The incidence and wage effects of overeducation using the worker's self-assessment of skill utilization

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Discussion Paper 2012-14

Institut de Recherches Économiques et Sociales
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The incidence and wage effects of overeducation using the worker's self-assessment of skill utilization

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June 9, 2012

Abstract

This paper proposes an improved concept of educational mismatch that combines a statistical measure of over- and undereducation with the worker's self-assessment of skill utilization. In that way, we account for worker heterogeneity in skills whose omission may generate biased estimates of the incidence and wage effects of over- and undereducation. Using cross-sectional data from the Swiss Household Panel survey, the empirical analyses provide the following results: (a) at least two third of the statistically defined overeducated workers perceive their skills as adequate for the job they hold and are then apparently overeducated; (b) among the overeducated with a given schooling level, the wage return to education is lower for those who are mismatched in skills than for those who are not; (c) apparently overeducated workers have similar wage returns compared to others with the same schooling level but who are statistically matched. These findings confirm that most of those overeducated according to the statistical measure have unobserved skills that allow them to work in a job for which they are well-matched.

Keywords: Educational mismatch, skill utilization, wages

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1 Introduction

The past three decades have seen a growing literature on the incidence and the wage effects of educational mismatch, also referred to as over- or undereducation.[1] Overeducated workers are those whose educational qualifications exceed the educational requirements of their job; conversely, undereducated workers have less education than it is required for their job. Most measures of over- and undereducation have been merely derived from the relationship between actual years/level of schooling of the workers and years/level of schooling required for the jobs. For that reason, a few authors have raised the issue of whether overeducated workers are genuinely mismatched in skills (e.g. Allen and van der Velden, 2001; Green and McIntosh, 2007; Quintini, 2011). One crucial aspect of their findings is that overeducation is weakly correlated with underutilization of skills. In other words, the worker's educational attainment does not necessarily reflect her skills endowment; thus, as pointed out by Chevalier (2003), traditional methods of measuring educational mismatch fail to account for heterogeneity in skills among workers with the same years/level of schooling. As a result, basic measurement methods may generate biased estimates of the incidence and wage effects of over- and undereducation. In this paper, we address this issue by presenting and exploiting an improved measure of educational mismatch that accounts for worker heterogeneity in perceived skill utilization.

A number of studies have proposed alternative ways of defining educational mismatch. While some disregard any comparison between actual and required years/level of education by, for example, relying on the match between the worker's field of study and his job (Robst, 2007a,b; Nordin et al., 2010), others attempt to better account for worker heterogeneity when measuring educational mismatch based on quantity of schooling (e.g. Chevalier, 2003; Robst, 2008; Chevalier and Lindley, 2009; Green and Zhu, 2010). We contribute to the latter strand of the literature by questioning the assumption that educationally mismatched workers are de facto mismatched in skills. We first consider that a worker is either over- or undereducated when his actual education is respectively higher or lower than the modal education within his occupation. We then argue that educational mismatch is apparent when an over- or undereducated worker reports having adequate skills for his job, otherwise it is genuine.[2] Our descriptive results show that most over- and undereducated workers are well-matched in terms of skills; therefore, previ-

[1] In the literature, there exist different corresponding terms such as over/underschooling, over/underqualification or surplus/deficit schooling.

[2] Thereafter, we use the terminology introduced by Chevalier (2003) when subdividing educational mismatch into *genuine* or *apparent* mismatch.

ous studies that have neglected the existence of skill heterogeneity among equally educated workers have exaggerated the incidence of educational mismatch. We subsequently estimate two versions of the ORU (Over-, Required and Undereducation) wage equation in which either the basic or the alternative measure of educational mismatch is incorporated. While the estimates derived from the standard specification are in line with earlier findings from the literature, those derived from the augmented specification indicate that the wage returns to actual education are broadly similar for workers being apparently overeducated and adequately educated. Accordingly, apparently overeducated workers are those high-educated who have low levels of skills to carry out their job and are then less skilled compared to those adequately educated with the same educational background.

This paper is organized as follows. Section 2 briefly describes the data source used throughout this paper. The first part of Section 3 is devoted to the criteria adopted for defining educational mismatch, while the second part presents the regression specifications considered in the analysis. Section 4 reports the incidence of educational mismatch and the estimation results of its impact on wages. Section 5 discusses, in conclusion, the main results.

2 Data description

Data used in this study are drawn from the Swiss Household Panel (SHP) survey conducted annually since 1999. They include a first sample of 5074 households in 1999 (*SHP_I* sample) and a refreshment sample of 2704 households in 2004 (*SHP_II* sample). The SHP dataset contains variables providing detailed information on worker and job characteristics.[3] For the analysis, the first waves of both samples are pooled as a cross-section; accordingly, cross-sectional individual weights are used to produce nationwide representative estimates.[4] Among the *SHP_I* and *SHP_II* samples, we select the occupied labour force belonging to the working-age population (15-65 for

[3]Complete interview data are available for 7799 and 3654 individuals in 1999 and 2004, respectively. The net response rates (referring to all called individuals minus those with neutral problems such as invalid telephone number or foreign language) are quite high, attaining 85% in 1999 and 76% in 2004. The random samples were stratified according to seven large regions of Switzerland, proportionally to the number of phone connections in the comprehensive Swiss phone directory. Interviews were carried out in German, French and Italian using computer-assisted telephone interviewing. Further details on the sampling methodology and questionnaires are available at www.swisspanel.ch.

