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Reducing automation risk through career mobility: where and for whom?

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Abstract

Automation risk prevails less in large cities compared to small cities but little is known about the drivers of this emerging urban phenomenon. A major challenge is that automation risk is quantified by work-related tasks that allows for measurement through occupation, which is in turn implicitly related to local economic structure and to individual career paths. This paper examines the role of working in cities on changes in automation risk through individual career mobility. Using panel data on Swedish workers, we show that the metropolitan effect of reducing automation risk is mainly induced through inter-firm job mobility. Separate estimates for different groups show that this effect accrues mostly to native, high-skilled and male workers.

Keywords: automation risk, cities, career mobility, jobs, multinomial logit models

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1. Introduction

Automation influences labour markets by replacing human workforce in certain tasks (Autor, Levy, & Murnane, 2003; Brynjolfsson & McAfee, 2014). Whether this threatens existing jobs or facilitates creation of new jobs depends on the type of investments into automation, worker skills and their potential renewal (Acemoglu & Restrepo, 2020a). Because investments into technologies as well as the skill level of human workforce typically differ across regions, the problem has a necessary spatial dimension. Accordingly, workers in small cities have been found to face higher automation risks than workers in large cities (Frank et al., 2018, Crawley et al., 2021). Further evidence suggests that investments into labour replacing technologies in metropolitan regions lead to employment growth in the long run because robots supplement automatable tasks that trigger upgrades in local skills (Leigh et al., 2020). Nevertheless, how individuals adopt their skills to avoid the threat of automation and how geography facilitates this process is one of the important questions in this quickly evolving, but still largely uncovered, field (Frank et al., 2019).

In this paper, we expand on recent aggregate analyses (e.g., Crawley et al., 2021) by detailing the micro-mechanisms explaining the role of agglomeration in relation to regional automation vulnerability. Specifically, we look at how working in cities facilitates career upgrades and prevents automation risks. We argue that large labour markets create more favourable conditions for job mobility, through which individuals are able to reduce their exposure to automation. The role of cities in reducing automation risk therefore lies in facilitating upward career mobility. According to central tenets in urban economics, two mechanisms take place in cities in this regard. First, the demand for non-automatable tasks is high in cities due to their functional specialization (Duranton & Puga, 2005). Second, cities are arenas of learning that offer additional opportunities for individual workers to advance their career and perform tasks that are difficult to replace (Glaeser & Maré, 2001; Gordon, 2015; De la Roca & Puga, 2017).

However, workers are not homogenous in their ability to learn in cities, which arguably depends on their individual skill base and other personal attributes that may determine career mobility. High-skilled workers, for example, can further upgrade skills by learning while low-skilled workers enjoy the demand for low-skilled non-automatable jobs (MacKinnon, 2017).

The recent empirical analysis exploits employer-employee matched data covering a 10% random sample of the Swedish workforce over the 2005-2013 period. We apply the occupation-level risk measure introduced by Frey and Osbourne (2017) to quantify how much an individual is exposed to automation. Descriptive statistics help us understand the role of cities in getting a low-risk job. Further, we apply multinomial logit models of occupation mobility that enables us to examine the role of large cities in helping workers to upgrade careers and prevent technology-driven displacement.

Our results show that there are stark differences between small and large regions concerning the distribution of high- and low-risk automatable jobs. During this period, Sweden experienced a remarkable rise in the share of low-risk jobs that concentrated in metropolitan regions with a growing intensity. The largest cities of Sweden accounted for 58% of overall job creation between 2005 and 2013, which was 65% in the case of low-risk jobs. Workers in large cities have significantly higher chances of getting a low-risk job, which holds when controlling for unobserved individual heterogeneity. We find that workers decrease automation risk differently, depending on their sex and skill level. Evidence implies that high-skilled male workers (at least a college degree) realize dynamic career upgrades suggesting that networking and learning in cities helps them prevent automation risk. However, for female workers, low educated workers (less than college degree) and immigrants these effects are relatively smaller. Our finding that it is much easier for skilled workers to find automation-proof jobs in metro areas provide some empirical support for Moretti's (2012) idea that one of the major factors behind the spatial selection of skilled workers is the ongoing clustering of new 'innovative'

jobs.

After this introductory section, the paper proceeds in four steps. The next section provides a review of the literature that is followed by an explanation of our estimation strategy. The fourth section introduces data and sets the stage for the individual-level econometric analysis in the fifth section. The paper then ends with some concluding remarks.

2. Static and dynamic career upgrades

As recent advances in the fields of automation technologies change everyday life, their prospective effects on the labour market have, unsurprisingly, become the subject of public concern. In a recent OECD report, Nedelkoska and Quintini (2018) argue that about 46% (ca 210 million) of all jobs across 32 different countries face at least a 50% chance of being replaced by machines in the near future. At the same time, divergence and increasing regional differences characterize regional development in many developed economies (Storper, 2018; Iammarino et al., 2019). This accentuates further challenges in sustaining employment and welfare in many non-core regions. Although broad discussions in society premise the 'end-of-work' by stressing the adverse labour market effects of automation, it is still a matter of academic debate how automation will indeed influence labour markets. While some argue that the development and widespread adoption of artificial intelligence, robotics and other computer-aided manufacturing technologies imply the displacement of workers performing 'rule-based' routine tasks (Autor, Levy, & Murnane, 2003; Levy & Murnane, 2004; Brynjolfsson & McAfee, 2014; Autor, 2014; Heyman 2014; Acemoglu & Restrepo, 2018a; 2019), others emphasize that automation increases the demand for labour in high-skill complementary tasks (e.g. programming, maintenance, design), and other seemingly unrelated non-tradable activities (e.g. culture, arts, leisure, personal services) through inter-industry spillovers (Autor & Salomons, 2018; Moretti, 2010).

Whether disruptive technological innovations will influence the future of work independently from the location of jobs is however a rarely addressed question. Some studies using aggregate data on robot adoption have recently showed that automation reduce the employment share of workers performing production-related routine tasks (Graetz & Michaels, 2018; Autor & Salomons, 2018; Acemoglu & Restrepo, 2020). Although the absence of detailed data limits our understanding on how automation-driven displacement may unfold in the spatial economy, these findings suggest that differences across local economies in terms of motivation and ability to adopt such technologies might be present.

Research antecedents on the locational patterns of job-creation suggest that the labour market effects of automation could indeed vary across space and hence affect workers differently depending on their location. Since production-related routine occupations are easier to manage and control remotely by codified rules, they tend to be located on the outskirts of cities or in rural areas, where land rents and wages usually are lower (Scott, 2009; Moretti, 2012; Storper, 2013). At the same time, the demand for both creative and high-skill jobs is higher in cities as well as the demand for low-skill service jobs (e.g. catering service workers, childcare workers, geriatric nurses, janitors, cleaners, hairdressers etc.) (Scott, 2009). Additionally, technology-driven job-creation tends to be confined to larger urban areas where related activities, innovation capabilities and market knowledge competences have been already present (Shutters et al., 2016; Muneepeerakul et al., 2013). Consequently, as with the general geography of displacement, small cities and rural areas are likely to be hit harder by job displacement via the automation of production-related tasks, while large cities remain resilient or could even benefit from the positive employment effects of the on-going technological change (Eriksson & Hane-Weijman, 2017; Andersson et al., 2020).

A recent study on U.S. MSAs corroborates this perspective by showing that small cities have higher average automation risk than large cities (Frank et al., 2018). Since the automation risk

measures frequently adopted for such empirical analyses are usually calculated at the occupation-level (see e.g. Frey & Osbourne, 2017; Arntz et al., 2016), the findings of Frank et al. (2018) and other similar studies (see e.g., Henning et al. (2016) for similar Swedish findings on regional automation risks and Crawley et al. (2021) for European NUTS regions) should be interpreted with caution. The average 'automation risk' of a geographical unit (or an industry) compresses all the information that the local occupational mix hides within itself. Given that the occupational structure of a region is primarily shaped by the local demand for tasks, spatial differences in automation risk reflect a set of location-specific attributes and also factors associated with the local industry structure.

