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Abstract:

Using a very large comprehensive matched employer-employee panel of the Norwegian workforce (19 million observations), I find a higher likelihood of job change across sectors and occupations, namely labor churning, in populous areas. Further investigation shows that this result is driven by high skilled groups, assumed to have more transferable skills. Moreover, educated urban workers are more likely to switch to sectors and occupations that they have prior experience with and that are similar in the use of human capital. Together, these novel results complement previous research by illuminating how the tradeoff between better labor matching and accumulating specific skills affect churning decisions for heterogeneous workers.

Keywords: turnover, urban scale, human capital, sector, occupation

JEL classification: J24, J63, R12, R23

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Sammendrag

Arbeidstakere har ulike muligheter basert på størrelsen til arbeidsmarkedet de tilhører. Arbeidere i byene tilhører større arbeidsmarkeder med flere potensielle arbeidsgivere relativt til arbeidere i rurale strøk med begrensede valgmuligheter i det lokale arbeidsmarkedet. Størrelsen på arbeidsmarkedet har dermed implikasjoner for arbeiderenes karrieremuligheter og mulighet til å søke en bedre jobb. I denne studien sammenligner jeg urbane og rurale arbeideres sannsynlighet for å foreta jobbskifter på tvers av sektorer og yrker. Denne typen jobbskifter har blitt ansett som uheldige ved at sektor- og yrkesspesifikke ferdigheter ikke er anvendbare i ny jobb. I likhet med studier på samme tema finner jeg at yngre og mindre erfarne arbeidere har større sannsynlighet for å foreta slike skifter. Dette er i tråd med humankapital-teori, som sier at man akkumulerer spesifikke ferdigheter over tid og at man dermed bør gjennomføre slike skifter tidlig i karrieren. Tilsynelatende i motsetning til denne teorien finner jeg større sannsynlighet for å skifte sektor eller yrke i byer for hele utvalget.

Studiene på dette feltet har generelt gitt blandede resultater. Den amerikanske litteraturen finner både negative og ikke-signifikante sannsynligheter for å skifte sektor eller yrke i byområder, mens jeg finner en høyere sannsynlighet. De sprikende resultatene kan potensielt forklares med ulik atferd for heterogene arbeidere. Jeg undersøker om atferden varierer basert på utdanningsnivå, som anvendes som et mål på hvor generelle ferdigheter arbeideren har. Har de med generelle ferdigheter (høy utdanning) en annen jobbskifteatferd enn de med spesifikke ferdigheter (lav utdanning)? Den positive jobbskifte-sannsynligheten ser ut til å stamme kun fra de med høyere utdanning. De med høy utdanning står generelt sterkere i arbeidsmarkedet, slik at den observerte jobbskifteatferden mest sannsynlig er fordelaktig for arbeideren. Det gir argumenter for at generelle ferdigheter, i større grad enn det man tidligere trodde, er bestemmende for hvilke jobbskifter som er hensiktsmessige.

Spesifikke ferdigheter ser derimot også ut til å spille en rolle for jobbskifteatferd, og ikke bare tidlig i karrieren. Jeg finner at høyt utdannede i byområder skifter til yrker og sektorer som er relaterte til tidligere yrke og sektor. De har høyere sannsynlighet for å skifte til en sektor med liknende yrkesstruktur, og til yrker som besittes av arbeidere med liknende utdanning som i sitt forrige yrke. I sum viser disse resultatene en mer kompleks jobbskifteatferd enn det som har blitt funnet for arbeidere i byer tidligere, og resultatene komplementerer tidligere funn ved å anvende humankapital-teori til å teste tilstedeværelsen av heterogene responser.

1 Introduction

A central question for both policymakers and researchers is why some places are more productive than others. Policymakers have directed substantial resources to spur less developed regional economies; for instance, the regional policy program is the largest budget post of the European Union, accounting for just over one third of the Union budget for the 2014-2020 financing period. The designing of efficient policy requires knowledge on the sources causing disparate outcomes. Urban economists have come to a robust consensus that agglomeration economy partially explains the regional productivity differentials, but the mechanisms are less clear (Glaeser and Gottlieb, 2009). A candidate mechanism is labor market pooling. Worker job mobility might be affected by the scale of the local labor market, and higher mobility might ultimately result in improved labor matching and knowledge diffusion (Duranton and Puga, 2004). Consequently, efforts to understand worker job mobility decisions in labor markets of different sizes might provide important insights related to regional productivity.

The present paper study a particular type of job mobility that entails a change of sector or occupation (labor churning).[1] Specifically, I investigates how the probability of labor churning is affected by the scale of the local labor market and how this relationship varies along the skill and experience gradients. The context of the study is Norway in the period 1994-2009. In contrast to studies with small and perhaps unrepresentative samples, I have detailed information from administrative registers on all workers and employment links over an extended period. The data are highly suited for a indepth study of job mobility, as I am enabled to pay close attention to career trajectories, investigate heterogeneous responses, and apply strategies to better understand and mitigate sorting issues.

Workers have different job opportunities dependent on the size of their local labor market. Rural workers face a limited choice of local employers, while urban workers have a greater number and variety of jobs in close proximity. Having the luxury of choice, workers in cities should demonstrate job mobility behavior that serves them relatively better. In the related literature labor churning has often been perceived as disadvantageous since the worker then foregoes specific skills accumulated through industry and occupation experience. However, it is not obvious that churning behavior is unfortunate since the worker might expect the returns from a better labor match to exceed the loss from foregoing specific skills. If we observe higher probability of churning in cities, ceteris paribus, this might indicate that finding a better employment match is on average the best strategy for the workers. If the likelihood is lower, this suggests that the accumulation of specific experience and skills might be the salient strategy for most workers.

[1] The definition of labor churning varies somewhat in the literature. The definition in this paper corresponds to the one set out in the study by Bleakley and Lin (2012).

The evidence from the literature leans towards the latter conclusion, but there are few studies that relate churning to labor pooling. For instance, Parent (2000) and Kambourov and Manovskii (2009) show that there are returns from industry and occupation experience of about 10% and 20% respectively over a 10-year period. Couch and Placzek (2010) demonstrate that displaced workers receive lower wages if they change industry affiliation. Bleakley and Lin (2012) find a lower likelihood of churning in densely populated areas, whereas the study of Wheeler (2008) finds no significant relationship between urban scale and probability of industry switching for the average worker. I, on the other hand, find a positive churning probability in cities. The result is robust to adjustments for worker heterogeneity and sorting, and corrections for endogenous population size. How can it be that the estimated relationship between churning probabilities and urban scale differs across these three studies? A potential source is heterogeneous worker responses to labor market scale based on experience and skills.

The quality of a labor match might be uncertain ex ante and might need to be experienced to be evaluated (Jovanovic, 1979). Through search and experimentation workers learn about their abilities and preferences, and we should therefore expect the rate of job switching to decrease as workers converge to better matches (Topel and Ward, 1992). Neal (1999) shows that the matching process often happens in two steps where the worker first engage in a series of complex job changes across industry and occupation, followed by simple changes of employer only. Corresponding to the contentions that search should be done early in the career rather than later and that urban workers have advantages in the search process, both Wheeler (2008) and Bleakley and Lin (2012) find that the likelihood of churn is positively related to urban scale for younger workers. I arrive at the same conclusion.

The ability to exploit the opportunities provided by thicker labor markets might depend on the workers' human capital and the portability of their skills. Based on transferability, Becker (1964) divided skills into two broad classes — general-purpose skills and firm-specific skills. Neal (1995) expanded on human capital theory by introducing the concepts of industry- and occupation-specific skills. The idea that human capital is related to the nature of the work is further discussed utilizing the concept of task-specific skills in Gibbons and Waldman (2004) and Gathmann and Schönberg (2010).[2] The relative importance of industry- and occupation-specific skills is assessed when estimating the likelihood to churn in cities. How the transferability of workers' skills affects urban churning behavior is harder to retrieve, since we do not observe general skill endowments. An indirect way to evaluate the importance of general skills is to study differences by educational attainment, as education should make students ready for working life and

[2]In recent studies the distinction between cognitive and non-cognitive skills have been emphasized. Cognitive skills refer to the conventional operationalization of skills, while non-cognitive skills encompass other aspects of the individual; for instance, perseverence, motivation, and self-control. Non-cognitive skills have been found to affect both schooling, wages and occupational choice (Heckman et al., 2006).

consequently equip them with skills that are useful in many settings.[3]

To my knowledge, there exist no studies that focus on how human capital endowments affect churning behavior in cities.[4] However, the level of education has been found to increase geographic mobility and the probability to reside in a city (Machin et al., 2012), as well as inter-firm mobility (Andersson and Thulin, 2013). The importance of skills has been investigated in agglomeration economy studies estimating the relationship between urban scale and individual wage. In this strand of literature education is of substantial consequence. These studies typically find positive agglomeration effects on wages that are increasing in education level (Wheeler, 2001; Rosenthal and Strange, 2008; Bacolod et al., 2009). Moving from static to dynamic agglomeration effects, Matano and Naticchioni (2016) and Carlsen et al. (2016) find that the returns from experience in cities vary across skill groups. Switching jobs within thick labor markets have positive effects for high skilled groups, while tenure is positive for low skilled groups. The heterogeneous effects in the urban wage studies motivate corresponding exploration of churning behavior in cities, as the mechanisms underlying these outcomes might be similar.

