Employment Transitions and Human Capital Loss:

The Effect of Occupational Mobility on Qualification Mismatch

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Abstract

From the perspective of individual career path, switching occupation is a more complex step than a job change within the same occupation. The purpose of the paper is to shed light on the impact of occupational switch on the job match quality, providing insights into possible outcomes of occupational mobility in the labour market. The outcome of interest is qualification mismatch between the qualification level attained by a worker and the required one to do his or her job. The analysis, based on univariate as well as bivariate binary and ordered probit models, is carried out using the German Socio-Economic Panel data over the last two decades (1994-2013). According to the findings, occupational change decreases the likelihood of a good qualification match and increases the likelihood of overqualification. However, adopting the correlated random-effects approach, a substantial reduction in the size of the impact is observed, which suggests a need for proper consideration of unobserved heterogeneity in studies on matching jobs to job seekers. This evidence hints at the validity of the hypothesis that mismatched workers compensate for heterogeneity in their skills and innate abilities.

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Keywords: occupational mobility, job match quality, overqualification, specificity of human capital, bivariate probit

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1. INTRODUCTION

Employment transitions have been broadly examined in the human capital literature, which emphasizes the costs associated with labour market mobility. According to the findings of Topel (1991) for the US, a male worker with 10 years of job tenure would lose roughly a quarter of his wage in case of exogenous job termination. From the perspective of individual career path, switching occupation is a more complex step than a job change within the same occupation. The most recent literature documents the relationship between occupational switch, skills mismatch, and earning losses. In the context of occupational changes, the type of skill mismatch is an important channel through which negative earning effects emerge. In fact, switchers to occupations that leave existing skills unused experience the largest earning losses (Nedelkoska et al. 2015).

Using the data from the US Panel Study of Income Dynamics (PSID), Kambourov and Manovskii (2009) find evidence of significant returns to occupational tenure. Indeed, inclusion of individuals' occupational experience in the model largely reduces the importance of tenure within a firm or an industry in explaining the wage profile. The results of Sullivan (2010) support the hypothesis that human capital is to a large extent occupation-specific. According to Parrado et al. (2007), occupational change is associated with loss of occupation-specific skills, which in turn leads to poor relative wages. Thus, barriers to occupational mobility arise from loss of specific human capital, which is only partially transferable across occupations. Therefore, components of human capital appropriate in the pre-switch occupation become redundant, while a part of human capital required in the post-switch occupation is deficient. Based on the German Qualification and Career Survey (QCS) and Sample of Integrated Labour Market Biographies (SIAB), Nedelkoska et al. (2015) identify exogenous job separations with workers' displacements due to plant closures and mass-layoffs. The authors define a measure of occupational distance based on skills content, which serves as a proxy for skill transferability across occupations in terms of skill redundancy and skill shortage. Their results suggest that displacement increases occupational switching and skill mismatch. The latter arises mainly due to mobility to less skill-demanding occupations. Furthermore, these moves are the primary driving factor of earning losses related to displacement.

In an individual's career there are two major scenarios for an occupational change. Certain occupational switches are endogenous to the worker's career track, as they are purposely chosen by the individuals and come mostly along with an upgrading of skills (Sicherman and Galor 1990). These occupational changes generally take place when a worker, having acquired sufficient skills, is qualified to assume a higher position. This selection process identifies a voluntary occupational switch and is rather unlikely to entail human capital losses. Another possible scenario associates occupational changes with individuals' labour market situations such as job separations on the one hand, or an unfavourable state of economy on the other one. Furthermore, Kambourov and Manovskii (2008) register growing occupational mobility in the US labour market, which can be largely explained by occupation-specific productivity shocks due to technological shifts, changes in international trade, and government regulations. The latter may be responsible for workers' productivity decline, which in turn force them to switch occupation.

This study aims to contribute to the empirical evidence on human capital specificity and the ensuing barriers to occupational mobility. The purpose of the paper is twofold. In the first place, it is intended to analyse the loss of occupation-specific human capital from the perspective of the job match quality, providing insights into possible outcomes of occupational mobility in the labour market. Furthermore, the paper contributes to the debate on educational mismatch, examining the extent to which individuals' formal qualification can compensate for skills and abilities not captured by the educational attainment. In this context, the quality of the job match is measured with respect to the degree of match between the qualification level attained by a worker compared to the required one to carry out the job and is a subject that has received extensive attention from the empirical research community. The growing literature on workers' overeducation addresses determinants as well as consequences of this widespread phenomenon in the labour market. Leuven and Oosterbeek (2011) provide an overview of the main empirical findings in this stream of literature and discuss the reliability of the estimates. However, the effect of occupational switch on qualification mismatch has not been previously studied. This paper is intended to fill the gap.

The modern empirical mismatch literature starts with the modelling of the Duncan and Hoffman (1981) wage equation. The latter explicitly estimates the returns to overeducation defined as additional years of education that are not required for a job (O), years of education required for a job (M), and undereducation, when workers attained less education than required (U). This framework is largely referred to as the OMU theory and is a conventional approach in the overeducation literature (Sicherman 1991, Hartog and Oosterbeek 1988).

Duncan and Hoffman (1981) conclude that overeducated workers earn c.p. more, and undereducated less than their co-workers with the adequate years of schooling. But overeducated workers earn less and undereducated workers receive more than workers with the same educational attainment being employed in jobs for which they are adequately educated. Similar results are found in Verdugo and Verdugo (1989) who employ a random sample of males from the 1980 Census. In the growing literature on overeducation, negative wage effects of educational mismatch have become a stylized fact. However, the necessity to address the problem of unobserved heterogeneity in this context is emphasized in various papers. Using the Socio-Economic Panel (SOEP), Kleibrink (2013) studies the effect of educational mismatch on wages in Germany by means of FE and IV models. The author finds that unobserved heterogeneity does not explain the wage differences between actual years of education and years of required education. This outcome allows him to reject the hypothesis that mismatched workers compensate for heterogeneity in their abilities. Conversely, Bauer (2002) contributes to the literature and analyses the wage effects of educational mismatch exploiting the panel nature of the SOEP data. The estimated differences between adequately and inadequately educated workers largely decrease if unobserved heterogeneity is accounted for. Economists, such as Chevalier (2003) and Bauer (2002), focus on the driving factors of overeducation as well. They underline the importance to account for unobserved differences in personal characteristics, such as motivation, ability, other unmeasured skills and quality of education. Moreover, the authors point to strong inconsistency in the results across measurement methods, questioning the reliability of the estimates.

Boll et al. (2014) examine the impact of characteristics at the individual level on overqualification in Germany. According to their results, labour market biography and workplace-related features affect the likelihood of overeducation more than the household context. Furthermore, part-time employment is positively associated with overeducation, as more demanding jobs are usually restricted to full-time workers (Wirz and Atukeren 2005). It should be kept in mind that qualification mismatch applies to formal education, and does not necessary entail a skill mismatch. The latter reveals a relation between job content and individual abilities, and can be defined as a measure of the extent to which the possessed knowledge and skills of the workers are actually used to perform the current job, whereby skill deficit is the counterpart of underqualification and skill underutilization is the counterpart of overqualification. Qualification mismatch and skill mismatch are only weakly correlated (Allen and van der Velden 2001). Green and McIntosh (2007) confirm the moderate correlation between being overqualified and being overskilled, which amounts to only 0.2. This insight advocates the idea, that overqualified workers are not inevitably overskilled.

In the literature on job mismatch, overeducation is associated not only with wage penalties but also with poorer well-being. In fact, the existing findings suggest that overeducation negatively affects individual's job satisfaction, psychological well-being, and life satisfaction in general. Haisken-DeNew and Kleibrink (2013) study the impact of overeducation on life satisfaction in Germany. They define a job in which workers' education or skills are underutilized as downchange, which is referred to as "hidden unemployment". Controlling for observable and unobservable individual characteristics, the authors find a significant negative effect of downchange on well-being amounting to about one half of the size of unemployment. This outcome can be interpreted as workers' preference for a poorer match at the new job over their old job, which is potentially followed by unemployment spell. Fine and Nevo (2008), examining the perceived cognitive overqualification in the workforce in the US, conclude that it is negatively associated with job satisfaction. This finding advocates the shared practice among personnel managers to decline overqualified job applicants with the idea that the latter are more inclined to adverse job attitudes, such as lower productivity and higher absenteeism (Tsang and Levin 1985, Sicherman 1991). A negative relationship between overeducation and job satisfaction is also confirmed in Vanoverberghe et al. (2008), who examine the impact of overeducation at the labour market entry for a sample of Flemish school leavers. The relationship between perceived overqualification and psychological well-being is explored in Johnson and Johnson (1996). The authors conclude that overqualification causes personal frustration. The detrimental psychological effect of overeducation is also extensively documented in Verhaest and Omey (2009). Hence, qualification mismatch is an undesirable labour market phenomenon for workers as well as for employers, raising the question to what extent occupational mobility contributes to qualification mismatch.

