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The Role of Skills and Wages in Early Career Occupation Mobility: Evidence from Hungary

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ABSTRACT
This study investigates the patterns and determinants of occupation mobility among young workers with medium-level qualifications in Hungary during their first 4-8 years in the labor market. Utilizing linked employer-employee panel data augmented with standardized test scores from grade 10, we examine the relationship between occupation mobility, wages, and skills. Our findings indicate that wages are generally negatively associated with occupation mobility, both within broad occupation categories and specific occupations. However, occupation mobility shows little correlation with test scores. High-wage workers are less likely to change occupations, but when they do, they tend to move to higher positions within the occupational hierarchy, similar to high-skill workers. These results suggest that while wages and occupation mobility are interconnected, the role of direct skill measures in explaining mobility patterns is limited. The study contributes to the understanding of early career dynamics and the factors influencing occupational transitions.

JEL codes: I26, J24, J31
Keywords: Occupation mobility, labor markets, skills, sorting, earnings mobility

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A kereset és a készségek szerepe a fiatalok foglalkozási mobilitásában: Magyarországi eredmények

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ÖSSZEFOGLALÓ

Ez a tanulmány a középfokú végzettséggel rendelkező fiatal munkavállalók foglalkozási mobilitásának mintáit és meghatározó tényezőit vizsgálja Magyarországon, a munkaerőpiacon eltöltött első 4-8 évük során. A 10. évfolyamos standardizált teszteredményekkel kiegészített, összekapcsolt munkáltató-munkavállaló paneladatokat felhasználva elemezzük a foglalkozási mobilitás, a bérek és a készségek közötti kapcsolatot. Eredményeink azt mutatják, hogy a bérek általában negatív összefüggést mutatnak a foglalkozási mobilitással, mind a szélesebb foglalkozási kategóriákon belül, mind az egyes foglalkozásokon belül. Ugyanakkor a foglalkozási mobilitás kevéssé korrelál a teszteredményekkel. A magas bérű munkavállalók kevésbé hajlamosak foglalkozást váltani, de amikor mégis váltanak, hajlamosak magasabb pozíciókba kerülni a foglalkozási hierarchián belül, hasonlóan a magas készségekkel rendelkező munkavállalókhoz. Ezek az eredmények azt sugallják, hogy bár a bérek és a foglalkozási mobilitás összefüggnek, a készségeket közvetlenül mérő teszteredmények szerepe a mobilitási minták magyarázatában korlátozott. A tanulmány hozzájárul a fiatal munkavállalók karrierje dinamikájának és a foglalkozási átmeneteket befolyásoló tényezők megértéséhez.

JEL kód: I26, J24, J31

Kulcsszavak: Foglalkozási mobilitás, munkaerőpiac, készségek, kereseti mobilitás

1 Introduction

Occupation mobility is a key component of career and wage growth for many young workers, and this way, it is also closely related to wage inequalities (Kambourov and Manovski, 2009). Accordingly, young persons more often change occupations and mobility decreases with age (e.g. Bachmann et al., 2020). At the same time, the empirical evidence on patterns and drivers of occupation mobility at the first stage of labor market career is limited, and little is known about the role of various mechanisms explaining these patterns. Most explanations focus on worker skills and matching quality between these and job requirements. First, occupation mobility might be a step of human capital accumulation, i.e., additional investments augmenting the existing human capital of the worker, while in other cases, it means losing the returns on previous investment (Sanders, 2012). This implies that the costs of mobility are higher for workers with more occupation-specific skills (Geel et al., 2010). At the same time better general skills make it easier to learn new occupations, thus enhancing mobility (Hanushek et al., 2017). Second, workers can be assumed to change occupations when there is a mismatch between their skills and job requirements. This implies that workers with insufficient skills, and therefore low wages are more likely to change occupation. However, high-wage workers might also be more likely to move if a high wage reflects high skills, which is not fully utilized in their current occupation (Groes et al., 2015). The mismatch argument points to inaccurate information on skills: not only are employers unable to observe individual skills precisely (Altonji and Pierret, 2001), but it may take time for workers themselves to discover their true productivity (Sanders, 2012; Groes et al., 2015). Using Danish data Groes et al. (2015) find that this generates a U-shape pattern association between occupation mobility and wages.

Another related stand in the literature suggests that wage returns to skills, measured by test scores, are increasing with age and labor market experience (Hanushek et al., 2015, Watts, 2020). Hermann (2025) finds a similar pattern in Hungary for young workers during their first 10 years in the labor market. These results can be explained by higher additional human capital investments of the more able workers, but it is also consistent with occupation mobility and decreasing mismatch of high-skill workers.

In this paper, we explore the occupation mobility patterns of young workers in their first 4-7 years in the labor market with medium-level qualifications in Hungary. We look at the associations between occupation mobility and wages on the one hand, and standardized math and reading test scores on the other. While most papers consider wages as a proxy of individual skills, we use direct skill measures along with this indirect measure. To compare similar workers, we explore these associations within groups of workers in the same broad occupation categories, as well as within occupations.

We use linked employer-employee panel data (Admin3), augmented with test score data measured in grade 10 in secondary education. Based on monthly observations, we measure occupation mobility at a quarter-to-quarter level. Our sample covers 50% of students in 5 school cohorts. We can observe these students' education and labor market history up to 9 years after grade 10. As university graduates enter the labor market only close to the end of this period, and some of them are still studying at the end of it, we focus on workers with no university degree. Workers with no secondary education are also excluded, as most of them drop out before grade 10.

Our results show that wages are negatively related to occupation mobility, overall, as well as within broad occupation categories and occupations. At the same time, occupation mobility is only weakly related to test scores. Regarding the direction of occupation mobility along the wage hierarchy of occupations, the results are mixed. Within occupations, both higher wages before the move and higher test scores go together with moving upwards along the occupation ladder in bigger steps. Within broader occupation groups, these associations are more ambiguous. Overall, high-wage workers are less likely to move, but when they move, they improve their occupation position more than their peers, similarly to high-skill movers.

The paper is structured as follows. Section 2 introduces the data and estimation method and provides descriptive analysis. Section 3 presents results on the association between occupation mobility and wages and test scores. Section 4 covers results on the direction of occupation mobility along the occupation hierarchy and short-run wage growth for the subsample of movers. Section 5 concludes.