I demonstrate that the relationship between urban scale and labor churning is monotonically increasing in formal skill levels. Actually, workers with education exceeding compulsory schooling are the sole contributors to higher probability of churn in urban labor markets. Holding in mind which group of workers that churns, it is hard to believe that this job switching process is disadvantageous. The general skills of highly educated workers might give them a comparative advantage in cities by accessing a labor market with a larger pool of potential employers. The results imply that high skilled groups might be the ones able to exploit the matching opportunities in urban areas and perhaps bring about knowledge externalities. Nonetheless, by closer examination of career paths in thick labor markets, also specific skills seem to play a role in the choice of new employer. Urban workers are more likely to switch to sectors and occupations they have prior experience with. In addition, I find that educated workers in cities are more likely to select sectors that have similar employment structure as their old sector. They are also more likely to switch to similar occupations, in the sense that new and old occupation tend to be held by workers with the same educations. Overall, the analysis complements earlier findings by investigating experience and skill heterogeneity in churning behavior in thick labor markets. This provides some novel results that reflect the complexity intrinsic to job mobility decisions.

The structure of the remaining part of the paper is as follows: Section 2 presents the

[3]Some might argue that at high levels of education further education is only specializing. This is a strong assumption as high level education also entails, for instance, the ability to understand complex problems and work methods for solving challenging tasks.

[4]In robustness checks Wheeler (2008) runs the analysis for groups with different formal education. With a sample size of approximately 4,500 observations, the Wald test renders few cross-education estimates significantly different.

estimation approach and section 3 describes the data. Section 4 displays the full sample results and robustness tests. In section 5 I investigate how churning depends on education and other worker traits. In addition, I study other characteristics of the job switching process related to the similarity of the old and new job. Section 6 provides concluding remarks.

2 Estimation approach

I use a linear probability model to estimate the likelihood of churning in thick labor markets.[5] C is either an indicator of industry or occupation churning. To simplify the presentation, let C_{irt} be an indicator of industry churning for worker i with residence in region r in year t. The probability of churning can then be expressed as:

$$C_{irt} = \beta_0 + \beta_1 City_r + \beta_2 SCity_r + \mathbf{X_i}\boldsymbol{\beta_3} + \mathbf{X_f}\boldsymbol{\beta_4} + \mathbf{Y_r^N}\boldsymbol{\beta_5} + \mathbf{Y_r^L}\boldsymbol{\beta_6} + \delta_j + \gamma_t + \epsilon_{irt} \quad (1)$$

where $City$ and $SCity$ (small city) are the variables of interest and reflect the urban scale of the region. β_1 and β_2 are coefficients of the urban-rural churning differentials, expressed as conditional marginal probabilities. I compute standard errors that are heteroscedasticity robust and clustered at the region level.

A general concern is unobserved heterogeneity that causes the error term ϵ to be correlated with urban scale. I therefore add an extensive battery of controls at the worker, firm and region level; and employ fixed effect strategies. $\mathbf{X_i}$ is a vector of personal characteristics — gender, immigrant status (Western and non-Western immigrant), education categories (high school and college/university), tenure[6], indicator of part-time job in addition to full time contract, the number of subsequent years in-a-row out of the labor market, and 5 year age group indicators. $\mathbf{X_f}$ is a vector of firm characteristics such as firm employment size indicators (11-50, 51-100, 101-250, 251-500 and over 500 employees) and an indicator of decreasing firm employment between year $t-2$ and $t-1$. $\mathbf{Y_r^N}$ is a vector of natural regional characteristics that might affect the productivity and labor market in the region — land area, mountain area share, average slope, January temperature, wind speed, precipitation and coast length. $\mathbf{Y_r^L}$ is a vector of regional labor market characteristics and consists of net migration and unemployment rate. δ_j and γ_t are respectively industry and year fixed effects. I add occupation fixed effects in the specification with occupation churning as the dependent variable and in sensitivity tests of the industry churning result.

The specification is similar to those in the related literature, but differs in two respects.

[5] Initial tests with the probit model gave very similar results. The probit estimator was abandoned as it has unfavorable properties with fixed effects estimation (Greene, 2004).

[6] Tenure is computed as the number of years in the same firm and is censored to the left since the first observation year is 1993.

First, it takes into account natural characteristics of the region. The natural endowments of a region might affect productivity, industry and occupation composition, and also population size. These region covariates are not influenced by human behavior, evading that particular endogeneity concern. Second, utilizing the longitudinal properties and the frequency of the data, I can take into account intermediate periods out of the labor market. It is reasonable to believe that duration of unemployment and probability of job loss are correlated with the extent of the labor market. For instance, it would be harder to obtain a new job in rural areas where positions are scarce, and the competition between firms in urban labor markets might be higher and might inflate job destruction and job creation. If churning is unfavorable, duration of the unemployment spells might also affect the probability of switching between sectors and occupations. In Table B.3 I investigate different ways of controlling for period out of the labor market with close to unchanged results.

Utilizing multiple estimation strategies, the sensitivity of the results are tested further in section 4.2. I investigate several additional channels of heterogeneity bias, instrument urban scale to mitigate the influence of two-way causality and worker sorting, assess the importance of job loss and conduct the analyses for subgroups where treatment is arguably more exogenous.

3 Data

I use a matched employer-employee data set from Statistic Norway encompassing the universe of Norwegian workers for the years 1993-2010. The employment and education registers provide the links between workers and firms, work contracts (number of work days and type of contract), sector affiliation, age, sex, immigration status, highest completed education and home region of the worker.

This study focuses on workers between the age of 25 and 65. For each year I restrict the sample to workers with no more than three contracts where at least one of them is a full-time contract (30 hours' work or more per week). I do not want to neglect the possibility that for some workers the transition to a new job might include overlapping part-time work at the future full-time workplace. Since I only observe the main employer of the worker, I include an indicator of additional part-time work in the analyses.

I use two measures of intra-region churning. Using Statistics Norway's industry standard (NACE codes), I allocate workers to 60 sectors. I use this information to create an industry churning indicator with a value equal to one if a worker has a different NACE code the subsequent year. In much the same way as the industry churning variable, I create an occupation churning variable using STYRK codes that identify 365 separate occupations. Unfortunately, I have only reliable STYRK codes from the year 2007 on, since missing values before that year do not seem to be random. For both churning variables I disregard interregional job changes since it confounds the employment decision with a migration decision. On average, each year 8.9 percent switch industry during the period 1994-2009 and 14.7 percent switch occupation in 2007-2009. Simple summary statistics can be found in Appendix A.

Since the churning variables are derived from having a different sector and occupation the next year, the worker observations from year 2010 drop out because of missing dependent variable. The same goes for the observations from 1993 in creation of the contracting employment size control, which is retrospective. The procedure left me with a total of 19.1 million worker-year observations for the industry churning analysis and 3.7 million for the occupation churning analysis.

The variable of interest, population size, is at the labor market level. Following Statistics Norway, I therefore divide Norway into 89 economic regions. The regions are based on commuting intensities and correspond to European NUTS-4 regions. This would also minimize the probability of living in one region and working in another. Since Norwegian regions have large unpopulated areas, I follow Carlsen et al. (2016) and use region population size indicators as measures of urban scale. I create a binary city variable equal to unity for the seven regions that comprise the four largest cities in Norway - Oslo, Bergen, Trondheim and Stavanger.[7] All regions over 150,000 inhabitants in 2010 are therefore classified as city regions. Next, I define the 13 regions with population size between 100,000 and 150,000 as small city regions. Alternative measures of urban scale are investigated in Table B.4, but have little bearing on the results.

4 Likelihood of industry and occupation churning in populous regions

4.1 Full sample results

Panel A and B of Table 1 display the results for industry churning and occupation churning respectively. I include additional control variables stepwise to the right. Contrary to in related studies, there is a positive relationship between population size and the probability of churning for the full sample. This relationship is robust across specifications. With the full sample and all covariates included, the likelihood of industry churn increases by 0.71 and 0.41 percentage points by working respectively in a city and small city region compared to regions with less than 100,000 inhabitants (see Panel A, Column (6)).

[7]The regions Bærum/Asker, Lillestrøm and Drammen are considered part of the Oslo city area.

These responses might not seem like large effects at first glance, but remember that these probabilities affect the entire local labor force in urban regions. Let us say that for each hundred person in a city region we have 0.7 extra sector changes. That would sum up to about 4,200 extra sector switches in the great Oslo city area.[8] Consequently, the results sum up to substantial differences in this type of labor market mobility across regions of different population sizes.