The remainder of the paper is organized as follows. Section 2 describes the theoretical framework. Section 3 illustrates the identification strategy and estimation method. Section 4 presents the data and measurement issues. Section 5 shows the results and robustness checks. Section 6 concludes with a short summary and discussion of the main findings.

2. THEORETICAL FRAMEWORK

A common approach in estimating the costs of occupational mobility is to examine the tasks performed by workers in occupations. Human capital accumulated in an occupation can be partially transferred to other occupations in which the set of tasks performed is similar. But occupational transitions can differ substantially in terms of the extent of task change they entail (Lazear 2003, Gathmann and Schönberg 2010). Based on the data from the Dictionary of Occupational Titles (DOT), Cortes and Gallipoli (2015) construct a measure of distance between occupation pairs, which captures the extent to which the two occupations are similar with respect to the accomplished tasks. The authors further find that task distance has a strong impact on costs of switching occupations, pointing to the importance of task-specific component of human capital. Therefore, the barriers to occupational mobility entail losses of human capital that arise when workers need to adapt the tasks already familiar to them or acquire new skills in order to carry out different tasks upon switching.

Occupation-specific component of human capital is anchored to a well-defined set of tasks and, thus, skills required to perform these tasks (Poletaev and Robinson 2008). The implicit assumption is that an occupational switch takes place when there is an apparent change in the tasks carried out by a worker. Furthermore, occupational titles also carry information about the necessary qualification, i.e., required training or education level, which in turn captures the skills indispensable to do the job in a certain occupation. Occupational mobility, measured with respect to a change in occupational codes, is assumed to entail a more drastic change in tasks and therefore skills, when occupational codes are aggregated at higher levels. For instance, occupational switches based on an aggregation of occupational codes at the 3- or 2-digit level imply a larger distance between occupations, involving larger transition costs, than when disaggregated at the 4-digit level. Therefore, the extent of transition costs depends on the particular occupation individuals work in and the one they intend switching to. One important component in this context may be worker’s mental health status. In fact, in the literature on employee turnover, changing jobs or even occupations is one of the behavioural outcomes of occupational burnout (Hughes 2001). Aiming at utility maximization, once workers observe their utilities in pre- and post-switch occupations, they choose to switch occupation if their utility associated with occupational change is larger than the utility when remaining in their actual occupation. Consequently, individuals may prefer a change in occupation, which can occur at the expense of a good job match. The purpose of the paper is to examine the effect of occupational switch on qualification mismatch.

Multiple theories attempt to explain the origin of educational mismatches as well as their incidence and impact in the labour market. Within the framework of the *human capital theory*, the model of Becker (1964) assumes that each worker is paid his or her marginal productivity, which reflects the level of human capital a worker has accumulated over time. An empirical development of the model is introduced in the Mincerian wage equation, according to which wages are determined by workers' characteristics. Their earnings are a function of schooling and experience or, in other words, supplied human capital, which is independent of a worker's job (Mincer 1974). Firms, thus, adapt the production process to the level of skills supplied by the workers. As a result, no mismatch can arise. Nevertheless, if a worker, compared to an individual with the same educational level, is paid less than the due market rate, two scenarios are possible. A mismatch can originate if the skills of a worker with a certain schooling level do not correspond to the expected ones or if it is only a transitory phenomenon. In fact, overqualification can be justified if understood as investment in experience. In the *human capital compensation hypothesis*, advocated by Korpi and Tåhlin (2009), excess education serves as compensation for deficient human capital needed to carry out the job. Therefore, educational mismatch is not the result of a structural mismatch of skill demand and supply in the labor market, but mismatched workers compensate for skills and abilities not captured by their educational attainment. Hence, overeducation can be interpreted as a substitute for scarce training, experience or innate ability, while undereducated workers may supplement their insufficient formal education with high ability and job experience. Under this scenario individuals with different years of education but similar levels of human capital may perform the same jobs.

My research question draws upon the theories mentioned above and contributes to the literature on human capital specificity and educational mismatch. Occupational switches entail losses of occupation-specific human capital and can give rise to skills deficit that may be compensated by the formal qualification level of a worker. In line with this idea, I test the following hypotheses adopting univariate binary and ordered probit models. Furthermore, in an effort to exclude any source of endogeneity in my analysis, I additionally implement recursive bivariate binary and ordered probit models. For a detailed description of these models, see Greene (2002).

Hypothesis I: *upon occupational switching, the likelihood of overqualification increases, while that of a good qualification match decreases.*

The distance between occupation pairs, i.e., pre- and post-switch occupations, can be measured with respect to different aggregation levels of occupational codes, assuming that the higher the level of aggregation, the more drastic the change in required skills upon occupational change and the less transferable the skills across occupations.

Hypothesis II: *the size of the impact of occupational mobility on qualification match quality increases with the aggregation level of occupational codes.*

If the human capital compensation hypothesis holds, then surplus or lacking skills in a new occupation can be compensated by formal qualification. It seems further plausible to assume that deficient skills and experience are compensated by a higher qualification level resulting in overqualification. Furthermore, ignoring unobserved heterogeneity introduces the omitted variable bias in the model. Hence, unobserved workers' characteristics that are not controlled for correlate with occupational switch that captures also heterogeneity in workers' skills and innate abilities.

Hypothesis III: *in the explanation of qualification match quality, the marginal effect of occupational mobility decreases in magnitude and loses significance at conventional level when unobserved individuals' heterogeneity is taken into account.*

3. IDENTIFICATION STRATEGY

3.1. Univariate Probit Model

The baseline model is a univariate probit model with the following underlying latent model:

$$Y_i^* = X_i'\beta + \delta T_i + \varepsilon_i \tag{1}$$

where Y_i^* denotes the latent overqualification, X_i is the vector of exogenous variables, T_i is the treatment and ε_i is the error term, which is i.i.d. with a standard normal distribution, independent of X_i. The latent variable Y_i* determines the observed outcome Y_i for the *i*th individual:

$$Y_i = \begin{cases} 0 \; if \; Y_i^* < 0 \\ 1 \; if \; Y_i^* \geq 0 \end{cases} \tag{2}$$

The outcome of interest is the likelihood of overqualification, i.e., $Y_i=1$, conditional on X_i*:*

$$P[Y_i = 1 \mid X_i] = \Phi(X_i'\beta + \delta T_i) \tag{3}$$

where $\Phi(\cdot)$ is the standard normal cumulative distribution function, while β is a conformable vector of coefficients. The treatment variable T_i I focus my attention on in this study is occupational switch, so that δ is the parameter of interest to be estimated. The covariates[2] in X_i include personal characteristics (sex, age, education, nationality), household context (number of members, children under age 16, marital status, real income), job characteristics (firm size, tenure, job change with new employer) as well as 15[3] German federal states and year dummies. Moreover, in order to reduce the omitted variable bias the specification is enriched with information on individual employment history (unemployment experience, full-time and part-time employment experience in years) and parents' education (mother and father with tertiary education). Given normality, the model can be estimated via maximum likelihood, which yields consistent and asymptotically efficient estimates.

The binary response model at issue may yield substantially biased results if it fails to take endogeneity into account, which may arise for three reasons. First, in case of omitted variable bias, overqualification and occupational change depend on correlated observed covariates and on unobserved components. If, for instance, unobserved characteristics have an impact on both overqualification and occupational change, then the univariate probit model produces

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[2] The set of covariates mentioned does not change across model specifications.

[3] The German federal states include Baden-Wuerttemberg, Bavaria, Berlin, Brandenburg, Bremen, Hamburg, Hesse, Lower Saxony, Mecklenburg-West Pomerania, North Rhine-Westphalia, Saxony, Saxony-Anhalt, Schleswig-Holstein, Thuringia, Rhineland-Palatinate and Saarland, whereas the last two states are merged into one due to data limitation.

biased estimates. Second, there may be simultaneity. If an individual changes occupation in order to escape overqualification, then occupational change is induced by individual qualification mismatch. In this case, the dependent variable has a feedback effect on the regressor of interest, so that reversed causality arises. Third, there may be a measurement error if occupational mobility is based on self-reported occupational codes. Self-reporting may result in a mismeasure of actual occupational mobility and will introduce endogeneity bias if the measurement error is correlated with self-reported codes. In the presence of endogeneity the univariate probit model is biased and yields unreliable estimates of the effect of occupational switch on overqualification. In order to remove endogeneity bias, I adopt an instrumental variable approach, which I implement in a recursive bivariate probit model.