2 Data, variables and methods

Data

Our analysis is based on a large linked longitudinal administrative dataset that were compiled from several sources for research purposes for the Centre for Economic and Regional Studies. This database is a 50% sample of the Hungarian population (above age 3) in 2003, and contains monthly information between 2003 and 2017.

We used data on labor market outcomes from 2012-2017, for several reasons. (i) The occupation codes changed in 2011, and the way data was reported changed in 2012, contributing to a greater reliability of potentially capturing occupational mobility. (ii) Educational data is only available from 2008. Our primary source was the National Pension Insurance data, which contains detailed insurance (employment and wage) histories. This data contains reported occupational classifications, and data are supplied at the monthly frequency per employer. However, if the individual changes occupations (at a given employer), or changes employers this represents two different records.

We concentrate on a sample of young men who finished (upper) secondary education, but did not continue their studies. There are two distinct educational categories in this group. (i) Vocational schools (ISCED 3C) where studies typically last for 3-4 years and which prepare students for a relatively narrow profession. Youth who graduate from these institutions cannot continue to tertiary education. (ii) Secondary schools (both academic [ISCED 3A] and vocational [ISCED 3B]) where studies last 4-5 years, and which give general education enabling the student to (potentially) continue to tertiary education.

We use these educational categories, as we have access to their educational data as well as a relatively long labor market history. A key component of educational data is young persons' competency test scores. The National Assessment of Basic Competencies (NABC) database contains standardized reading literacy and mathematics test scores and various parental background measures of all 6th, 8th, and 10th-grade students since 2008. We use test scores from 10th grade, which is taken at age 16-17, one to three years prior to finishing secondary education. It measures general skills, and we assume that it is correlated with productivity. Our sample consists of individuals who attended the NABC test in 2008-2012, and subsequently finished secondary education between 2010-2015. Finally, we only use males in our sample, since we are concerned that a substantial portion of young women might be out of the labor force due to childbearing or other reasons.

Variables

We define employment as working full time as an employee. Accordingly, earnings are defined as full-time equivalent monthly earnings, as we adjust earnings for the number of days not worked (due to sick leave etc.). We exclude observations with earnings less than half the minimum wage and more than 20 times the minimum wage.

Our main outcome of interest is quarterly mobility, defined at the four-digit occupation level (there are 389 different occupations in our sample). Occupational mobility is defined only for individuals who were employed in two subsequent observation periods, three months apart. Using quarterly frequency is a compromise between having a large number of observations and allowing for short intervening non-employment spells. In line with this, spells of non-employment which last 3 or more months are excluded from our data. We use the month of January, April, July and October of each year.

We also extract variables characterizing wage distributions for each occupation and year, including quintiles and medians. This is based on all full-time employees below age 40. We use quintiles to classify individuals' relative wage position within the given occupation. Finally, we extract the median skill level in each occupation from data on an aptitude test (mathematical and reading competences) taken in 10th grade. Since this data is only available for 2008 onwards, this is calculated for those age 25 and younger in 2017, so small sample sizes occur in a few cases. Thus, we exclude all observations in these occupations, but this affects a minimal number of observations. For all occupation-level measures, we extract the median, as well as five quintiles. Persons in our sample will be categorized into one of these quintiles.

Our main control variables are defined at the individual level. First, the level and type of education: vocational school, academic secondary school, vocational secondary school. We also use the time since leaving school as a proxy for (potential) experience – we do not use actual experience, as it might be endogenous to occupational mobility. The summary statistics of all key variables can be found in Table 1.

Table 1: Means of main variables used in the analysis

Time invariant characteristics	
N (individuals)	41,671
School attended (in 10th grade)	
Academic high school	5,275 (12.7%)
Vocational upper secondary school	22,389 (53.7%)
Basic vocational school	14,007 (33.6%)
School-leaving certificate	
vocational school	13,473 (32.3%)
secondary school	28,198 (67.7%)
Time-varying characteristics	
N (individual-quarter observations)	371,004
Occupational mobility	0.060 (0.237)
(Potential) experience (years)	2.222 (1.500)
Earnings (log)	12.084 (0.376)
Occupational earnings quintile	
Bottom	107,570 (29.0%)
2	68,695 (18.5%)
3	74,560 (20.1%)
4	69,762 (18.8%)
Top	50,417 (13.6%)
Occupational math skill quintile	
Bottom	63,968 (17.2%)
2	73,478 (19.8%)
3	77,052 (20.8%)
4	80,522 (21.7%)
Top	75,984 (20.5%)
Occupational reading skill quintile	
Bottom	82,681 (22.3%)
2	78,019 (21.0%)
3	75,973 (20.5%)
4	72,362 (19.5%)
Top	61,969 (16.7%)

Method of analysis

We used linear regression models for each of our outcome variables, to keep estimation time limited. We estimate models of the form:

$$Y_{it} = X'_i\beta + Wage\_Quintile'_{it}\gamma + Occup_{it} + Time_t + \varepsilon_{it} \quad (1)$$

The outcome variables are (i) occupational mobility and (ii) wage changes. The vector X includes all relevant background and educational characteristics. The key independent variables are Wage Quintiles (as well as Score Quintiles). The regression also includes occupational fixed effects as well as time (year and quarter) effects. Occupational fixed effects mean that we control for all potential omitted occupation characteristics which could influence occupational mobility. Furthermore, we control for a full set of time (year, quarter) effects. To take into account that decisions of the same worker at different times are correlated we cluster standard errors at the individual level.