If we narrowly think of churning as a change of sectorial affiliation we might only partially capture the essence of labor churning. For instance, an accountant might perform the same tasks in the dairy sector as in the petroleum sector. To investigate job switches that most likely involves a change in tasks, I regress occupation churning on urban scale in Panel B. I find a very similar result for occupation churning and industry churning both in sign and size of the city coefficient (Column 6). Urban workers are more likely to switch occupations compared to their rural counterparts.[9]

The positive urban churning results are not driven by aggregation of the churning variables, as can be seen from Table B.4 where I use aggregated codes for industry and occupation. The sample from the years 2007-2009 might be affected by the financial crisis, since quit rates have been reported to be procyclical (Davis et al., 2012). This means that the likelihood of occupation churning in urban areas might be understated. By restricting the industry churning analysis to the same years I test this assumption. As expected the urban industry churning probability is somewhat lower. Controlling for occupation fixed effects leaves the results close to unchanged in Column (8) for both churning variables.[10]

A possible interpretation of the results is that for the average worker the expected benefits of a better industry and occupation match exceed those from further accumulating sector and activity specific experience. However, there are some caveats that need to be explored further. I do not observe if the job separations are voluntarily or not. If, for instance, the probability of job loss in cities is higher because of stronger competition in urban business environments, this might affect the result. Two-way causality might also be an issue. Job switching in cities might be linked to a higher level of job creation, which suggests a positive effect of churning on city size. There might also be an influx of people to cities that might be more career-oriented and ambitious, and these people might switch jobs more often. This brings up the topic of sorting. Before we move on to investigate heterogeneous effects, I will test the sensitivity of the result to these complicating matters.

[8] I use 4th quarter 2010 register-based workforce data to compute this number.

[9] It is clear that workers in some urban industries are more prone to switch sectors and occupations. Table B.5 in Appendix B suggests that industries in the manufacturing sector are candidates. It is not obvious that differences in industry composition should be removed. One of the benefits of thick labor markets might be the diverse industry mix. Nonetheless, that is the conventional way of doing it in the literature and therefore the subsequent results are reported conditional on industry fixed effects.

[10] The results for sector and occupation churning are robust to a jack-knife procedure with stepwise removal of one by one sector (60 sectors) and occupation (32 and 10 aggregate occupations), respectively.

Table 1: Churning and population size

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Dependent variable: Industry churning								
City	0.0108***	0.0105***	0.0124***	0.0125***	0.0074***	0.0071***	0.0052***	0.0048***
	(3.78)	(4.85)	(5.48)	(9.47)	(6.39)	(5.76)	(5.55)	(5.00)
Small city	0.0064***	0.0068***	0.0076***	0.0047**	0.0041***	0.0042***	0.0039**	0.0039**
	(4.03)	(3.87)	(4.09)	(2.51)	(3.03)	(2.97)	(2.28)	(2.35)
Adjusted R-Square	0.04	0.07	0.07	0.07	0.08	0.08	0.05	0.06
Years	1994-09	1994-09	1994-09	1994-09	1994-09	1994-09	2007-09	2007-09
N	19,076,904	19,076,904	19,076,904	19,076,904	19,076,904	19,076,904	3,669,773	3,669,773
Panel B: Dependent variable: Occupation churning								
City	0.0188***	0.0137***	0.0107***	0.0090***	0.0051***	0.0066***	-	0.0055**
	(5.09)	(4.58)	(3.95)	(3.55)	(2.79)	(3.55)		(2.49)
Small city	0.0091***	0.0078**	0.0064**	0.0044	0.0042*	0.0056***	-	0.0057**
	(2.78)	(2.46)	(2.25)	(1.63)	(1.89)	(2.68)		(2.57)
Adjusted R-Square	0.01	0.03	0.03	0.03	0.03	0.03	-	0.04
Years	2007-09	2007-09	2007-09	2007-09	2007-09	2007-09	-	2007-09
N	3,669,773	3,669,773	3,669,773	3,669,773	3,669,773	3,669,773	-	3,669,773
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Personal characteristics	N	Y	Y	Y	Y	Y	Y	Y
Firm characteristics	N	N	Y	Y	Y	Y	Y	Y
Natural characteristics	N	N	N	Y	Y	Y	Y	Y
Industry fixed effects	N	N	N	N	Y	Y	Y	Y
Labor market characteristics	N	N	N	N	N	Y	Y	Y
Occupation fixed effects	N	N	N	N	N	N	N	Y

Dependent variables: Industry churning in Panel A and occupation churning in panel B, respectively. In Panel A Columns (1)-(6) show the results for the years 1994-2009, whereas Panel A Columns (7)-(8) and Panel B display results for the years 2007-2009.

Personal characteristics are gender, immigrant status, education (upper secondary and tertiary education), tenure, indicator of part-time job and age group dummies. Firm characteristics are firm size dummies and indicator of being in a downsizing firm. Natural characteristics are January temperature, precipitation, wind speed, coast length, region area size, share of mountainous land in the region and average slope. Labor market characteristics are regional unemployment rate and net migration. 60 industry fixed effects and 337 occupation fixed effects are included from the NACE-codes and STYRK-codes, respectively. In addition, all regressions include a constant term and control for number of years out of the labor market.

Robust t statistics clustered on region are in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1

4.2 Robustness checks of the positive propensity to churn in cities

4.2.1 Expanding and contracting firms

Since I do not observe if the worker is laid off, a concern is that the results are affected by the differences across regions in the probability of becoming displaced. I investigate this possibility using two strategies. First, I control for region specific unemployment rates in the baseline specification. Reassuringly, the inclusion does not change the result much. Second, I investigate how firm specific employment shocks impact urban churning probabilities. Specifically, I display results for subsamples of firms that either are expanding or contracting employment from year $t-2$ to $t-1$. I operate with two thresholds — more than 5 and 10 percent change in firm employment.

Table 2: Churning and population size. Estimates for workers in firms with changed employment size

	Contracting firms with at least		Expanding firms with at least	
	5% lower employment	10% lower employment	5% higher employment	10% higher employment
	(1)	(2)	(3)	(4)
Panel A: Dependent variable: Industry churning				
City	0.0105***	0.0098***	0.0040***	0.0033**
	(6.70)	(5.62)	(3.49)	(2.33)
Small city	0.0060***	0.0042**	0.0029**	0.0034**
	(2.89)	(2.11)	(2.25)	(2.30)
Adjusted R-Square	0.09	0.09	0.08	0.09
Years	1994-09	1994-09	1994-09	1994-09
N	4,218,389	2,727,106	6,843,615	4,997,699
Panel B: Dependent variable: Occupation churning				
City	0.0073***	0.0071***	0.0055**	0.0068***
	(3.26)	(2.84)	(2.37)	(2.78)
Small city	0.0057**	0.0030	0.0061**	0.0052
	(2.35)	(1.15)	(2.29)	(1.62)
Occupation fixed effects	Y	Y	Y	Y
Adjusted R-Square	0.05	0.05	0.05	0.05
Years	2007-09	2007-09	2007-09	2007-09
N	786,002	497,997	1,345,573	971,249

Dependent variables: Industry churning in Panel A and occupation churning in Panel B.

I control for the same individual, firm and region characteristics as in column (6) of Table 1. Industry fixed effects are included in both panels, while occupation fixed effects are included in Panel B only.

Robust t statistics clustered on region are in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1

In columns (1)-(2) of Table 2 the results for firms with staff reductions are reported. As expected, the urban labor market with more outside options displays higher likelihood of both industry churning (Panel A) and occupation churning (Panel B) than for the baseline result. These results are likely to reflect workers getting fired and how workers react to negative career prospects signaled by reductions in staff. Columns (3)-(4) show the results for firms with staff expansions. These are the subsamples of workers that are expected to have the lowest observed mobility because of good prospects in the firm and small chances of involuntary separations. Workers in firms with expanding employment size have somewhat lower probability of industry churning in thick markets than the baseline result, but still positive and significant coefficients. Also the occupation churning results are robust and positive, but vary in size around the effect for the full sample.[11] The results suggest that dismissals of employees and firm deaths are not driving the results in Table 1.

4.2.2 Sensitivity tests: worker heterogeneity, endogenous population size and sorting

In this section I test the importance of two channels of worker heterogeneity related to further education and part time work. The supply of educational services is higher in urban regions. Consequently, higher propensity to change jobs in cities might partially be driven by urban workers being more likely to obtain further education. I therefore include an indicator of change in detailed education codes in column (1) of Table 3. The result does not change much. The baseline specification includes an indicator for part-time job since that might be a stepping-stone into a new job. Urban workers might be more likely to use this channel of career promotion because of higher job supply in cities. In column (2) I test this assumption by excluding individuals who have a part-time job in addition to their full-time position. The results are robust to these changes.

Another concern is feedback between job switching and urban scale. A labor market with larger worker flows might be more prone to grow. In columns (3) I instrument the city indicator with the number of early Iron Age graves (500 B.C to 500 A.D.) as in Leknes (2015). The Iron Age graves instrument is a proxy for very early population size in Norway. I assume that drivers of population size today are different from back then, in line with the literature by Ciccone and Hall (1996) and Combes et al. (2010). The instrument predicts city size strongly as can be seen from the first stage F-value and Table B.6. The effect of urban scale on churning probability increases with IV-estimation, which is reassuring, but somewhat unexpected. A potential explanation is measurement error stemming from the crude categorization of the variabel of interest. Bleakley and Lin (2012) give some evidence that this might be a problem in this setting. Another possibility for the higher coefficient is unobserved region heterogeneity.

A common worry when comparing areas of different population scale is the non-random

[11] The occupation churning results might to some extent showcase how expanding firms assign new roles to senior staff in periods of expansions. Recoding the occupation churning variable to be conditional on changing firm, the results are very similar and actually more sharply estimated.

