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Abstract

Graduates from Science, Technology, Engineering, and Mathematics (STEM) are usually found to have higher wages and a lower risk of overqualification. However, it is unclear whether we can interpret the effect of STEM subjects on overqualification and wages in a causal way, since individuals choosing these subjects might differ systematically in unobserved characteristics, such as ability. Using data on German male graduates we show that unobserved heterogeneity indeed matters for differences in the risk of overqualification and wages when STEM graduates are compared to the Business & Law group, while it plays only a minor role for the difference between STEM graduates and the Social Sciences & Humanities group.

JEL-classification: I21, J24, J31

Keywords: qualification mismatch, wages, sorting, graduates, field of study

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1 Introduction

There is a widespread belief in the public debate that Science, Technology, Engineering and Mathematics (STEM) are important drivers of innovations and play a key role for economic growth (Atkinson and Mayo, 2010). There is also some scientific evidence that the social returns to STEM education exceed the private benefits. For example, Winters (2013) finds that human capital externalities are especially high for STEM graduates. Hence, it is often claimed in western economies that the number of STEM graduates is too low and that policy makers should engage in increasing it.[1] This gave rise to recent policy initiatives for promoting STEM fields, for example in the US[2] or in Germany[3]. Since STEM graduates earn on average higher wages (Daymont and Andrisani, 1984; James et al., 1989; Grogger and Eide, 1995; Arcidiacono, 2004) and face a lower risk of overqualification (Dolton and Vignoles, 2000; Frenette, 2004; McGuinness, 2006) than non–STEM graduates, policies pushing pupils to study STEM subjects might also positively affect individual careers.[4] Moreover, such policies could enhance the efficiency of the tertiary education system by providing the graduates who are demanded by the labor market, if these policies would really reduce the risk of overqualification.

The positive effects of these policies on individual careers and on the skill match in the economy critically depend on the assumption that differences in overqualification and wages between subjects are attributable to the subjects studied rather than individual characteristics (sorting). However, there is evidence that STEM subjects are associated with more challenging studies and require higher ability (Betts and Morell, 1999; Rask, 2010; Arcidiacono et al., 2013). This is reflected in higher drop-out rates for students in STEM subjects. For example, the drop-out rate for mathematics and science in Germany is 39% and 48% for engineering, as compared to 24% in economics, social sciences and law.[5]

[1]For the US, see for example National Academies (2010) and ManpowerGroup (2013). For Germany, see for example the report of Anger et al. (2013) on skilled labour in STEM fields.

[2]For example, the National Science and Mathematics Access to Retain Talent (SMART) Grant or the “Educate to Innovate” initiative of the Obama administration.

[3]For example, the program “Komm Mach MINT” seeks to increase the number of female students in STEM fields of study (http://www.komm-mach-mint.de/). Other programs, which are often, but not always, publicly sponsored, are listed in the website of the STEM gateway “MINT Zukunft schaffen”: www.mintzukunftschaffen.de.

[4]Overqualification corresponds to a “vertical” educational mismatch denoting the possession of a higher qualification than the one necessary for the job. In the paper, we use the term skill mismatch and overqualification interchangeably. In particular, we refer to overqualified employees as (skill) mismatched employees and vice versa.

[5]Heublein et al. (2012), numbers for bachelor students based on the alumni year group 2010 in Germany.

Further, there is evidence from the US that pupils choosing STEM subjects have better results in both mathematics and verbal pre-college tests (Arcidiacono, 2004). Therefore, students in STEM subjects are likely to differ in their personal characteristics, such as ability, as compared to other students. This implies that the effect of the university field of study on wages and overqualification rates cannot be interpreted in a causal way unless controls for all relevant personal characteristics are appropriately included (Altonji et al., 2012). Employing a dynamic discrete choice model for the US, Arcidiacono (2004) finds indeed that most of the differences in wage returns to fields of study decrease after controlling for ability sorting. Policies promoting STEM subjects might thus push pupils into fields of study which do not fit their abilities. This would negatively affect the efficiency of these policy measures concerning the aim of providing adequate STEM graduates. Moreover, the overall effects of such policies on individual careers are unclear and could be even adverse.