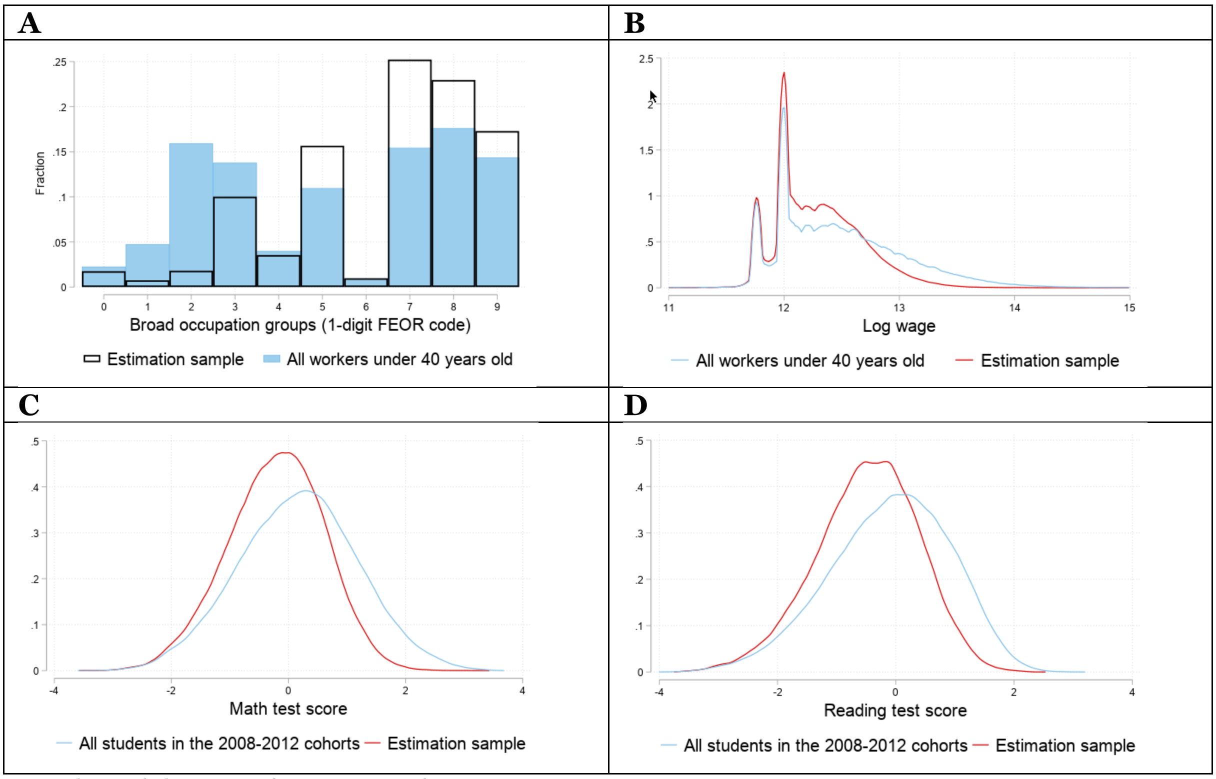
Descriptive analysis

Figure 1 compares the estimation sample and the relevant part of the total sample regarding the wage, occupation, and test score distributions. As workers with a university degree are excluded from our sample, distributions in the total and estimation samples are quite different. Workers in the estimation sample had lower test scores. They are unlikely to work in high-skill occupations (FEOR 1-2) and are overrepresented in simple service and blue-collar occupations (FEOR 5-9), while they are also present in simple white-collar occupations (FEOR 3-4). Regarding the wage distribution, workers in the estimation sample are concentrated more in the middle. High wages are rare, while a more significant fraction of workers get the skilled minimum wage. At the same time, the share of workers paid at the unskilled minimum wage is the same in the estimation sample and the total sample of young workers. This is because not only university graduates are excluded from the estimation sample, but also workers with no vocational or secondary school qualifications.

Figure 2 displays the average probabilities of quarter-to-quarter occupation mobility for each year of potential labor market experience (Panel A). Occupation mobility most frequently occurs in the first year after labor market entry and is decreasing substantially later. The same pattern can be observed for workers with vocational school and secondary school qualifications. However, even in the 7th year in the labor market, 5-5.5 percent of workers move to another occupation in each quarter of the year. Panel B distinguishes between within-firm and between-firm occupation mobility. Within-firm job changes are much less frequent in our sample, and it is mostly unrelated to years of experience. The overall decrease in occupation mobility is driven by between-firm job changes, which are accompanied by occupation changes that are becoming less likely with experience.

Table 2 describes the cumulative number of occupation mobility events by years of experience. In the first year after labor market entry, 13.4 percent of the workers changed occupations at least once. By the end of the second year, this share increases to 22 percent. By the end of the seventh year, almost half of the workers have changed occupations at least once. Moreover, two out of ten workers moved twice or even more times to another occupation.

Figure 1 Wage, occupation, and test score distribution in the estimation sample and total sample



Note: kernel densities for wages and test scores.

Figure 2 Average probability of quarter-to-quarter occupation mobility and years of potential experience, by education and firm

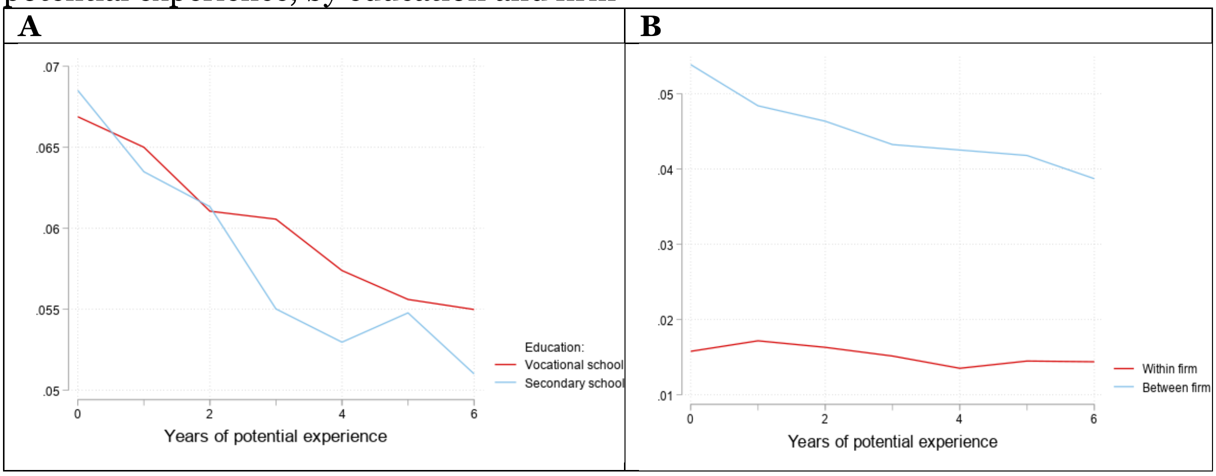


Table 2 Distribution of workers by the cumulative number of occupation mobility events up to the end of experience years, %

Years of potential experience	Cumulative number of occupation mobility events up to the end of experience year					N
	0	1	2	3	4 or more	
0	86.56	12.12	1.22	0.1	0	20045
1	78.01	17.89	3.43	0.58	0.09	27586
2	71.6	21.24	5.63	1.2	0.32	31458
3	65.87	23.69	7.64	2.12	0.69	29191
4	60.83	25.81	9.34	2.84	1.18	22394
5	56.63	27.02	10.79	3.73	1.83	13590
6	53.41	27.44	12.32	4.26	2.57	7847

3 Occupational mobility

We will examine occupational mobility as a function of background and occupational characteristics. We are primarily interested in the correlation between relative wage position (within an occupation) or relative skill and the probability of changing occupations.