The demand for non-automatable tasks tends to be higher in large cities because of functional specialization (Duranton & Puga, 2005). Information- and communication technologies (ICT) allows firms to rationalize their production in space, move routine tasks offshore and keep only managerial tasks, creative activities and their supporting services in the largest cities. Some of these jobs do not require high educational attainment but social skills that usually are considered as 'bottlenecks' of automation (Autor, Levy & Murnane, 2003; Levy & Murnane, 2004; Frey & Osbourne, 2017). Since the overall share of less-automatable jobs tends to be higher in cities, workers who move to large cities are therefore expected to have a better chance of starting such low-risk jobs. We refer to this as the *static upgrade* in the career of moving to a city which prevails when the worker gets a relatively less-automatable job in a large city irrespective whether job search precedes moving or vice versa. Static upgrades can also be considered as occupational shifts that cause an one-off reduction in the automation risk by allowing workers to find less-automatable jobs in large cities with relative ease.[1] Therefore, these one-time career upgrades cannot be considered as pure "city-effects" because they stem from simply the occupational structure of the local labour demand.

[1] Gordon (2015) labelled this one-off impact of moving to large cities as '*elevator effects*'.

Another way through which working in cities contributes to the prevention of automation risk is that workers in cities can step ahead in their career within a shorter period of time. Career progression in cities particularly depends on jobs that offer access to highly-valued elements of tacit knowledge and professional networks (Gordon 2015). That is, being exposed to cutting-edge skills, gathering experience at top ranked employers and making valuable personal and business connections might have long-lasting effects on the career-path and job prospects of workers (De la Roca & Puga, 2017). Hence, individuals with urban work experience gain access to a wider range of better job positions, or become entrepreneurs easier (Faggio & Silva, 2014). We refer to these vertical shifts along the career ladder as *dynamic upgrades* because they develop over time through the accumulation of knowledge and networking capital within cities. Recently, De la Roca and Puga (2017) provided some indirect evidence on such dynamic upgrades by showing that working in cities is associated with faster average wage growth.[2] Since tasks performed at higher levels of the career ladder (e.g., providing expertise, managing resources, negotiating, and interfacing with customers etc.) require interpersonal skills of different types (Borghans et al., 2008), occupational mobility through dynamic upgrades accompanies a reduction of automation risk.

Note that the mechanisms underlying within-city dynamic upgrades are much more diverse than in the case of static upgrades where downward changes in automation risk stem from the fact that low-risk jobs tend to concentrate in large cities. Rather, dynamic upgrades in cities are, in part, the consequence of learning opportunities (Glaeser, 1999; Glaeser & Maré 2001; Gordon, 2015; De la Roca & Puga, 2017), effective information-exchange through social networks (Ioannides & Loury, 2004), and increased early-career job turnover (Wheeler 2008). Hence, the role of cities in reducing individual automation risk can be grasped through dynamic

[2] D'Costa and Overman (2014) found that the urban wage growth premium is larger for young workers.

career upgrades. However, to properly examine the extent to which such within-city upgrades help reduce automation risk, one has to rule out other factors determining occupational structure, especially unobserved worker heterogeneity. Controlling for worker heterogeneity is extremely important because the probability of getting a non-automatable job is likely to vary by unobserved abilities. As shown by Heckman, Stixrud & Urzua (2006) and many others, non-cognitive abilities and personality traits determine occupational preferences and the career path of workers.

Taking individual characteristics into account when examining dynamic upgrades is also important because workers with different backgrounds may benefit from urban career opportunities to different degrees. In this sense workers in cities are not necessarily protected from technology-induced unemployment to the same extent. As argued by Sicherman and Galor (1990) upward career mobility is more likely among educated workers due to their better capabilities to adapt to various work situations. Therefore, workers with high educational attainment (college degree or more) are expected to be the primary beneficiaries of the dynamic upgrades in cities. Beside human capital, however, there are other individual and structural factors that determine workers' potential for career mobility (e.g., family background, household division of labour, labour market discrimination etc.) These factors may influence workers' networking behaviour, access to job information and therefore cause substantial differences between women and men, native workers and immigrants in career mobility. By examining effect heterogeneity across workers with different attributes one can identify the less resilient worker groups that remain susceptible to automation irrespective of their location.

3. Modelling individual automation risk dynamics

We begin with a simple conceptual framework in which changes in workers' automation risk are linked to individual attributes through occupation mobility choices. Since the extent to

which workers are exposed to the threat of automation depends mainly on the task-content of their jobs, most of the changes in automation risk necessarily stem from movements across jobs. More precisely, it comes from job mobility that involves the change of occupation. Hence, any factor that influences job mobility options has an indirect effect on individual exposure to automation.

As in Sicherman and Galor (1990), job changes are assumed to result from an intertemporal utility maximization problem in which workers seek for a sequence of jobs that form an optimal career path. Expected lifetime utility is a function of potential earnings but the choice set of job mobility options are constrained by both individual attributes (e.g. personality traits, skills, education, family background etc.) and a set of other factors external to the worker. For example, intra-firm mobility is uncertain in the sense that within-firm job transfers and promotions are subject to the employers' decision, whereas inter-firm mobility is constrained by the availability of local job opportunities. Consequently, at any point in time workers choose from a constrained set of mobility options. Then, this choice determines the direction of temporal shifts in the worker's automation risk.

Consider a panel of $i = 1, 2, ..., N$ workers in which automation probability and other covariates are observed for $t = 1, 2, ..., T$ periods. Between any consecutive periods t and $t+1$, workers go through one of the following alternatives described by j: moves to a job with lower automation risk ($j = 1$), moves to a job with higher risk ($j = 2$), or neither ($j = 0$). Suppose that, for each worker i and transition alternative j there is a continuous measure, y^*_{ijt}, that describes the feasibility of transition j for worker i. Since each transition alternative results from job changes (occupation changes), y^*_{ijt} depends on all factors that influence worker i's choice set of mobility options:

$$y^*_{ijt} = x_{it}{}'\beta_j + \epsilon_{ijt}, \tag{1}$$

where x_{it} is a vector of observed variables.[3] Assuming that ϵ_{ijt} is i.i.d. across all outcomes and follows a type-I extreme value (Gumbel) distribution gives rise to a multinomial logit (ML) model where the probability of transition *j* can be written as:

$$\Pr\left(y_{it} = j \mid x_{it}\right) = \frac{\exp\left(x_{it}{}'\beta_j\right)}{\sum_j \exp\left(x_{it}{}'\beta_j\right)}. \tag{2}$$

where y_{it} is the actual outcome for individual *i* in period *t*. As discussed in Section 2, the size of the urban labor market may also influence the choice set of individual job mobility. Therefore, it is reasonable to include a variable into x_{it} that reflects the size of the urban labor market where individual *i* works. Specifically, we assume that $x_{it}{}'\beta_j = z_{it}{}'\delta_j + d_{it}\gamma_j$, where z_{it} is a vector of individual attributes (such as sex, age, marital status, educational attainment etc.) and d_{it} is a dichotomous variable that takes value 1 if the individual works in a large metropolitan area. Since the paper aims to examine the role of large urban areas in reducing automation risk we focus on the identification of γ_j for *j = {1,2}*. To the extent that working in metro areas positively affects mobility into low-risk jobs, one would expect that γ_1 has a positive sign. Such reasoning, however, raises at least two issues. First, since the probability of each transition alternative *j* is explained by variables observed right before the transition itself, γ_j coefficients in Eq. (1) capture multiple career-upgrading mechanisms depending on whether job mobility between *t+1* and *t* involves changes in location or not. While in the case of workers who change jobs within metro areas, γ_1 captures the career upgrading effects discussed by Fielding (1992) and Gordon (2015), workers who decide to accept a job in a smaller labor market, the same coefficient captures the 'static downgrading effect' of moving into a rural or small urban area where the access to low-risk jobs within a reasonable commuting time is much more limited. For the same reason, γ_2 might be biased toward zero as well.[4]

[3] Sicherman and Galor (1990) used a similar model to investigate the role of education in intra- and interfirm career mobility.