Against this background, the present paper tests the hypothesis that higher wages and lower risk of overqualification of STEM graduates compared to other graduates are at least partly driven by differences in unobserved characteristics. We compare STEM graduates to graduates of Business & Law subjects and of Social Sciences & Humanities. The analysis is based on data from the German Socio–Economic Panel (GSOEP) for employed male graduates, which includes detailed information about the current job, such as a subjective evaluation of the required qualifications, and information on parental background and the educational career. To ensure that the results are not affected by the transition process from university to the labor market, we rely on employed individuals only who graduated at least five years prior to the survey. We use an instrumental variable approach to control for the selection of the individuals into subjects groups when estimating the effects of the subjects on wages and the risk of overqualification. Our exclusion restrictions are the difference in mathematics and German grades from the last school report (using average school grades as a control variable) and a binary variable indicating whether the individual played a music instrument in youth. Making use of linear and non-linear IV techniques, we find that selection matters for differences in the risk of overqualification and wages when STEM graduates are compared to the Business & Law group, while it plays only a minor role for the difference between STEM and the Social Sciences & Humanities graduates.

The rest of the paper is organized as follows. In Section 2 we provide a concise review of the literature. In Section 3 we discuss the role of sorting into subjects and how we take account of sorting in our econometric specification. In Section 4 we describe our data and we provide definitions, as well as summary statistics, for the variables included in the analysis. Section 5 contains the results of our estimations, while Section 6 concludes.

2 Literature Review

The approach of this paper is motivated by Job Assignment Models (c.f. Sattinger, 1993). In those models there exist different types of workers and different types of jobs. Workers choose jobs based on utility maximization and there is a certain technology which links workers with specific characteristics to jobs with specific characteristics. The quality of the match between workers and jobs affects the work productivity and thus leads to different labour market outcomes. There is growing empirical evidence in favor of Job Assignment Models (McGuinness, 2006). While the empirical literature building on these models usually focuses on the wage effects of overqualification, we are interested in the effects of worker characteristics on the quality of job matches. In particular, we are interested in how the field of study affects overqualification and wages as two key aspects of the quality of job match. We interpret them as outcomes of the assignment problem. There exist two strands of literature, which already deal with these issues.

The **first** strand of literature has grown rapidly in recent years with an increasing attention towards the variation of economic returns to university education by field of study. These studies provide evidence that STEM graduates earn higher wages than graduates in art, humanities and social sciences (Daymont and Andrisani, 1984; James et al., 1989; Grogger and Eide, 1995; Arcidiacono, 2004; Robst, 2007). The differences in the returns to higher education across subjects are found to be substantial and possibly larger than differences in returns to college quality (James et al., 1989). However, most studies do not account properly for selection into fields of study and simply use OLS with a large set of control variables. Selection might be a substantial problem, since students are likely to choose particular subjects based on the heterogeneity of returns. Moreover, omitted variables that influence both the choice of the fields of study and earnings may also lead to biased estimates. It is therefore not clear whether we can consider in this case OLS estimates as estimates of the causal impact of university subjects (Altonji et al., 2012). In particular, there is evidence that individuals choosing STEM fields perform better in both cognitive and verbal tests than individuals choosing other fields (Arcidiacono, 2004). Thus, OLS estimates are likely to overestimate the earnings returns to STEM subjects. Only few analyses attempt to address selection into fields of study. Webber (2014) uses a simulation approach and various assumptions about selection on unobservables to argue that large disparities in lifetime earnings between fields of studies remain even after addressing selection. Arcidiacono (2004) employs a dynamic discrete choice model and finds that most of the differences in wage returns to fields of study persist after controlling for selection, albeit they decrease in size. While structural models are very valuable to understand how individuals make sequential educational choices and can account for educational costs, they generally impose strong simplifications. In their recent review of the literature Altonji et al. (2012) state that "given the complexity and pitfalls of estimation based on dynamic structural models, we expect careful studies using IV strategies or OLS with rich controls to continue to play a critical role in the literature going forward". To the best of our knowledge, the only papers using an instrumental variable or a regression discontinuity approach to deal with selection into fields of study are Berger (1988) and Hastings et al. (2013). While Berger is mainly interested in estimating the impact of expected future earnings on subject choice, the author investigates also the wage returns to fields of study in the US. He focuses on five subject groups and uses some individual and family background characteristics, such as father's occupation, ethnic origin and parental education, as exclusion restrictions in the subject choice equation. However, the validity of these instruments might be questioned, since it is likely that family background characteristics could affect skills and earnings directly and not only through the subject choice channel. Hastings et al. instead estimate the returns to fields of study in Chile and use the thresholds in the centralized Chilean admission system to apply a regression discontinuity approach. They find large and significant differences in returns by field of study with higher returns for business, law and technical fields than for arts, architecture and humanities.