Overall, occupational mobility is just below 6 percent in our sample, which is significantly higher than the mobility measured for the whole population (see Csillag and Varga 2024)1. however it is strongly negatively correlated with wages (before occupational mobility), see Figure 3 panel (a).2 However, this picture is rather different for the variation of mobility with relative (within-occupation) wage position.3 In Figure 3 panel (b) we can see a weak negative correlation, however, no definite U shape pattern. In panel (c) plotting the relationship between mobility and median occupational wages, we again see a strong negative correlation. Young men also tend to leave occupations with higher median skill levels to lesser extent, as can be seen in panel (d).

This is detailed in Table 3 below, where we first show the distribution of the sample by education and wage quintiles (calculated within detailed occupation). First, we can notice that our sample is over-represented in the bottom quintile, which is natural,

[1] Please note that most papers do not rely on administrative data to measure occupational mobility, so it is difficult to find a valid comparison.

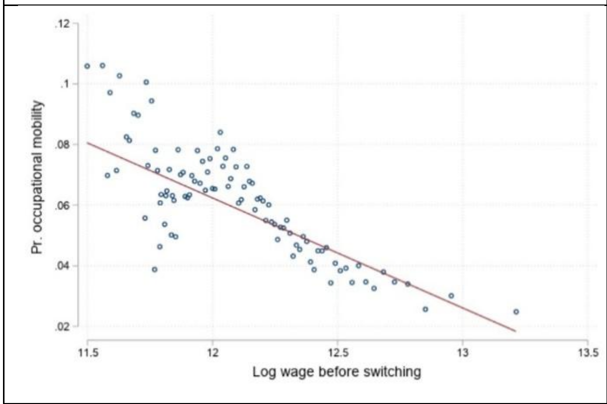
[2] We find similar negative correlation between occupational mobility and occupational median wages , as well as median skill levels.

[3] Here, relative wage is defined as the distance between the individual's and the occupational mean wage, and we normalise this be the occupational standard devation of wages.

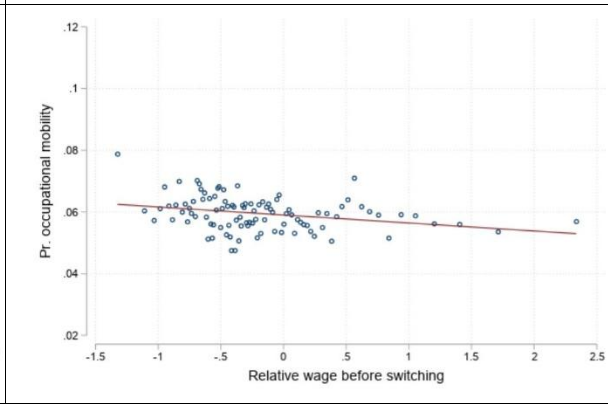
given that they have less than five years' experience. Second, we can notice that there is not much difference across education categories neither in the distribution of the sample, nor the overall mobility rates. Third, there is no clear pattern of mobility by wage quintiles, we see neither a downward trend nor a U shape. Fourth, there is a small difference in mobility patterns across education categories: while for vocational school graduates, mobility rates are higher in the bottom two quintiles relative to the top three quintiles, as well as relative to secondary graduates in these quintiles; there is no such pattern in the case of upper secondary graduates.

Figure 3 Occupational mobility against wages, median occupational wages, within-occupation wage position and medial occupational skill

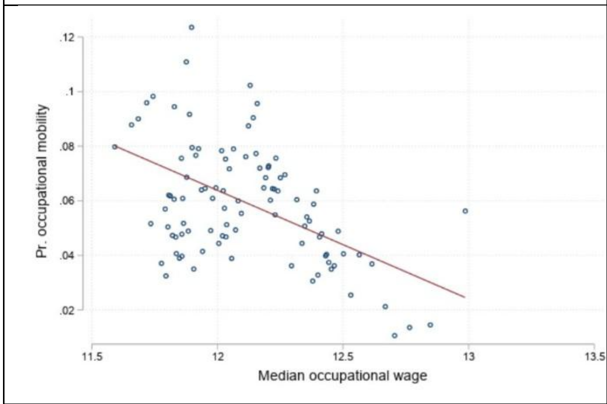
A



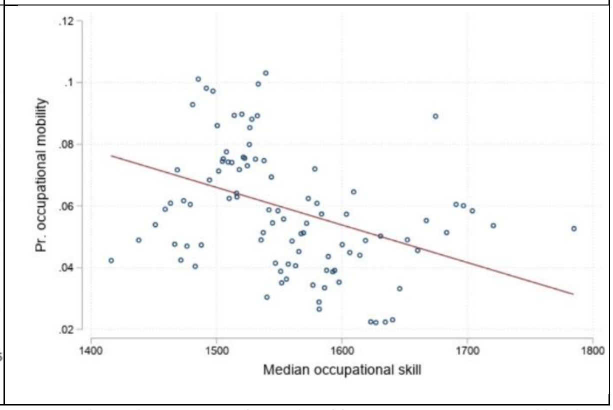
B



C



D



Note: Binscatter plots with 100 equally sized bins. Calendar year fixed effects are controlled for.

Table 3 Distribution of the sample, and mobility rates by wage quintiles (4 digit occupation) and education

	Distribution			Mobility		
	Vocational	Secondary	Total	Vocational	Secondary	Total
Bottom wage quintile	29.3	29.9	29.7	6.18	5.68	5.86
2nd wage quintile	17.0	19.2	18.4	6.80	6.12	6.35
3rd wage quintile	20.5	19.5	19.8	6.02	6.10	6.07
4th wage quintile	19.3	18.2	18.6	5.45	5.73	5.62
Top wage quintile	14.0	13.3	13.6	5.72	6.03	5.91
Total	100.0	100.0	100.0	6.05	5.90	5.96

We go on to analyze (via linear probability models) the relationship between occupational mobility and relative wage (and relative skills) (Table 4). In our initial specification, we use 1-digit occupations to calculate these relative measures, as these might serve as a broader reference group for the individuals working in specific four-digit occupations. In this specification, we can clearly see that those in the upper two quintiles have a markedly lower probability to switch occupations. The coefficient in the top quintile is large, it represents a 37 percent decrease relative to the mean occupational probability. It is also somewhat puzzling that those in the bottom quintile also tend to have lower occupational probability. [4] At the one digit level, there seems to be no connection between relative skills and occupational mobility.

