of study, industry, house prices and dummies if a parent or a sibling lives in the same region. *** and ** are statistically significant at least at the 1% and 5% significance levels, respectively. N = 312,369 for routine cognitive workers in panel A; N = 416,104 for routine manual workers in panel A. N = 28,121 for routine cognitive workers in panel B; N = 33,385 for routine manual workers in panel B.

Appendix A

Figure A1. Changes in employment shares by 1-digit occupation (1995 vs. 2009/2012)

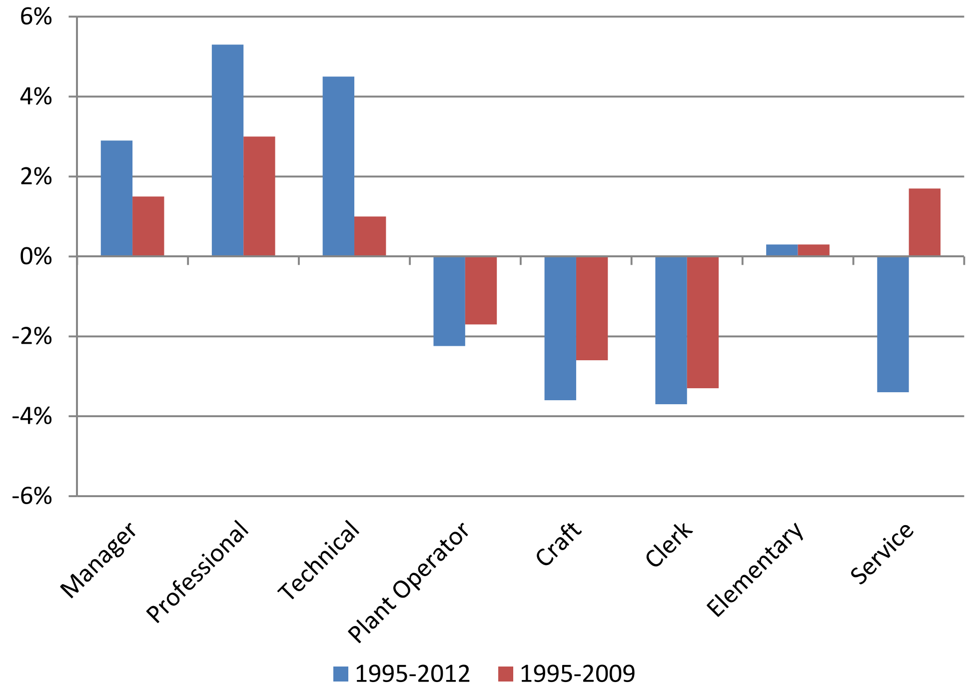

Figure A2 Polarization of 19 local labor markets

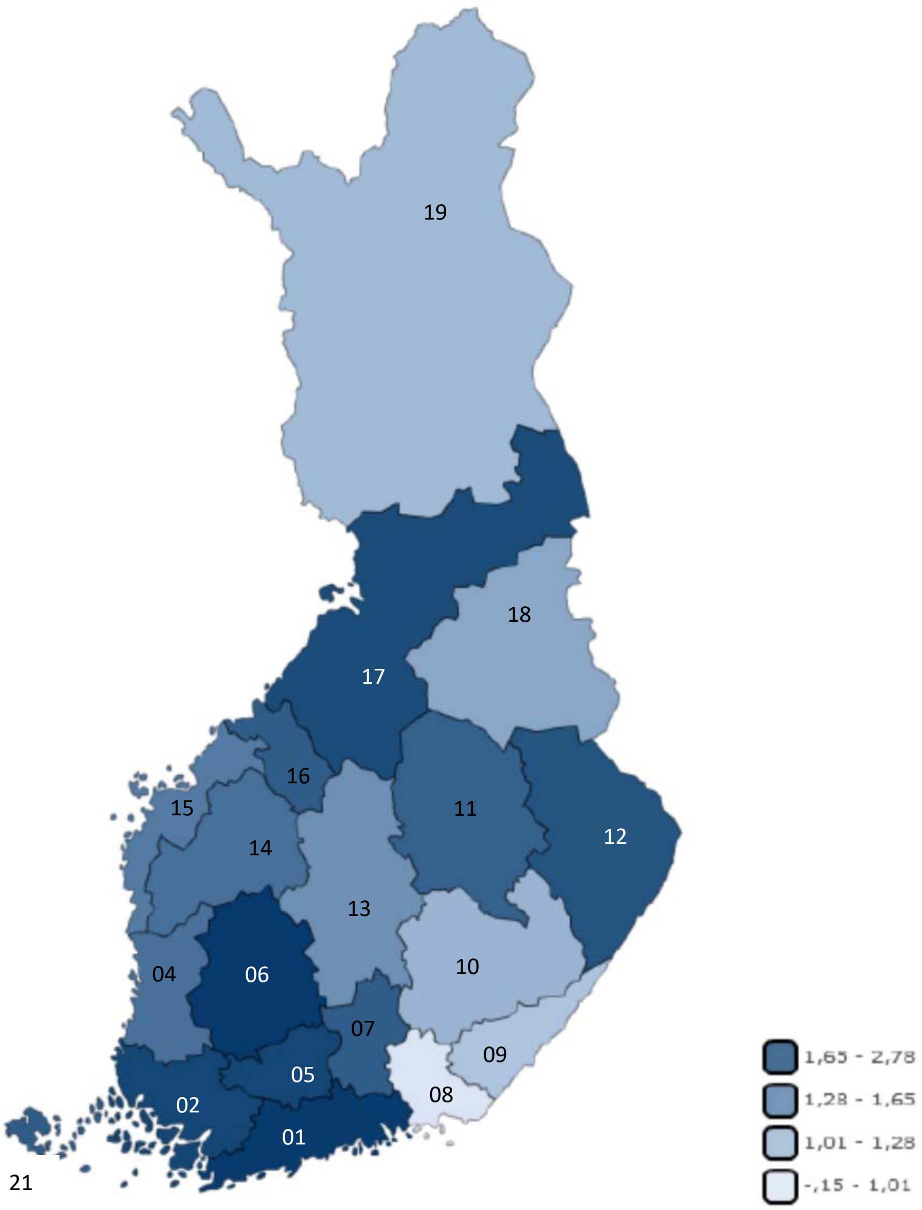

Table A1. Description of NUTS 3-level regions in 2015

Region	Code[a]	Population	Unemployment%	Share of total export, %
Entire Finland		5,487,308	9.4	100
Uusimaa	01	1,620,261	8	31.4
Varsinais-Suomi	02	474,323	10.2	8.6
Satakunta	04	222,957	9.1	6.2
Kanta-Häme	05	174,710	8.2	2.4
Pirkanmaa	06	506,114	10.7	7.7
Päijät-Häme	07	201,615	9.5	3.2
Kymenlaakso	08	178,688	11.8	8.8
South Carelia	09	131,155	10.2	2.4
