Movements upwards and downwards the occupational complexity: human capital destruction, over-qualification and human capital shortage

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Abstract

Recent research has shown that skills, which constitute an important part of human capital, are more portable across occupations than previously thought. We show that there are non-negligible asymmetries in the transferability of human capital when comparing a job move from occupation i to j to a job move from j to i. We propose quantifying such asymmetries by developing measures that (1) capture human capital losses, (2) human capital shortage, and (3) over-qualification for cross-occupational job-switchers. We provide preliminary evidence for the predictive power of these measures. The explanatory power of our asymmetric measures goes beyond the effect of a mere symmetrical measure of occupational distance. In particular, we find that, when individuals change jobs, they move to occupations that minimize the loss of human capital gained at the previous job. Human capital shortages and over-qualification play a less significant role in the choice of a new occupation. Moreover, the patterns differ for direct (job-to-job) switchers and involuntary (job-unemployment-job) switchers.

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1. Introduction

In modern economies, one of the most important resources is human capital. Human capital is accumulated by individuals over the course of their lives through education and work experience. Recent literature concedes that human capital should not be considered as a homogenous mass but rather as specific in a number of different dimensions. For instance, Neal (1995) and Parent (1999) investigate the relative importance of firm specific and industry specific human capital. Poletaev and Robinson (2008) and Kambourov and Manovskii (2009) provide ample evidence that human capital is strongly occupation specific. The fact that human capital is distinct for the particular job of an individual means that job switches are in general costly because the job specific component of the employee's human capital is rendered useless by moving to a new job.

In recent research, authors have investigated the effects of human capital specificities in job switches of human capital (Pavan, 2009; Poletaev and Robinson, 2008; Kambourov and Manovskii, 2009; Gathmann and Schönberg, forthcoming). This research has focused on occupational specificities in human capital. A crucial insight is that the amount of human capital that is lost in a job switch depends on the similarities in task structures that are associated with the occupation in the old and in the new job. The more similar these task structures are the less human capital is lost in a job move. This insight has led to the development of occupational distance measures that are based on detailed descriptions of occupational task structures.

These occupational distances have strong effects on the intensity of inter-occupational labor flows and wage dynamics. However, we claim that the concept of "occupational distance" fails to appreciate the inherent complexity asymmetry in occupation pairs. People can move upward the occupational complexity ladder, but downward movements are also possible. For instance, a high school teacher may start teaching at an elementary school. It seems reasonable to assume that the former occupation requires a more complex set of skills than the latter. Therefore, we would say that high school teachers who becomes an elementary school teacher are involved in qualitatively different job moves compared to elementary school teachers who become high school teachers. This asymmetry remains hidden when using the symmetric occupational distances between occupations that have been developed so far. In this paper, we therefore develop a measure of occupational distance that is asymmetric. In particular, we typify a combination of occupations by three different measures: human capital destruction, human capital shortage and a measure of over-qualification. Human capital destruction measures the amount of human capital associated with the first job that has no value in the second job. Human capital shortage quantifies how much human capital an employee requires in the second job that had not yet

been acquired in the first job. Finally, over-qualification refers to the human capital associated with the first job that is useful but strictly speaking not needed in the second job.
The better appreciation of occupational relatedness thus gained and its implications for job switches and wage dynamics should be of considerable value when designing more effective requalification programs for employees whose occupations are adversely affected by technological or structural change.

In the remainder of this abstract, we will first explain how these human capital variables are constructed using occupational task information. Next, we present some findings on occupational mobility and show that our measures add information compared to a simple symmetrical distance measure. Finally, we will indicate some further questions we plan to answer in the paper.