Apart from earnings returns, graduates in STEM fields seem to be also better off with respect to non–wage labour market outcomes than their peers graduating in other subjects. There is a general public perception that these subjects enable a better link to the labour market and that the skills provided by these curricula are more useful for future jobs. The **second** strand of literature therefore investigates how skill mismatch for graduates varies across fields of study (see Berlingieri and Erdsiek (2012) for a survey of the literature on skill mismatch in Germany). Most of these studies have focused on the discrepancy between the type of qualification (i.e. possessing a higher qualification than required) among graduates of different fields of study (Dolton and Vignoles, 2000; Frenette, 2004; Green and McIntosh, 2007).[6] Except for graduates of some specific majors, such as education or medicine, for whom this type of mismatch is close to zero, graduates majoring in STEM fields appear to have a lower risk of overqualification than graduates in humanities and social sciences (Büchel and Matiaske, 1996; Dolton and Vignoles, 2000; Frenette, 2004; McGuinness, 2006; Fehse and Kerst, 2007). Similarly to most of the studies on wage returns to university subjects, these studies focus on estimates from simple logit or probit regressions. However, the potential bias is likely to be larger for studies on qualification mismatch, since they typically fail to include fundamental control variables, such as high school grades. In fact, high school grades are found to be key predictors of both university subject choice and earnings (Rose and Betts, 2004). Since overqualification is typically associated to lower earnings, failure to take into account high school grades (or other proxies for ability) is likely to lead to an overestimation of the differences in job mismatch across fields of study. Moreover, to the best of our knowledge, no previous study on overqualification has tried to address directly the selection problem. It is still not clear if the cross–subject differences in qualification mismatch persist after controlling for the selection into different fields of study and, if so, how large is the bias when predictors of subject choice are omitted.

Further, as this paper addresses the role of sorting into subjects, it is related to studies which focus on the role of individual characteristics for the choice of the field of study. In the literature, individual characteristics such as gender and parents education (Boudarbat and Montmarquette, 2009), tastes and motivations (Hilmer and Hilmer, 2012) or expected earnings (Arcidiacono et al., 2012; Beffy et al., 2012; Freeman and Hirsch, 2008) have been found to be important predictors for subject choice. Notably, differences in ability affect the subject choice of college majors (Turner and Bowen, 1999). Moreover, Arcidiacono et al. (2012) show that students subject choice depends on the subject-specific abilities of

[6] Another literature investigates the role of fields of study for horizontal mismatch, i.e. mismatch between the content of the field of study and occupational content (see for example Robst, 2007).

the individuals. This suggests that differences in labor market outcomes between graduates of different subjects might be affected by the differences in omitted or unobserved individual characteristics.