3.2. Bivariate Probit Model

I assume that latent variable Y_i* determines the observed outcome Y_i for the *i*th individual:

$$Y_i^* = X_i'\beta + \delta T_i^* + \varepsilon_i \tag{4}$$

$$Y_i = \begin{cases} 0 \; if \; Y_i^* < 0 \\ 1 \; if \; Y_i^* \geq 0 \end{cases} \tag{5}$$

The bivariate probit model echoes the univariate probit model, where the parameter of interest is δ. But because occupational switch T_i can be endogenously determined, I also specify the treatment equation, which is given as follows:

$$T_i^* = X_i'\alpha + \gamma Z_i + \upsilon_i \tag{6}$$

$$T_i = \begin{cases} 0 \; if \; T_i^* < 0 \\ 1 \; if \; T_i^* \geq 0 \end{cases} \tag{7}$$

where Z_i is the instrumental variable, X_i is the vector of exogenous variables as in (1) , and ν_i is the error term. Confidence intervals are bootstrapped to reduce sampling noise (Chiburis et al. 2012). All standard errors are clustered at the individual level to control for intra-individual correlation. The latent errors ε_i and ν_i are assumed to have a standard joint normal distribution with correlation rho (ρ). If $\rho=0$, the univariate probit model yields the treatment effect, i.e., the effect of occupational change on overqualification status. If $\rho \neq 0$, the unobserved random determinants of overqualification are correlated with the unobserved random determinants of occupational change. In this case occupational change is said to be endogenous and a joint estimation of equations (4) and (5) is required. A further assumption consists in the instrumental variable Z_i to be independent of ε_i, ν_i, and X_i. Given normality, the model can be estimated via maximum likelihood, which yields consistent and asymptotically efficient estimates.

The coefficient of T_i is informative about the direction of the treatment effect. However, it does not report the size of the causal effect of occupational change on overqualification. Therefore, I calculate the average treatment effect (ATE), i.e., the average causal effect of occupational change. Thus,

$$\begin{aligned} ATE &= E[Y_{1i} - Y_{0i}] = E(Y_{1i} \mid T = 1) - E(Y_{1i} \mid T = 0) \\ &= E\{1[X_i'\beta + \delta > -\varepsilon_i] - 1[X_i'\beta > -\varepsilon_i]\} \end{aligned} \tag{6}$$

computes the expected effect of occupational change on the probability of overqualification for an individual selected at random from the population, where Y_{1i}-Y_{0i} indicates the difference in outcomes due to the treatment and $1[\cdot]$ is the indicator function, which takes on the value of one if the statement in the brackets is true and zero otherwise. Moreover, I report the average treatment effect on the treated (ATT), which reveals the expected effect of occupational change for an individual only among those who switched their occupations:

$$\begin{aligned} ATT &= E[Y_{1i} - Y_{0i} \mid T = 1] = E(Y_{1i} \mid T = 1) - E(Y_{0i} \mid T = 1) \\ &= E\{1[X_i'\beta + \delta > -\varepsilon_i] - 1[X_i'\beta > -\varepsilon_i] \mid X_i'\alpha + \gamma Z_i > -\nu_i\} \end{aligned} \tag{7}$$

An alternative method of the estimation of average treatment effects is presented by Angrist and Pischke (2009), who recommend implementing IV estimation on equation (4) neglecting the binary nature of the outcome variable. Nevertheless, Imbens and Angrist (1994) argue that linear IV methods capture only local average treatment effects (LATE) independent of the nature of the outcome variable. In fact, LATE identifies the average treatment effect of occupational change for compliers only, i.e., for those individuals who receive treatment only if they are assigned to the treatment condition. Thus, the related LATE is:

$$LATE = E[Y_{1i} - Y_{0i} \mid T_i(Z_1) = 1, T_i(Z_0) = 0] \quad (8)$$

where $T_i(Z_1)$ is the potential treatment status when the instrument takes on the value of Z_1 and $T_i(Z_0)$ is the potential treatment status when the instrument takes on the value of Z_0. Each value of the instrument yields a different LATE. The linear IV is a consistent estimator of LATE only and does not necessary reveal the correct ATE. Indeed, LATE diverges from ATE when the absolute value of the correlation rho (ρ) is large, and the probability of treatment is far from 1/2, which is here the case (Fagan and Bilgel 2015). Moreover, additional discordance between IV and bivariate probit estimates emerges when the sample size is below 5000 (Chiburis et al. 2012).

The instrumental variable Z_i is the index of occupational concentration across sectors, which has been also used in other studies to instrument occupational change. For example, Lazareva (2009) examines the effect of occupational change on health and health-related behaviour. The author comes to the conclusion that occupational change has a significant negative effect on individual health. The choice of the instrument is driven by the idea that the higher the index, the more difficult it is for an individual to change occupation. Investments in occupation-specific skills can make occupational mobility less attractive, so that occupational switch is a rather undesired event in an individual's career. In line with this consideration, I use the degree of occupational skills specificity, proxied by occupational concentration index, as an instrument for the probability to change occupation. The index of occupational concentration across sectors is generated as follows. First, I compute the share of people in a particular occupation *O* working in each sector *i* of the economy and then construct an index (HH_O) equal to the sum of squared shares:

$$HH_O = \sum_{i=1}^{n} \left(\frac{E_{Oi}}{E_O} \right)^2 \quad (9)$$

This index alludes to the Herfindahl-Hirschman index of concentration and can range from values very close to zero to one. If HH_O index equals one, then the related occupation exists only in one sector. For instance, own calculations based on the German SOEP data suggest that for *Bus and Tram Drivers* (4-digit code: *8323*) the correspondent mean HH_O index is 0.80, whereas for *Dentists* (4-digit code: *2222*) its value amounts to 0.86. Consequently, skills in these occupations are very occupation-specific, and, therefore, least transferable to another occupation. On the contrary, when an occupation is dispersed across various sectors, its skills are likely to be more general and the related HH_O index is small. For example, in case of *Electrical Mechanics Fitters and Services* (4-digit code: *7241*) the mean HH_O index amounts to 0.13, meanwhile for *Secretaries* (4-digit code: *4115*) it is only 0.07. In line with this idea, I expect the relationship between the index of occupational concentration and the probability to change occupation to be negative. In particular, a higher HH_O index decreases the probability that an individual changes occupation due to occupation-specific skills, whose transferability across occupations is limited.

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It seems plausible to argue that the chosen instrument[4] is correlated with occupational change but uncorrelated to unobservable individual characteristics that affect job match quality. As follows, variation in occupational mobility that is independent of overqualification is isolated. Endogeneity bias is, therefore, removed, which allows an analysis of the impact of the exogenous variation in occupational mobility on overqualification. Indeed, the instrument appears to be a strong predictor of an individual's probability to change occupation. In support of the validity of this assumption, Angrist-Pischke multivariate F-test of excluded instruments from the IV linear probability model reports the value of 35.86, which suggests that my results do not suffer from the problem of weak instruments.

3.3. Univariate Ordered Probit Model

The link between the observed subjective match quality and the latent match quality index is assumed to be of the ordered probit type. The outcomes of interest are the likelihood of overqualification $Y_i=1$, the likelihood of adequate qualification $Y_i=2$, and the likelihood of underqualification $Y_i=3$, conditional on a vector of exogenous variables X_i. The natural order of the match quality variable relies on the idea that individual's level of attained education is assumed to remain constant over time, while the variation stems only from the formal qualification level required by the employer. Accordingly, overqualification is observed when the required level of education is higher than the one attained by a worker, adequate

[4] The nature of the instrument determines the exclusion of sector dummies as covariates in the model.

qualification points to a qualification level match, while underqualification arises when the required qualification level is lower than the attained one.

$$\begin{aligned} P[Y_i = 1 \mid X_i] &= \Phi(\kappa_1 - X_i'\beta - \delta T_i) \\ P[Y_i = 2 \mid X_i] &= \Phi(\kappa_2 - X_i'\beta - \delta T_i) - \Phi(\kappa_1 - X_i'\beta - \delta T_i) \\ P[Y_i = 3 \mid X_i] &= 1 - \Phi(\kappa_2 - X_i'\beta - \delta T_i) \end{aligned} \tag{10}$$

where $\Phi(\cdot)$ is the cumulative density function of the standard normal distribution, β is a conformable vector of coefficients, while $\kappa_0 = -\infty$ and $\kappa_3 = \infty$. The remaining threshold parameters $\kappa_1,\ldots,\kappa_2$ are freely estimated together with β. The underlying latent model is the following:

$$Y_i^* = X_i'\beta + \delta T_i + \varepsilon_i \tag{11}$$

where Y_i* denotes the latent match quality and ε_i is the error term, which is i.i.d. with a standard normal distribution, independent of X_i. The latent variable Y_i* determines the observed outcome Y_i for the *i*th individual:

$$Y_i = \begin{cases} 1 \text{ if } Y_i^* < \kappa_1 \\ 2 \text{ if } Y_i^* \in [\kappa_1, \kappa_2) \\ 3 \text{ if } Y_i^* \geq \kappa_2 \end{cases} \tag{12}$$

3.4. Bivariate Ordered Probit Model

The outcome Y_i is match quality, which I assume to be determined by the latent index:

$$Y_i^* = X_i'\beta + \delta T_i^* + \varepsilon_i \tag{13}$$

where T_i is the occupational change, X_i is a vector of exogenous variables, ε_i is the error term. The latent variable Y_i* determines the observed outcome Y_i for the *i*th individual:

$$Y_i = \begin{cases} 1 \text{ if } Y_i^* < \kappa_1 \\ 2 \text{ if } Y_i^* \in [\kappa_1, \kappa_2) \\ 3 \text{ if } Y_i^* \geq \kappa_2 \end{cases} \tag{14}$$

where $\kappa_0 = -\infty$ and $\kappa_3 = \infty$. The remaining threshold parameters $\kappa_1,\ldots,\kappa_2$ are freely estimated. I distinguish occupational change on the basis of the reason of job termination, which can be voluntary or involuntary. The treatment equation is given as follows:

$$T_i^* = X_i'\alpha + \lambda Z_i + v_i \tag{15}$$

$$T_i = \begin{cases} 0 \; if \;\; T_i^* < 0 \\ 1 \; if \;\; T_i^* \geq 0 \end{cases} \tag{16}$$

where Z_i is the instrumental variable, X_i is the vector of exogenous variables as in (1) , and v_i is the error term.