2. Asymmetric occupational distance

We base our measures for occupational distance on the task data in the German Qualification and Career Survey 2005/2006. In this database, people are asked questions about their jobs and personal characteristics. We extract from this survey a set of 52 questions that focus on the tasks that are associated with a particular job. Next we aggregate this information to the level of occupations to shed light on the relative importance of different tasks in different occupations. In principle, similarity of an occupation i and occupation j could now be constructed by comparing how similar the answers given by people in occupation i are to the ones given by people in occupation j. In fact, as the work of Gathmann and Schönberg (forthcoming) shows, this is quite informative. However, we think it is possible to improve on this approach by taking two additional facts into consideration. First, some questions actually refer to very similar tasks, and if a person's human capital is sufficient for one task, it is likely that it would be sufficient for carrying out the other task as well. Therefore, we propose to collapse questions into a limited number of task dimensions by the use of factor analysis. Second, current methods do not take the complexity of occupations into account. The quantification of this complexity, however, enables us to reconceptualize occupational distance as an asymmetric relation.

Step 1: factor analysis

The Qualification and Career survey is a random sample of around 20,000 German employees conducted in the years 2005 and 2006. From this extensive survey, we use the answers on 52 questions that provide information on the task structure associated with the job of the respondent and information on his or her education. As we are interested in the task structure associated with particular occupations, for each occupation, we calculate averages of the scores on the questions and of the individual's schooling. After dropping all occupations with fewer than 15 respondents we have a sample of 19,852 respondents in 119 different occupations.

It is plausible that these 52 questions actually capture only a limited number of abstract tasks (or skills needed to carry out these tasks). Some of the tasks referred to in the 52 questions might therefore not really require different skills but can be carried out with the same human capital. In fact, the average absolute cross-correlation between the answers to the 52 questions is 39%. Therefore, we chose to deviate from the approach used by Gathmann and Schönberg who treat each question as corresponding to a separate task. Instead we use factor analysis to extract 6 factors that account for 87% of total variation. The resulting factors could be labeled (1) cognitive, (2) manual, (3) engineering, (4) interactive, (5) commercial and (6) a stress factor that seems to capture the ability to cope with pressure.
For each occupation, we now calculate factor scores representing the relative importance of each factor within a specific occupation. Next, we follow Poletaev and Robinson (2008) and normalize the factor scores of occupations by calculating ranks. As a result, we can now represent each occupation as a six dimensional vector in skill or task space.

Step 2: Quantifying human capital complexity

The length of the vector may not be very informative, as it is unclear whether respondents are more likely to judge the importance of a task in their job relative to the other tasks they have to carry out, or relative to the intensity of this task in other occupations. We therefore normalize the vectors so that they all have unit length. In principle, the angle between two vectors indicates whether occupations have similar relative task structures. However, some occupations require more complex skills than other occupations. As such, the relative importance of a task (and its corresponding skill) may not tell much about the human capital similarity between two occupations. For instance, the relative importance of the interactive factor may be similar for an ordinary sales person and for a professional negotiator. However, the absolute intensity of this task factor is likely to be far greater for the latter than for the former. The reason is that although the negotiator can be thought of as an advanced sales person, his job is vastly more complex. An indication for how complex an occupation is can be found in the months of schooling the average respondent in an occupation took. To reflect this information in the occupational task or skill vectors, we set the lengths of these vectors equal to the average levels of schooling in an occupation.

Figure 1 depicts two occupations, occ1 and occ2, in a simplified task space that consists of only two tasks. Occ1 relies relatively heavily on task factor 2 but also requires some of the skills needed to perform the tasks in task factor 1. For occ2, the relative task intensities are turned around and task factor 1 is more important than task factor 2. However, as is evident from the shorter length of occ2's task vector, occ2 is considerably less complex compared to occ1.