In summary, graduating in a STEM subject is related to on average higher wages and a lower risk of overqualification. We hypothesize that this relationship is partly driven by sorting into fields of subject. That is, we expect that, if differences in (unobserved) individual characteristics are taken into account, the positive effect of graduating in STEM versus other fields on wages and the negative effect on the risk of overqualification decrease.

3 Econometric methods

In this paper, we apply instrumental variable (IV) techniques to control for the selection into subjects when estimating the effects of graduating in a subject on the risk of overqualification and wages. We first present the approach of our paper for modeling the probability of overqualification and wages, before we discuss our choice of instrumental variables. Finally, we present the implementation of our approach.

3.1 Approach

The aim of this paper is to estimate the effect of fields of study on wages and the probability of overqualification for graduates. Ideally, we would estimate the probability of an individual to work in a matched vs. mismatched job with a probit model,

$$Pr(\text{overqualified}_i = 1) = Pr(\beta X_{1,i} + \sum_{j=1}^{2} \phi_j \text{subject}_{ji} + \epsilon_i > 0) \ ; \ j = 1, 2 \tag{1}$$

where overqualified indicates whether individual i is overqualified (0 for non–overqualified and 1 for overqualified) and subject_{ji} is a dummy variable equal to 1 if the individual i graduated in the university subject j, taking into account other relevant covariates $X_{1,i}$. We distinguish between three groups of subjects j: STEM ($j = 0$) as the base category, Business & Law ($j = 1$) and Social Sciences & Humanities ($j = 2$).

Analogously, we are interested in the effect of the field of subject on wages, using log wages as the dependent variable. Ideally, we would estimate log wages in a linear specification:

$$\log \text{wage} = \delta X_{1,i} + \sum_{j=1}^{2} \varphi_j \text{subject}_{ji} + \varepsilon_i \ ; \ j = 1, 2 \tag{2}$$

The key problem for analyzing the effects of subjects on wages and overqualification is that the choice of the subject itself depends on observable and unobservable characteristics of the individuals. Assume that the utility U_{ji} of individual i to study subject j is a function of observable characteristics $X_{2,i}$ and unobservable characteristics η_{ji}, $U_{ij} = \theta_j X_{2,i} + \eta_{ji}$. Individual i will study subject j when his utility from studying this subject is higher than the utility from any other subject k and the probability that he will study subject j is

$$Pr(\text{subject}_{ji} = 1) = Pr(\theta_j X_{2,i} + \eta_{ji} > \theta_k X_{2,i} + \eta_{ki}) \ ; \ j \neq k \tag{3}$$

where $X_{2,i}$ represents covariates which influence the subject choice and might overlap with X_1.[7] There might be unobserved characteristics of the individuals that influence both, the choice of the subject and the probability of a mismatch resp. wages. For example, individuals choosing STEM university subjects might have on average a higher ability than individuals choosing other subjects. There might also be other unobserved characteristics which could affect both, the choice of the field of subject and labor market outcomes, such as for example motivation or ambition. These qualities are highly rewarded in the labour market and potentially decrease their probability of overqualification in the job resp. increase their wages. If this is the case, there will be a non–zero correlation between the error–terms of the equations, i.e. between η_{ji} and ϵ_i resp. ε_i.[8]

Then subject$_{ji}$ contains η_{ji}, which is correlated with ϵ_i and ε_i. Therefore, the estima-

[7] In the analysis we include in $X_{1,i}$ and $X_{2,i}$ demographic characteristics, family background and educational background characteristics. The two matrices differ with respect to two instrumental variables, which are included only in $X_{2,i}$. The detailed list and description of the variables included in the analysis is presented in Section 4.