Etelä-Savo	10	150,305	9.6	0.7
Pohjois-Savo	11	248,129	9.7	2.1
North Carelia	12	164,755	10.7	1.4
Central Finland	13	275,780	11.5	4.0
South Ostrobothnia	14	192,586	8.9	1.0
Ostrobothnia	15	181,679	6.9	5.8
Central Ostrobothnia	16	69,032	5.7	3.2
North Ostrobothnia	17	410,054	10.3	2.6
Kainuu	18	75,324	14.9	0.3
Lapland	19	180,858	11.8	7.0
Åland Island	21	28,983	4.7	0.2

Note: [a] Region codes are based on the Statistics Finland classification (see also Figure A2). Source: Statistics Finland and Finnish Customs.Sources: Statistics Finland and Finnish Customs.

Table A2: Main activity group in 2009

Main activity group in 2009:	Routine job	Non-routine manual job	Intermediate non-routine cognitive job	Higher non-routine cognitive job	Unemployed	Self-employed	Other	Mean age in 1995
Occupation group in 1995:								
Routine	44%	5%	6%	7%	7%	4%	27%	45
Non-routine manual	13%	41%	7%	5%	5%	4%	25%	45
Intermediate non-routine cognitive	12%	2%	39%	15%	4%	4%	24%	46
Higher non-routine cognitive	5%	1%	5%	58%	3%	4%	24%	47