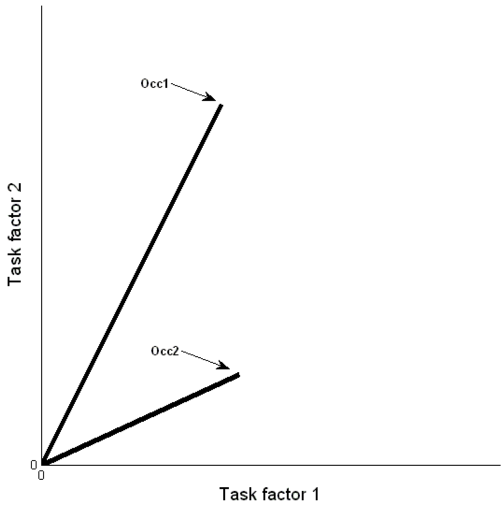

Figure 1: Occupation 1 in two-dimensional task space

Step 3: Human capital destruction, deficit and over-qualification

When people move from occ1 to occ2, a substantial part of their human capital becomes redundant. In fact, by mapping occ1's task vector onto occ2's task vector, it is possible to decompose the task vector of occ1 in a component that runs parallel to occ1's task vector and a component perpendicular to it. The former represents the amount of human capital that is required in occ1 but is still useful when an individual moves from occ1 to occ2. Figures 2.a and 2.b illustrate this mapping graphically.

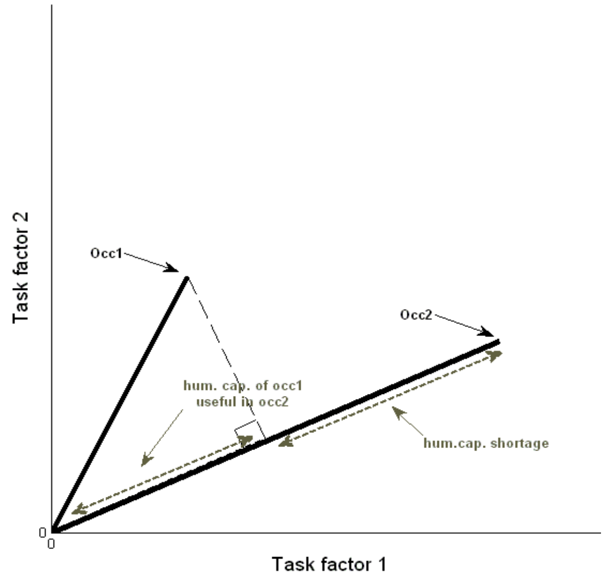

Figure 2a: human capital destruction in situation of under-qualification

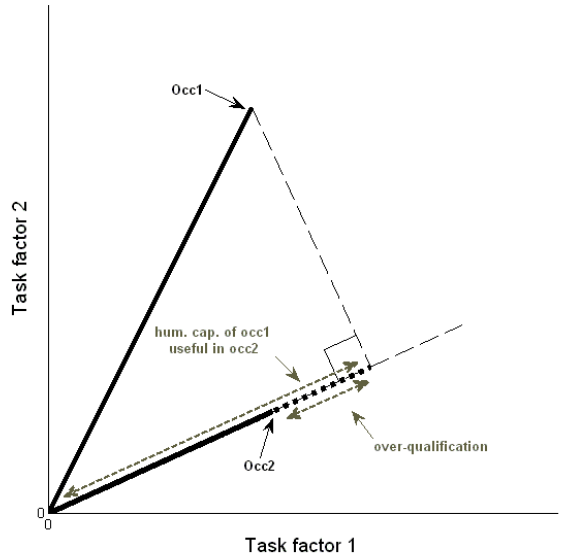

Figure 2b: human capital destruction in situation of over-qualification

In Figure 2.a, the human capital requirements of occ1 contain a substantial component that runs parallel to the human capital requirements in occ2. However, this component is insufficient to cover the entire amount of skill requirements in occ2. In the graph, this human capital deficit is indicated with the double headed arrow "hum.cap. shortage." There are thus two human capital aspects to a move from occ1 to occ2. First, the projection of occ1's task vector onto occ2's task vector is shorter than the original task vector of occ1. In other words, when moving from occ1 to occ2, a certain amount of human capital is destroyed. Let L_1 and L_2 be the length of occ1's and occ2's task vectors respectively and let furthermore $P_{1,2}$ be the length of the projection of occ1's task vector onto occ2's task vector (i.e., the line segment indicated by "hum.cap. of occ1 useful in occ2"). We can now calculate the human capital destruction involved in a move from occ1 to occ2 as:

$$(1) \qquad HC\_dest_{1,2} = \begin{cases} \frac{L_1 - P_{1,2}}{L_1} & if\ P_{1,2} > L_2 \\ \frac{L_1 - L_2}{L_1} & if\ P_{1,2} \leq L_2 \end{cases}$$