[4] Since learning activities do not necessarily involve job mobility, γ_j coefficients cannot capture the whole

A convenient way to identify the career-upgrading effects of cities is using data *only* for periods when workers did not move in or out of the same region type, that is, removing 'move-years' from the sample. By doing so we can eliminate the one-off static effect of migration and focus only on within-city dynamic upgrades that happen during the stay in the same region type.[5]

Another issue concerning the estimation of γ_js in Eq. (1) is spatial sorting arising from the endogenous location choice of individuals. For instance, it seems plausible that individuals with specific career preferences choose to locate in large cities, because they expect continued career growth after moving in, or because certain job opportunities are simply not available elsewhere (e.g., prestigious jobs in high-tech industries or jobs requiring higher education). At the same time, as shown by Bacolod, Blum and Strange (2009), cognitive and social skills are rewarded more in large urban areas which might also push workers with such skills toward cities. Since these skills are also important determinants of occupational choice (see, e.g. Borghans et al., 2008; Heckman et al., 2006), they may also influence the probability of moving to a low-risk job. To properly examine the extent to which within-city career upgrading mechanisms help reduce automation risk, unobserved worker heterogeneity has to be ruled out. A straightforward way to address this issue is introducing worker fixed effects (α_i) into Eq. (1) which implies the following transition probabilities:

$$\Pr\left(y_{it} = j \mid x_{it}\right) = \frac{\exp\left(\alpha_i + x_{it}{}'\beta_j\right)}{\sum_j \exp\left(\alpha_i + x_{it}{}'\beta_j\right)}, j = 0,1,2.$$

As it is well-known, introducing fixed effects into logit models makes the maximum likelihood estimator (MLE) inconsistent. However, as shown by Chamberlain (1980), time-invariant fixed effects can be eliminated by using a likelihood function that conditions on the counts $\boldsymbol{s_{ij}}$ of the number of observations for each person *i* in which $y_{it} = j$. Let v_{ijt} be an indicator variable that

spectrum of dynamic career effects discussed in Section 2, only those that result in occupation mobility.

[5] This strategy follows that of D'Costa and Overman (2014) to identify the urban wage premium.

takes value 1 if $y_{it} = j$ and define $\boldsymbol{s_{ij}} = \sum_{\boldsymbol{t=1}}^{\boldsymbol{T_i}} v_{ijt}$. The conditional log-likelihood function to be maximized is

$$\log L_c = \sum_{i=1}^{N} \log \left[\frac{\exp\left(\sum_{t=1}^{T_i} v_{ijt} x_{it}{}' \beta_j\right)}{\sum_{w \in \Upsilon_i} \exp\left(\sum_{t=1}^{T_i} w_{jt} x_{it}{}' \beta_j\right)} \right], \tag{3}$$

where $\Upsilon_i = \{w = (w_{11}, \dots, w_{JT}) \mid w_{jt} = \{0,1\}, \sum_{t=1}^{T} w_{jt} = s_{ij}\}$ is the set of all permutations of the observed sequence of transitions for individual i. Conditional maximum-likelihood estimates obtained by maximizing Eq. (3) are consistent and asymptotically normal, but due to the information loss that comes from using only within-group variation, it is not fully efficient (Greene 2012).[6] Moreover, when fixed-effects are introduced into the model, estimates of γ_j's come from the sub-sample of those who moved across region types, because for immobile workers location is a time-invariant fixed effect. Since move-years are dropped from the sample in order to get rid of the static effect of migration, in the presence of fixed-effects the identification of within-city dynamic upgrades is based on the observations that pertain to the 'non-move years' of those who moved to another region-type at least once.

Given that mobile workers choose from a wider set of suitable job opportunities and therefore climb the career ladder much faster (van Ham, Mulder & Hooimeijer, 2001), they might not be representative of the whole workforce. Hence, in the presence of individual fixed effects the resulting estimates of γ_js cannot be referred to the whole population. Nonetheless, estimating Eq. (3) and excluding observations for move years are the best we can do to examine the role of cities in reducing individual automation risk.[7] Of course, this approach can be used to identify the effects of more than one urban category or, indeed, a full set of city-region

[6] Note that, for workers where $\boldsymbol{s_{ij}} = T$, are not used by the MLE, because their log-likelihood is equal to zero.

[7] Estimating Eq. (3) also has the drawback that average partial effects cannot be evaluated without specifying the distribution of α_i Therefore, the results are interpreted as odds-ratio effects.

dummies. Since figures on the distribution of automation risk (see Figures 1-2) suggest that low-risk jobs tend to concentrate in the three Swedish metropolitan areas and a few other large cities, in some of the specifications we consider multiple urban categories (metros and large urban city-regions).

4. Data and measurement

We use matched employer-employee data from Statistics Sweden covering the years between 2005 and 2013. In this data, the annual wages of individuals active on the Swedish labour market, as well as their occupations, place of work and place of residence at the municipality level are recorded (along with other individual attributes like age, sex, family status etc.). The period 2005-2013 is chosen due to two reasons (c.f., Henning & Eriksson 2021): Previous accounts have not identified labour market polarization tendencies in Sweden prior to the initial year of our analysis, which makes this period particularly suitable for our purpose as we can expect substantial occupational shifts to occur. Second, the final year is chosen due to a revision in occupation codes from 2013 and onwards which makes comparisons prior and after 2013 virtually impossible. To define occupations, the 4-digit SSYK-96 occupation nomenclature is used which is broadly consistent with the international ISCO-88 classification.

Workers are allocated to municipalities using the address of the workplace. The municipalities are then classified into three region-types; metro areas, large urban areas and small regions. The ’Metro areas’ category labels the three largest cities of Sweden (Stockholm, Göteborg and Malmö), ‘Large urban areas’ labels other urbanized areas and university cities such as Umeå, Linköping, Karlstad etc. while ‘Small regions’ refers to the remaining, mostly sparsely populated, regions of Sweden. Originally, Statistics Sweden distinguishes between five categories of which the first and second correspond to our ‘Metro’ and ‘Large’ categories, and the rest makes up our ‘Small’ category. We focus on a small number of predefined region

categories because in fixed-effects ML models identification relies on observing outcomes for workers who move across region types (as discussed in Section 3). Hence, considering a full set of region dummies would not be reasonable due the relatively small amount of worker mobility in the data.

As shown in Table A1 in the appendix, almost half of the population resides in the three metropolitan regions (49% in 2013) and about 52% of all employees. It is also where the greatest job growth has taken place (11.8%), while the number of employees has declined by about 1% in the small regions. Although the income levels are lower in the smallest regions the employment decrease is accompanied with the greatest relative increase in incomes. Manufacturing industries as well as occupations closely connected to manufacturing (e.g., machine operators and assemblers belonging to SSYK-codes 7 and 8) has withdrawn in a similar pace in all region-types but in the larger regions this is more accompanied with an increase in occupations requiring a college degree. This implies a divergence in the structural change as manufacturing jobs usually not requiring a college degree are replaced with new jobs requiring a college degree in the largest regions while that is not the case in the smallest regions (Henning & Eriksson, 2021). It also signals the spatial division of employment in Sweden as manufacturing indeed is present in the larger regions but that is often administrative units while more of the production units (employing the machine operators and assemblers) to a greater extent is found in the smaller regions.

Measuring automation risk

We measure automation risk using the estimates of Frey and Osbourne (2017) who looked at the US Department of Labor's O*NET database to assess the probability of computerisation for 702 elements of the 6-digit Standard Occupational Classification (SOC).[8] Automation

[8] In their study Frey and Osbourne (2017) proposed a mixed methodology that involves both expert evaluations

scores were matched to the Swedish data in two steps. We mapped SOC-10 codes onto the SSYK-96 classification using official correspondence tables between SOC-00, ISCO-88 and SSYK-96. As neither of the conversion tables provide a one-to-one correspondence, in the case of multiple correspondences automation scores were averaged out. As a result, 352 (out of 355) of the 4-digit SSYK-96 occupations were given a score.

Although the O*NET dataset offers detailed information on the task content of occupations, its limitation for the measurement of automation risk is substantial. Most significantly, it provides data on job characteristics at the level of occupations and not workers**.** Since the actual task content of an occupation may vary across regions, it is possible that moving to another region type but staying in the same occupation may result in considerable changes in the automation risk of the individual. Moreover, workers may acquire new skills to become less susceptible to automation. As a result, some employees will be more valuable for the firm than others, even within the same occupation.[9] Since learning activities does not necessarily involve any form of job mobility, the coefficient on workplace location (γ_j) cannot therefore capture the whole spectrum of dynamic career effects discussed in Section 2, only those that result in horizontal or vertical occupation mobility.