Our main specification is the one where we rely on four digit occupations to calculate relative wages, as it represents relative productivity within a job fairly accurately (Table 5). In this specification, there seems to be a clear negative relationship between relative wages and occupational mobility. Indeed, the difference between the top and the bottom quintiles is 1.3 percentage points, which is slightly more than 20 percent of the mean mobility rate. Thus, we find little support for the hypothesis of a U shape of occupational mobility. As before, there is very little association between relative skills and mobility, except that those in the top quintile of the reading skill distribution, who tend to switch occupations to a slightly larger extent. The most important determinant of occupational mobility seems to be labour market experience, as our estimates imply that after 5 years' experience, occupational changes are lower by about 3.5 percentage points.

[4] Although we have to note that they might move out of the labour force, rather than switch occupations, which is not present in our sample.

Table 4 Regression estimates of occupational mobility, within broad occupation groups (1 digit FEOR codes)

	(1)	(2)	(3)	(4)	(5)
Bottom wage quintile	-0.0040***			-0.0040***	-0.0039***
	(0.0013)			(0.0013)	(0.0013)
2nd wage quintile	0.0010			0.0010	0.0010
	(0.0013)			(0.0013)	(0.0013)
4th wage quintile	-0.0123***			-0.0123***	-0.0124***
	(0.0012)			(0.0012)	(0.0012)
Top wage quintile	-0.0226***			-0.0225***	-0.0226***
	(0.0014)			(0.0014)	(0.0014)
Bottom math quintile		0.0019		0.0013	
		(0.0015)		(0.0015)	
2nd math quintile		0.0015		0.0012	
		(0.0013)		(0.0013)	
4th math quintile		-0.0003		-0.0001	
		(0.0013)		(0.0013)	
Top math quintile		-0.0010		-0.0004	
		(0.0014)		(0.0014)	
Bottom reading quintile			0.0006		0.0003
			(0.0014)		(0.0014)
2nd reading quintile			-0.0006		-0.0006
			(0.0013)		(0.0013)
4th reading quintile			0.0012		0.0015
			(0.0014)		(0.0014)
Top reading quintile			0.0022		0.0026*
			(0.0015)		(0.0015)
Vocational secondary school	0.0050***	0.0056***	0.0060***	0.0049***	0.0053***
	(0.0014)	(0.0014)	(0.0015)	(0.0014)	(0.0014)
Vocational school	0.0007	0.0019	0.0031	0.0002	0.0014
	(0.0020)	(0.0021)	(0.0021)	(0.0021)	(0.0021)
(Potential) Experience	-0.0082***	-0.0097***	-0.0097***	-0.0082***	-0.0082***
	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)
Experience squared	0.0011***	0.0012***	0.0012***	0.0011***	0.0011***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Constant	0.0775***	0.0726***	0.0720***	0.0773***	0.0767***
	(0.0032)	(0.0032)	(0.0032)	(0.0033)	(0.0033)
N observations	370,491	370,491	370,491	370,491	370,491
N individuals	41626	41626	41626	41626	41626
R2	0.0124	0.0113	0.0113	0.0124	0.0124

Dependent variable: occupational mobility defined at the four-digit level. Wage quintiles were calculated by broad occupation group (1-digit FEOR code) and by year, for workers below 40 years of age. Test score quintiles were calculated by broad occupation group (1-digit FEOR code) in 2017, for young workers with test scores. Controls in each model: calendar year FEs, micro-region FEs, broad occupation group FEs. Standard errors clustered at the individual level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 5 Regression estimates of occupational mobility, within detailed occupation groups (4 digit FEOR codes)

	(1)	(2)	(3)	(4)	(5)
Bottom wage quintile	0.0052***			0.0052***	0.0052***
	(0.0012)			(0.0012)	(0.0012)
2nd wage quintile	0.0033**			0.0033**	0.0033**
	(0.0013)			(0.0013)	(0.0013)
4th wage quintile	-0.0072***			-0.0072***	-0.0072***
	(0.0013)			(0.0013)	(0.0013)
Top wage quintile	-0.0080***			-0.0080***	-0.0080***
	(0.0014)			(0.0014)	(0.0014)
Bottom math quintile		0.0012		0.0010	
		(0.0014)		(0.0014)	
2nd math quintile		0.0004		0.0003	
		(0.0013)		(0.0013)	
4th math quintile		0.0007		0.0009	
		(0.0013)		(0.0013)	
Top math quintile		0.0006		0.0009	
		(0.0014)		(0.0014)	
Bottom reading quintile			0.0009		0.0007
			(0.0013)		(0.0013)
2nd reading quintile			0.0001		-0.0000
			(0.0013)		(0.0013)
4th reading quintile			0.0017		0.0018
			(0.0013)		(0.0013)
Top reading quintile			0.0041***		0.0042***
			(0.0014)		(0.0014)
Vocational secondary school	0.0033**	0.0033**	0.0036**	0.0034**	0.0037**
	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0015)
Vocational school	-0.0013	-0.0010	-0.0001	-0.0012	-0.0003
	(0.0021)	(0.0021)	(0.0021)	(0.0021)	(0.0021)
(Potential) Experience	-0.0081***	-0.0088***	-0.0088***	-0.0080***	-0.0080***
	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)
Experience squared	0.0011***	0.0012***	0.0012***	0.0011***	0.0011***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Constant	0.0716***	0.0725***	0.0716***	0.0709***	0.0701***
	(0.0032)	(0.0032)	(0.0032)	(0.0033)	(0.0033)
N observations	370,481	370,481	370,481	370,481	370,481
N individuals	0.0203	0.0199	0.0199	0.0203	0.0203
R2	41625	41625	41625	41625	41625

Dependent variable: occupational mobility defined at the four-digit level. Wage quintiles were calculated by detailed occupation group (4-digit FEOR code) and by year, for workers below 40 years of age. Test score quintiles were calculated by detailed occupation group (4-digit FEOR code) in 2017, for young workers with test scores. Controls in each model: calendar year FEs, micro-region FEs, broad occupation group FEs. Standard errors clustered at the individual level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

4 Wage changes after switching occupation

In this section, we explore how the direction of occupation mobility is related to individual wages and test scores. To characterize the direction of mobility, we measure the difference between log median wages in the target and initial occupations for all events when a worker moves. Note that we could measure the occupation hierarchy in terms of skills (test scores) instead of wages, as well. We analyze occupation wages but not occupation skills for two reasons[5]. First, the two measures are relatively strongly correlated. Second, workers are primarily interested in wages when making decisions on occupation mobility.