4. DATA SET AND MEASUREMENT ISSUES

4.1. Data and Estimation Sample

The analysis is carried out using the data from the German Socio-Economic Panel (SOEP), which is a representative longitudinal study of private households. Since 1984 the SOEP provides information on household composition, labour market participation, income, education, health and satisfaction levels. The variables relevant for my research question are based on responses of individuals about their qualification level and occupational mobility, whereas socio-economic and demographic traits serve as covariates. The time period is restricted to the years from 1994 to 2013, which on the one hand includes the most recent data available, but on the other hand lacks information prior to 1994 due to data limitation in the pertinent variables. The focus is on career path of workers over the life cycle and the sample is defined accordingly. The sample is restricted to full-time employed individuals aged between 20 and 60. Individuals in training or education as well as self-employed or civil servants are excluded from the sample. A further necessary restriction refers to the panel length of at least two consecutive years, which allows capturing occupational switches in the estimation sample. The final sample in the preferred specification consists of 75,142 observations, which corresponds to 13,939 individuals with the average panel length of 5.4 years.

4.2. Qualification Mismatch

The principal outcome variable across model specifications is qualification mismatch, which occurs whenever the qualification level of a worker does not meet the required qualification to carry out the job. This variable is generated comparing the highest attained level of education of a worker (*no education / training, completed vocational training*, *received college degree*[5]) to the educational level required for the current job. The exact question is:

What type of education or training is usually required for this type of work?

Possible responses are: *no completed vocational training, completed vocational training, degree from a specialized college of higher education*, and *degree from a university or other institution of higher education*[6]. Qualification mismatch can assume three forms, i.e., overqualification, adequate qualification, and underqualification. An individual is adequately qualified whenever attained and required qualification levels coincide. Overqualification is observed when attained qualification level is higher than the one required for the job. For instance, an individual with a college degree, doing a job for which no education / training or completed vocational training is required, is classified as overqualified. Underqualification is defined analogously.

Workers' self-assessment of required education is by definition subjective and, as such, may give rise to a measurement error. Hartog (2000) argues that individuals tend to overstate the job requirement in order to upgrade the status of their position. Moreover, the stated question is not unambiguously formulated. In fact, respondents can interpret it in at least two ways, namely the required education / training can refer to recruitment standards or to performance in the job. There are two alternative approaches to determine the required educational level, but they cannot be considered superior to self-assessment. A possible benefit of self-assessment consists in accounting for all relevant information. In fact, self-report is a far more valid measure than the job-analyst method, as shown by Van der Velden and Van

[5] This category includes *specialized college of higher education* and *university or other institution of higher education*.

[6] *Specialized college of higher education* and *university or other institution of higher education* are merged into one category.

Smoorenburg (1997). According to the latter approach the required schooling level is measured based on information contained in occupational classifications. Such job analyses conducted by the pertinent experts may be worthy of consideration, but their main weaknesses, namely, not updated and inaccurate data, call into doubt the reliability and validity of this measure (Hartog 2000). The third method, i.e., realized matches, is empirical and identifies the required amount of schooling for a worker with the mean of completed schooling of all workers in the same occupation (Verdugo and Verdugo 1989). Thus, an individual is defined overschooled or underschooled if his schooling level deviates at least one standard deviation from the mean in his occupation. A variation of this method is proposed in Kiker et al. (1997). The required schooling level in an occupation is referred to as a mode of the completed schooling levels of the individuals employed in that occupation. Workers who have higher or lower schooling levels than the mode are considered over- or undereducated. Realized matches can be automatically updated with every wave of a panel dataset and are not subject to individual misreports in a survey. However, also this approach has shortcomings. The choice of the cut-off at one standard deviation from the mean is arbitrary, and as such, lacking in rigor. Moreover, this measure ignores variation in the required schooling level across jobs within the same occupation, which is also a common feature in the method based on job analysis. The most relevant drawback is, nevertheless, the reflection of not only job requirements, but also demand and supply forces in the labor market. For these reasons, my choice falls on self-assessment.

4.3. Occupational Mobility

In the SOEP occupations are coded according to the International Standard Classification of Occupations (ISCO-88), which distinguishes 390 occupations at the most disaggregated level (4-digit level), 116 occupations at the 3-digit level, 28 occupations at the 2-digit level and 10 occupations at the 1-digit level. The related survey question is:

What is your current position / occupation? Please give the exact title: For example, do not write “clerk”, but “shipping clerk; not “blue-collar worker”, but “machine metal worker”. If you are engaged in public employment, please give your official title, for example, “police chief” or “lecturer”. If you are an apprentice or in vocational training, please state the profession associated with your training.

The implicit assumption is that occupational change will be observed whenever there is an apparent change in the tasks performed by the worker. Four categories[7] of employees can be distinguished with respect to their occupations measured at the 1-digit level:

a) *high skilled white collar* (codes 1, 2 and 3) includes legislators, senior officials and managers, professionals and technicians and associate professionals;
b) *low skilled white collar* (codes 4 and 5) includes clerks and service workers and shop and market sales workers;
c) *high skilled blue collar* (codes 6 and 7) includes skilled agricultural and fishery workers and craft and related trade workers;
d) *low skilled blue collar* (codes 8 and 9) includes plant and machine operators and assemblers and elementary occupations.

The most detailed code level provides comprehensive information about the career changes (Burda and Bachmann 2008, Moscarini and Vella 2008). Occupational switch is, thus, identified whenever a change in a respondent's occupational code measured at the 4-digit level is observed between *t-1* and *t* during the panel period. The importance to study occupational mobility at the most disaggregated level can be exemplified by occupations assigned to the major group *Professionals* with the respective 1-digit code of *2*. This category includes both *Meteorologists* (4-digit code: *2112*) and *Chemists* (4-digit code: *2113*). As a result, it is impossible to identify a significant career change of becoming a chemist after having worked as a meteorologist if the classification of occupations is aggregated at the 3-digit level. In fact, both occupations refer to a common category of *Physicists, Chemists and Related Professionals* with the respective code of *211*.

Please insert Table 1 about here

Measurement errors in the occupational coding are a common issue in many micro datasets. They can arise, e.g., due to confusing answers of the respondents, coding errors or survey structure. In order to obtain more accurate occupational affiliation data, I adopt a correction method (Moscarini and Thomsson 2007). Occupational mobility is considered genuine only when it is accompanied by other labour market changes such as change of employer, industry

[7] Armed forces are excluded.

or position in the company. If such a change is not reported, the previous occupational code is kept. Consequently, no occupational change is referred to as a base category, which includes no job change as well as job change within occupation (Kambourov and Manovskii 2008; Parrado et al. 2007). Not each occupational change observed in the data can be considered an unfavourable event. Unfortunately, the SOEP data adopted in this study do not provide survey information on whether occupational change has been "forced", e.g., due to technological and structural shocks rendering certain skills obsolete, which would allow to explicitly distinguish between involuntary and voluntary occupational mobility. In fact, movements on the career ladder due to promotions also entail a change in the occupational code, which, however, reflects a higher position assumed by a worker. I explicitly take into account this stage of an individual's career progression, which is coded as no occupational change within the purpose of my analysis. A detailed description of the correction method can be found in Isaoglu (2010). Moreover, I consider only continuous employment in two consecutive periods. Therefore, individuals with employment interruptions due to periods in either unemployment or out of labour force are excluded from the sample, which may result in an underestimation of occupational changes (Kambourov and Manovskii 2008). This restriction is intentionally implemented, because I am interested in patterns of employment reallocation isolated from the effect of jumps typical of recessions. In fact, the probability of changing occupation is higher after a non-employment spell (Burda and Bachmann 2008).