Table 3: Endogenous population size, and worker heterogeneity and sorting

	Change of education	Only workers without part-time job	Iron Age graves instrument	Sample of permanent stayers	Population size in birth region instrument	1900 population size in birth region instrument
	OLS	OLS	2SLS	OLS	2SLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Dependent variable: Industry churning						
City	0.0072***	0.0071***	0.0195***	0.0072***	0.0183***	0.0194***
	(5.78)	(5.88)	(3.02)	(4.91)	(5.50)	(5.26)
Small city	0.0042***	0.0042***	-	0.0038**	-	-
	(2.95)	(3.00)		(2.27)		
Adjusted R-Square	0.08	0.07	-	0.11	-	-
First stage F-value	-	-	13.25	-	59.60	43.16
Years	1994-2009	1994-2009	1994-2009	1994-2009	1994-2009	1994-2009
N	19,076,904	17,921,686	19,076,904	14,570,732	15,374,920	15,374,920
Panel B: Dependent variable: Occupation churning						
City	0.0056**	0.0054**	0.0234***	0.0043*	0.0090**	0.0077*
	(2.51)	(2.42)	(2.83)	(1.77)	(2.55)	(1.87)
Small city	0.0057**	0.0059***	-	0.0060**	-	-
	(2.56)	(2.65)		(2.43)		
Occupation fixed effects	Y	Y	Y	Y	Y	Y
Adjusted R-Square	0.04	0.04	-	0.05	-	-
First stage F-value	-	-	17.89	-	51.55	43.56
Years	2007-2009	2007-2009	2007-2009	2007-2009	2007-2009	2007-2009
N	3,669,773	3,472,057	3,669,773	2,715,197	3,094,594	3,094,594

Dependent variables: Industry and occupation churning.

In Column (1) an indicator of change of education is included. In Column (2) the sample only includes workers with full-time contracts. In Column (3) the city indicator is instrumented with the number of Iron Age graves in the region. In Column (4) the sample is reduced to workers that do not move at all during the period. In Column (5) the city indicator is instrumented with population size in the birth region of the worker. In Column (6) the city indicator is instrumented with year 1900 population size in the birth region of the worker. I control for the same individual, firm and region characteristics as in column (6) of Table 1. Industry fixed effects are included in both panels, while occupation fixed effects are included in Panel B only.

Robust t statistics clustered on region are in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1

sorting of individuals across space. For instance, the most able individuals might move to larger cities to attend high-quality schools there. Workers with high innate ability might select themselves into urban regions where the industries and firms are cutting edge. I use three different strategies to test and mitigate the potential effect of sorting on the results. First, I control for characteristics of the employees that are correlated with higher skill and ability. For example, in the baseline results I include indicators of education. Second, I investigate if the movers display different behavior than the stayers in a region. Third, I instrument urban scale by contemporaneous and historical population size in birth region of the worker, omitting residents born abroad.

In column (4) I exclude all workers that moved sometime during the period I observe. The results are also robust to this change. In columns (5)-(6) I use contemporaneous and historical population size in birth region of the worker to instrument the city indicator. Both instruments have very large first stage F-values. The city coefficient is higher with instrumentation, suggesting that sorting is not causing the positive result, rather understating it.

5 Heterogeneous responses to labor market scale

Estimations with full sample of workers have provided mixed results. The study of Bleakley and Lin (2012) shows negative urban scale coefficients, Wheeler (2008) finds statistically insignificant coefficients and this study gives a positive result. A potential explanation is that workers of disparate characteristics react differently to labor market size. The average effect might provide information on the best career strategy for the full sample, but the composition of the sample might vary across analyses and lead to divergent results. Actually, the related literature finds that there are heterogeneous effects along the age and overall experience gradient with younger workers and workers early in their careers displaing greater likelihood of urban churning. This motivates explorations of heterogeneous responses along alternative gradients related to skill level.

First, similar to the studies mentioned above, I will investigate if the urban scale effect on churning differs across age groups and for groups with different job switching histories. If churning intensities are highest for younger and less experienced workers, this might reflect convergence to more favorable employment matches over the span of the career. In addition, obtaining similar results as in related studies might indicate that the results are comparable and might be generalizable. Second, workers vary in skill endowments. Higher skilled groups have more transferable skills, and this might be crucial for their ability to exploit the opportunities provided by thick labor markets. I will therefore investigate how the churning results vary along the skill specificity gradient. Finally, sectors and occupations might be similar across several dimensions and therefore the job change might not signify large changes in work tasks and methods. I pursue this line of thought by comparing how similar the new and old jobs are for switchers in rural and urban areas.

5.1 How does worker age and job switching history affect the likelihood of churning?

The likelihood of both industry and occupation churning in cities decrease with worker age, as can be seen from Figures 1a and 1b. The positive churning results for young workers are consistent with the results of Bleakley and Lin (2012) and Wheeler (2008). In the literature the decreasing propensity to churn with age and experience has been interpreted as a convergence to better employment matches. This might not only be because of the quantity of jobs. Urban workers might converge faster to better matches if the expected quality of the match is higher in cities (Helsley and Strange, 1990).

I find a similar decreasing pattern in churning probabilities when I split the sample according to the number of sector switches. In Figure 1c the result for all workers is displayed, while in Figure 1d I present the result for workers with full work histories born in 1968 or later. The same pattern emerges, over time the propensity to churn decreases for urban workers. The results are fairly consistent across these measures of overall experience and also with similar specifications in other studies. This seems to indicate that one should make industry and occupation switches early in one's career, and suggests that specific skills are not without consequence for career path choices.

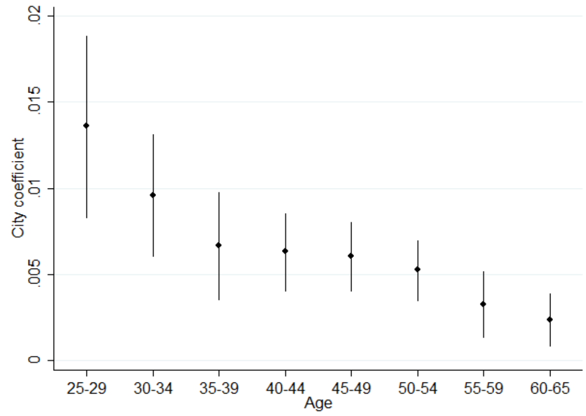
5.2 Human capital and the propensity to churn

The effect of labor market size on churning might vary systematically with worker skills, as the portability of skills might vary. This means that some skill groups might contribute disproportionally to the average urban churning effect. In this paper I proxy worker endowments of general purpose skills with educational attainment, assuming that students learn skills that can potentially be used in many settings. Metropolitan areas have been found to contain a disproportionate number of college-educated residents (Glaeser, 1999; Costa and Kahn, 2000) and there is evidence that highly educated workers change jobs more often in populous areas (Andersson and Thulin, 2013).[12] The pattern of high skilled concentrations in cities is also found for Norway. As can be seen from Figure 2, the proportion of workers with higher education has increased over time in Norway and eventually became the largest group in city regions.

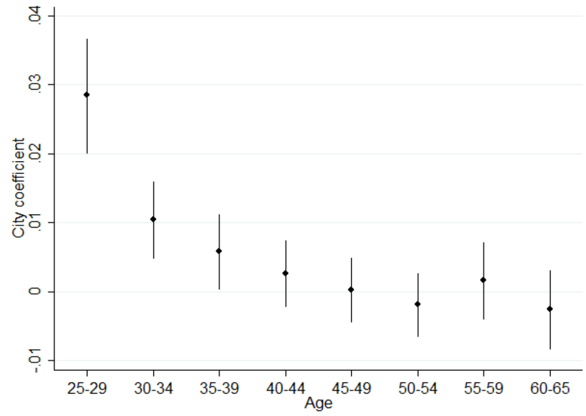
[12] On the other hand, very specialized workers might have a thinner labor market overall in the sense that few vacancies fit their specialization.