[4]The SHP dataset includes cross-sectional weights for each wave to adjust for non-response at the individual and household level. See Graf (2009) for a detailed description of the procedures that have been implemented for computing weights in the SHP. Using Stata's `svy` command, all descriptive and regression analyses incorporate cross-sectional

men, 15-62 for women); we also remove the self-employed and those currently in education.[5] Taken together, the final sample in the first waves contains 2,504 and 1,042 individuals, respectively, for *SHP_I* and *SHP_II* samples.

3 Empirical methods

3.1 Measuring educational mismatch

This subsection begins by summarizing basic methods to measure educational mismatch and highlighting their weak points. Then, we present an alternative measurement method that accounts for heterogeneity in skills among workers being over- and undereducated according to the statistical method of realized matches.

3.1.1 Critical overview of existing methods

In the literature, three methods are generally used for measuring required schooling (see, e.g., Hartog, 2000, for a complete overview). The first measure is obtained from the *job analysis* method; according to this objective method, the level of education required to perform a particular job is obtained from a systematic job evaluation. It is important to note that this information is actually unavailable for Switzerland. Second, some surveys include the *worker's self-assessment* of educational requirement; this subjective method consists in asking workers directly how much education is required to get or do their job. Finally, required schooling can be defined by the *realized matches* method. There exist two main measures derived from this objective and statistical method. First, the required education is defined as a band around the mean level of education within each occupation (Verdugo and Verdugo, 1989). Workers are then overeducated (resp. undereducated) if their actual education expressed in years diverges by more than one standard deviation above (resp. below) the mean value for a given occupation. The

individual weights to take into account the sampling design of the SHP and thus obtain reliable estimates concerning the population of interest. Accordingly, Stata calculate robust standard errors using the 'linearization' variance estimator based on a first order Taylor series linear approximation. For more information on variance estimation approaches used in Stata for commonly estimated survey statistics, we refer readers to Eltinge and Sribney (1997e,c,a,d,b).

[5]See Table 4 of the appendix for more details on the sample selection procedure. In the empirical analysis, we use the Heckit method to test if the OLS estimators are biased due to sample selection.

required education can also be established from the modal rather than the mean level of education (Kiker et al., 1997). Accordingly, workers are overeducated (resp. undereducated) if their educational attainment falls above (resp. below) the modal value for a specific occupation.

All the measures of required schooling have been criticized for various reasons (for comprehensive discussions, see Hartog, 2000; Borghans and Grip, 2000; Chevalier, 2003; McGuinness, 2006; Verhaest and Omey, 2006; Leuven and Oosterbeek, 2011). Given its expensive and lengthy implementation, the job analysis approach cannot be updated on a regular basis. Accordingly, the job requirements are assumed to be fixed over time when using this measurement method. However, the characteristics of a given occupation may change over time, as the education required to perform it. If the correspondence between education and job classification is not regularly updated, such approach may bias the incidence of educational mismatch. The measure based on the worker's self-assessment also tend to be subject to measurement error, in particular if the formulation of the question lacks detailed instructions regarding the evaluation of the job requirements. In other words, respondents may report the required schooling according to different criteria that are not necessarily observed by the researcher. At the same time the subjective method is more attractive than others since it allows one to relax the assumption that all jobs within a given occupation have the same requirements. Whereas the statistical measure can always be computed, it presents the disadvantage of being sensitive to how levels of completed schooling or occupations are aggregated in order to estimate reliable parameters of the education distribution across jobs (namely the mean, the standard deviation or the mode). As noted by Kiker et al. (1997) and Mendes de Oliveira et al. (2000), the standard deviation procedure has the disadvantage, with respect to the modal measure, that it is more sensitive to the presence of outliers in the data. In addition, it relies on the strong assumption of symmetry, while the modal level of education within a particular occupation better reflects the potential asymmetry of the distribution. Last, applying the realized matches method on the basis of the whole labour force may lead to a systematic underestimate of the required educational level, given that this method implicitly neglects skill acquisition through experience and on-the-job training.

A serious drawback of basic measurement methods stems from the assumption that overeducated workers with a given level of schooling are perfect substitutes. Indeed, a few studies (see, for instance, Chevalier, 2003; Robst, 2008; Green and Zhu, 2010; Pecoraro, 2011) show that this hypothesis may substantially bias both the incidence and wage effects of overeducation in the context of the graduate labour market. These studies suggest that overeducated graduates form a heterogeneous group. Chevalier (2003) proposes an

alternative measure based on objective overeducation and job satisfaction. Derived from the job analysis method, overeducation is then either *apparent* or *genuine*, according to whether overeducated workers are satisfied or not with the match between their education and their job. Taking a different look, Robst (2008) considers educational mismatch based on both the quantity and type of schooling. After measuring over- and undereducation from realized matches, he decomposes overeducated workers into three groups, depending on whether they assess their job as closely, somewhat or not related to their degree field. In the spirit of Chevalier's approach, Green and Zhu (2010) disaggregate self-assessed overeducation into two categories: overeducated workers are in a state of *formal* or *real* overeducation, in accordance with whether skills are reported to be fully utilized or underutilized. Chevalier (2003), Robst (2008) and Green and Zhu (2010) respectively show that a significant percentage of all overeducated graduates (i) are satisfied with the match between their education and their job, (ii) work in jobs closely related to their degree field or (iii) fully utilize their skills. They also establish that the aforementioned groups of overeducated graduates undergo relatively small wage losses with respect to well-matched graduates.

3.1.2 Alternative measurement method

We follow Chevalier (2003), Robst (2008) and Green and Zhu (2010) by rejecting the assumption that educationally mismatched workers are homogeneous. As pointed out by Green and McIntosh (2007), individuals with the same level of education have different actual skill levels, so that they can be overeducated, while their skills are actually appropriate for the jobs that they do. We propose an alternative measure of educational mismatch based on a statistical measure of required education (through the *realized matches* method) that incorporates the *worker's self-assessment* of skill utilization.