Please note that if the useful component of the occ1's human capital is larger than what is needed in occ2, human capital destruction is even larger. This situation of over-qualification will be discussed later on. The second human capital aspect in the move depicted in figure 2.a is the relative human capital deficit that the job switcher faces in his new job. We can calculate this as follows:

$$(2) \qquad HC\_short_{1,2} = \begin{cases} \frac{L_2 - P_{1,2}}{L_2} & if\ L_2 > P_{1,2} \\ 0 & if\ L_2 \le P_{1,2} \end{cases}$$

In other words, as long as the useful component of occ1's human capital is shorter than the required human capital in occ2, there is a human capital shortage that is defined as the percentage of human capital that remains to be acquired to carry out all the tasks associated with occ2. However, as already pointed out, it is also possible that occ1's mapping onto occ2 exceeds the length of occ2. In that case, employees in occ1 are overqualified for occ2. This situation is depicted in figure 2.b. The extent of over-qualification can now be quantified as:

$$(3) \qquad HC\_excess_{1,2} = \begin{cases} \frac{P_{1,2} - L_2}{L_2} & if\ P_{1,2} > L_2 \\ 0 & if\ P_{1,2} \le L_2 \end{cases}$$

The combination of these three quantities characterizes the asymmetric aspects of human capital changes associated with a change of occupation. This set of measures is considerably richer than corresponding symmetric distances like the angle between the task vectors of occ1 and occ2 or, taking into account the complexity of the occupations, the Euclidian distance between the tips of the task vectors of occ1 and occ2.

To illustrate these measures, consider an electrical engineer ("Elektroingenieur") that becomes a mechanic ("Maschinenbautechniker"). This person would destroy 19.3% of his human capital and be 16.8% over-qualified in his new job. The reason is that, although the electrical engineer uses quite similar skills as compared to the mechanic (the angle between the task vectors is 19.4°) his education is typically 24% longer.. The reverse move, from mechanic to electrical engineer, would involve far less human capital destruction: only 5.7% of the mechanic's human capital is rendered useless. However, the mechanic would face major problems in acquiring the skills needed for his new job: the human capital shortage for this move is 23.4% or 4.3 years of schooling.

In general, the asymmetries that arise when comparing a move from an occupation i to an occupation j with the reverse move conform to the intuition we have about such moves. For instance, university professors destroy more human capital when they become high school professors than vice versa, and the same holds for medical doctors that become nurses. However, this information is lost in the currently available distance measures. For instance, regardless of the direction of the move, the Euclidian distance between an electrical engineer and a mechanic is 6.5 years of education and the angular distance is about 19°. In the next section, we show that these asymmetries indeed add to our understanding of cross-occupational labor mobility and the wage dynamics involved.

3. Empirical tests

3.1. Random versus non-random mobility

As a first step we design a set of tests to check the predictive power of our measures. To this end we use a 2% sample of the German population subject to social security. This is the Regional Scientific User File of the IAB Employment Sample (IABS Regional), where IAB stands for Institute for Employment Research. We make use of an unbalanced panel of full-time employed male individuals that have experienced job switches in the period 1999-2004. We distinguish two types of switches: involuntary, or job-unemployment-job moves, and direct, or job-job moves. Up to now we cannot reliably isolate plant closures in order to identify displaced workers. Nevertheless, this is possible with a slight extension of our dataset and will be implemented in the 2010 versions of the paper.

In the first test, we verify whether the distributions of random and observed direct and involuntary mobility significantly differ in terms of occupational distance, human capital destruction, human capital shortage and over-qualification. The kernel densities of these distributions are given in Figures 3.a, 3.b, and 3.c[3]. Figure 3.a is comparable with figure 2 in Gathmann and Schönberg (2010). In the figure we compare kernel densities of observed labor mobility to the kernel densities of labor mobility if this had been random. The random mobility is the prediction of a probit model where the moves (direct, job-to-job, or involuntary,job-unemployment-job) are regressed on the total employment of the old and new occupation, as well as on the mean occupational wages in these occupations[4]. This shows what the distribution of moves for different values of human capital destruction and shortage measures would have been, if switches had depended only on the size and wage levels of both occupations.