Figure 1: Churning and population size. Estimates for age groups and for workers with different number of sector changes

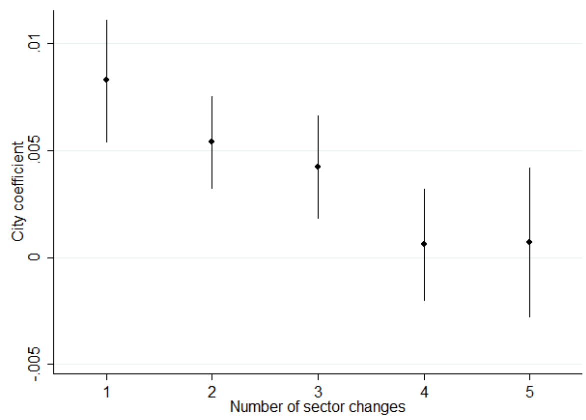
(a) Industry churning in city regions by age



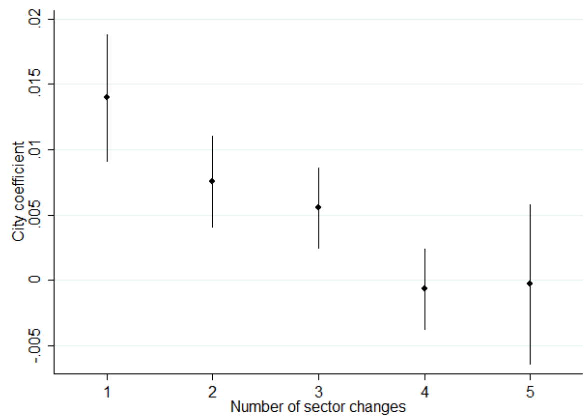
(b) Occupation churning in city regions by age



(c) Industry churning in city regions by the number of sector changes, all workers



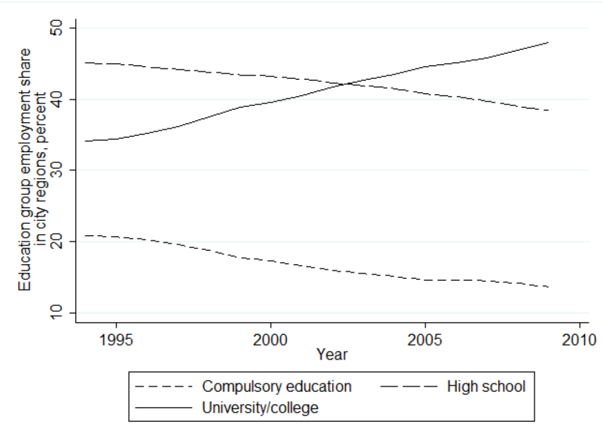
(d) Industry churning in city regions by the number of sector changes, young workers



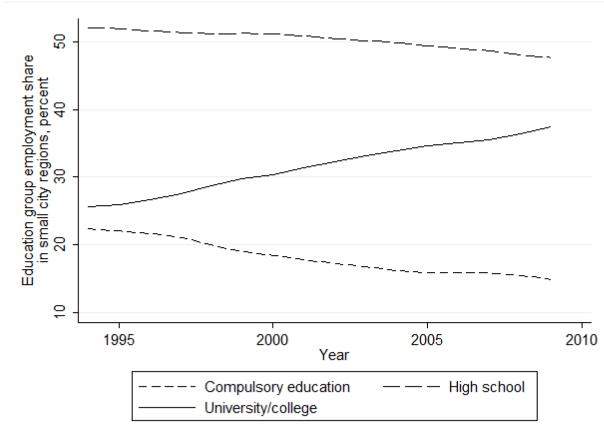
Dependent variables: Industry and occupation churning indicators. Figures show the coefficient for the probability to churn in cities for subsamples of age and for workers with different number of sector switches. The number of sector switches is counted from 1993 for the whole sample in figure (c), while in figure (d) I only count switches for workers where we observe their full work history born in 1968 or later. 95% confidence intervals are displayed using robust standard errors clustered at the region level. I control for individual, firm and region characteristics. I control for the same individual, firm and region characteristics as in column (6) of Table 1. Industry fixed effects are included in all figures, while occupation fixed effects are included in figure (b) only.

Figure 2: Proportion of workers in each education group over time, percent

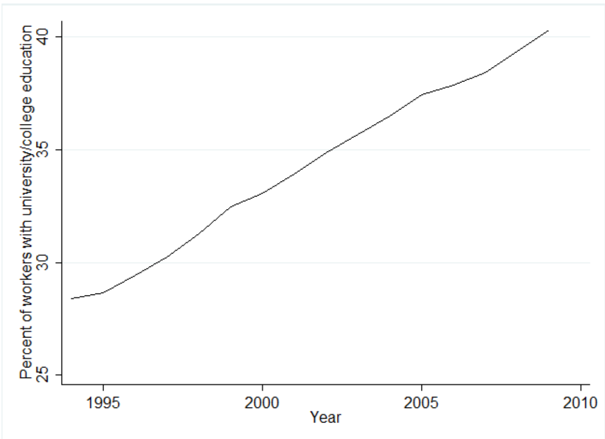
(a) City regions



(b) Small city regions



(c) National level



Workers with specific skill, the low skilled and vocationally trained workers, are expected to perform relatively badly in the urban competition for new jobs compared to those with general skills. The strategy of those with specific skills should therefore be to not change jobs, but rather have longer tenures that increase job security by accumulating specialized experience. However, if urban labor markets are faster to adopt new technologies of production, these workers might find their competencies becoming obsolete at a faster rate and inflate their probability to churn. The overall effect for those with low levels of education is therefore unclear. Highly educated people should on the other hand benefit from churning in cities as long as the expected returns from matching are higher than those from further experience.

Table 4: Relation between churning and urban scale for skill groups

	Compulsory education	High school	College/ university	Compulsory education	High school	College/ university
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Dependent variable: Industry churning						
City	-0.0004	0.0045***	0.0123***	0.0010	0.0030**	0.0074***
	(-0.19)	(3.05)	(7.04)	(0.56)	(2.22)	(6.83)
Small city	0.0028*	0.0035**	0.0061***	0.0045*	0.0047**	0.0022
	(1.71)	(2.35)	(4.38)	(1.66)	(2.57)	(1.40)
Adj. R-Square	0.11	0.09	0.07	0.07	0.06	0.06
Panel B: Dependent variable: Occupation churning						
City				0.0005	0.0031	0.0088***
				(0.23)	(1.55)	(2.84)
Small city				0.0009	0.0067**	0.0052
				(0.32)	(2.52)	(1.65)
Adj. R-Square				0.05	0.05	0.06
Occupation FE	N	N	N	Y	Y	Y
Years	1994-09	1994-09	1994-09	2007-09	2007-09	2007-09
N	3,455,753	8,966,763	6,654,388	557,843	1,657,272	1,454,658

Dependent variables: Industry and occupation churning.

I control for the same individual, firm and region characteristics as in column (6) of Table 1. Industry fixed effects are included in both panels, while occupation fixed effects are included in Panel B only.

Robust t statistics clustered on region are in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1

To investigate how general skills affect urban churning, I split the sample three-way based on education — compulsory education, high school and college/university education.[13] In Panel A of Table 4 I investigate how the likelihood of industry churning varies with urban scale across education groups. The likelihood of switching industries increases monotonically with the education level of the worker. The results follow the same pattern when

[13] In 1997 the compulsory education in Norway was extended from nine to ten years with pupils attending first grade in the year of their sixth birthday instead of seventh. Upper secondary/High school is usually attended for 3 years. Vocationally trained students attend for 4 years with part of their time in suitable firms and institutions.

using more disaggregated education groups as displayed in Table B.7. The results are similar both for the full length period and for the shorter period with occupation fixed effects included as displayed in columns (1)-(3) and (4)-(6), respectively. The point estimate of the probability to change sectors in urban areas is more than twice as large for college and university educated workers compared to workers with high school. The relationship is insignificant at conventional confidence levels for workers with compulsory schooling as their highest level of education. This might suggest that workers with low levels of general skills have few employment opportunities and stick to the strategy of accumulating specific experience. In contrast, those with high school or college/university education churn more in cities. This might indicate that job search across sectors are advantageous for educated workers and that general skills enables workers to take advantage of the possibilities provided by the thicker labor markets.

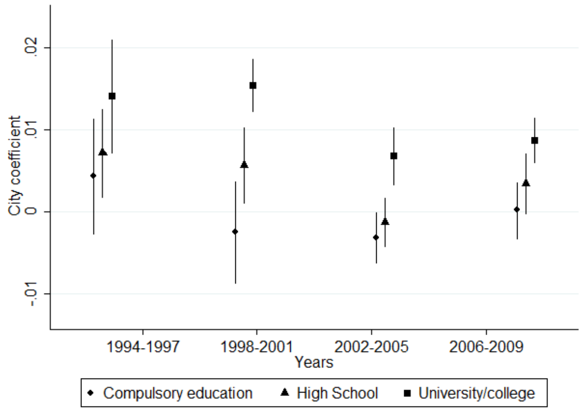
In Panel B of Table 4 the results for occupation churning are reported. Similarly to the results for industry churning, those with higher levels of education are more likely to switch occupations in cities. The result is specific to those with university and college education, while workers with high school education churn more in small city regions. As can be seen from Figure 2b, workers with high school education comprise the largest education group in small city regions. This might cause labor pooling effects that are specific to the education group, which might explain the positive churning result. The same explanation might then be used to explain the relatively high coefficient for industry churning in small city regions.

By dividing the sample in four equally long periods in Figure 3, I can investigate whether the differences in industry churning propensities across education groups are stable over time. This seems to be the case. For all for periods there is a monotonically increasing propensity to churn with education in city regions (see Figure 3a). The pattern is more noisy for the small city coefficients in Figure 3b. Workers with university/college education are most likely to churn in the first three periods, but not in the last. The other education groups tend to have point estimates that are not significantly different from zero. This is different in the last period, 2006-2009, where workers with high school education have significantly higher propensity to churn compared to the insignificant results of the other education groups. This might suggest that the higher churning in small city regions for those with high school education is not a robust result, but an artifact of the specific conditions in the last period.