4.4. Descriptive Statistics

According to the adopted definition of qualification mismatch, 73.8% of the 75,142 observations are adequately matched, 18.9% of observations are overqualified and 7.3% are underqualified. Occupational mobility is relatively low. Only 1.5% change occupation following a voluntary job separation. 1.0% change occupation due to involuntary job separation. In the estimation sample 34.6% are female. Keeping in mind that my sample is restricted to full-time employed individuals and assuming that females are generally employed in part-time jobs, the low female share is not astonishing. The average age in the sample is 41.1 years. 5.5% of observations have non-German nationality. With respect to parents' education, mothers with tertiary education (6.1%) are fewer than the fathers (12.8%), while 67.0% of observations in the sample have vocational training. The average number of persons in the household is 2.8, 35.9% of observations have children under age 16. The log real household income amounts on average to 8.0, which corresponds to €3,274.9. The employment biography variables distinguish between full-time employment experience (on average 18.0 years), part-time experience (on average 0.9 years) and unemployment experience (on average 0.4 years). 30.0% of observations are employed in a firm with 20-200 employees, 24.6% in a firm with more than 2000 employees, 20.0% in a small firm with fewer than 20 employees, while 25.5% work in a firm with 200-2000 employees. The average tenure is 11.5 years, while only 3.8% of observations switch to a new job. Public sector employees are 21.8%.

Please insert Table 2 about here

5. ESTIMATION RESULTS AND ROBUSTNESS CHECKS

5.1. Estimation Results

In the interpretation of my findings[8] I mainly focus on the effect of occupational mobility on the quality of the match between the qualification level of a worker and the one required to perform his or her job. The residual variables, although carry relevant information as well, enter the model as covariates and are not discussed in the detail. Nevertheless, a brief insight is provided. **Table 3** presents the estimation results from the baseline model, i.e., univariate probit model.

Please insert Table 3 about here

As expected, occupational switch, or, in other words, job change across occupations, seems to be a rather undesired event in an individual's career from the job match quality perspective. Indeed, occupational change has a statistically significant negative impact on the qualification match compared to job change within occupation or no job change at all. This kind of labor market mobility significantly increases the probability of being overqualified by 7.5 percentage points at the 0.001 level (Table 3, column (1)). Because the mean of the dependent

[8] All statistical analyses are performed in Stata 13.1.

variable (0.189) is rather small in magnitude, the relative marginal effect is more informative for the economic interpretation than the absolute marginal effect. Accordingly, individuals, who switch occupation, are on average 39.7[9] percent more likely to be overqualified (Table3, column (2)). Furthermore, the likelihood of a good match, i.e., a worker's adequate qualification, decreases by 7.2 percentage points (Table 3, column (3)), which results in 9.8 percent on average (Table 3, column (4)). The marginal effect for underqualification is small in magnitude and not significant at the conventional levels (Table 3, column (5)), but it can be informative about the direction of the relationship between occupational switch and being underqualified. In fact, these two variables are inversely related, which is consistent with the findings previously discussed. The reported results, however, might be biased resulting in over- or underestimation of the true effect in the presence of potential endogeneity of the occupational change variable, which the univariate probit model ignores.

The model is enriched with socio-demographic information in order to reduce the potential bias. With respect to personal characteristics, sex, age, and education level are significant predictors of overqualification and underqualification statuses. In fact, women are more likely to be overqualified and less likely to be underqualified compared to their counterparts. Non-Germans do not significantly differ from the Germans in each of the job match outcomes. In line with the adopted definition of required and attained education levels, the reference category for individuals with vocational degree varies across columns. The contingency **Table 4** illustrates the frequency distribution of the two variables.

Please insert Table 4 about here

According to the results from cross-tabulation, individuals with no vocational degree, i.e., the lowest qualification level attained, are either adequately qualified or underqualified at work, but cannot be overqualified. Conversely, individuals with the highest level of education completed that is identified with college degree can be either overqualified or adequately qualified, but not underqualified. As a result, in Table 1 the reference category for *vocational degree (dummy)* is *college degree* in column (1), *no vocational degree* or *college degree* in column (3), and *no vocational degree* in column (5). Therefore, workers with vocational

[9] The relative marginal effect is calculated dividing the absolute marginal effect by the mean dependent variable.

training are 2.6 percentage points less likely to be overqualified than those with college degree, 8.4 percentage points less likely to be underqualified than those with no vocational training at all, and 11.6 percentage points more likely to be adequately qualified than those with education other than vocational training. In fact, individuals with completed vocational training can be either overqualified or underqualified when they are not adequately qualified to perform the job. This observation allows running the same regression model for a subsample of workers with vocational training only for sensitivity check[10] purposes. The estimation results largely confirm the findings discussed above, nevertheless, the composition of the sample matters.

Interestingly, higher parents' education level captures part of the labor market success of their children, reducing the probability of underqualification and increasing that of a good match. Household context also correlates with job match quality. The presence of children under age 16 decreases the likelihood of overqualification, whereas a higher number of household members increases it. Married individuals are more likely to accept jobs, for which they are overqualified. Higher real household income, which serves as a certain financial security in the family, seems to significantly decrease the probability of overqualification. However, keeping in mind the existing literature, this covariate might be endogenous and its inclusion in the model can give rise to reversed causality. In fact, overqualified individuals earn, as a rule, less, compared to their counterparts who are adequately matched and attained the same education level. Unemployment experience leaves scars, increasing the probability of a bad job match. An intuitive explanation is that acceptance of an unsuitable job compensates for skills depreciation due to passivity on the labor market. In large firms (more than 20 employees) the likelihood of overqualification is higher. Tenure, public sector, and job change with new employer jointly have a negative impact on overqualification and a positive one on adequate qualification; however, the size of the marginal effect differs in favor of the new job variable.

Please insert Table 5 about here

[10] Results from sensitivity checks are available upon request.

In **Table 5** I report the estimates from a recursive bivariate probit model[11], where in an attempt to detect endogeneity occupational change is instrumented with the index of occupational concentration as described above. The latent errors are assumed to have a standard joint normal distribution with correlation rho (ρ). Through columns (1) - (3), the Wald test of ρ rejects the null hypothesis that the bivariate probit error correlation is zero, i.e., occupational change is endogenous, and, thus, univariate and bivariate probit estimates significantly differ. The 95% confidence intervals of the marginal effect of interest in the models do not overlap, which supports the endogenous nature of the treatment variable. The unobserved random determinants of overqualification, adequate qualification, and underqualification statuses are, therefore, correlated with the unobserved random determinants of occupational change, which is confirmed by statistical significance of the error correlation rho (ρ). This evidence implies a bias in the estimated effect of occupational change on job match outcomes in the univariate probit model. According to the results, the average treatment effect of occupational change on overqualification is 24.8 pp (Table 5, column (1)), on adequate qualification 16.5 pp (Table 5, column (2)), and on underqualification 9.4 pp (Table 5, column (3)). The results are highly statistically significant across job match outcomes.

In the next step a differentiation of job termination with respect to its voluntary or involuntary nature is introduced in order to further explore the issue of potential endogeneity of occupational switches. Job separations due to own resignation are coded as voluntary, while the ones due to dismissal or closure of place of work as involuntary. The whole sample is split in two mutually exclusive subsamples which justifies their unequal number of observations, and occupational change is now re-defined in the following way.

Please insert Table 6 about here

Table 6 Panel A reports the frequency distribution of occupational switches in response to involuntary job separations. 1.16 percent of observations terminated an employment relationship due to dismissal or closure of place of work accepting a new job in another occupation. Accordingly, 98.84 percent either did not change job at all or involuntarily

[11] The bivariate probit model is implemented in STATA using `biprobittreat`, Chiburis et al. (2012).

changed job within the same occupation. Panel B provides information on occupational switches upon voluntary job terminations. 1.69 percent switched occupation in a new job following a job separation due to own resignation compared to 98.31 percent without this type of mobility.

Please insert Table 7 about here

Table 7 presents the results from the bivariate ordered probit model for the two subsamples described above. The analysis based on sample restriction by the nature of job termination provides a deeper insight into occupational mobility of workers and reveals the following findings. The error correlation ρ is not statistically significant and the Wald test of ρ does not reject the null hypothesis that the error correlation is zero (Table 7 columns (1) and (2)). This result points to the exogenous nature of occupational change when reasons of job separation are taken into account, underlying the importance to control for them in this context. The remaining analysis builds on this knowledge gain.