[3] We do not display the figure illustrating the overqualification densities because this measure peeks highly at zero and has a very long right tail for all distributions, which makes the visualization through a graph difficult.

[4] This is somewhat more conservative than the illustration in Gathmann and Schönberg where the random mobility is only predicted by the total employment in both occupations.

The figures clearly show that observed distributions are shifted away from the random distribution and they look very similar for both, direct and involuntary moves. The way they are shifted suggests that job switchers rather move to (1) less distant than to far occupations (Figure 3.a)[5], (2) occupations where they can minimize human capital destruction (Figure 3.b), and (3) occupations where they have little of human capital deficits (Figure 3.c).

Conventional tests of distributional difference (both t-tests and Mann-Whitney tests) confirm that the observed differences are statistically significant. Moreover, the comparisons between the random and observed mobility for different values of the over-qualification measure also point out that job switchers rather avoid movements towards occupations where they are over-qualified.

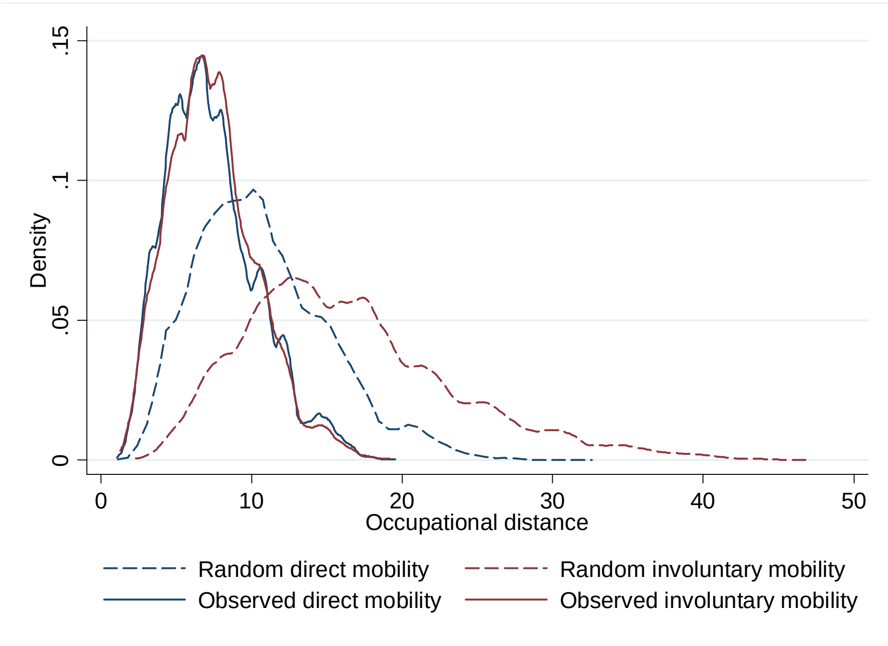

Figure 3.a. Observed mobility is shifted towards movements at lower occupational distances

[5] Gathmann and Schönberg find a bimodal distribution for labor mobility plotted against occupational distances. By contrast, using our measure of occupational distance this distribution becomes unimodal, which seems to be more intuitive because there is no obvious reason to expect a second peak in the distribution.