We derive required schooling from the mode of workers' actual educational attainment in each occupation,[6] separately by survey year (i.e. 1999 and 2004) using the selected sample as specified in Section 2.[7] In order to avoid any impact from labour market discrimination against the first and

[6]The modal-based measure is preferred since it is less sensitive to the presence of outliers in the data, and it also enables to relax the assumption of symmetry inherent to the standard deviation method.

[7]The small number of selected individuals in the *SHP_II* sample might lead to unreliable estimates because we have not enough observations in some occupations. To handle this problem, it was decided to add individuals from the *SHP_I* sample, also interviewed in 2004, when computing the modal measure of required education. However, it should be noted that our descriptive and estimation results do not change when using only the selected individuals in the *SHP_II*. These results are available upon request.

second generations of immigrants (naturalized included), we calculate the modal values on the basis of workers of Swiss origin (i.e. with the Swiss citizenship and at least one parent that is/was Swiss by birth). The highest level of education achieved consists of 10 levels classified in an increasing hierarchical order; each educational level is translated into the total number of years of schooling (see Table 5 in the appendix).[8] For the occupation level, we rely on the International Standard Classification of Occupations (ISCO) disaggregated on a 2-digit level with at least 10 observations in a year; this amounts to about thirty occupation levels.[9] Keep in mind that a worker is considered as overeducated (resp. undereducated) when his actual education is higher (resp. lower) than the modal value of education for his occupation.

Unlike Chevalier (2003) who relies on a measure of match satisfaction prone to endogeneity,[10] we decompose educationally mismatched workers according to perceived skill utilization. Respondents were asked 'How do you estimate your qualifications with regard to your current job?' with four possible answers (after omitting non-response items): [1] qualifications correspond to the job, [2] qualifications are too important, [3] qualifications are not sufficient or [4] qualifications are not related to the job. While the second and third answers refer to the cases of over- and underskilling respectively, the latter may reflect situations in which acquired skills are not utilized. In the remainder of the analysis, we consider two outcomes: skills are either adequate (i.e. corresponding to the job) or not adequate (i.e. too important, not sufficient or not related to the job).

As previously stated, the realized matches method may produce downward biased estimates of required education since it does not account for skill acquisition in the labour market. The subjective measure of skill utilization reduces the bias associated with the statistical approach, as it identifies whether skills among over- and undereducated individuals are adequate or not for their job. As a matter of fact, it allows us to verify if the statistical mismatch is genuine or apparent. Overeducated individuals that assess their skills as adequate (resp. not adequate) are defined as apparently (resp. genuinely) overeducated. Identically, undereducated individuals that assess their skills as adequate (resp. not adequate) are defined as apparently (resp.

[8] A duration of zero years has been attributed to workers with incomplete compulsory school.

[9] Further information on the ISCO classification are available at the ILO website (http://www.ilo.org/public/english/bureau/stat/isco/index.htm).

[10] As pointed out by Robst (2008), job satisfaction may be a function of earnings. The fact that low earnings can increase workers' dissatisfaction may in part explain Chevalier's result that the pay penalty associated with overeducation is larger when overeducated workers indicate low levels of satisfaction with their job.

Table 1: Alternative measure of educational mismatch

	Educational mismatch	
	Genuine	Apparent
Statistically overeducated		
▷ adequately skilled		×
▷ overskilled	×	
▷ underskilled	×	
▷ skills not related	×	
Statistically undereducated		
▷ adequately skilled		×
▷ overskilled	×	
▷ underskilled	×	
▷ skills not related	×	

genuinely) undereducated. As in Chevalier (2003), we do not consider the self-assessment of individuals being adequately educated. Assuming that adequately educated workers cannot assess their skills as inadequate has the disadvantage that we underestimate the aggregate incidence of skills mismatch. Table 1 summarizes how the statistical measure of educational mismatch is disaggregated. Note that decomposing genuine educational mismatch into three categories (depending on whether skills are too important, not sufficient or not related to the job) does not alter our findings, although, as shown later, we get less reliable estimates for each new subcategories given their smaller size.

3.2 Returns to educational mismatch

Our point of departure is the Mincer wage equation (Mincer, 1974) widely used in empirical economics:

$$\ln w_i = \alpha^a S_i^a + \beta_1 EXP_i + \beta_2 EXP_i^2 + X_i\delta + \epsilon_i \tag{1}$$

where w_i is the gross hourly wage for individual i, S^a corresponds to actual years of schooling, α^a is the rate of return to actual schooling, EXP denotes the potential work experience, X is a vector of observed personal characteristics and ϵ_i represents the error term. In order to study the wage effects of educational mismatch, Duncan and Hoffman (1981) propose an extension

of previous equation in which actual years of education are decomposed into three terms: $S^a = S^r + S^o - S^u$, with S^r being years of required education, S^o being years of overeducation and S^u being years of undereducation. Recall that S^r is obtained through the realized matches method. If $S^a > S^r$ (case of overeducation) then $S^o = S^a - S^r$ and $S^u = 0$; conversely, if $S^a < S^r$ (case of undereducation) then $S^o = 0$ and $S^u = S^r - S^a$. Finally, $S^o = S^u = 0$ when $S^a = S^r$ (case of adequate education). Decomposing actual years of schooling in equation 1, we get the "standard" ORU specification:

$$\ln w_i = \alpha^r S_i^r + \alpha^o S_i^o + \alpha^u S_i^u + \beta_1 EXP_i + \beta_2 EXP_i^2 + X_i\delta + \epsilon_i \qquad (2)$$

where α^r is the return to required education, α^o is the return to overeducation and α^u is the return to undereducation. According to this specification, over- and undereducated workers are compared to those correctly matched in the same occupation.[11]