Table 1 lists some SSYK-96 occupations from the top and bottom of the automation risk distribution. The less-susceptible occupations include medical doctors, psychologists, special education teaching professionals, therapists and nurses. Clearly, this group of occupations involve tasks such as caring, communication and social perceptiveness. The most susceptible occupations, however, involve routine tasks and mostly require physical skills. This group

and machine learning methods. As a first step, a group of AI experts were asked to hand-label 70 occupations, assigning 1 if automatable, and 0 if not. Then, the authors identified several O*NET variables that describe the level of perception and manipulation, creativity, and social intelligence required to perform these occupations. These variables were used to train a machine learning algorithm that provided a probabilistic assessment of automation risk for all 6-digit SOC occupations (including the 70 test occupations). Estimates are available in the appendix of Frey and Osbourne (2017).

[9] Especially, when employees have access to certain firm-specific knowledge assets.

contains occupations such as manufacturing workers, assemblers and low-skilled clerks.

The spatial division of labour imply that regions vary considerably in terms of what kind of activities are exposed to automation. Table 2 provides a short list of the most common low- and high-risk occupations for each region-type. As shown in the upper panel, in metro regions the least susceptible occupations mainly refer to sales activities and high-skill occupations (such as computer designers, programmers and high-education teaching professionals) while in large and small regions preschool and primary-level teaching are the most common low-risk activities. Conversely, in small and large urban regions employment in high-risk occupations is mostly found among different forms of machine operators and assemblers, while in metro regions it concerns clerks and service workers (lower panel). As depicted in Figure 1, these occupational disparities between region types concern the spatial concentration of low-risk occupations. The larger the region in terms of employment, the greater the concentration of low-risk occupations. Comparing 2005 with 2013, we also find indications that average automation probability tends to increase in smaller regions while remaining fairly stable in the largest ones. Hence, during the period we study in this paper, smaller regions have become increasingly susceptible for automation.

This is partly related to the ongoing spatial division of job creation and destruction in Sweden, as the creation of new jobs have been mainly attributed to the large urban regions during the last decades (Eriksson & Hane-Weijman, 2017). As shown in Figure 2 (right) employment has mainly increased in the largest regions, while the relatively few remaining jobs in smaller and peripheral regions to the north-western border and central parts of Sweden is associated with an increasing automation risk over time (left).

Sample characteristics

Summary statistics of our variables are reported in Table 3 which distinguishes between movers (i.e., those who move at least once across region-types) and stayers (i.e., those who stay in the same region-type). Since in fixed-effects multinomial logit models, the identification of region-type dummies is based on movers only (for reasons discussed in Section 3), it is important to see whether there are any systematic differences between the group of movers and stayers.

Only 12% of the observed workers changed location at least once during the period 2005 to 2013. The average mover is five years younger than the average stayer (43 years). Workers between 16 and 34 years moving for the first job or education are thus more geographically mobile (Lundholm, 2007). The largest number of observations can be found in the '35-44 years' age category in the full sample, however, movers concentrate in the category '25-34 years'. 48% of the observed workers are women and 43% have at least one child. Along these attributes slight differences can be seen between movers and stayers. Among movers there are fewer women and parents. One-third of the overall sample have a college degree, while in the case of movers the proportion of highly educated workers is 7 percentage points higher (40%). On average, 87% of the observations are individuals working in metros or other large cities in year *t*, and metro regions alone represent half of the overall sample. The regional division however conceals considerable differences between moving categories. More stayers tend to work in metro areas (52%) than movers while more movers locate in large cities (43% compared to 36%). These figures, by and large, confirm previous studies on mobility in Sweden showing that the main flows are between small and large regions, and large regions and metros, respectively (Eriksson & Rodriguez-Pose, 2017).

Considering non-move years only, 6.1% percent of the observations correspond to years when workers decrease their automation risk by moving to low-risk jobs in metro areas. The prevalence of downward changes in automation risk is 5.2% in large urban regions and 5.1%

in small regions. Similar patterns can be found when focusing on occupation mobility that involves upward changes in automation risk. While in metro areas 22.3% of the observations relate to such risk changes, in small regions this ratio is 20.7%. According to these statistics job mobility that involves changes in automation susceptibility increases with the size of the region. Moreover, job mobility is more common among movers in any type of region.

In order to make the discussion on automation risk dynamics more concrete, it is worthwhile considering some typical examples of occupation mobility that involve downward/upward changes in automation risk. Table A2 in the Appendix lists the most common occupational transitions for each region type. As can be seen there, these occupational changes are independent of location and happen within a narrow range of activities. In most cases workers seem to choose occupations in which they can utilize their expertise and previously acquired knowledge (e.g., nurses/midwives, cashiers/salespersons, construction workers/frame builders) and this motivation is independent of whether the occupational switch involves downward or upward changes in automation risk.

5. Results

Reducing automation risk in metro areas

We begin by estimating Eq. (2) ignoring unobservable individual heterogeneity but removing periods when workers moved to another region type. In this baseline multinomial logit model transition probabilities are explained by a set of individual characteristics such as sex, age, education, place of birth, having children and also a dummy for working in metro areas. Given that the domain of automation probability is the interval [0,1] the automation risk of the worker's current occupation is also included into the model to control for further career upgrading opportunities. Since workers in the lower tail of the automation risk distribution (e.g., medical doctors, dieticians and speech therapists, see Table 1) are hardly able to further

reduce their automation exposure by changing occupations, one would expect that changes in automation risk between $t+1$ and t is negatively correlated with the initial risk level observed in period t.

Columns (1) and (2) of Table 4 report the logarithm of relative risk-ratios for the baseline model. These estimates show that individuals in metro areas are more likely to change occupations than those who work elsewhere. Working in metro areas is associated with a 16.2% increase in the relative risk ratio of downward changes in automation risk and a 5.2% increase in the relative risk ratio of upward changes (relative to the baseline of no change). As discussed earlier, however, unobserved individual attributes such as personality traits and skills may be important determinants of job mobility. Because such unobservables are correlated with workplace location, these estimates are likely to be biased. Columns (3) and (4) report the maximum-likelihood estimates obtained by maximizing the conditional log-likelihood function in Eq (3). Since the conditional MLE removes subjects where the dependent variable does not vary in time, the number of observations drops by 0.8%. The results show that working in metro areas is associated with a significant increase (19.5%) in the odds of reducing automation risk by moving to less susceptible occupations versus staying in the same occupation. At the same time, the effect on the relative chance of upward changes drops and becomes insignificant. The last model in columns (5) and (6) introduces another locational dummy for large urban areas but the results remain unchanged. The probability of moving to jobs with lower automation risk is only higher in metros (relative to small regions) and working in metros or other large urban regions does not increase the odds of upward changes in automation exposure.

Results in Table 4 suggest that only workers in metros are more likely to reduce their automation susceptibility through occupational changes. However, as argued in the previous section, a large proportion of observed job changes are horizontal movements that take place

between occupations with more or less similar task-contents. This naturally raises the question of whether metro areas only contribute to horizontal job mobility or also facilitate career upgrades that imply larger drops in automation risk. Since the baseline model is unable to answer this question at its current form, we proceed by estimating the same model with a threshold for minimum risk changes. By looking at changes that exceed this threshold, we can separately examine whether working in metros (and other large urban areas) promotes faster career advancement. The threshold was chosen to match the variance of annual risk changes (10 percentage points), which modified the set of transition alternatives in the dependent variable as follows: (i) moves to a job where automation risk is at least 10 percentage points lower (ii) moves to a job where risk is at least 10 percentage points higher, (iii) neither.[10]

Point estimates for relative risk-ratios in the first two columns of Table 5 suggest that workers in metro areas are more likely to undertake occupation shifts that result in greater changes in automation risk. Working in metros is associated with a 21.9% increase in the odds of decreasing automation susceptibility at least 10 percentage points. Compared to metros, large urban areas have a much smaller impact on career upgrades which completely disappears in the conditional ML model that allows for fixed effects (columns 3 and 4). This model shows that working in metro areas increases the odds of reducing automation risk by at least 10 percentage points (by 20.6%) and also decreases the odds of increasing automation susceptibility (by -11.1%). Thus, not only the chance of horizontal job mobility is higher in cities, but also, upward job mobility that reduces individual susceptibility to a greater extent.

Overall, there is evidence of a broad contrast between the workers of the largest Swedish metros and those who work in other parts of the country. Workers in metropolitan areas are more likely to reduce their automation exposure through occupational mobility. Since the models are

[10] Given that the results may be sensitive to the choice of the threshold, we also ran the ML model using other values (i.e 25 percentage points) but they led to the same conclusion.

cleared of unobserved worker heterogeneity and the confounding effects of migration (by dropping all observations corresponding to move years) this result can be attributed to the dynamic career upgrading or "escalator" effect of metropolitan areas.