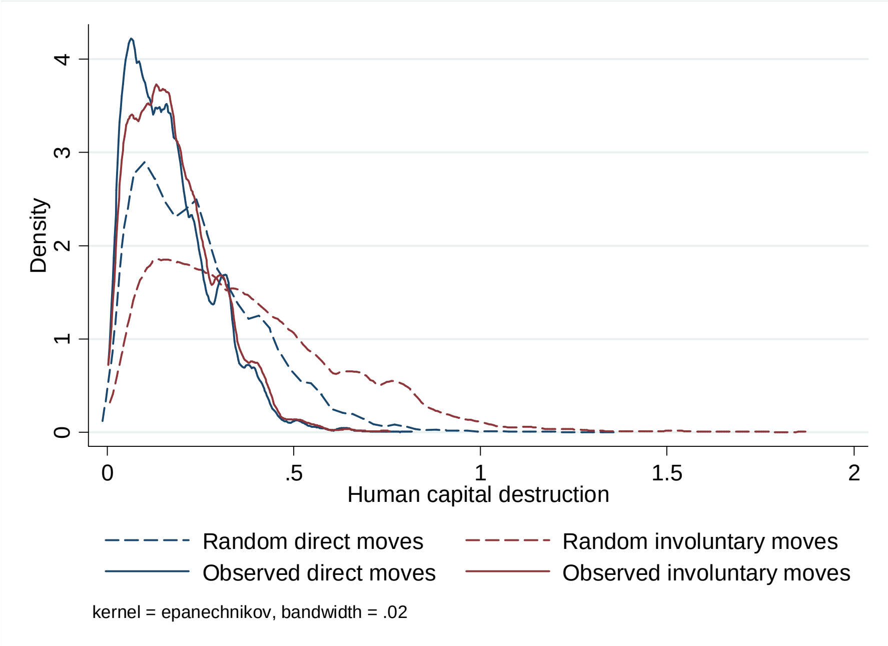

Figure 3.b. Observed mobility is shifted towards low human capital destruction movements

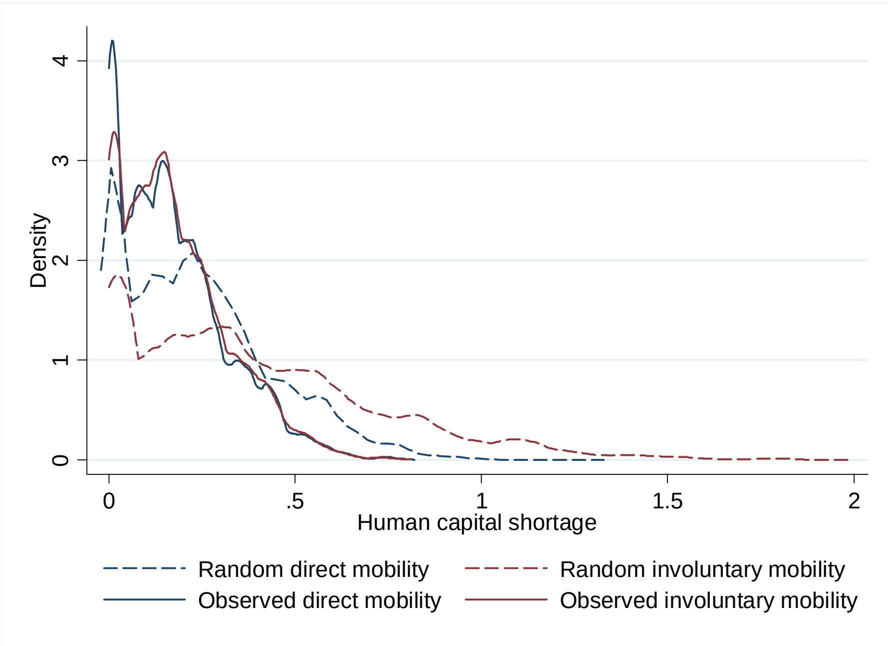

Figure 3.c. Observed mobility is shifted towards low human capital shortage movements

3.2. Predicting direct and indirect moves between occupations

Our sample consists of job switches that are not randomly assigned to new jobs. In both, the direct and the involuntary movements we suspect strong self-selection. Direct movements are likely to capture most of the voluntary switches where employees intentionally change jobs in search for better matches or simply where they want to move upward the career ladder. Involuntary movements, although very likely not often willingly displaced, consist of the fraction of the unemployed who managed to find a way out of unemployment. Therefore, they are also self-selected into new jobs. Because individuals to large extent actually choose their new jobs, the effect of occupational distances in a wage regression of job switchers without modelling the new job selection would be hard to interpret in terms of causality. Instead of that, we test whether our measures of occupational distance, human capital destruction, shortage and over-qualification can predict the frequency of movements between occupational pairs.