As noted by Leuven and Oosterbeek (2011), two theoretical models can fit the data on the basis of the ORU specification. First, the *human capital model* (Becker, 1964) states that educational mismatch is a temporary phenomenon, since the labour market is supposed perfectly competitive with flexible wages ensuring that workers are paid their marginal product. Consequently, wages depend on worker's characteristics and the job requirements do not matter in the wage determination process; that is $\alpha^r = \alpha^o = -\alpha^u$ and equation 2 reduces to equation 1. A second theoretical explanation stems from the *job competition model* (Thurow, 1975). Contrary to the human capital model, the marginal product resides in the job rather than the worker's characteristics.[12] Hence, wages are entirely determined by required education: $\alpha^o = \alpha^u = 0$. If previous models fail to fit the data, which means that $\alpha^r \neq \alpha^o \neq |\alpha^u|$, the

[11]There exists another specification proposed by Verdugo and Verdugo (1989) where educational mismatch is incorporated into equation 1 through dummy variables. In comparison to the ORU specification, this specification is conceptually less attractive, since it neglects the continuous character of required, surplus and deficit years of education. The ORU specification is then preferred, as it allows to identify the returns to educational mismatch in contrast to the return to adequate schooling.

[12]In the job competition model, useful job skills are mostly acquired through on-the-job search and learning-by-doing. While the wage is no longer the variable of adjustment between the supply and demand for labour, there is a queue of workers competing against each other for job opportunities based on their relative training costs. Since these costs are assumed to decrease with workers' level of education, the latter will determine their position in the queue, those at the head of it being hired first. Workers will then have incentives to invest in terms of education in order to protect their place in the queue by offering better traits than their competitors, so that they appear more trainable to potential employers. These incentives should be even more important in case of a higher supply of educated labour. This model therefore provides an explanation for educational overinvestment and thus overeducation.

ORU specification will be consistent with a model in which wages are jointly given by worker and job characteristics. Most earlier studies lend support to this conclusion (Hartog, 2000; McGuinness, 2006; Leuven and Oosterbeek, 2011), in particular: (1) return to overeducation is positive and lower than return to required education, i.e. $\alpha^r > \alpha^o > 0$, (2) return to undereducation is negative and lower than return to required education in absolute value, i.e. $\alpha^u < 0$ and $\alpha^r > |\alpha^u|$. Point (1) amounts to the following statement: overeducated workers earn less than well-matched workers with the same educational attainment, but more than well-matched workers in the same occupation. According to point (2), undereducated workers earn more than well-matched workers with the same educational attainment, but less than well-matched workers in the same occupation.

In a next step, we present a new version of equation 2 that incorporates our alternative measure of educational mismatch. The following equation is designated as the "new" ORU specification:

$$\ln w_i = \alpha^r S_i^r + \alpha^o S_i^o + \alpha^u S_i^u + \widetilde{\alpha}^o \widetilde{S}_i^o + \widetilde{\alpha}^u \widetilde{S}_i^u + \beta_1 EXP_i + \beta_2 EXP_i^2 + X_i\delta + \epsilon_i \quad (3)$$

where $\widetilde{S}^k = \widetilde{D} \times S^k$, with $k \in \{o, u\}$. $\widetilde{D}$ is a dummy variable indicating if skills are not adequate. The coefficient α^k measures then the return to apparent mismatch, while the coefficient $\widetilde{\alpha}^k$ measures the differential effect of genuine mismatch as opposed to apparent mismatch.

From now on, we consider two hypotheses that are generally verified in the ORU literature. To begin, we test whether the human capital or the job competition models are both rejected, meaning that the coefficients in equation 2 are not equal i.e. $\alpha^r \neq \alpha^o \neq |\alpha^u|$ (referred to as ***Hypothesis A***). Allen and van der Velden (2001) and Green and McIntosh (2007) show that individuals not adequately utilizing their skills suffer from a pay penalty compared to individuals whose skills correspond to their job. Accordingly, we expect that over- and undereducated workers with adequate skills earn more than over- and undereducated workers with inadequate skills. This argument leads to ***Hypothesis B*** in the context of equation 3: $\widetilde{\alpha}^k < 0$, with $k \in \{o, u\}$. In a sense, this expected result has certain similarities to the findings of previous studies that consider overeducated graduates as a heterogeneous group (Chevalier, 2003; Robst, 2008; Green and Zhu, 2010); in particular, overeducated workers that are only mismatched on the basis of the quantity of schooling are less penalized in terms of earnings than those also (i) dissatisfied with the match between their education and their job, (ii) in jobs not related to their degree field or (iii) underutilizing their skills.

Equations 1 to 3 are estimated using the Ordinary Least Squares (OLS) with the first waves of both *SHP_I* and *SHP_II* samples pooled as a cross-section (the cross-sectional individual weights are taken into account in this

estimation procedure). The dependent variable in all equations is the natural logarithm of gross hourly earnings in the respondent's current job,[13] while X includes dummy variables for gender, national origin and the *SHP_II* sample. All the explanatory variables are presented in Table 6, while descriptive sample statistics are presented in Table 7 (see the appendix).