Please insert Table 8 about here

Table 8 presents the average marginal effects from an ordered probit model, which explicitly differentiates between types of occupational mobility. In particular, job changes, whether due to voluntary or involuntary job terminations, within or across occupations, enter the model directly as dummies, whereas the reference category is no job change. The results suggest that occupational switch, defined as job change across occupations, has a statistically significant negative effect on qualification match, independently from the reason of job separation, compared to a situation with no job change. More precisely, involuntary job change across occupations decreases the probability of qualification match by 3.1 percentage points, while the effect of voluntary job change across occupations is slightly mitigated, amounting to 3.0 percentage points (Table 8, column (3), Panel A). Although the stated absolute marginal effects seem moderate, the associated relative marginal effects amount to 4.2 and 4.1 percent on average respectively (Table 8, column (4), Panel A). The correspondent probability of overqualification increases and that of underqualification decreases. In fact, occupational switch upon involuntary job termination increases the likelihood of overqualification by 6.4 percentage points or 33.9 percent on average in the new job, whereas the correspondent marginal effects for voluntary job change that involves occupational switch are 6.2 percentage points or 32.8 percent on average (Table 8, columns (1, 2), Panel A. These types of occupational mobility also significantly decrease the probability of being underqualified in the new job. An intuitive explanation lies in the accumulation of occupation-specific human capital, which hampers smooth occupation switches. The human capital loss, which comes along with occupational mobility, translates into a poorer match between the qualification level of a worker and the one required to do the job. Hence, the findings in Panel A support the hypothesis I formulated above.

I further address the statement in hypothesis II which relates the aggregation level of occupational codes to the size of the impact of occupational mobility on qualification match quality. Therefore, occupational codes used to generate occupational switches are aggregated at a higher level, i.e., at the 3-digit level in Panel B and at the 2-digit level in Panel C. If a higher aggregation level of occupational codes captures, upon occupational switch, a larger distance between occupations in terms of performed tasks, the skills necessary to carry out the job are less transferable across occupations. Moreover, if lacking skills in a new occupation can be compensated by a worker's formal qualification, the marginal effects in absolute values in Panel A and Panel B should be larger than those in Panel A. As expected, aggregation at a higher level of occupational codes leads to a more pronounced effect of occupational change. The results suggest that occupations are indeed anchored to skills needed to perform a specific set of tasks. Furthermore, the weaker the transferability of skills, the higher is the impact of occupational mobility on the mismatch between a worker's formal education level and the required one to do the job, as if the formal qualification compensated for deficient skills. However, in order to gain a more profound understanding of the phenomenon in an attempt to test the hypothesis of compensated human capital, **Table 9** explicitly addresses the relationship between skills and formal qualification testing hypothesis III.

Please insert Table 9 about here

In Table 9 I exploit the panel structure of the data and adopt the random-effects ordered probit model, enriched with Mundlak (1978) correction. The latter enables a control for individual heterogeneity by including the means of time-variant covariates in the regression such as occupational mobility dummies with respect to voluntary or involuntary job termination; children under age 16, household size (dummy); vocational training (dummy); logarithm of real household income; unemployment, full-time, and part-time experience (years); firm size (categorical variable); tenure (years); job change with new employer (dummy); public sector (dummy); federal states (categorical variable). Time-invariant variables are allowed to correlate with individual unobservable traits. Using the correlated random-effects ordered probit approach I aim at reducing omitted variable bias, which captures individuals' unobserved ability and, hence unmeasured skills. According to the results[12], marginal effects of occupational mobility dummies become much smaller and their significance at conventional levels disappears. These findings point to the fact that ignoring unobserved heterogeneity leads to biased results. In fact, in the ordered probit model in Table 6 the marginal effects capture the impact of occupational switch correlated with unmeasured skills surplus or deficit upon occupational change, which explains the size and significance of the impact of occupational mobility on qualification mismatch. This evidence suggests that there is indeed a very strong component of occupation specificity in human capital characterized by a specific set of skills that can be at least partially compensated by formal qualification. This conclusion supports the human capital compensation hypothesis.

5.2 Robustness Checks

The results are robust to a number of sensitivity checks[13]. Estimation of the model parameters in binary and ordered probit models using or omitting robust standard errors does not reveal any noteworthy discrepancy neither in the magnitude of the average marginal effects nor in significance levels. This outcome is interpreted as evidence of no model misspecification and, hence, reliability of the results discussed above.

Please insert Table 10 about here

Table 10 summarizes the relevant findings and allows an immediate comparison with the baseline model estimates. The first robustness check is carried out with respect to the sample composition restriction including part-time employed individuals in the sample. The intuition behind this check is that part-time workers might be more mobile from the labour market perspective, and, at the same time, more prone to accept a worse job match. Indeed, the

[12] The complete table provides results for all covariates and is available upon request.

[13] Results from all robustness checks are available upon request.

average marginal effect is slightly larger. The results are in line with the stream of literature, which emphasizes the sensitivity of the findings with respect to the sample composition.

In a further robustness check I include occupation dummies based on occupational codes aggregated at the 3-digit level. In this way, I test the hypothesis that the choice of occupation, inevitably involved in a transition from one occupation to another, captures part of the negative impact of occupational mobility. The results suggest that the type of occupation chosen plays an important role in the job match quality. In fact, the average marginal effect of occupational change decreases in magnitude.

6. DISCUSSION

Labour market mobility does not yield unambiguous outcomes. Keeping in mind that individuals primarily aim to maximize their utility, a change in their labour market behavior implies a utility change. Thus, occupational mobility is observed in individuals' behaviour if they expect a net gain in utility. However, labour markets overflow with rigidities that entail constraints in workers' decisions. Productivity shocks due to technological shifts, changes in international trade and government regulations may induce individuals to switch occupation accepting potential job mismatches. The purpose of my paper is to analyse the impact of occupational change on the job match quality. I find strong evidence in favour of the thesis that this type of labour market mobility is harmful from the perspective of the match between the qualification level of a worker and the one required to carry out the job. However, accounting for individual unobservable traits, a substantial reduction in the size of the effect of occupational switch on qualification mismatch originates. This observation suggests a need for proper consideration of unobservable characteristics of individuals in studies on matching jobs to job seekers. Further research in this regard is encouraged.

The use of an instrumental variable in a recursive bivariate probit model serves as a test for potential endogeneity of occupational change, or, in other words, selection into the treatment by the switchers. Interestingly, the results suggest that accounting for the reason of job termination by distinguishing between voluntary and involuntary, occupational switch loses its endogenous nature. This finding entails a twofold consideration. In the first place, ignoring the distinction between the driving factors of job change implies that occupational switch captures not only the impact of transition to another occupation, but also partly the effect of leaving a job and transitioning to a new one. Secondly, occupational change can be treated as exogenous to the worker's career path and can involve human capital losses.

Although affected by the choice of the instrumental variable, the failure of rejection of the exogeneity assumption points to the reliability of my results from the univariate probit models. Moreover, in this way I overcome a potential shortcoming of the instrument. To my best knowledge, the official statistics on employment by occupations (according to the ISCO-88 classification) and sectors (according to the NACE classification) is not available. Therefore, the instrument, i.e., index of occupational concentration across sectors, is generated based on individuals' responses in the SOEP questionnaire, which are inevitably subject to measurement errors. In spite of multiple cross-checks of the data, the information used to construct the index still relies on subjective statements about occupations and sectors in which individuals are employed. This shortcoming, however, turns out not to be the crucial point. Noteworthy is the observation that within the scenario of occupational switch due to voluntary or involuntary job separation, the instrument has a different predictive power. In fact, the size of the impact of occupational concentration index on occupational change is ca. 1.7 times larger in case of voluntary transitions to a new job. This evidence suggests that the contemplation whether to switch occupation, attributable to a terminated employment relationship by one's own choice, involves concerns about the degree of occupational skills transferability to a larger extent than in case of involuntary job mobility. The impact of other covariates on job match quality is in line with the existing literature in the field.

In the light of my findings and observations, the design of selected survey questions in the SOEP should be reconsidered. In particular, with respect to "*what type of education or training is usually required for this type of work?*" a more precise formulation of the question would lead to its unambiguous understanding by the respondents, allowing a more accurate measurement of the mismatch. Moreover, homogeneous questionnaires at the international level would enable a more straightforward comparison the researchers' findings across countries.

In the context of occupational mobility, overqualification suggests an inefficient allocation of workers to occupations. Overeducation is not only a reason of concern for single individuals, but also requires particular attention of the government. If additional education is mainly unproductive, as pointed out by Kleibrink (2013), overeducation generates a massive waste of public resources. In fact, the government invests substantial amounts of its resources in education, and, therefore, should be interested in the realization of the expected returns. The government can attempt to interfere by actively manipulating the demand for and supply of educated workers in the economy (Tsang and Levin 1985). In the private sector the demand for labour can be influenced by macroeconomic policies such as providing tax incentives for firms that adequately employ higher-skilled and better-educated workers. Moreover, the educational attainment and the following labour supply of more educated individuals can be affected changing the private costs of education, e.g., introducing tuition fees. These calculations, nevertheless, should not obscure the benefit of education in a broader perspective, as human capital is largely recognized as an essential factor in maintaining a sustainable level of economic growth.