Table 1 shows the results of a Poisson regression where the count of direct job to job movements between all possible occupational pairs is regressed on our four measures of interest. The unit of analysis is an occupational pair (except of same-occupation pairs).

In the bivariate model of direct movements and occupational distance the effect is as expected: one standard deviation increase in the occupational distance correlates with 76% decrease in the frequency of job-to-job movements.

Table 1. Explaining the direct (job-to-job) mobility

	Model I	Model II	Model III	Model IV	Model V
Dep. var. count of direct movements					
Occupational distance	-0.760***		-0.320***		-0.288***
	(0.04)		(0.09)		(0.08)
HC destruction		-0.868***	-0.559***	-0.769***	-0.487***
		(0.05)	(0.10)	(0.04)	(0.09)
HC shortage		0.003	0.050	-0.053	-0.017
		(0.04)	(0.05)	(0.05)	(0.05)
Overqualification		0.058	0.039	0.103***	0.072**
		(0.04)	(0.04)	(0.03)	(0.03)
Mean log wage of first occupation				-0.627***	-0.414*
				(0.21)	(0.22)
Mean log wage of second occupation				0.565***	0.712***
				(0.16)	(0.17)
Log employment of first occupation				1.069***	1.062***
				(0.03)	(0.03)
Log employment of second occupation				1.112***	1.101***
				(0.03)	(0.03)
Constant	0.956***	0.911***	0.922***	-19.76***	-21.21***
	(0.04)	(0.04)	(0.04)	(1.35)	(1.41)
Observations	12432	12432	12432	12432	12432
Log likelihood	-74929.6	-74523.7	-74252.6	-38199.1	-38064.9

*** p<0.01, ** p<0.05, * p<0.1

Robust standard errors in parentheses. All variables are standardized.

In model II, we use our asymmetric human capital variables. Here we find that human capital destruction is negatively correlated with the number of direct job moves. When adding all four measures together in model III we notice that human capital destruction appears to be more informative in the prediction of the movement than occupational distance[6]. In essence, we find that when keeping the distance between occupations constant, individuals move to new jobs in a manner that reduces their human capital losses.

Model IV adds controls for the mean log wage of the old and the new occupation, as well as the total number of employees in an occupation. The controls have the expected signs and magnitudes. Keeping wages and occupational sizes constant, human capital destruction remains a strong predictor of the size of cross-occupational labor flows. Moreover, over-qualification on the new job has a positive effect. Although it may not be intuitive at the first sight why individuals switch to jobs for which they are over-qualified, some preliminary results (not shown here) indicate a positive correlation between the over-qualification and the wage growth on the new job. Finally, model V includes all measures of interest plus the controls. All three asymmetric measures, occupational distance, human capital destruction, and over-qualification remain statistically and economically significant. Human capital destruction has the highest explanatory power and has a significantly larger effect than the symmetric occupational distance variable. It is also noteworthy that human capital shortage does not appear to be a relevant factor in direct movement frequency.

Now we turn to the results for the sample of involuntary mobile (see table 2). In the bivariate model the coefficient of occupational distance is very similar to the one in the sample of job-to-job movers. In model II, we again see a negative correlation between human capital destruction and labor flows. Moreover, both shortage and over-qualification become negative and significant. Once controlling for occupational distance the sign of human capital destruction reverses (model III).

It is important to note that the sample consists of involuntarily mobile individuals. The positive sign of human capital destruction in model III indicates that, unlike job-to-job moves that are directed towards occupations with low human capital losses, in this second sample, people are forced to switch to occupations where they actually lose much human capital. The reason is that we control for the distance between the occupations. As a result, the interpretation of the positive coefficient on human capital becomes that people that are forced to move to another job are more likely to choose a job that is less complex than a job that is more complex. However, once we control for employment and wage levels of occupations in model V, we see that the coefficient of human capital destruction in model III actually captures the effect of the mean wage of the second occupation: involuntarily mobile individuals are

[6] Notice that the four variables of interest we have are standardized with a mean zero and deviation one and their coefficients are therefore directly comparable.

forced to move to occupations with lower wages relative to the old one. Once we however control for wages, individuals in fact still move to jobs where they can reduce the loss in human capital. They, however, also move to occupations where they have higher shortage of human capital relative to the old occupation.