4 Results

4.1 Descriptive statistics

Table 2 presents how the incidence of educational mismatch evolves over time. The upper part of this table shows proportions derived from the realized matches method. According to the modal measure, the majority of workers are adequately educated and their share is ranging between 60% and 64% over the period under consideration. About a fifth are overeducated in 1999 and this proportion has significantly decreased by 4 percentage points five years later. Also around a fifth are undereducated, but the extent of undereducation has remained stable since 1999. It appears that these proportions of over- and undereducated workers are generally below the overall means reported by existing studies included in the latest meta-analysis provided by Leuven and Oosterbeek (2011), i.e. 30% and 26% for the proportions of over- and undereducated workers, respectively. This pattern is also consistent with the cross-country findings of Quintini (2011) showing, on the basis of the modal method, that Switzerland has both very low incidences of over- and undereducation. In the literature, there exist different explanations for cross-country differences in overeducation. For instance, Di Pietro (2002) have found that the incidence of overeducation is positively related to the educational composition of the labour force and the strictness of employment protection legislation, but negatively related to the level of R&D investment. Other factors put forward to explain these cross-country differences are the quality and orientation (general versus specific) of the educational system (see Verhaest and Van der Velden, 2012).

When focusing on the alternative measure of educational mismatch, previous results are clearly overestimated. Among the whole group of overeducated workers, less than a third are in a situation of genuine overeducation, the remainder of this group being then apparently overeducated. Besides,

[13] We calculate gross hourly earnings by dividing the gross monthly earnings by the reported number of hours worked per week multiplied by 4.3 (weeks); this method of calculating gross hourly earnings is standard in empirical studies of wages (e.g. Dustmann and Soest, 1997; Zaiceva, 2010). Moreover, earnings are deflated into 2000 Swiss francs.

there is no significant change in the prevalence of genuinely overeducation between 1999 and 2004. The low proportion of genuinely overeducated workers (5%) is in line with the fact that there is a shortage of qualified labour in Switzerland (Huth, 2004; Schellenbauer et al., 2010). Concerning undereducated workers, at least 4/5 of them are apparently undereducated; among all workers, it corresponds to a proportion of 16% in either 1999 or 2004. Lastly, the share of genuinely undereducated also remains stable across both samples and does not exceed more than 4%.

Table 2: Incidence of educational mismatch

Year Sample	1999 *SHP_I*	2004 *SHP_II*	Total
Modal measure			
Adequately educated	0.606	0.635	0.614
	(0.010)	(0.016)	(0.009)
Overeducated	0.209	0.168**	0.197
	(0.009)	(0.012)	(0.007)
Undereducated	0.185	0.197	0.188
	(0.009)	(0.014)	(0.007)
Alternative measure			
Adequately educated	0.606	0.635	0.614
	(0.010)	(0.016)	(0.009)
Apparently overeducated	0.153	0.121**	0.143
	(0.008)	(0.010)	(0.006)
Genuinely overeducated	**0.057**	**0.047**	**0.054**
	(0.005)	**(0.007)**	**(0.004)**
Apparently undereducated	0.156	0.161	0.158
	(0.008)	(0.013)	(0.007)
Genuinely undereducated	**0.029**	**0.036**	**0.031**
	(0.004)	**(0.006)**	**(0.003)**
Observations	2,504	1,042	3,546

Linearized standard errors in parentheses

Source: Swiss Household Panel, first waves of both *SHP_I* and *SHP_II* samples, data are weighted.

Note: Test for a significant difference in proportions across *SHP_I* and *SHP_II* samples (** p<0.05, * p<0.10).

4.2 Return to educational mismatch

In order to assess the wage effects of educational mismatch, we estimate equations 1 to 3 using the OLS regression technique that takes into account cross-sectional weights to get nationally representative results. Estimates are shown in Table 3. The first line of the first column shows a positive rate of return to an additional year of actual schooling, amounting to 0.063. According to a review of the existing literature on the returns to schooling in Switzerland (Weber and Wolter, 1999), this coefficient falls in the interval $(0.055, 0.091)$, the lower and upper bound corresponding to the lowest and highest coefficients obtained from estimations of the Mincer wage equation without or with only a few additional control variables. In line with Hartog (2000), we find that the return to required schooling in equation 2 is higher than the return to actual schooling in equation 1, i.e. $0.075 > 0.063$. In addition, estimates based on the ORU specification give support to the joint inequality $\alpha^r \neq \alpha^o \neq |\alpha^u|$ as in most earlier studies. Indeed, workers earn a positive return of 0.067 for a year of overeducation and a negative return of -0.044 for a year of undereducation, their absolute value being lower than the return to required education. ***Hypothesis A*** is confirmed by the rejection of formal tests of the human capital and the job competition models using the F statistic (i.e. $H_{01} : \alpha^r = \alpha^o = -\alpha^u$ and $H_{02} : \alpha^o = \alpha^u = 0$ respectively).