Overall, 60 percent of occupation mobility events, as defined above, entail a move into a higher-wage occupation relative to the starting occupation. On average, movers gain 0.082 log points, approximately 8 percent in terms of median occupation wage. At the same time, there is a large variation in the size of this gain. Figure 4 displays this variation by former occupation median wage and actual individual wage.

Differences by former occupation show a strong reversion to the mean (Figure 4 panel A). While in the majority of occupations, movers, on average, move upwards on the occupation wage ladder, workers in high-wage occupations tend to switch to lower-paying occupations. Moreover, the size of the gain is negatively related to the median wage in the previous occupation, i.e., the higher the occupation median wage is before the move, the smaller the average gain in terms of occupation median wage.

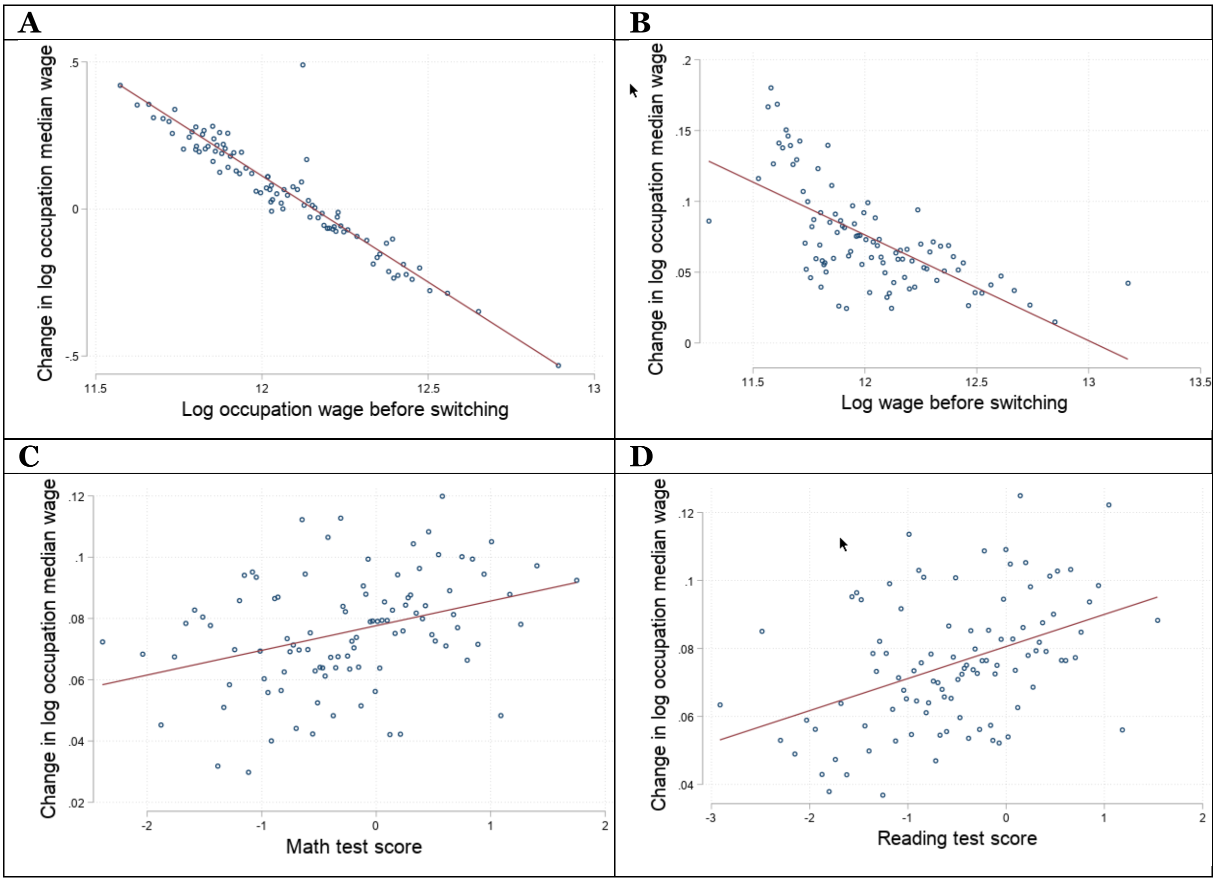
Differences by former actual individual wages show a similar but less unambiguous picture (Figure 3.1 panel A). Workers with low wages before the move tend to switch to higher-wage occupations, on average, than workers with a medium or high wage. At the same time, excluding the group with particularly low former wages, the correlation is weaker. It's also worth noting that within each former wage percentile group, the average worker moves upwards on the occupation ladder, i.e., gains in terms of occupation median wage.

Differences by test scores tell another story (Figure 3.1, panels C and D). Workers with better skills, as measured by higher test scores, gain more on average in terms of

[5] Correlation coefficients in 2017, weighted by the number of workers, between log median wages and median math and reading test scores at the occupation level are 0.62 and 0.54 respectively.

occupation median wage, though this correlation is rather weak. Again, gains on average are positive within each test score percentile group.

Figure 4 Changes in log occupation median wage, wages before switching occupation and test scores



Note: Binscatter plots with 100 equally sized bins. Calendar year fixed effects are controlled for.

To further explore the association between the gains of mobility and wages before the move and test scores, we estimate similar regression models for this outcome that we used in the previous section, controlling for education attainment, labor market experience, and other factors. As before, we focus on patterns within occupations and broader occupation groups. In contrast with estimates in the previous section, here the sample is restricted to movers. Outliers with extreme actual wage changes (more than +/- 150 percent) are also excluded.

Table 6 displays regression estimates of the direction of occupation mobility as a function of individual wages before the move and test scores within broad occupation categories (1-digit FEOR codes). This way, we compare low-wage and low-test score workers with similar peers earning a higher wage and having higher test scores who work in similar occupations. We assume that these broad occupation categories define the general reference group for the individual workers, i.e. they compare themselves to these workers when evaluating their situation and labor market opportunities. As the sample is restricted to movers, coefficients should be interpreted as associations conditional on occupation change.