The role of inter- and intra-firm upgrades

Given that our data provide information on employer-employee matches we can distinguish between two types of job mobility through which automation risk can be reduced. The first is inter-firm mobility (when the workers move across firms), and the second is intra-firm mobility (when they are promoted or transferred to another job within the same firm). As argued in Section 2, large labour markets provide more opportunities to reduce automation risk through inter-firm mobility, however, the relationship between the size of the labour market and within-firm job mobility is less clear. Wheeler (2008) argues that workers in cities converge to efficient job matches earlier because large urban markets allow them to try themselves in a wider range of jobs and thus learn more quickly about their abilities. As job turnover decreases with work experience in cities, intra-firm upward mobility becomes more important as a source of career upgrading that reduces workers' susceptibility to automation. Since breaking up productive matches is not in the interest of the employer, firms in urban areas might prefer promoting their proven employees in order to keep them. On the other hand, if large urban labour markets allow firms to enhance productivity by recruiting skilled workers at lower costs and productivity gains from channeling external knowledge are sufficiently high, employers may prefer hiring new employees (poaching) over investing and promoting one of their existing staff members.

To unravel the relative role of intra- and inter-firm career upgrades in the reduction of individual automation risk we consider another model where the dependent variable consists

of the following transitions: (i) moves to a job with *lower* automation risk *within* the same firm, (ii) moves to a job with *lower* automation risk in *another* firm, (iii) moves to a job with *higher* automation risk (iv) neither. We do not distinguish between intra- and interfirm mobility in case of increasing automation risk because intrafirm job changes that increase automation risk are rarely observed in the sample. Considering a distinct outcome for these rare events would thus lead to biased estimates (see e.g. King and Zeng, 2001).

Given that the number of potential employers within the region strongly influences the possibility of movement between employers, we include the number of firms per 1000 persons as a further control. If interfirm job mobility in large cities is driven by the need to improve matches and to acquire new knowledge assets, the probability of interfirm upgrades should still be higher in cities even after controlling for the local number of firms.

Results reported in columns 1-3 of Table 6 show that workers in metro areas are more likely to reduce their automation risk by changing employer and occupation at the same time. Working in the largest metros increases the odds of inter-firm upgrades relative to the base outcome by 35.0% while its effect on the odds of intra-firm upgrades is only 20.1%. Similar results are obtained from the threshold model that looks at larger (> 10 percentage points) changes in automation risk (columns 4-6). According to this model, the odds of experiencing a large interfirm upgrade increase by 22.9% while the odds of large intrafirm upgrades increase by 19.7%. We can thus conclude that although metros facilitate risk reduction through both inter- and intrafirm mobility, the primary source of within-city career upgrading is interfirm mobility. When we look at changes that exceed 10 percentage points, location seems to have a similar effect on both mobility types.[11]

The finding that intra-firm upward mobility is more common in metros suggest that urban firms

[11] For the 'Metro areas' variable, the difference between the estimated relative effects on upward inter- and intrafirm mobility in the first model is 0.108, with z-score 1.910 ($p < 0.001$), while for the 'Large urban areas' variable the difference is 0.098 with 1.80 ($p < 0.001$). For the threshold model reported in columns 4-6, the difference between the effects on inter- and intrafirm mobility (0.026) is not significant.

provide better career opportunities for their proven employees and prefer promotion over hiring new employees for higher positions.[12] However, this finding might be the consequence of automation itself. Dauth et al. (2018) found that employers react to the penetration of robot technologies by changing the tasks for their workers to avoid layoffs. If labour replacing technologies spread faster among urban firms, intra-firm job mobility might be more common in cities.

Heterogeneous upgrades for different worker groups

Since workers with different characteristics benefit from working in large metros to a varying degree, full sample estimates might obscure considerable differences between worker groups. In our context, examining the extent of heterogeneity in the effects of cities is crucial to identify groups for which long-term automation exposure is expected. For instance, it is possible that women are less likely than men to benefit from the career opportunities offered by cities due to limited access to networks, gender differences in household responsibilities and labour market discrimination (Rosenthal and Strange, 2012).[13] Although women are generally more likely to fill positions with lower automation risk (e.g., nursing, teaching and different forms of clerical work) they are disadvantaged relative to men in opportunities for career advancement.

Another susceptible group is immigrants whose career mobility is often hindered by the limited international transferability of human capital, the lack of intangible assets involving linguistic proficiency and access to effective search channels. Although upward mobility in occupational

[12] Our finding that interfirm career upgrades are more likely in metro areas is in line with the results of Andersson and Thulin (2013).

[13] Forrett and Dougherty (2004) showed that there are substantial differences in networking behavior between women and men which might also affect the extent to which women and men can benefit from dynamic career upgrades in cities.

status might set in through economic assimilation (Chiswick et al., 2005; Rooth and Ekberg, 2006), low mobility at the outset lead to long-term occupational mismatches by pushing immigrants toward high-risk routine activities for a longer period of time. In the presence of these disadvantages and possible labour market discrimination one would expect that cities make less of a contribution to reducing automation risk along immigrants' careers.

Educational attainment is also an important attribute by which the career upgrading effect of cities might vary across the members of the workforce. In general, workers with college degrees (or more) have better capabilities to adapt and self-renew in an evolving labour market. This potential for "labour branching" (MacKinnon, 2017), is because they can apply to a wider range of jobs, have better access to employment opportunities with the potential for career advancement, and therefore have a higher chance to get low-risk jobs compared to their low-skilled peers whose job-search tend to be narrower. Recent studies on urban wage premium showed that for college educated workers the urban wage premium grows steadily with between-firm job shifts (Carlsen et al. 2016; Matano & Naticchioni, 2016). This suggests that the career upgrading effect of cities is expected to accrue mostly to skilled workers.

We examine effect heterogeneity across work groups by estimating the original specification in its general form for each group separately.[14] Each model contains controls for observed individual attributes, as individual fixed effects. Once again, move years are dropped from all models in order to get rid of the confounding "elevator effect" of migration.

Results reported in Table 7 show considerable differences in the relative-risk ratios of region types. Separate estimates for female and male workers confirm the expectation that men can take more advantage of their work location then women. While for men the relative probability of reducing automation risk is increased by 37,3% in metros, for women it is increased only by

[14] We estimate the model without any thresholds because downward changes that exceed 10 percentage points (or more) are rare events for most of the susceptible groups.

24%. Moreover, for men large urban areas also have a smaller positive effect (16%).

Our results for immigrants are in line with the above expectations in the sense that immigrants' upward mobility is constrained irrespective of their work location. Since the models filter out unobservables it is unlikely that our estimates reflect the lack of language skills, networking or other personal attributes. Apart from labour market discrimination they face, immigrants are often unable to utilize their human capital in the host country due to the limited international transferability of human capital. Even if the immigrant worker is highly qualified, in the absence of country-specific knowledge (such as legal practices, local norms) she/he might be unable to find employment in her/his own field (Rooth and Ekberg, 2006). As a result, immigrants' automation risk may decrease at a slower rate throughout their careers. Since native workers do not face such disadvantages, they can more readily enjoy the career benefits of metros.

Finally, the last rows of Table 7 provide some insights on the role of education in exploiting career opportunities offered by large labour markets. For low-skilled workers (less than college degree) we find that working in cities slightly increase the relative probability of downward changes in automation risk (by 18.3%), and it also reduces the chance of upward changes by 12.3%. At the same time, in the case of workers with college degrees (or more), metros are associated with a 41.5% increase in the odds of downward changes in automation risk relative to the base outcome of no change. Although these results suggest that more educated workers can take advantage of the career opportunities offered by cities to a greater extent, less educated urban workers may have brighter career prospects in cities as well. As low-skilled service jobs in cities have lower automation risk, it is also easier for less educated workers to escape from the potential labour market threat posed by AI and the spread of robot technologies.

6. Conclusions

Workers in small urban areas are usually depicted as being more exposed to the threat of technological unemployment caused by automation, because these regions tend to rely more on production-related routine skills and this is unlikely to change in the future (Frank et al. 2018). In this paper we examined whether, and for whom, large cities offer career opportunities which might imply the reduction of automation risk. This was accomplished by means of matched employer-employee data covering a 10 % random sample of the Swedish labour force during the period 2005-2013.