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Figures and Tables to be included in text

Figure 1: Predictive Margins of Occupational Change

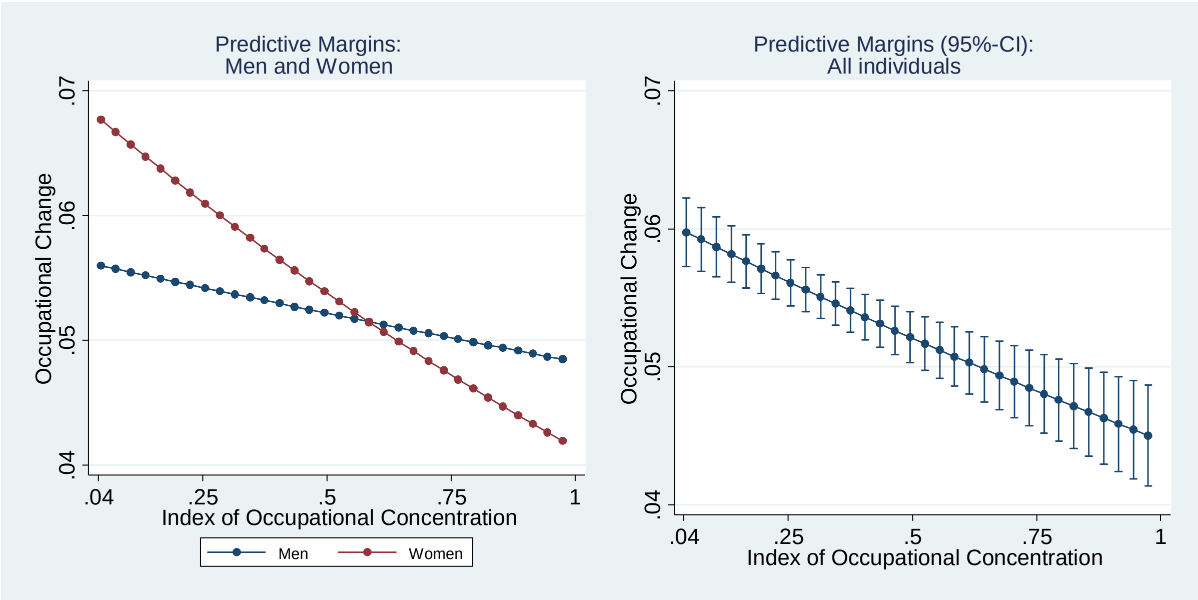

Table 1: International Standard Classification of Occupations (ISCO-88)

	Major Group 2: Professionals
211	Physicists, chemists and related professionals
2111	Physicists and astronomers
2112	Meteorologists
2113	Chemists
2114	Geologists and geophysicists

Source: SOEP.

Table 2: Descriptive Statistics

	Mean	SD	Min	Max	N
Overqualification (dummy)	0.189		0	1	75142
Adequate Qualification (dummy)	0.738		0	1	75142
Underqualification (dummy)	0.073		0	1	75142
Involuntary Job Change across Occupations (dummy)	0.010		0	1	75142
Involuntary Job Change within Occupation (dummy)	0.007		0	1	75142
Voluntary Job Change across Occupations (dummy)	0.015		0	1	75142
Voluntary Job Change within Occupation (dummy)	0.012		0	1	75142
Female (dummy)	0.346		0	1	75142
Age (years)	41.130	10.048	20	60	75142
Vocational Degree (dummy)	0.670		0	1	75142
Non-German (dummy)	0.055		0	1	75142
Father with Tertiary Education (dummy)	0.128		0	1	75142
Mother with Tertiary Education (dummy)	0.061		0	1	75142
Children under Age 16 in HH (dummy)	0.359		0	1	75142
Number of Persons in HH	2.820	1.243	1	14	75142
Married (dummy)	0.636		0	1	75142
Log Real HH Income	7.974	0.446	5.664	12.185	75142
Unemployment Experience (years)	0.370	1.046	0	27	75142
Employment Experience (Full-Time) (years)	17.996	10.353	0	45.8	75142
Employment Experience (Part-Time) (years)	0.887	2.693	0	35	75142
Firm size < 20 Employees (dummy)	0.200		0	1	75142
Firm size 20-200 Employees (dummy)	0.300		0	1	75142
Firm size 200-2000 Employees (dummy)	0.255		0	1	75142
Firm size > 2000 Employees (dummy)	0.246		0	1	75142
Tenure (years)	11.472	9.389	0	46	75142
Public Sector (dummy)	0.218		0	1	75142
Job Change with New Employer (dummy)	0.038		0	1	75142

Notes: Sample contains only full-time employed individuals aged between 20 and 60. Individuals in training or education as well as self-employed or civil servants are excluded. SOEP 1994-2013, own calculations.

Table 3: Probit (Average Marginal Effect)

Dependent variables	***Overqualification***		***Adequate Qualification***		***Underqualification***	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Occupational Change (dummy)	0.075***	0.397	-0.072***	0.098	-0.002	0.027
	[0.008]		[0.009]		[0.006]	
Job Change with New Employer (dummy)	-0.053***		0.046***		0.010	
	[0.008]		[0.009]		[0.005]	
Personal Characteristics						
Female (dummy)	0.023**		-0.009		-0.015**	
	[0.008]		[0.009]		[0.005]	
Age	0.011***		0.001		-0.012***	
	[0.003]		[0.003]		[0.002]	
Age Squared / 10	-0.001***		0.001		0.001**	
	[0.000]		[0.000]		[0.000]	
Vocational Degree (dummy)	-0.026**		0.116***		-0.084***	
	[0.008]		[0.009]		[0.006]	
Non-German (dummy)	0.017		-0.015		-0.002	
	[0.015]		[0.016]		[0.008]	
Parents' Education						
Father with Tertiary Education (dummy)	-0.022		0.045***		-0.020*	
	[0.012]		[0.013]		[0.008]	
Mother with Tertiary Education (dummy)	0.006		0.011		-0.017	
	[0.016]		[0.018]		[0.010]	
Household Context						
Children under Age 16 in HH (dummy)	-0.027***		0.020*		0.011*	
	[0.008]		[0.009]		[0.006]	
Number of Persons in HH	0.021***		-0.016***		-0.007**	
	[0.003]		[0.004]		[0.002]	
Married (dummy)	0.022**		-0.020*		-0.002	
	[0.008]		[0.009]		[0.005]	
Log Real HH Income	-0.110***		0.090***		0.023***	
	[0.008]		[0.009]		[0.005]	
Employment Biography						
Unemployment Experience	0.022***		-0.032***		0.007***	
	[0.003]		[0.004]		[0.002]	
Employment Experience (Full-Time)	0.004***		-0.010***		0.006***	
	[0.001]		[0.001]		[0.001]	
Employment Experience (Part-Time)	0.003		-0.008***		0.005***	
	[0.002]		[0.002]		[0.001]	
Job Characteristics						
Firm size 20-200 Employees (dummy)	0.018*		-0.022*		0.005	
	[0.008]		[0.009]		[0.005]	
Firm size 200-2000 Employees (dummy)	0.042***		-0.044***		0.003	
	[0.010]		[0.010]		[0.006]	
Firm size > 2000 Employees (dummy)	0.019*		-0.023*		0.004	
	[0.009]		[0.010]		[0.006]	
Tenure	-0.004***		0.004**		0.001	
	[0.001]		[0.001]		[0.001]	
Tenure Squared	-0.000		-0.000		0.000	
	[0.000]		[0.000]		[0.000]	
Public Sector (dummy)	-0.031***		0.040***		-0.007	
	[0.009]		[0.010]		[0.006]	
Federal States (dummies)	Yes		Yes		Yes	
Years (dummies)	Yes		Yes		Yes	
Mean Dependent Variable	0.189		0.737		0.074	
Observations	69520		69520		69520	

Notes: Standard errors are clustered at the individual level and are displayed in parentheses. Odd (even) columns report absolute (relative) marginal effects. Reference category for "Vocational Degree" is: *College Degree* (column 1), *No Vocational Degree* or *College Degree* (column 3), *No Vocational Degree* (column 5). * p<0.05, ** p<0.01, *** p<0.001.