Table 6 Regression estimates of change in log occupation median wage for movers, within broad occupation groups (1 digit FEOR codes)

	(1)	(2)	(3)	(4)	(5)
Bottom wage quintile	0.0208***			0.0213***	0.0213***
	(0.0058)			(0.0058)	(0.0058)
2nd wage quintile	0.0051			0.0054	0.0053
	(0.0059)			(0.0059)	(0.0059)
4th wage quintile	0.0098*			0.0094	0.0097*
	(0.0058)			(0.0058)	(0.0058)
Top wage quintile	0.0252***			0.0246***	0.0249***
	(0.0067)			(0.0068)	(0.0067)
Bottom math quintile		-0.0101		-0.0099	
		(0.0063)		(0.0063)	
2nd math quintile		0.0039		0.0042	
		(0.0060)		(0.0060)	
4th math quintile		0.0083		0.0084	
		(0.0058)		(0.0058)	
Top math quintile		0.0149**		0.0147**	
		(0.0059)		(0.0059)	
Bottom reading quintile			-0.0058		-0.0057
			(0.0059)		(0.0059)
2nd reading quintile			-0.0052		-0.0051
			(0.0058)		(0.0058)
4th reading quintile			0.0007		0.0010
			(0.0059)		(0.0059)
Top reading quintile			0.0174***		0.0175***
			(0.0064)		(0.0064)
N observations	22,054	22,046	22,041	22,046	22,041
N individuals	14982	14975	14973	14975	14973
R2	0.1701	0.1699	0.1697	0.1707	0.1705

Dependent variable: difference in log occupation median wage due to occupational mobility. Wage quintiles were calculated by broad occupation group (1-digit FEOR code) and by year, for workers below 40 years of age. Test score quintiles were calculated by broad occupation group (1-digit FEOR code) in 2017, for young workers with test scores. Controls in each model: education attainment, track in grade 10, experience, linear and squared, calendar year FEs, micro-region FEs, broad occupation group FEs. Standard errors clustered at the individual level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Regarding the initial wage distribution, we see a U-shaped pattern: movers in the bottom and top wage quintiles make a larger leap on average upwards on the occupation ladder than workers in the middle of the distribution. This result is insensitive to controlling for test scores.

In the test score distribution, the top quintile stands out: high-skill movers gain the most in terms of occupation median wage, while there is no difference between the other four quintiles. Again, the coefficients remain the same when wage quintiles are included.

Next, we estimate similar regression models focusing on relative wages and skills within occupations (4-digit FEOR codes), i.e., comparing workers with identical occupations before switching (Table 7). The results are significantly different. First, low-wage workers do not move faster on the occupation ladder; on the contrary, they gain the least by moving. Second, differences along the wage and test score distributions are more marked: movers in higher quintiles always end up in relatively higher-paying occupations on average than their peers with a weaker initial position. Third, the size of the differences is remarkable. Recall that the average worker in the sample moves to an occupation paying about 8 percent more than his initial occupation. The estimated difference between two movers in the bottom and top wage quintile of the same occupation is more than 10 percent. As their initial occupation is the same, this implies that the high-wage worker’s new occupation tends to pay 10 percent more in general than the low-wage worker’s destination occupation. Regarding the test score distribution, the difference between the top and bottom quintiles is 3.5 percent.

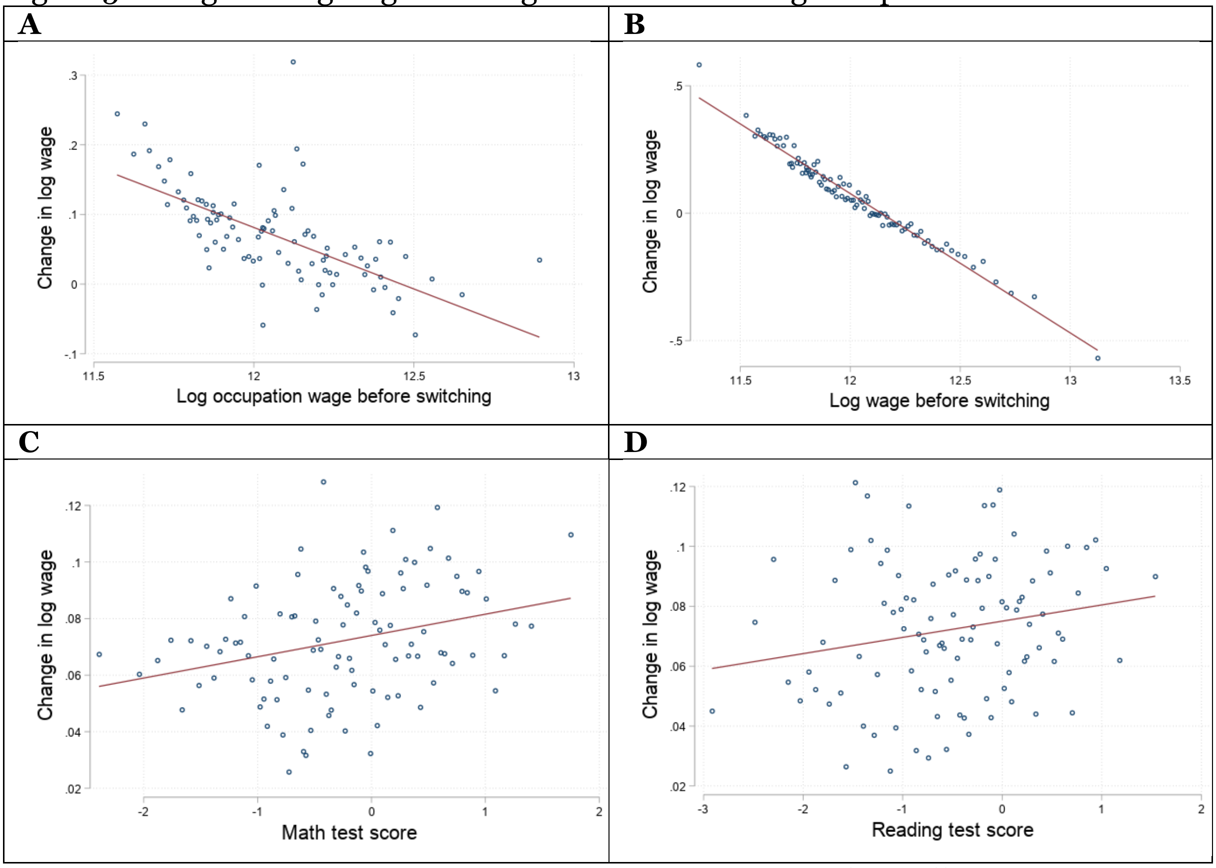
Table 7 Regression estimates of change in log occupation median wage for movers, within occupations (4 digit FEOR codes)