When examining the estimates in equation 3, in which educational mismatch is decomposed according to perceived skill utilization, it appears that we cannot reject ***Hypothesis B*** (i.e. $\widetilde{\alpha}^k < 0$, with $k \in \{o, u\}$). In other words, genuinely over- and undereducated workers suffer from a pay penalty compared to apparently over- and undereducated workers. While the latter receive a return of 0.072 for a year of overeducation and a return of -0.039 for a year of undereducation, the former are confronted to a decrease in their returns to over- and undereducation corresponding to -0.017 and -0.035 respectively. Furthermore, apparently overeducated workers have similar wage returns compared to others with the same schooling but who are properly matched. This is not surprising since those apparently overeducated work in jobs commensurate with their skills, so that an additional year of schooling is rewarded equally among both adequately educated and apparently overeducated workers. Interestingly, the absolute value of the total return to genuine undereducation (i.e. $\alpha^u + \widetilde{\alpha}^u$) is equal to the return to required education. As a result, genuinely undereducated workers are paid their marginal product: their wages are solely determined by attained level of schooling independent of the job requirements. Hence, the human capital hypothesis holds for workers being apparently overeducated or genuinely undereducated (the null hypothesis $H_{03} : \alpha^r = \alpha^o = -(\alpha^u + \widetilde{\alpha}^u)$ is not rejected according to the

Table 3: Wage returns to educational mismatch: OLS results

Equation	(1)	(2)	(3)
S^a	0.063**		
	(0.003)		
S^r		0.075**	0.076**
		(0.005)	(0.005)
S^o		0.067**	0.072**
		(0.004)	(0.005)
S^u		-0.044**	-0.039**
		(0.006)	(0.006)
$\widetilde{S}^o$			-0.017**
			(0.008)
$\widetilde{S}^u$			-0.035**
			(0.014)
$H_{01} : \alpha^r = \alpha^o = -\alpha^u$		11.65**	
$H_{02} : \alpha^o = \alpha^u = 0$		167.84**	
$H_{03} : \alpha^r = \alpha^o = -(\alpha^u + \widetilde{\alpha}^u)$			0.14
$H_{04} : \alpha^o = \alpha^u + \widetilde{\alpha}^u = 0$			117.49**
$H_{05} : \alpha^r = \alpha^o + \widetilde{\alpha}^o = -\alpha^u$			14.66**
$H_{06} : \alpha^o + \widetilde{\alpha}^o = \alpha^u = 0$			62.06**
Observations	3,546	3,546	3,546
R^2	0.253	0.261	0.264

Linearized standard errors in parentheses, ** p<0.05, * p<0.10

Source: Swiss Household Panel, first waves of both *SHP_I* and *SHP_II* samples pooled as a cross-section, data are weighted.

Note: Unreported controls are potential experience, experience squared, a dummy for gender, a dummy for origin and a dummy for *SHP_II* sample. Full regression equations are reported in Table 8 of the appendix.

F statistic). Lastly, note that $\alpha^r > \alpha^o + \widetilde{\alpha}^o > 0$, $\alpha^r > |\alpha^u|$ and $\alpha^u < 0$. Thus, genuinely overeducated workers earn less than well-matched workers with the same educational attainment, but more than well-matched workers in the same occupation. Conversely, apparently undereducated workers earn more than well-matched workers with the same educational attainment, but less than well-matched workers in the same occupation. This pattern is verified by the rejection of the null hypotheses $H_{05} : \alpha^r = \alpha^o + \widetilde{\alpha}^o = -\alpha^u$ and $H_{06} : \alpha^o + \widetilde{\alpha}^o = \alpha^u = 0$ using the F statistic.

Decomposing genuine over- and undereducation into three categories (depending on whether skills are too important, not sufficient or not related to the job) does not alter our findings. The estimation results using this more detailed decomposition are presented in Table 9 of the appendix. At first sight, the estimated returns to apparent over- and undereducation remain equivalent to those computed from equation 3. All the coefficients associated with interactions between years of over/undereducation and the different forms of skills mismatch are negative, although most of them are weakly or not significant given the smaller size of each new subcategories. It is worth mentioning that overeducated workers whose skills are not related to their job face a marked and significant decrease in their return to excess schooling compared to those overeducated but matched in skills. Actually the return to overeducation in case of unrelated skills falls to zero, since we cannot reject the hypothesis that the sum of α^o and the coefficient associated with the interaction 'skills not related' $\times S^o$ is equal to zero (the F statistic is equal to 1.13 with a p-value of 0.2885). Put differently, the wages of the overeducated workers with unrelated skills are only determined by required education.

Given that our OLS estimates are based on a selected sample of salaried employees, it is important to test for the presence of selectivity bias when estimating equations 1 to 3. For that purpose, we use the maximum likelihood version of the *Heckit* method which consists in adding the inverse Mills ratio $\hat{\lambda}$ (computed on the basis of the whole working age population) as an additional regressor in the original OLS regressions and test for significance using a t test (Heckman, 1979). When estimating the Heckit model, we follow most of the papers in the literature (e.g. Sloane et al., 1999; Dolton and Vignoles, 2000; Di Pietro and Cutillo, 2006): we use the number of children in household (under 18 years) that is assumed to affect sample selection (i.e. the likelihood of being salaried employees) but not the dependent variable (i.e. the log of gross hourly earnings). As stressed by Manning and Petrongolo (2008), "this is a very strong assumption that may not, in reality, be any better than the exogeneity assumption that this is supposed to replace". However, they also admit that it is difficult to find a variable affecting the selection indicator but not earnings directly. The results of the Heckit proce-

dure (presented in Table 10 of the appendix) show that the inverse Mills ratio is not significant, meaning there is no evidence of selectivity bias. The Heckit estimates are very similar to those assuming the exogeneity assumption in Table 3.

All these results confirm that apparently overeducated workers receive broadly similar returns for a year of actual education than those adequately educated with the same schooling. Accordingly, the human capital hypothesis is relevant for a majority of those overeducated, which indicates the need to account for the heterogeneity in skills when measuring educational mismatch in the labour market.