Our descriptive evidence suggest that the concentration of susceptible jobs is higher in smaller regions and that the urban-rural divide has increased over the period studied here (covering the Great Recession). In that sense, our findings confirm previous results of Crawley et al. (2021) that automation exposure decreases with the degree of agglomeration. By means of the level of detail of our data, we can however show that the groups of workers at risk of automation differs across the regional hierarchy. While the highest concentrations of workers in susceptible occupations in metro-regions are different forms of clerks and service workers, a greater share of manufacturing workers are at risk outside the city-regions. In that sense, the spatial division of labour entails that *different* groups of workers are at greater risk of facing automation-related displacement in *different* types of economic spaces. Given the fact that completely new tasks tend to occur in large cities with diversified economies where the higher potential for spillovers and learning fosters the birth of new activities (Duranton & Puga, 2001), we can expect that these spatial differences also entail increasing transaction costs for susceptible groups of workers to adjust to the ongoing realignments of the labour markets if better local alternatives are deteriorating over time. Since the majority of new jobs have been created in the largest labour markets in Sweden (c.f., Eriksson & Hane-Weijman, 2017), and the remaining jobs in smaller regions are becoming increasingly susceptible as shown in the

results presented here, this would entail that migration to larger regions is the main viable strategy to adapt. Especially, because the probability of a job to appear in a region is higher if related jobs are already present (Muneepeerakul et al., 2013; Shutters et al., 2016), we should expect that the majority of new jobs in the service sector are more likely to be created in large cities, where the employment share of services is larger.

The logical consequence of this finding is that workers in large cities have better chances of finding a non-automatable job as years go by. Our empirical results indeed show that working in cities have a positive and statistically significant effect on the relative probability of downward changes in automation risk even after controlling for a wide range of individual attributes influencing occupation choice and labour market opportunities. However, these benefits of urban life cannot be reaped without effort. Rather, it involves learning, networking and intense competition on the part of ambitious and skilled workers seeking for jobs that promise advancement in their careers. Every factor that hampers these activities impairs the chances of reducing the automation-driven risk of displacement. Such factors include, for example, the lack of skills, family background, limited access to professional networks or labour market discrimination. Workers who face these barriers are less likely to benefit from the career upgrading effect of cities. In this regard the most susceptible workers are the immigrants, but women and workers without college degrees also benefit relatively less from the career advantages cities offer.[15] Hence, government responses to technology-driven labour market disruptions have to combine several instruments in order to be efficient for different groups of workers. Mobility enhancing instruments that encourage migration toward cities (e.g., travelling and housing allowances or improving housing accessibility) might be useful tools to alleviate technological unemployment (c.f., Storper, 2018) but only for the most

[15] The financial crisis of 2008 probably further worsened the chances of these susceptible groups and therefore increase the extent of effect heterogeneity between worker groups. Finding out how career upgrading in cities developed in different phases of the crisis is certainly a policy-relevant question that deserves further attention and careful empirical investigation, therefore it is left for further research.

skilled. In the case of more vulnerable, less-skilled, workers, the emphasis should be on creating general conditions for job mobility (e.g., by providing training and up-to-date information on the availability of low-risk jobs).

Finally, if indeed about 46% of all jobs in the OECD face a significant risk of being replaced by machines in the near future as suggested by Nedelkoska & Quintini (2018), a greater awareness needs to be put on the fact that this will not only vary across nations but also vary greatly within economies. This calls for political attention and is clearly connected to the current debate concerned with the link between structural change and political polarization and discontent challenging established post-war political structures around Europe on the one hand (Rodríguez-Pose, 2018), and calls for a new "place-sensitive distributed development policy" on the other (Storper, 2018; Iammarino et al., 2019).

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Table 1: Automation risk of least and most susceptible occupations

TOP 10 least susceptible occupations		TOP 10 most susceptible occupationss	
Occupation title	Auto. risk	Occupation title	Auto. risk
Medical doctors	0.001	Electrical-equipment assemblers	0.908
Dieticians	0.004	Pharmaceutical assistants	0.920
Speech therapists	0.005	Metal wheel-grinders and tool sharpeners	0.925
Psychologists and related professionals	0.007	Government tax and excise officials	0.930
Teaching professionals, academic subjects	0.008	Cashiers and ticket clerks	0.934
Geriatric nurses	0.009	Jewellery and precious-metal workers	0.950
Medical care nurses	0.009	Debt-collectors and related workers	0.950
District nurses	0.009	Library and filing clerks	0.958
Special education teaching professionals	0.010	Numerical clerks	0.959
Production managers in education	0.010	Paperboard, textile products assemblers	0.970

Table 2: The most common occupations with lowest and highest automation risk in different region types.

Top 5 occupations with lowest automation probability					
Metro regions		**Large regions**		**Small regions**	
Occupation title	*Emp. share*	*Occupation title*	*Emp. share*	*Occupation title*	*Emp. share*
Technical and commercial sales representatives	2,94	Pre-primary education teaching pros	2,49	Pre-primary education teaching associate pros	2,30
Computer systems designers, analysts and programmers	2,77	Primary education teaching pros	2,11	Primary education teaching pros	2,19
Pre-primary education teaching associate pros	1,88	Technical and commercial sales representatives	1,76	Technical and commercial sales representatives	1,42
Primary education teaching pros	1,75	Public service administrative pros	1,36	Nursing associate pros	1,00
College, university and higher education teaching pros	1,28	Nursing associate pros	1,34	Social work pros	0,87
Top 5 occupations with highest automation probability					
Metro regions		**Large regions**		**Small regions**	
Occupation title	*Emp. share*	*Occupation title*	*Emp. share*	*Occupation title*	*Emp. share*
Other office clerks	2,29	Other office clerks	2,01	Other office clerks	2,04
Helpers in restaurants	1,98	Helpers in restaurants	1,75	Machine-tool operators	1,98
Numerical clerks	1,26	Machine-tool operators	1,29	Helpers in restaurants	1,69
Accountants	0,86	Numerical clerks	1,09	Numerical clerks	1,15
Receptionists	0,74	Other machine operators and assemblers	1,04	Other machine operators and assemblers	0,98

Notes: Authors' own calculations based on a 10% random sample of the Swedish Admin Data containing 3,327,846 observations for 499,507 workers.

Table 3: Descriptive statistics

	Overall	Movers	Stayers
Sex (%)	48.5	43.5	49.1
Age (years)	42.8	37.8	43.2
16-24 years (%)	7.5	12.5	6.9
25-34 years (%)	21.0	32.6	19.6
35-44 years (%)	26.3	25.7	26.3
45-54 years (%)	24.7	18.6	25.4
55+ years (%)	20.3	10.3	21.5
Having a child (%)	42.7	41.2	42.9
Born in Sweden (%)	87.8	90.7	87.4
Less than college degree (%)	66.8	60.1	67.6
College degree or more (%)	33.1	39.8	32.3
Workplace location (%)			
- Metro regions	50.3	38.4	51.8
- Large urban regions	36.6	42.6	35.9
- Small regions	12.9	18.9	12.2
Job changes + downward changes in auto. risk (%)			
- Metro regions	6.1	7.4	5.7
- Large urban regions	5.2	7.0	4.9
- Small regions	5.1	6.6	4.7
Job changes + upward changes in auto. risk (%)			
- Metro regions	19.7	22.3	19.2
- Large urban regions	18.9	21.0	18.3
- Small regions	18.7	20.7	18.3
Number of workers	499,507	58,896	440,611

Note: Notes: Authors' own calculations based on a 10% random sample of the Swedish Admin Data containing 3,327,846 observations for 499,507 workers.