	(1)	(2)	(3)	(4)	(5)
Bottom wage quintile	-0.0559***			-0.0553***	-0.0552***
	(0.0050)			(0.0050)	(0.0050)
2nd wage quintile	-0.0304***			-0.0304***	-0.0304***
	(0.0054)			(0.0054)	(0.0054)
4th wage quintile	0.0223***			0.0220***	0.0225***
	(0.0054)			(0.0054)	(0.0054)
Top wage quintile	0.0491***			0.0483***	0.0487***
	(0.0059)			(0.0059)	(0.0059)
Bottom math quintile		-0.0170***		-0.0157***	
		(0.0058)		(0.0058)	
2nd math quintile		0.0046		0.0037	
		(0.0055)		(0.0054)	
4th math quintile		0.0126**		0.0109**	
		(0.0053)		(0.0053)	
Top math quintile		0.0229***		0.0202***	
		(0.0055)		(0.0055)	
Bottom reading quintile			-0.0129**		-0.0118**
			(0.0056)		(0.0055)
2nd reading quintile			-0.0055		-0.0045
			(0.0054)		(0.0054)
4th reading quintile			0.0091*		0.0079
			(0.0055)		(0.0054)
Top reading quintile			0.0236***		0.0224***
			(0.0060)		(0.0059)
N observations	22,016	22,008	22,003	22,008	22,003
N individuals	14960	14953	14951	14953	14951
R2	0.4012	0.3913	0.3908	0.4025	0.4021

Dependent variable: difference in log occupation median wage due to occupational mobility. Wage quintiles were calculated by occupation (4-digit FEOR code) and by year, for workers below 40 years of age. Test score quintiles were calculated by occupation (4-digit FEOR code) in 2017, for young workers with test scores. Controls in each model: education attainment, track in grade 10, experience, linear and squared, calendar year FEs, micro-region FEs, occupation FEs. Standard errors clustered at the individual level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Changes in occupation median wages indicate the expected long-run wage impact of occupational mobility. At the same time, it's also worth exploring wage changes immediately after switching. On average, workers experience about a 6 percent increase in their wages. Figure 5 displays the association of wage change with initial wage, occupation median wage, and test scores. The association with the initial wage suggests mean reversion: the wages of low-wage workers increase faster, while those at the top and of the distribution actually suffer a wage loss in the short run (Figure 3.2, panel B). The pattern is similar regarding the wage level of the initial occupation, though the association is much weaker (panel A). Test scores seem to positively correlate with wage growth after switching, albeit the correlation is rather weak (panels C and D).

Figure 5 Changes in log wage and wages before switching occupation



Note: Binscatter plots with 100 equally sized bins. Calendar year fixed effects are controlled for.

Table 8 provides estimates of regression models of actual wage growth, focusing on relative wages and skills within occupations (4-digit FEOR codes). We omit similar models for broad occupation categories as they give qualitatively identical results. Regarding initial wages, we see mean reversion also within occupations: the higher the initial wage is, the lower wage growth can be expected. At the same time, skills measured by test scores are very weakly related to wage growth. Workers with the lowest math skills experience lower immediate wage gains compared to their peers in the same occupation, while the wages of high-skill workers seem to grow more, though these coefficients are significant only when the initial wage is also included in the model.

Table 8 Regression estimates of change in log wage for movers, within occupations (4 digit FEOR codes)

	(1)	(2)	(3)	(4)	(5)
Bottom wage quintile	0.2119***			0.2124***	0.2124***
	(0.0059)			(0.0059)	(0.0059)
2nd wage quintile	0.0883***			0.0884***	0.0885***
	(0.0061)			(0.0061)	(0.0061)
4th wage quintile	-0.1012***			-0.1015***	-0.1015***
	(0.0065)			(0.0065)	(0.0065)
Top wage quintile	-0.2724***			-0.2732***	-0.2726***
	(0.0081)			(0.0081)	(0.0081)
Bottom math quintile		-0.0153**		-0.0205***	
		(0.0074)		(0.0068)	
2nd math quintile		-0.0077		-0.0035	
		(0.0071)		(0.0064)	
4th math quintile		0.0010		0.0098	
		(0.0070)		(0.0063)	
Top math quintile		0.0046		0.0174***	
		(0.0070)		(0.0064)	
Bottom reading quintile			0.0002		-0.0057
			(0.0070)		(0.0065)
2nd reading quintile			0.0012		-0.0037
			(0.0071)		(0.0064)
4th reading quintile			0.0092		0.0134**
			(0.0072)		(0.0065)
Top reading quintile			0.0098		0.0151**
			(0.0072)		(0.0067)
N observations	21,904	21,896	21,891	21,896	21,891
N individuals	14903	14896	14894	14896	14894
R2	0.2520	0.0650	0.0646	0.2531	0.2525

Dependent variable: difference in log wage due to occupational mobility. Wage quintiles were calculated by occupation (4-digit FEOR code) and by year, for workers below 40 years of age. Test score quintiles were calculated by occupation (4-digit FEOR code) in 2017, for young workers with test scores. Controls in each model: education attainment, track in grade 10, experience, linear and squared, calendar year FEs, micro-region FEs, occupation FEs. Standard errors clustered at the individual level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

5 Conclusion

We used high quality administrative data to estimate occupational mobility among young, middle-educated young men in Hungary. We not only found mobility to be substantial, but also that is is negatively correlated with wages, including with relative wages within the given occupation. At the same time, we find little correlation between relative skills and occupational mobility. Overall, this does not support the notion of mismatch mobility among young men, following a U shaped pattern. We also find that those at the top of the wage and skill distribution in a given occupation, when they move, they upgrade to a higher paying (and higher skilled) occupation. The inverse is true for those at the bottom of the wage distribution.

In further work, it will be worth investigating the differing patterns of mobility across vocational school and secondary school graduates, since the two groups possess very different set of skills. We also need to examine why there seems to be a reversion to the mean in terms of individual wages. Finally, our paper is on the immediate consequences of occupational mobility, but we need to take a look at the slightly longer term wage evolution of those who switch occupations.

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