5 Conclusion

This study has provided an empirical contribution to the literature on the incidence and wage effects of educational mismatch using cross-sectional data from the Swiss Household Panel survey. When measuring over- and undereducation, we have departed from the usual assumption that educationally mismatched workers are implicitly mismatched in skills since standard measures of educational mismatch simply refer to the concept of either excess or deficit schooling and do not account for worker heterogeneity in skills. Instead, we have proposed an alternative measure of educational mismatch based on the statistical evaluation of required education that incorporates the worker's self-assessment of skill utilization. Over- and undereducated workers, identified through the realized matches method, are considered as apparently or genuinely mismatched depending on whether they assess their skills as corresponding or not to their job. This decomposition is important not only for determining the true extent of educational mismatch within workers, but also for mitigating the bias in the estimated returns to over- and undereducation due to the measurement error induced by the realized matches method.

Based on the assumption of worker homogeneity, the statistical method actually overestimates the incidence of educational mismatch. Among all workers, at least 20% are overeducated but only 5% are overeducated and, at the same time, perceive their skills as not adequate (i.e. genuine overeducation). In other words, the majority of overeducated workers carry out a job commensurate with their skills (i.e. apparent overeducation). The low proportion of genuinely overeducated workers is consistent with the view that the Swiss labour market is experiencing a shortage of qualified professionals.

Within the ORU framework, two hypotheses generally confirmed by previous studies have been tested. First, the wage returns to over-, required and

undereducation should not be equal in the sense that the human capital or the job competition models are both rejected (***Hypothesis A***). Second, when decomposing educational mismatch according to perceived skill utilization, genuinely over- and undereducated workers should incur a wage penalty compared to those apparently over- and undereducated (***Hypothesis B***). Our OLS estimation results give support to these hypotheses. Estimated returns to required, surplus and deficit years of education in Duncan and Hoffman's wage equation are significantly different; in particular, the total return to education is lower (resp. higher) among overeducated (resp. undereducated) workers than among well-matched workers with the same level of education, while it is higher (resp. lower) among overeducated (resp. undereducated) workers than among well-matched workers in the same occupation. Moreover, being mismatched in both education and skills is associated with a reduction of 1.7% (resp. 3.5%) in returns to overeducation (resp. undereducation) as opposed to overeducated (resp. undereducated) workers with adequate skills. Most importantly, apparently overeducated workers receive broadly similar returns for a year of actual education than those adequately educated with the same schooling. Therefore, the human capital hypothesis is relevant for a majority of those overeducated, which indicates the need to account for the heterogeneity in skills when measuring educational mismatch in the labour market.

Finally, it should be pointed out that our estimation results may still be plagued by the omitted ability bias since we have assumed that unobserved ability is uncorrelated with educational mismatch. If this assumption turns out to be violated, the OLS estimates of the rates of return to over- and undereducation are biased. Indeed, in case of a negative correlation between unobserved ability and overeducation, the omission of unobserved ability underestimates the rate of return to overeducation. On the other hand, a positive correlation between unobserved ability and undereducation leads to an overestimation of the rate of return to undereducation. As the SHP dataset has a longitudinal structure, we could control for unobserved ability by means of fixed effects. However, given that there is little or no variation in actual education over time, we are unable to properly identified the fixed effects estimates of the returns to over- and undereducation.[14]

[14]Since years of actual education are decomposed into years of over-, required and undereducation in Duncan and Hoffman's wage equation, the within-individual variation in years of over-, required and undereducation is characterized by perfect multicollinearity for persons whose actual education is constant across time.

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A Appendix

Table 4: Individuals retained in the empirical analysis

Selection criteria	Sample/Year			
	SHP_I/1999		*SHP_II*/2004	
	No. of i	%	No. of i	%
Individual interview completed	7,799	100.0	3,654	100.0
Working age population	6,297	80.7	2,856	78.2
Valid information on the national origin*	6,182	79.3	2,856	78.2
Employed**	4,810	61.7	2,386	65.3
Valid information on employment status	4,764	61.1	2,036	55.7
Salaried employees***	3,460	44.4	1,357	37.1
Valid information on occupational category	3,399	43.6	1,350	36.9
Occupation with at least 10 observations	3,378	43.3	1,336	36.6
Valid information on perceived skill utilization	3,361	43.1	1,330	36.4
Valid information on gross hourly earnings	2,504	32.1	1,042	28.5

Source : Swiss Household Panel, first waves of both *SHP_I* and *SHP_II* samples.

Note : Observations with 'valid information' are observations without missing values.

* National origin is measured by the respondent's citizenship and their parents' nationality at birth.

** We exclude individuals who reported being unemployed or not in the labour force.

*** We exclude individuals who reported being self-employed or enrolled in education.

Table 5: Conversion scale between levels and years of education

Description	Years of schooling
Primary and lower secondary level	
Compulsory school, elementary vocational training	9
Domestic science course, 1 year school of commerce	10
Upper secondary level	
General training school	12
Apprenticeship	12
Full-time vocational school	12
Maturity (high school)	12
Tertiary level	
Technical or vocational school	15
Higher vocational college	15
University	18
PhD	21

Source: Codebook for CNEF variables in the SHP (Lipps and Kuhn, 2009).