Table 2. Explaining the involuntary (job-unemployment-job) mobility

	Model I	Model II	Model III	Model IV	Model V
Dep. var. count of involuntary movements					
Occupational distance	-0.740***		-0.964***		-0.548***
	(0.03)		(0.07)		(0.07)
HC destruction		-0.647***	0.261***	-0.669***	-0.159**
		(0.04)	(0.07)	(0.04)	(0.07)
HC shortage		-0.101***	-0.0217	0.0685*	0.113**
		(0.03)	(0.04)	(0.04)	(0.04)
Overqualification		-0.084*	-0.154***	0.089***	0.038
		(0.05)	(0.05)	(0.03)	(0.03)
Mean log wage of first occupation				-1.382***	-1.020***
				(0.14)	(0.15)
Mean log wage of second occupation				-1.431***	-1.154***
				(0.13)	(0.14)
Log employment of first occupation				0.977***	0.968***
				(0.03)	(0.03)
Log employment of second occupation				1.081***	1.066***
				(0.03)	(0.03)
Constant	-0.083***	-0.049	-0.094***	-7.148***	-9.828***
	(0.03)	(0.03)	(0.03)	(1.06)	(1.11)
Observations	12432	12432	12432	12432	12432
Log likelihood	-28107.8	-28843.4	-27996.7	-16209.5	-16050.9

*** p<0.01, ** p<0.05, * p<0.1

Robust standard errors in parentheses.

4. Preliminary conclusions

We propose a set of asymmetric measures of human capital that are of relevance for job switchers who also change occupations. These measures render information that is beyond the one contained in balanced measures of occupational distance. As shown in the empirical tests, there are important asymmetries to be reckoned when studying human capital transferability in job switches. People sort into jobs that minimize their human capital losses. Human capital shortages and over-qualification are less important aspects in the choice of a new occupation. In the extension of this text, we will look more carefully into these issues. For instance, we will use a slightly richer dataset to identify more sharply who moves voluntarily and who does not. Furthermore, it seems likely that employees have an incentive to protect their human capital and they will therefore concentrate on the human capital destruction that is involved in a job switch. In contrast, employers will be more interested in human capital deficits. We will therefore inspect more closely what the asymmetric human capital measures can tell us about the matching procedure of employees to employers.

A second line of questions involves wage dynamics during and after job switches. We expect that there are qualitative differences between labor moves up the career ladder and downward labor moves. However, as our investigations have already shown, there are strong sorting effects in choosing new occupations. This indicates that wage dynamics are hard to study by just looking at the changes in the wages of job switchers. We hope to solve this issue by finding suitable instruments that are likely to influence the decision to choose a certain occupation but not the wage dynamics during and after the job switch.

References

Gathmann, C. and Schoenberg U. (2010) “How general is human capital?: A task-based approach”, *Journal of Labor Economics*, Vol. 28, No. 1, pp. 1-50.

Poletaev, M. and Robinson C. (2008) “Human capital specificity: Evidence from the Dictionary of Occupational Titles and Displaced Worker Surveys, 1984-2000”, *Journal of Labor Economics,* Vol. 26, No. 3, pp. 387-420

Kambourov, G. and Manovskii, I. (2009) “Occupational specificity of human capital”, *International Economic Review*, Vol. 50, No. 1, pp. 63-115.

Neal D. (1999) “The complexity of job mobility among young men”, *Journal of Labor Economics,* Vol. 17, No. 2, pp. 237-261.

Parent D. (2000) “Industry-specific capital and the wage profile: Evidence from the National Longitudinal Survey of Youth and the Panel Study of Income Dynamics”, *Journal of Labor Economics,* Vol. 18. No. 2, pp. 306-323.

Pavan, R. (2009) “Career choice and wage growth” unpublished manuscript http://mail.rochester.edu/~rpavan/research/paper-WG.pdf