Table 4: Frequency Distribution of Attained Education and Match Quality

	Highest Level of Education Attained			
Match Quality	[1] No Vocational Degree	[2] Vocational Degree	[3] College Degree	**Total**
[1] Overqualification	0	8,640	4,500	13,140
[2] Adequate Qualification	3,335	35,344	12,591	51,270
[3] Underqualification	2,849	2,261	0	5,110
Total	6,184	46,245	17,091	69,520

Table 5: Bivariate Probit (Average Treatment Effect)

Dependent variables	***Overqualification***	***Adequate Qualification***	***Underqualification***
	(1)	**(2)**	**(3)**
Occupational Change (dummy)	0.783***	-0.478***	-1.407**
	[0.128]	[0.127]	[0.429]
Job Change with New Employer (dummy)	-0.455***	0.273***	0.932***
	[0.069]	[0.068]	[0.278]
Constant	1.288***	-1.923***	0.012
	[0.323]	[0.289]	[0.403]
Treatment variable		***Occupational Change (dummy)***	
Occupational Concentration (index)	-0.362***	-0.359***	-0.324***
	[0.045]	[0.045]	[0.052]
Constant	-0.792**	-0.743*	-0.838**
	[0.287]	[0.326]	[0.304]
ATE	0.248***	-0.165***	-0.094***
	[0.046]	[0.047]	[0.025]
ATT	0.173***	-0.145***	-0.490**
	[0.021]	[0.033]	[0.189]
Bootstrap replications	199	199	199
Error correlation rho (ρ)	-0.247***	0.126***	0.761***
	[0.057]	[0.062]	[0.121]
Wald test of rho (ρ) - χ^2(p-value)	17.213(0.000)	3.967(0.046)	11.961(0.001)
Personal Characteristics	Yes	Yes	Yes
Parents' Education	Yes	Yes	Yes
Household Context	Yes	Yes	Yes
Employment Biography	Yes	Yes	Yes
Job Characteristics	Yes	Yes	Yes
Federal States (dummies)	Yes	Yes	Yes
Years (dummies)	Yes	Yes	Yes
Observations	69520	69520	69520

Notes: Standard errors are clustered at the individual level and are displayed in parentheses. Reported values are coefficients, except for ATE (average treatment effect) and ATT (average treatment effect on the treated). Wald test of rho (ρ) reports chi-square statistic for the null hypothesis that the bivariate probit error correlation is zero (i.e., occupational change is exogenous). * p<0.05, ** p<0.01, *** p<0.001.

Table 6: Frequency Distribution of Occupational Change

	Panel A	
Occupational Change due to Involuntary Job Termination	Frequency	Percent
[0] Involuntary Job Change within Occupation or No Job Change	65,004	98.84
[1] Involuntary Job Change across Occupations	760	1.16
Total	65,764	100.00
	Panel B	
Occupational Change due to Voluntary Job Termination	Frequency	Percent
[0] Voluntary Job Change within Occupation or No Job Change	65,323	98.31
[1] Voluntary Job Change across Occupations	1,121	1.69
Total	66,444	100.00

Table 7: Bivariate Ordered Probit

Subsample	**I: Involuntary Job Termination**	**II: Voluntary Job Termination**
	(1)	**(2)**
Dependent variable	***Match Quality***	
Occupational Change (dummy)	-0.414***	-0.238
	[0.116]	[0.172]
Job Change with New Employer (dummy)	0.293***	0.184*
	[0.048]	[0.074]
Treatment variable	***Occupational Change (dummy)***	
Occupational Concentration (index)	-0.353***	-0.608***
	[0.096]	[0.088]
Constant		
Cut 1,1	43.862***	44.801***
	[3.815]	[3.768]
Cut 1,2	46.300***	47.244***
	[3.817]	[3.769]
Cut 2,1	-40.305*	-1.653
	[19.100]	[15.062]
Error correlation rho (ρ)	0.030	-0.047
	[0.049]	[0.097]
Wald test of rho (ρ) - χ^2(p-value)	0.36(0.546)	0.24(0.626)
Personal Characteristics	Yes	Yes
Parents' Education	Yes	Yes
Household Context	Yes	Yes
Employment Biography	Yes	Yes
Job Characteristics	Yes	Yes
Federal States (dummies)	Yes	Yes
Years (dummies)	Yes	Yes
Observations	65764	66444

Notes: Standard errors are clustered at the individual level and are displayed in parentheses. The Wald test of rho (ρ) reports chi-square statistic for the null hypothesis that the error correlation is zero (i.e., occupational change is exogenous).

Table 8: Ordered Probit (Average Marginal Effect)

Dependent variable: Match Quality	***Overqualification***		***Adequate Qualification***		***Underqualification***	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Panel A:* *Preferred Specification	***Occupations disaggregated at the 4-digit level***					
Involuntary Job Change across Occupations (dummy)	0.064***	0.339	-0.031***	0.042	-0.033***	0.452
	[0.019]		[0.009]		[0.010]	
Involuntary Job Change within Occupation (dummy)	-0.044*	0.233	0.021*	0.028	0.023*	0.315
	[0.018]		[0.009]		[0.009]	
Voluntary Job Change across Occupations (dummy)	0.062***	0.328	-0.030***	0.041	-0.032***	0.438
	[0.019]		[0.009]		[0.010]	
Voluntary Job Change within Occupation (dummy)	-0.016	0.085	0.008	0.011	0.009	0.123
	[0.019]		[0.009]		[0.010]	
Panel B	***Occupations aggregated at the 3-digit level***					
Involuntary Job Change across Occupations (dummy)	0.067***		-0.032***		-0.035***	
	[0.019]		[0.009]		[0.010]	
Involuntary Job Change within Occupation (dummy)	-0.038*		0.018*		0.020*	
	[0.018]		[0.009]		[0.009]	
Voluntary Job Change across Occupations (dummy)	0.065***		-0.031***		-0.033***	
	[0.019]		[0.009]		[0.010]	
Voluntary Job Change within Occupation (dummy)	-0.014		0.007		0.007	
	[0.018]		[0.009]		[0.009]	
Panel C	***Occupations aggregated at the 2-digit level***					
Involuntary Job Change across Occupations (dummy)	0.079***		-0.038***		-0.041***	
	[0.020]		[0.010]		[0.010]	
Involuntary Job Change within Occupation (dummy)	-0.035*		0.017*		0.018*	
	[0.017]		[0.008]		[0.009]	
Voluntary Job Change across Occupations (dummy)	0.064***		-0.031***		-0.033***	
	[0.019]		[0.009]		[0.010]	
Voluntary Job Change within Occupation (dummy)	-0.005		0.003		0.003	
	[0.018]		[0.009]		[0.009]	
Personal Characteristics	Yes		Yes		Yes	
Parents' Education	Yes		Yes		Yes	
Household Context	Yes		Yes		Yes	
Employment Biography	Yes		Yes		Yes	
Job Characteristics	Yes		Yes		Yes	
Federal States (dummies)	Yes		Yes		Yes	
Years (dummies)	Yes		Yes		Yes	
Mean Dependent Variable	0.189		0.738		0.073	
Observations	75142		75142		75142	

Notes**:** Standard errors are clustered at the individual level and are displayed in parentheses. Odd (even) columns report absolute (relative) marginal effects. Reference category for occupational mobility dummies is no job change. * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

Table 9: Correlated Random-Effects Ordered Probit (Average Marginal Effect)

Dependent variables	***Overqualification***	***Adequate Qualification***	***Underqualification***
	(1)	**(2)**	**(3)**
Involuntary Job Change across Occupations (dummy)	0.023	-0.020	-0.003
	[0.013]	[0.011]	[0.002]
Involuntary Job Change within Occupation (dummy)	0.002	-0.002	-0.000
	[0.013]	[0.011]	[0.002]
Voluntary Job Change across Occupations (dummy)	0.020	-0.017	-0.003
	[0.013]	[0.011]	[0.002]
Voluntary Job Change within Occupation (dummy)	-0.001	0.001	0.000
	[0.013]	[0.011]	[0.002]
Personal Characteristics	Yes	Yes	Yes
Parents' Education	Yes	Yes	Yes
Household Context	Yes	Yes	Yes
Employment Biography	Yes	Yes	Yes
Job Characteristics	Yes	Yes	Yes
Federal States (dummies)	Yes	Yes	Yes
Years (dummies)	Yes	Yes	Yes
Observations	75142	75142	75142

***Notes*:** Standard errors are clustered at the individual level and are displayed in parentheses. Reference category for occupational mobility dummies is no job change. * p<0.05, ** p<0.01, *** p<0.001.

Table 10: Probit (Average Marginal Effect) - Robustness Checks

Dependent variables	***Overqualification***	***Adequate Qualification***	***Underqualification***
	(1)	**(2)**	**(3)**
Panel A		***Baseline Model***	
Occupational Change (dummy)	0.075***	-0.072***	-0.002
	[0.008]	[0.009]	[0.006]
Observations	69520	69520	69520
Panel B		***Sample with Part-Time Employed***	
Occupational Change (dummy)	0.082***	-0.079***	-0.005
	[0.007]	[0.008]	[0.005]
Observations	90117	90117	90117
Panel C		***Occupation Dummies (3-digit level)***	
Occupational Change (dummy)	0.061***	-0.055***	-0.006
	[0.008]	[0.009]	[0.005]
Observations	69426	69504	69050
Personal Characteristics	Yes	Yes	Yes
Parents' Education	Yes	Yes	Yes
Household Context	Yes	Yes	Yes
Employment Biography	Yes	Yes	Yes
Job Characteristics	Yes	Yes	Yes
Federal States (dummies)	Yes	Yes	Yes
Years (dummies)	Yes	Yes	Yes

Notes: Standard errors are clustered at the individual level and are displayed in parentheses. * p<0.05, ** p<0.01, *** p<0.001.