Table 6: Explanatory variables included in the empirical analysis

Continuous variable	Dummy variable	Ref.
Years of actual education (S^a)	**Gender**	
Years of required education (S^r)	*Male*	×
	Female	
Years of overeducation (S^o)	**Origin**	
	Swiss	
Years of undereducation (S^u)	*Foreign*	×
Potential experience (= Age − S^a − 6)	**Sample/Year**	
	SHP_I/1999	×
Potential experience squared	SHP_II/2004	

Table 7: Summary statistics

Sample Year	*SHP_I* 1999	*SHP_II* 2004	Total
Years of actual education (S^a)	12.943 (0.066)	12.819 (0.096)	12.907 (0.054)
Years of required education (S^r)	12.704 (0.036)	12.967 (0.066)	12.781 (0.032)
Years of overeducation (S^o)	0.895 (0.041)	0.616 (0.045)	0.813 (0.032)
Years of undereducation (S^u)	0.656 (0.039)	0.764 (0.065)	0.688 (0.034)
Potential experience	21.949 (0.259)	23.653 (0.391)	22.448 (0.216)
Female	0.426 (0.010)	0.481 (0.016)	0.442 (0.009)
Swiss origin	0.733 (0.010)	0.717 (0.016)	0.728 (0.009)
Gross hourly earnings (Swiss francs)	38.695 (0.824)	35.353 (1.120)	37.716 (0.669)
Observations	2,504	1,042	3,546

Linearized standard errors in parentheses.

Source: Swiss Household Panel, first waves of both *SHP_I* and *SHP_II* samples, data are weighted.

Table 8: Wage returns to educational mismatch: full OLS results

Equation	(1)	(2)	(3)
S^a	0.063**		
	(0.003)		
S^r		0.075**	0.076**
		(0.005)	(0.005)
S^o		0.067**	0.072**
		(0.004)	(0.005)
S^u		-0.044**	-0.039**
		(0.006)	(0.006)
$\widetilde{S}^o$			-0.017**
			(0.008)
$\widetilde{S}^u$			-0.035**
			(0.014)
EXP	0.036**	0.037**	0.037**
	(0.003)	(0.003)	(0.003)
EXP^2	-0.001**	-0.001**	-0.001**
	(0.000)	(0.000)	(0.000)
Female	-0.183**	-0.180**	-0.179**
	(0.015)	(0.015)	(0.015)
Swiss origin	0.071**	0.084**	0.081**
	(0.017)	(0.017)	(0.018)
SHP_II sample	-0.058**	-0.061**	-0.060**
	(0.015)	(0.015)	(0.015)
Constant	2.269**	2.084**	2.076**
	(0.055)	(0.071)	(0.071)
$H_{01} : \alpha^r = \alpha^o = -\alpha^u$		11.65**	
$H_{02} : \alpha^o = \alpha^u = 0$		167.84**	
$H_{03} : \alpha^r = \alpha^o = -(\alpha^u + \widetilde{\alpha}^u)$			0.14
$H_{04} : \alpha^o = \alpha^u + \widetilde{\alpha}^u = 0$			117.49**
$H_{05} : \alpha^r = \alpha^o + \widetilde{\alpha}^o = -\alpha^u$			14.66**
$H_{06} : \alpha^o + \widetilde{\alpha}^o = \alpha^u = 0$			62.06**
Observations	3,546	3,546	3,546
R^2	0.253	0.261	0.264

Linearized standard errors in parentheses, ** p<0.05, * p<0.10

Source: Swiss Household Panel, first waves of both *SHP_I* and *SHP_II* samples pooled as a cross-section, data are weighted.

Table 9: Wage returns to educational mismatch: additional results

Decomposing genuine over- and undereducation	
S^r	0.075**
	(0.005)
S^o	0.072**
	(0.005)
S^u	-0.039**
	(0.006)
overskilled $\times$ S^o	-0.006
	(0.008)
underskilled $\times$ S^o	-0.031
	(0.024)
skills not related $\times$ S^o	-0.096**
	(0.023)
overskilled $\times$ S^u	-0.027*
	(0.016)
underskilled $\times$ S^u	-0.048*
	(0.027)
skills not related $\times$ S^u	-0.040
	(0.035)
EXP	0.037**
	(0.003)
EXP^2	-0.001**
	(0.000)
Female	-0.176**
	(0.015)
Swiss origin	0.079**
	(0.017)
SHP_II sample	-0.060**
	(0.015)
Constant	2.088**
	(0.071)
Observations	3,546
R^2	0.268

Linearized standard errors in parentheses, ** p<0.05, * p<0.10

Source: Swiss Household Panel, first waves of both *SHP_I* and *SHP_II* samples pooled as a cross-section, data are weighted.

Table 10: Wage returns to educational mismatch: Heckit results

Equation	(1)	(2)	(3)
S^a	0.063**		
	(0.003)		
S^r		0.075**	0.076**
		(0.005)	(0.005)
S^o		0.067**	0.073**
		(0.004)	(0.005)
S^u		-0.044**	-0.039**
		(0.006)	(0.006)
$\widetilde{S}^o$			-0.017**
			(0.008)
$\widetilde{S}^u$			-0.035**
			(0.014)
EXP	0.036**	0.038**	0.038**
	(0.003)	(0.003)	(0.003)
EXP^2	-0.001**	-0.001**	-0.001**
	(0.000)	(0.000)	(0.000)
Female	-0.186**	-0.185**	-0.185**
	(0.015)	(0.015)	(0.015)
Swiss origin	0.071**	0.085**	0.082**
	(0.017)	(0.018)	(0.018)
SHP_II sample	-0.059**	-0.064**	-0.063**
	(0.015)	(0.015)	(0.015)
Constant	2.251**	2.040**	2.024**
	(0.075)	(0.084)	(0.084)
$\hat{\lambda}$	0.0138	0.0345	0.0407
	(0.035)	(0.027)	(0.027)
Observations	3,546	3,546	3,546
F statistic	132.4**	126.8**	103.9**

Linearized standard errors in parentheses, ** p<0.05, * p<0.10

Source: Swiss Household Panel, first waves of both *SHP_I* and *SHP_II* samples pooled as a cross-section, data are weighted.

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ISSN 1379-244X D/2012/3082/014