[8] The sign of the correlation depends on the definition of the reference groups. In our case, graduating in STEM and being non–overqualified are the reference groups, so that we expect a positive correlation between η_{ji} and ϵ_i. This is because we expect that unobservables which are associated with a higher probability to graduate in STEM subjects are also associated with a lower probability of being overqualified. Analogously, we expect a negative correlation between η_{ji} and ε_i because we expect that unobervables which are associated with a higher probability to graduate in STEM subjects are associated with higher wages.

tion of the effect of subjects on the risk of overqualificaton resp. wages is inconsistent for β_1 and ϕ_j resp. δ_1 and φ_j. Hence, subject$_{ji}$ is a multinomial endogenous variable. In order to account for the potential endogeneity, we apply instrumental variable techniques. Through the instrumental variable approach we can estimate the effect of the fields of study on labor market outcomes excluding the effects of unobserved heterogeneity of the graduates. By comparing the estimates with and without the instrumental variables, we can visualize to what degree differences between fields of study are driven by unobserved heterogeneity. However, the precise underlying mechanisms cannot be identified. For example, unobserved heterogeneity might affect labor market outcomes through differences in ability, motivation or ambition between the graduates of different fields of study. Even though we cannot identify the precise underlying mechanisms, by distinguishing between the effects of unobserved heterogeneity and the direct effects of the fields of study, we can analyze whether policy measures aimed at improving individuals' labor market outcomes should focus on pre-university characteristics or on directly altering the relative number of students in different subjects. Further, we can discuss how promoting STEM subjects might affect labor market outcomes of those who are pushed in these subjects.

3.2 Instrumental variables

The key problem for our empirical analysis is that unobservable factors, such as ability, most likely not only affect the individual risk of overqualification and individual wages, but also the probability of graduating in a STEM vs. other subjects. We control for a wide range of individual characteristics. Further, we partly control for ability by using average school grades as a proxy. However, school grades only partly reflect ability, so that the unobserved variation of ability (which is not covered by school grades) still can lead to biased estimates for the effects of graduating in specific subjects. Moreover, there might be other unobservable characteristics which are linked to both, the choice of subjects and labor market outcomes, such as for example motivation or ambition. To address the selection problem, we employ two instrumental variables for the subject choice.

Our first instrumental variable is the difference of mathematics and German grades in the last year of school. We argue that, once we control for the average of high school grades in German and math as well as for other observables, the difference in grades has an effect on the job match and on wages only through the university subject. For example, assume that two individuals have the same overall ability, i.e. the same average math and German grades. The individual who has relative better math than German grades is more likely to choose a STEM subject, as this individual is likely to be more interested and has a comparative advantage in STEM topics. We argue that his comparative advantage in math does not have per se an effect on labour market outcomes. This might seem a strong assumption considering that there are studies stressing the role of high school mathematics grades on future earnings (Murnane et al., 1995; Joensen and Nielsen, 2009) and that, at least for the US, math courses might be more important for labour market outcomes than English courses (Rose and Betts, 2004). We conduct a series of robustness checks and informal tests to analyze whether this issue might be relevant in our case and to investigate if and in which direction our IV estimates might be biased. We conclude that, when controlling for broad field of study groups, mathematics grades do not have stronger effects on labour market outcomes than German grades. This is in line with novel evidence on returns to skills by Hanushek et al. (2013), who find that, contrary to the US, monetary returns to mathematical skills and to literacy skills are very similar in Germany. We are therefore convinced that the first instrument is valid.