Table 4: Multinomial logit models of changes in automation risk

	Model 1		Model 2		Model 3	
dep. var.: changes in auto. risk.	Downward changes in auto. risk (1)	Upward changes in auto. risk (2)	Downward changes in auto. risk (3)	Upward changes in auto. risk (4)	Downward changes in auto. risk (5)	Upward changes in auto. risk (6)
Metro areas	1.162***	1.052***	1.195***	0.983***	1.260***	0.955
	(0.006)	(0.003)	(0.032)	(0.022)	(0.05)	(0.032)
Large urban regions					1.067	0.966
					(0.041)	(0.030)
Sex	1.028***	0.951***				
	(0.003)	(0.003)				
Born in Sweden	1.250***	0.912***				
	(0.009)	(0.004)				
Having children	1.077***	0.825***				
	(0.005)	(0.002)				
Age	0.977***	1.005***	1.112***	2.284***	1.127***	2.282***
	(0.001)	(0.003)	(0.001)	(0.002)	(0.001)	(0.002)
College degree or more	3.404***	0.952***	4.212***	0.891***	4.212***	0.891***
	(0.075)	(0.048)	(0.093)	(0.02)	(0.093)	(0.020)
Auto. risk in period *t*	9.3370***	0.7100***	16681***	0.001***	16681***	0.001***
	(0.093)	(0.004)	(650.5)	(0.000)	(650.5)	(0.000)
Individual fixed effects	No		Yes		Yes	
Log-likelihood	-2,455,530		-905,581		-903,582	
N	3,643,033		3,616,988		3,616,988	

Note: The table reports relative-risk ratios and their standard errors. Estimation method: maximum-likelihood estimator. Transition $j = 0$ (no change in auto. risk) is chosen as the base outcome. Dependent variables are measured between t and $t+1$, all level variables are measured in t. *** indicates significant at the 1% level.

Table 5: Multinomial logit models of large changes in automation risk

	Model 1		Model 2	
dep. var.: changes in auto. risk.	Downward changes (min 10 pps) (1)	Upward changes (min 10 pps) (2)	Downward changes (min 10 pps) (3)	Upward changes (min 10 pps) (4)
Metro areas	1.219***	1.050***	1.206***	0.889***
	(0.011)	(0.003)	(0.061)	(0.037)
Large urban regions	1.040***	0.994	1.049	0.938
	(0.009)	(0.004)	(0.05)	(0.037)
Sex	1.104***	0.977***		
	(0.006)	(0.003)		
Born in Sweden	1.361***	0.890***		
	(0.012)	(0.004)		
Having children	1.077***	0.812***		
	(0.005)	(0.002)		
Age	0.972***	1.007**	1.232***	3.031***
	(0.001)	(0.001)	(0.002)	(0.006)
College degree or more	2.268***	0.990	5.104***	0.824***
	(0.014)	(0.005)	(0.138)	(0.021)
Auto. risk in period *t*	24.705***	0.720***	0.001***	0.000***
	(0.247)	(0.004)	(0.000)	(0.000)
Individual fixed effects	No		Yes	
Log-likelihood	-2,255,048		-653.663	
N	3,643,033		3,618,007	

Note: The table reports relative-risk ratios and their standard errors (in parentheses). Estimation method: maximum-likelihood estimator. Transition $j = 0$ (changes within the range of -10 and 10 percentage points) is chosen as the base outcome. Dependent variables are measured between t and $t+1$, all level variables are measured in t. ***, ** indicates significant at the 1 and 5% levels.

Table 6: Multinomial logit models of intra- and inter-firm career upgrades

	Model 1			Model 2 (with threshold)		
dep. var.: intra- and interfirm mobility	Intra-firm mobility + downward changes in auto. risk	Inter-firm mobility + downward changes in auto. risk	Upward changes in auto. risk	Intra-firm mobility + >10 pps decrease in auto. risk	Inter-firm mobility + >10 pps decrease in auto. risk	>10 pps increase in auto. risk
	(1)	(2)	(3)	(4)	(5)	(6)
Metro areas	1.201***	1.350***	0.952	1.197**	1.229**	0.887**
	(0.064)	(0.078)	(0.032)	(0.081)	(0.090)	(0.037)
Large urban regions	0.993	1.220***	0.948	1.001	1.107	0.919*
	(0.053)	(0.071)	(0.031)	(0.067)	(0.082)	(0.039)
College degree or more	1.111***	1.111***	2.282***	1.239***	1.226***	3.031***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.006)
Age	4.133***	4.450	0.932	4.855***	5.165***	0.824***
	(0.157)	(0.116)	(0.021)	(0.223)	(0.165)	(0.021)
Number of firms (per 1000 persons)	0.998	1.003***	0.999	0.997*	1.003*	0.999
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Automation risk in period *t*	21332.8***	13030.0***	0.000***	550179.6***	271305.3***	0.000***
	(1066.639)	(651.494)	(0.000)	(37962.4)	(18720.0)	(0.000)
Individual fixed effects		Yes			Yes	
Log-likelihood		-913,846			-658,636	
N		3,616,988			3,616,007	

Note: The table reports relative-risk ratios and their standard errors (in parentheses). Standard errors are clustered by regions. Estimation method: maximum-likelihood estimator. Base outcome: no change in auto. risk Dependent variables are measured between *t* and *t+1*, all level variables are measured in *t*. ***, ** and * indicate significant at the 1, 5 and 10% levels.

Table 7: Heterogeneous effects by worker groups

dep. var.: changes in auto. risk.	Downward changes in auto. risk (1)		Upward changes in auto. risk (2)	
Female				
Metro areas	1.275***	(0.069)	0.944	(0.042)
Large urban areas	1.028	(0.051)	0.994	(0.041)
Male				
Metro areas	1.443***	(0.087)	0.966	(0.049)
Large urban areas	1.183**	(0.067)	0.928	(0.044)
Swedish				
Metro areas	1.357***	(0.057)	0.859	(0.030)
Large urban areas	1.028	(0.04)	0.994	(0.032)
Immigrant				
Metro areas	1.186	(0.179)	0.859	(0.105)
Large urban areas	0.951	(0.139)	1.010	(0.119)
Less than college degree				
Metro areas	1.183**	(0.062)	0.877**	(0.039)
Large urban areas	1.070	(0.051)	0.952	(0.038)
College degree or more				
Metro areas	1.415***	(0.103)	1.050	(0.061)
Large urban areas	1.054	(0.073)	0.953	(0.051)

Note: Each model contains individual fixed effects and controls for age, education and auto. risk in period *t*. Education controls are not included in the last two models (less than college & college or more). The table reports log relative-risk ratios, their standard errors (in parentheses), and relative risk ratios (in brackets). The base outcome is "no change in auto. risk". Dependent variables are measured between *t* and *t+1*, all level variables are measured in *t*. ***, ** and * indicate significant at 1%, 5% and 10% level respectively.

Table A1: Summary statistics for region types

	Metro regions (N=3)			**Large regions (N=19)**			**Small regions (N=50)**		
	2005	2013	Ch.	2005	2013	Ch.	2005	2013	Ch.
Population	4 327 353	4 760 110	10.0%	3 429 596	3 544 470	3.3%	1 356 308	1 340 284	-1.2%
Employment	1 895 669	2 119 017	11.8%	1 418 748	1 442 349	1.7%	551 405	546 018	-1.0%
Median income	3025.9	3350.4	10.7%	2872.0	3205.0	11.6%	2730.6	3083.2	12.9%
College degree	33.5%	38.4%	5.0	26.8%	30.8%	4.0	19.8%	22.2%	2.3
Manufacturing	14.7%	11.0%	-3.7	20.8%	16.4%	-4.4	22.3%	18.8%	-3.5
SSYK 7-8	5.8%	4.5%	-1.3	11.7%	9.4%	-2.3	12.9%	11.6%	-1.3

Notes: Authors' own calculations based on the ASTRID database.