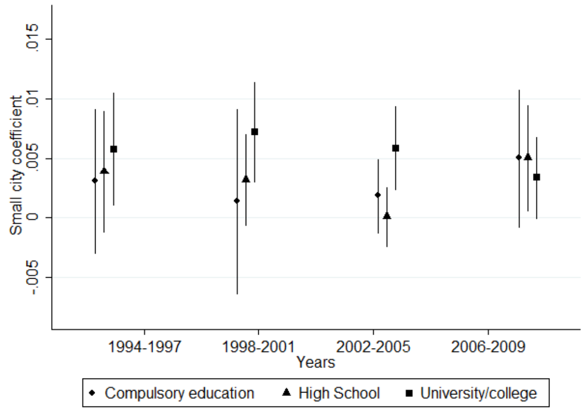
Overall, the churning results for education groups are consistent with studies of Matano and Naticchioni (2016) and Carlsen et al. (2016) that look at returns from experience. Using respectively Italian and Norwegian data they find that skilled workers benefit from better matching opportunities in cities by reaping greater returns to job changes in urban regions. They also show that unskilled workers benefit more from firm tenure once in cities.

Figure 3: Churning and urban scale. Estimates for education groups in different time periods

(a) City regions



(b) Small city regions



Dependent variable: Industry churning indicator. Figures show the coefficient for the probability to churn in cities (a) and small city (b) regions over time. 95% confidence intervals are displayed using robust standard errors clustered at the region level. I control for the same individual, firm and region characteristics as in column (6) of Table 1. Industry fixed effects are included.

The results might suggest that the high skilled groups are the ones that disproportionally contribute to better labor matching outcomes in cities and to knowledge diffusion across sectors and occupations in thick labor markets.

5.3 Convergence to better labor matches

I observe that urban workers are more likely to churn when they are young and inexperienced, which suggests a convergence process. The longitudinal properties of the data make it possible to do further tests of convergence to better employment matches. To ease the presentation, in Table 5 each cell displays the result from a different regression. In columns (1) and (2) I study the probability of urban workers switching back to a sector and occupation that they have prior experience with. If workers are uncertain of the employment match quality (also after experiencing the match), they might want to try several industries and professions before they settle. I create an indicator of switching back, and estimate the likelihood based on the sample of workers that switch. On average urban workers are more likely to return to a sector and occupation they have prior experience with by about 0.2 percentage points. The relationship is disproportionally driven by those with more education, which are also the ones that are most likely to switch jobs in cities.

In column (3) I investigate whether these 'converged' matches tend to last longer in urban regions. The dependent variable is then a count variable, summing the number of years in sector after switching back, and the sample consists of the switchers. There seems to be no rural-urban difference in the duration of the 'converged' matches. Urban workers are thus more likely to switch back and forth between sectors that they have experience with, without longer spells than rural workers. However, duration of an employment spell might be a misleading measure of match quality if rural workers have few alternative employers.

Table 5: Relationship between city size and measures of employment convergence, for education groups

	Likelihood of switching back to old sector, conditional on switching sectors	Likelihood of switching back to old occupation, conditional on switching occupations	Duration in sector after switching back (number of years)
	(1)	(2)	(3)
All workers	0.0021***	0.0017**	-0.0272
	(5.37)	(2.30)	(-0.62)
Compulsory education	-0.0000	-0.0013*	0.0164
	(-0.06)	(-1.90)	(0.30)
High school	0.0012**	0.0001	0.0073
	(2.16)	(0.13)	(0.15)
University/college	0.0042***	0.0035***	-0.0871
	(8.00)	(3.48)	(-1.65)
Occupation fixed effects	N	Y	N
Years	1994-2009	2007-2009	1994-2009

Each cell provides a result from different regressions displaying the city indicator coefficient. The first row shows the results using the full worker sample, while the other rows use subsamples based on education groups. In columns (1) and (2) the dependent variables are indicators equal to one if the worker switches back to a sector and an occupation where he has prior experience, respectively. The sample is restricted to only include switchers in the year of the change. In column (3) the dependent variable is the number of years (employment duration) in a sector the worker has prior experience with. The sample consists of workers switching back to a sector they have prior experience with. I control for belonging to a small city as well as the same individual, firm and region characteristics, as in column (6) of Table 1. Industry fixed effects are included in all columns, while occupation fixed effects are included in column (2) only.

Robust t statistics clustered on region are in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1

5.4 The importance of specific skills: investigating similarities between new and old job

I observe that educated urban workers churn more, suggesting that general skills might be important. That does not necessarily mean that specific skills are without consequence. The comprehensive longitudinal data enables me to do additional investigations of the importance of specific skills. Sectors and occupations might be related and connected, and thus coagglomerate (Ellison et al., 2010). Therefore, changes of sectors and occupations might not always signify large changes in work tasks and methods. I pursue this line of thought in Table 6. I compare characteristics of the new and old job, i.e. if workers move between qualitatively similar sectors and occupations. Again, each cell shows the result from different regressions. In column (1) I use a measure by Gabe and Abel (2016). I create an indicator equal to unity if the largest occupation group in both old and new sector is the same and estimate if switchers in cities are more likely to churn to a similar sector than switchers in rural areas. The result is highly dependent on education level. Urban workers with college or university education have 0.5 percentage point higher likelihood of switching between sectors with same major occupation share. For the other groups the coefficient is insignificant.

Table 6: Relationship between city size and measures of relatedness between new and old job, for education groups

	Same major occupation in sectors	Occupation share correlation between sectors	Same major education in occupations	Education share correlation between occupations
	(1)	(2)	(3)	(4)
All workers	0.0024	0.0076***	-0.0206***	-0.0053**
	(1.54)	(4.37)	(-4.52)	(-2.05)
Compulsory education	-0.0020	0.0044**	-0.0252***	-0.0155***
	(-1.20)	(2.43)	(-3.30)	(-4.14)
High school	0.0014	0.0085***	-0.0264***	-0.0113***
	(0.73)	(3.99)	(-4.70)	(-3.34)
University/college	0.0049***	0.0089***	-0.0056	0.0045*
	(2.76)	(4.07)	(-1.25)	(1.82)
Years	2007-2009	2007-2009	2007-2009	2007-2009

Each cell provides a result from different regressions displaying the city indicator coefficient. The first row shows the results using the full worker sample, while the other rows use subsamples based on education groups. In column (1) the dependent variable is an indicator of same major occupation share in old and new sector. In column (2) I use a labor correlation index similar to Ellison et al. (2010) with partial correlation between occupation shares in 337 detailed occupations between sectors. In column (3) the dependent variable is an indicator of same major education share in old and new occupation using 2-digit education codes. In column (4) I use a labor correlation index similar to Ellison et al. (2010) with partial correlation between education shares in 2-digit education codes between occupations. I control for belonging to a small city as well as the same individual, firm and region characteristics, as in column (6) of Table 1. Industry fixed effects are included in all columns, while occupation fixed effects are included in columns (3) and (4) only.

Robust t statistics clustered on region are in parentheses. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

In column (2) I use a labor correlation index similar to Ellison et al. (2010), which is a measure of similarity in the distribution of occupations within industries. Specifically, I compute the occupation shares for the full range of the 337 occupations in each sector, and then I estimate the partial correlation between occupation employment shares for pairwise sectors. This measure incorporate more information on the sectorial occupation structures than the measure by Gabe and Abel (2016). The churning workers are for each sector change assigned a correlation coefficient. The most correlated industries in 2008 are manufacturing of wood and wood products and manufacturing of furniture (0.89), while the least correlated sectors are health and social work and manufacturing of transport equipment (-0.04). The scores on the extreme sides of the pairwise correlation coefficient distribution are displayed in Table B.8. On average, there is a positive relationship. The churners in urban regions have a 0.008 unit higher score on the occupation similarity index compared to their rural counterparts. This translates into approximately 8 percent of a standard deviation change by using the number for 2008 (0.103). This relationship is increasing in education levels with roughly twice the size of the coefficient for those with high school and college/university compared to those with only compulsory education.

In columns (3) and (4) I use similar procedures as in (1) and (2) to find relatedness between occupations. Instead of occupation employment shares in sectors, I now turn to education shares in occupations. In column (3) I investigate to what extent the switchers end up in an occupation with same major education share as in the old job. The urban workers with education below university and college seem to have a lower probability of ending up in related occupation than their rural counterpart. The same pattern is replicated in column (4) with pairwise correlation between 2-digit education employment shares.[14] This might to some extent be affected by the stock of people with different education. Urban regions will naturally have more occupations with diverse education structure. Nonetheless, the most striking result is that the most educated are more likely to end up in a more similar occupation, although the estimate is not very sharp. Although those with higher education churn more in cities, which suggest an important role for general skills in forming career paths, the results on inter-sector and inter-occupation similarities support the claim that specific skills are also taken into account.

6 Concluding remarks

This paper has investigated job switching behavior across sectors and occupations in regions of different population sizes. In the related literature labor churning has often been seen disadvantageous as the worker then foregoes specific skills. Comparing urban and rural regions provides a test on the preferred churning behavior when the worker has the luxury of choice. In addition to presenting alternative evidence of labor churning probabilities in thick labor markets with register data, an additional contribution has been to study the heterogeneity in this behavior. Compared to many other studies, the use of comprehensive longitudinal data has enabled further investigations of urban churning behavior with respect to skill specificity, labor match convergence, and structural relatedness of sectors and occupations in the use of human capital. This has provided some novel results.

[14] The results are similar with 2-digit and 3-digit education codes.

I find on average higher probability of both sector and occupation churning in populous areas, questioning the understanding of this behavior as unfavorable. Further analyses demonstrate that the relationship between urban scale and labor churning is monotonically increasing with the formal skill level, which might also function as a proxy for the endowment of general skills. Workers with education exceeding compulsory schooling are actually the sole contributors to higher probability of churn in urban labor markets. This finding indicates that those with higher education are more able to take advantage of the possibilities provided by urban labor markets. Nonetheless, specialized skills seem to influence the job switching process. Educated urban workers are more likely to switch to sectors and occupations they have prior experience with. They are also more likely to select industries that have similar occupation shares as their old industry and occupations with similar education shares as their old occupation. Overall, these results suggest a more complicated conceptual model of churning behavior in labor markets of different sizes where human capital endowments should play a crucial role.

The results complement earlier findings in the literature by being able to reproduce comparable estimates along the age and overall experience gradients and by elaborating on the role of human capital. The new results also go a way in reconciling the results from studies focusing on the urban scale effect on job switching with the literature on returns to experience in cities for different education groups. The findings suggest some possible channels for agglomeration economy that should be explored further. Highly educated people might experience superior labor matching in cities, also across industries and occupations. High skilled individuals might also be the major contributors to knowledge diffusion across sectors and occupations.

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A Additional data details

A.1 Worker variables

Table A.1: Descriptive statistics: worker variables

	Mean	Std. dev.
Churning (60 sectors)	0.088	0.284
Churning (17 sectors)	0.076	0.265
Churning (353 occupations)	0.144	0.352
Churning (109 occupations)	0.132	0.338
Churning (32 occupations)	0.121	0.326
Churning (10 occupations)	0.105	0.307
Age	41.653	10.292
Age categories		
25-29 years	0.141	0.348
30-34 years	0.159	0.365
35-39 years	0.157	0.364
40-44 years	0.148	0.356
45-49 years	0.137	0.344
50-54 years	0.12	0.325
55-59 years	0.09	0.287
60-65 years	0.047	0.211
Education categories		
Compulsory	0.181	0.385
High-school	0.47	0.499
College/University (1-3 years)	0.258	0.438
College/University (> 3 years)	0.09	0.287
Male	0.619	0.486
Immigrant categories		
Western	0.078	0.269
Non-Western	0.025	0.157
Tenure	4.676	3.774
Part-time job	0.061	0.239
Education change	0.018	0.134
Mover	0.036	0.187
Years unemployed	0.089	0.635

Data for occupation churning are only available for the years 2007-2009.

A.2 Firm variables

Table A.2: Descriptive statistics: firm variables

	Mean	Std. dev.
Indicator of contracting employment size ($t-2$ - $t-1$)	0.323	0.467
Firm employment size categories		
1-10 employees	0.277	0.448
11-50 employees	0.318	0.466
51-100 employees	0.116	0.320
101-250 employees	0.119	0.324
251-500 employees	0.07	0.256
Over 500 employees	0.099	0.299
Firm staff expansion categories		
$> 2.5\%$	0.425	0.494
$> 5\%$	0.359	0.480
$> 7.5\%$	0.304	0.460
$> 10\%$	0.262	0.440
Firm staff reduction categories		
$> 2.5\%$	0.275	0.447
$> 5\%$	0.221	0.415
$> 7.5\%$	0.176	0.381
$> 10\%$	0.143	0.350

A.3 Regional variables

Regional **Mountain share** denotes area (square kilometers) covered by bare rock, gravel, block fields, perpetual snow and glaciers. The data are collected from Statistics Norway.

Slope is computed as a Herfindahl index of the following form: $HI = \sum_{i=0}^{n} a_r^2$, where a_r denotes the area share of land within each 20 meter band in altitude. This can be understood as a spread measure of area across different plateaus, and comprises information similar to an average slope variable. The data are collected from Norwegian Water Resource and Energy Directorate.

The **January temperature**, **Wind speed** and **Precipitation** variables are collected from Norwegian Meteorological Institute's climate database (eklima). **January temperature** is the mean January temperature in Celsius over the years 1994-2002. **Wind speed** is the mean monthly wind speed (meters per second) over the years 1994-2002, and **Precipitation** is the mean monthly precipitation (millimeters per month) over the years 1994-2002.

Coast length is collected from Statistics Norway, and gives regional data on kilometers of mainland coastline reported in 2003.

The **Unemployment rate** is collected from Statistics Norway, and denotes the average regional unemployment rate in percent for the period 1994-2002. The number of unemployed persons are registered at the Employment Office.

Iron Age grave sites is the number of grave sites from the Iron Age (500 B.C. till 500 A.D.) in each region. The Iron Age grave sites data are published by the Directorate for Cultural Heritage. The data are freely available at the url: www.kulturminnesok.no.

Area of land is denoted in square kilometers and is collected from Statistic Norway.

Net regional migration is collected from Statistic Norway.

Table A.3: Descriptive statistics: region variables

	Mean	Std. Dev.
City	0.439	0.496
Small city	0.136	0.343
log(population)	11.547	1.103
Unemployment rate	3.293	1.400
Net regional migration	235.563	643.398
Area of land (km^2)	2920.290	2772.095
Slope	0.046	0.032
Area share of mountain and perpetual snow	0.043	0.065
Coast length (km)	349.630	488.380
Precipitation	92.515	39.719
Wind speed	3.237	1.755
January temperature	-1.601	3.096

B Additional analyses and robustness tests

Table B.1: Turnover and population size

	General job switching	Intra-industry job switching
	(1)	(2)
City	0.0139***	0.0081***
	(8.81)	(8.22)
Small city	0.0053***	0.0020**
	(3.12)	(2.22)
Adjusted R-Square	0.11	0.04
Years	1994-2009	1994-2009
N	19,076,904	19,076,904

Dependent variables: Turnover defined as all job switching across firms in Column (1) and as job switching across firms conditional on staying in the same industry in Column (2).

I control for the same individual, firm and region characteristics as in column (6) of Table 1. Industry fixed effects are included in both panels.

Robust t statistics clustered on region are in parentheses.

Significance levels: *** p<0.01, ** p<0.05, * p<0.1

Table B.2: Churning and population size. Alternative specifications of urban scale

	Industry churning				Occupation churning			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(population size)	0.0023***				0.0015*			
	(4.79)				(1.94)			
Population size categories								
$> 150,000$ (City)		0.0069***	0.0071***	0.0055***		0.0048*	0.0044**	0.0028
		(4.78)	(5.76)	(4.30)		(1.98)	(2.11)	(1.34)
$100,001 - 150,000$		0.0040**	0.0042***			0.0048**	0.0043**	
		(2.25)	(2.97)			(2.05)	(2.28)	
$50,001 - 100,000$		-0.0017				0.0002		
		(-1.14)				(0.12)		
$25,000 - 50,000$		0.0011				0.0008		
		(0.81)				(0.42)		
$< 25,000$								
Occupation fixed effects	N	N	N	N	Y	Y	Y	Y
Adjusted R-Square	0.08	0.08	0.08	0.08	0.04	0.04	0.04	0.04
Years	1994-09	1994-09	1994-09	1994-09	2007-09	2007-09	2007-09	2007-09
N	19,076,904	19,076,904	19,076,904	19,076,904	3,669,773	3,669,773	3,669,773	3,669,773

Dependent variables: Industry and occupation churning.

I control for the same individual, firm and region characteristics as in column (6) of Table 1. Industry fixed effects are included in all columns, while occupation fixed effects are included in columns (5)-(8) only.

Robust t statistics clustered on region are in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1

Table B.3: Churning and population size. Estimates with different methods of correcting for workers being out of the labor market

	Industry churning			Occupation churning		
	Baseline: Control for years missing	Without correction	Dropped if subsequent year missing	Baseline: Control for years missing	Without correction	Dropped if subsequent year missing
	(1)	(2)	(3)	(4)	(5)	(6)
City	0.0071***	0.0073***	0.0073***	0.0055**	0.0056**	0.0056**
	(5.76)	(5.72)	(5.60)	(2.49)	(2.51)	(2.51)
Small city	0.0042***	0.0043***	0.0034**	0.0057**	0.0057**	0.0057**
	(2.97)	(2.79)	(2.40)	(2.57)	(2.56)	(2.55)
Occupation fixed effects	N	N	N	Y	Y	Y
Adjusted R-Square	0.08	0.05	0.05	0.04	0.04	0.04
Years	1994-09	1994-09	1994-09	2007-09	2007-09	2007-09
N	19,076,904	19,076,904	18,425,539	3,669,773	3,669,773	3,643,220

Dependent variables: Industry and occupation churning.

I control for the same individual, firm and region characteristics as in column (6) of Table 1. Industry fixed effects are included in all columns, while occupation fixed effects are included in columns (4)-(6) only.