Table A2: Most frequent occupation switches in different region types

	Metro areas		Diff. in
	Source occupation	Target occupation	auto. risk.
Decreasing auto. risk			
1	Nursing associate professionals	Nursing and midwifery professionals	-0.001
2	Metal-processing-plant operators	Metal- and mineral-products machine operators	-0.025
3	Mining and construction labourers	Building frame and related trades workers	-0.055
4	Computer associate professionals	Computing professionals	-0.071
5	Wood treaters, cabinet-makers	Building frame and related trades workers	-0.117
Increasing auto. risk			
1	Nursing and midwifery professionals	Nursing associate professionals	0.001
2	Legislators and senior government officials	Production and operations managers	0.071
3	Housekeepers and related workers	Helpers in restaurants	0.078
4	Architects, engineers and related professionals	Physical and engineering science technicians	0.035
5	Special education teaching professionals	Other teaching professionals	0.031
	Large urban areas		
	Source occupation	Target occupation	
Decreasing auto. risk			
1	Nursing associate professionals	Nursing and midwifery professionals	-0.001
2	Mining and construction labourers	Building frame and related trades workers	-0.055
3	Tellers	Stall salespersons	-0.148
4	Metal-processing-plant operators	Metal- and mineral-products machine operators	-0.025
5	Physicists, chemists and related professionals	Architects, engineers and related professionals	-0.035
Increasing auto. risk			
1	Nursing and midwifery professionals	Nursing associate professionals	0.001
2	Legislators and senior government officials	Production and operations managers	0.071
3	Pelt, leather and shoemaking trades workers	Textile-, leather-products machine operators	0.148
4	Architects, engineers and related professionals	Physical and engineering science technicians	0.035
5	Housekeepers and related workers	Helpers in restaurants	0.078
	Small regions		
	Source occupation	Target occupation	
Decreasing auto. risk			
1	Nursing associate professionals	Nursing and midwifery professionals	-0.001
2	Tellers	Stall salespersons	-0.148
3	Police officers and detectives	Public service administrative professionals	-0.399
4	Helpers in restaurants	Housekeepers and related workers	-0.078
5	Crop and animal producers	Animal producers and related workers	-0.234
Increasing auto. risk			
1	Nursing and midwifery professionals	Nursing associate professionals	0.001
2	Legislators and senior government officials	Production and operations managers	0.071
3	Architects, engineers and related professionals	Physical and engineering science technicians	0,035
4	Other sales and services elementary occup	Manufacturing labourers	0.051
5	Wood treaters, cabinet-makers workers	Wood-products machine operators	0.028

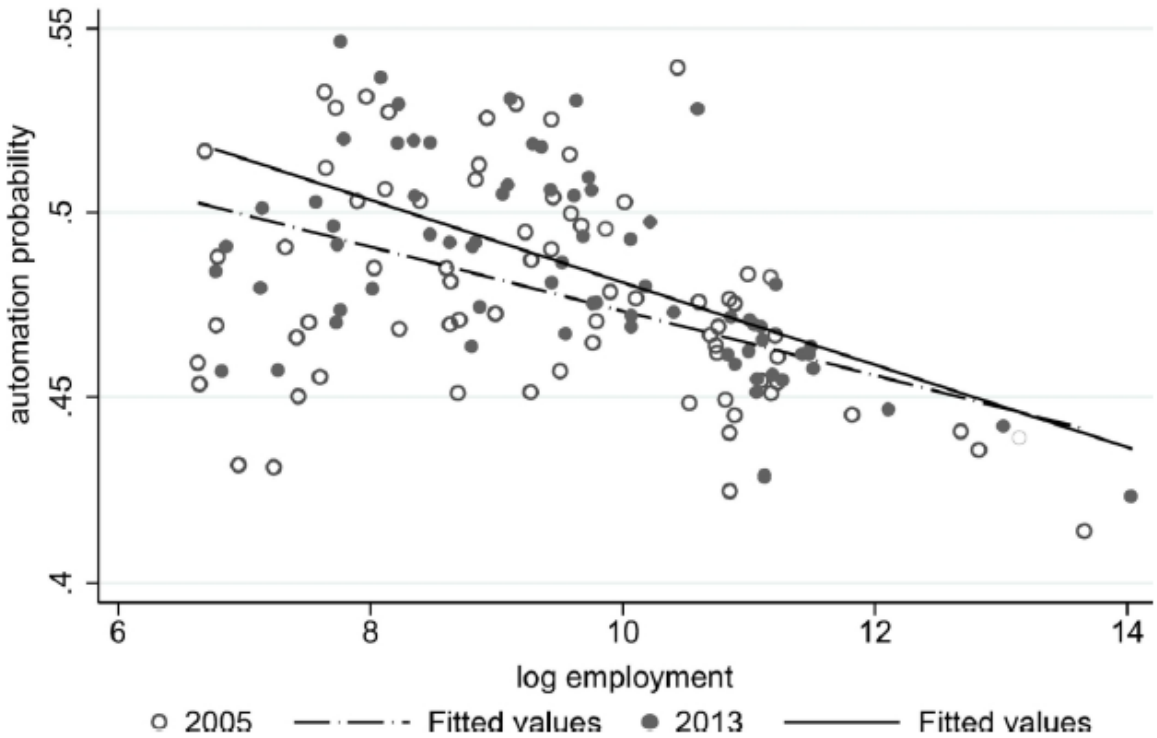

Figure 1: Average automation probability increases in small regions.

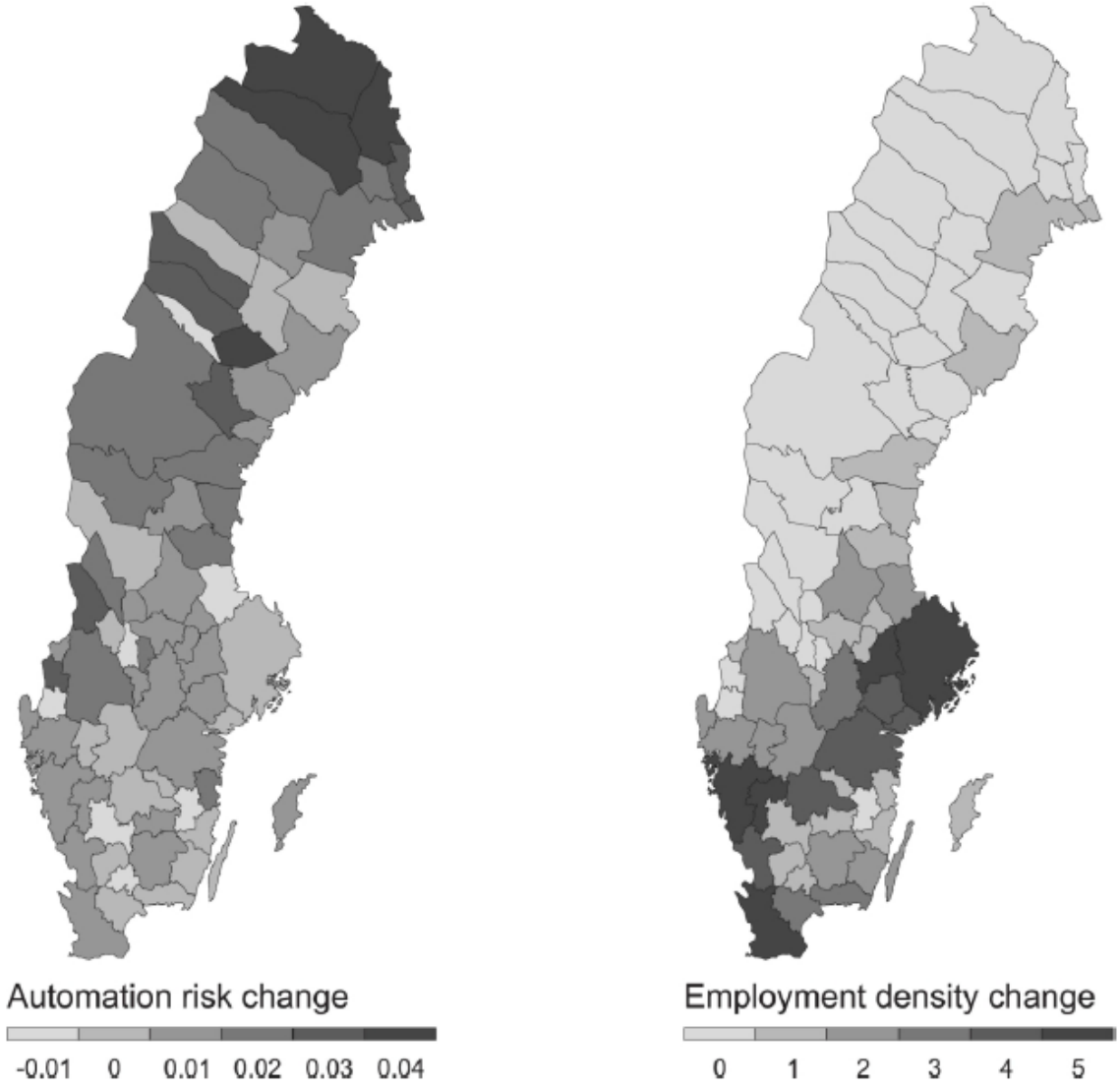

Figure 2: Changes in automation risk and employment density (2005-2013)