Robust t statistics clustered on region are in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1

Table B.4: Churning and population size. Estimates using alternative aggregations of industry and occupation groups

Dependent variable	Industry churning	Industry churning	Occupation churning	Occupation churning	Occupation churning	Occupation churning
Number of sectors/occupations	60	17	353	109	32	10
	(1)	(2)	(3)	(4)	(5)	(6)
City	0.0071***	0.0057***	0.0055**	0.0056**	0.0047**	0.0044**
	(5.76)	(5.00)	(2.49)	(2.59)	(2.19)	(2.11)
Small city	0.0042***	0.0025**	0.0057**	0.0055**	0.0050**	0.0043**
	(2.97)	(2.04)	(2.57)	(2.51)	(2.55)	(2.28)
Adjusted R-square	0.08	0.08	0.04	0.04	0.04	0.04
Occupation fixed effects	N	N	Y	Y	Y	Y
Years	1994-2009	1994-2009	2007-2009	2007-2009	2007-2009	2007-2009
N	19,076,904	19,076,904	3,669,773	3,669,773	3,669,773	3,669,773

Dependent variables: Sector churning and occupation churning with different aggregation of sector and occupation groups.

I control for the same individual, firm and region characteristics as in column (6) of Table 1. Industry fixed effects are included in all columns, while occupation fixed effects are included in columns (3)-(6) only.

Robust t statistics clustered on region are in parentheses. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table B.5: Churning and population size. Robustness of sectorial composition in sample

	Public employees omitted (1)	Agricultural employees omitted (2)	Hydro-power employees omitted (3)	Petroleum employees omitted (4)	Manufacturing employees omitted (5)
Panel A: Dependent variable: Industry churning					
City	0.0059***	0.0070***	0.0071***	0.0069***	0.0030**
	(4.10)	(5.77)	(5.81)	(5.62)	(2.55)
Small city	0.0051***	0.0041***	0.0042***	0.0040***	0.0024**
	(3.25)	(2.96)	(3.06)	(2.91)	(2.10)
Adjusted R-Square	0.09	0.08	0.08	0.08	0.08
Years	1994-09	1994-09	1994-09	1994-09	1994-09
N	13,551,998	18,898,011	18,875,390	18,707,987	15,822,014
Panel B: Dependent variable: Occupation churning					
City	0.0073***	0.0054**	0.0054**	0.0059**	0.0051**
	(4.16)	(2.50)	(2.39)	(2.48)	(2.12)
Small city	0.0055**	0.0058***	0.0058**	0.0055**	0.0064***
	(2.63)	(2.65)	(2.57)	(2.41)	(2.87)
Occupation fixed effects	Y	Y	Y	Y	Y
Adjusted R-Square	0.05	0.04	0.04	0.04	0.05
Years	2007-09	2007-09	2007-09	2007-09	2007-09
N	2,545,616	3,640,377	3,636,855	3,586,218	3,125,629

Dependent variables: Sector and occupation churning.

I control for the same individual, firm and region characteristics as in column (6) of Table 1. Industry fixed effects are included in both panels, while occupation fixed effects are included in Panel B only.

Robust t statistics clustered on region are in parentheses. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table B.6: First stage results from IV-estimation of the effect of urban scale on the probability to churn

	(1)	(2)	(3)
Panel A: Full sample for the 1994-2009 period			
Iron Age graves	0.0027***		
	(3.64)		
Present population size		0.0007***	
birth region (thousands)		(7.72)	
1900 population size			0.0013***
birth region (thousands)			(6.57)
Adjusted R-Square	0.47	0.50	0.49
N	19,076,904	15,374,920	15,374,920
Panel B: Partial sample for the 2007-2009 period			
Iron Age graves	0.0040***		
	(4.23)		
Present population size		0.0008***	
birth region (thousands)		(7.18)	
1900 population size			0.0013***
birth region (thousands)			(6.60)
Occupation fixed effects	Y	Y	Y
Adjusted R-Square	0.50	0.49	0.48
N	3,669,773	3,094,594	3,094,594

Dependent variable: City indicator.

I control for the same individual, firm and region characteristics as in column (6) of Table 1. Industry fixed effects are included in both panels, while occupation fixed effects are included in Panel B only.

Robust t statistics clustered on region are in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1

Table B.7: Churning and population scale. Estimates for detailed higher education groups

	Industry churning		Occupation churning	
Education	1-3 years college/ university	>3 years college/ university	1-3 years college/ university	>3 years college/ university
	(1)	(2)	(3)	(4)
City	0.0104***	0.0188***	0.0059**	0.0106**
	(6.25)	(7.94)	(2.00)	(2.34)
Small city	0.0055***	0.0081***	0.0047	0.0044
	(4.60)	(2.71)	(1.39)	(0.87)
Adjusted R-Square	0.08	0.05	0.06	0.07
Occupation fixed effects	N	N	Y	Y
Years	1994-2009	1994-2009	2007-2009	2007-2009
Number of observations	4,930,028	1,724,360	1,052,997	401,661

Dependent variables: Industry and occupation churning.

I control for the same individual, firm and region characteristics as in column (6) of Table 1. Industry fixed effects are included in all columns, while occupation fixed effects are included in columns (3)-(4) only.

Robust t statistics clustered on region are in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1

Table B.8: Industry labor correlation index: Pairwise industry correlations based on occupation employment shares, highest and lowest scores

Industry 1	Industry 2	Pairwise correlations
Panel A: Top ten correlated industry pairs		
Manufacture of wood and of products of wood and cork, except furniture, manufacture of articles of straw and plaiting materials	Manufacture of furniture, manufacturing n.e.c.	0.885
Manufacture of chemicals and chemical products	Manufacture of basic metals	0.874
Manufacture of electrical machinery and apparatus n.e.c.	Manufacture of radio, television and communication equipment and apparatus	0.836
Manufacture of fabricated metal products, except machinery and equipment	Manufacture of motor vehicles, trailers and semi-trailers	0.800
Mining of coal and lignite, extraction of peat	Mining of metal ores	0.772
Insurance and pension funding, except compulsory social security	Activities auxiliary to financial intermediation	0.732
Manufacture of machinery and equipment n.e.c.	Manufacture of motor vehicles, trailers and semi-trailers	0.704
Recycling	Sewage and refuse disposal, sanitation and similar activities	0.678
Manufacture of office machinery and computers	Manufacture of medical, precision and optical instruments, watches and clocks	0.653
Manufacture of television and radio transmitters and apparatus for line telephony and line telegraphy	Manufacture of medical, precision and optical instruments, watches and clocks	0.638
Panel B: Ten least correlated industry pairs		
Manufacture of other transport equipment	Health and social work	-0.036
Manufacture of machinery and equipment n.e.c.	Health and social work	-0.032
Manufacture of textiles	Public administration and defense, compulsory social security	-0.031
Manufacture of food products and beverages	Health and social work	-0.029
Manufacture of food products and beverages	Public administration and defense, compulsory social security	-0.029
Manufacture of fabricated metal products, except machinery and equipment	Public administration and defense, compulsory social security	-0.029
Construction	Health and social work	-0.029
Manufacture of motor vehicles, trailers and semi-trailers	Health and social work	-0.028
Manufacture of other non-metallic mineral products	Health and social work	-0.028
Manufacture of motor vehicles, trailers and semi-trailers	Public administration and defense, compulsory social security	-0.028

The pairwise correlations are based on 60 sectors (NACE-codes 2002) and 353 occupations (STYRK). The correlations procedure was executed each year from 2007-2009 and is similar to the one applied by Ellison et al. (2010). The correlations are reported as an average across the three years.

Table B.9: Occupation correlation index: Pairwise occupation correlations based on education group shares, highest and lowest scores

Occupation 1	Occupation 2	Pairwise correlations
Panel A: Top ten correlated occupation pairs		
Building, vehicle and related cleaners	Laborers in manufacturing	0.996
Material-recording and transport clerks	Storing and goods handling laborers	0.992
Blacksmiths, gunsmiths, locksmiths and related trades workers	Metal- and mineral-products machine operators	0.991
Fishery workers and hunters	Ships' deck crews and related workers	0.990
Nursing and midwifery professionals	Nursery and Registered Nurses for the Mentally Subnormal (RNMS)	0.990
Laborers in manufacturing	Storing and goods handling laborers	0.988
Glass, ceramics and related plant operators	Laborers in manufacturing	0.985
Founders, welders, sheet-metal workers, etc.	Blacksmiths, gunsmiths, locksmiths and related trades workers	0.984
Laborers in construction and maintenance, etc.	Laborers in manufacturing	0.984
Metal- and mineral-products machine operators	Assemblers	0.981
Panel B: Ten least correlated occupation pairs		
College, university and higher education teaching professionals	Ship and aircraft controllers and technicians	-0.042
College, university and higher education teaching professionals	Textile, garment and related trades workers	-0.033
College, university and higher education teaching professionals	Precision workers in metal and related materials	-0.029
College, university and higher education teaching professionals	Fish farmers, etc.	-0.029
College, university and higher education teaching professionals	Wood treaters, cabinet-makers, and related trades workers	-0.029
College, university and higher education teaching professionals	Oil, gas, mining- and mineral-processing plant operators	-0.029
College, university and higher education teaching professionals	Building finishers and related trades workers	-0.028
College, university and higher education teaching professionals	Building frame and related trades workers	-0.028
College, university and higher education teaching professionals	Chemical-processing-plant operators	-0.025
College, university and higher education teaching professionals	Personal care and related workers	-0.025

The pairwise correlations are based on 3 digit education and occupation codes. The correlations procedure was executed each year from 2007-2009 and the correlations are reported as an average across the three years.

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