Our second instrumental variable is a binary variable indicating whether the individual played a music instrument or was involved in other music activities in youth. Our argument is analogous to the above discussion. An individual, who played an instrument in youth is likely to have different interests compared to other individuals, hence choosing other subjects in university — holding constant all other variables. Once we control for average high school grades and other observables, such as family background characteristics, we argue that playing versus not playing an instrument affects wages and job match only through the university subject. Again, this might seem a strong assumption as there is literature arguing that playing an instrument in youth relates to outcomes such as skills, personality or educational achievement, even though such analyses usually do not detect causal effects (Hille and Schupp, 2013). Schellenberg (2004) provides evidence for a causal, albeit very small, effect on educational outcomes and IQ, while Hille and Schupp (2013) provide evidence for causal effects on skills, school grades and personality. Nevertheless, those effects are measured against the alternative of no extracurricular activity and for samples drawn from the whole population. As Schellenberg (2004) notes, other extracurricular activities might have very similar effects. Note that we focus on university graduates only, who are a homogeneous group, and that we rely on a rich set of covariates. If the alternative of playing an instrument is another activity with similar effects on skills, then differences in skills between those who played an instrument in the youth and those who did not are likely to be small and ambiguous. In a sample of graduates, who typically come from families with a higher social status, such as in our sample, this is more likely to be the case. Hence, we believe that there is only little room left for the variable "played an instrument in youth" to directly affect the remaining variation in overall ability, as we control for the most relevant variables which affect labour market outcomes and as we solely focus on graduates. Anyhow, we check whether the variable is a valid instrument using several strategies. First, we restrict our analysis to bivariate comparisons of subjects (STEM versus Business & Law and STEM versus Social Sciences & Humanities), so that we can check whether the two instruments are invalid using overidentification tests. The tests indicate that the instruments are not invalid. Second, we apply analogous robustness checks and informal tests as for the first instrument to analyze the validity of the second instrument. All tests suggest that the second instrument does not directly affect labour market outcomes when controlling for a rich set of control variables and broad field of study groups. We are therefore convinced that both instruments are valid.

3.3 Implementation

In order to implement our empirical approach, we rely on a probit specification for the risk of overqualification in equation (1) and a linear specification for log wages in equation (2). The key challenge is to account for the endogeneity of the subject choice. We therefore estimate the subject choice in equation (3) as a multinomial probit model. We then have two econometric models, one for subject choice and overqualification and one for subject choice and wages.

Having a probit specification for the risk of overqualification and a multinomial probit specification for the subject choice, we assume that the errors of both parts of the model follow a multivariate normal distribution, so that we can estimate a joint model of subject choice and overqualification using simulated maximum likelihood. Analogously, if we rely on a normally distributed error for our wage equation, we can estimate wages and subject choice in a joint model using simulated maximum likelihood. We rely on the Geweke-Hajivassiliou-Keane (GHK) algorithm for implementing the simulated maximum likelihood of these two mixed-process (MP) models (Geweke, 1989; Hajivassiliou and McFadden, 1998; Keane, 1994).

The two implementations are recursive models, where the endogenous variable of the multinomial probit part (the subject choice) appears as an explanatory variable in the probit part (risk of overqualification) resp. the linear part (log wages). Only the equation for the risk of overqualification resp. wages is fully specified. For the subject choice equations, we rely in both cases on instrumental variables to address the endogeneity problem. Hence, we apply a limited-information maximum likelihood estimator for the two models (Roodman, 2011).

In the multinomial probit model for the subject choice, we choose STEM as the base category, so that we can compare how choosing Business & Law or Social Sciences & Humanities over STEM affects wage and overqualification.[9] This implies that the base category is not included in equations (1) and (2) and that we use $\theta_0 = 0$ to define the base category in the multinomial probit in equation (3). Our multinomial probit part is based on the independence of irrelevant alternatives (IIA) assumption. We cannot relax this assumption because we do not have alternative-specific variables. However, we use tests to check whether this assumption is violated.

As we have two endogenous variables (in both, the model for wages and overqualification), we require two instrumental variables. We compare our main specifications, the MP models, with corresponding single-equation models for the risk of overqualification (probit model) and wages (ordinary least squares, OLS). We do so in order to compare how taking account the endogeneity affects the results, so that we can visualize the role of sorting into subjects for wages and overqualification.

Actually, we do not need any instruments to technically identify these models, since the non–linearity is already sufficient for technical identification. Moreover, the non–linearity will contribute to the identification of the model even if we do include instruments, such that it is hard to distinguish whether identification is due to the instruments or the non–linearity (Altonji et al., 2005). We therefore compare our basic specification to linear specifications where the identification solely relies on the instruments. In particular, we

[9]Choosing STEM as the base category might seem counterintuitive, given that we are mainly interested in the results for STEM. However, note that if we would choose e.g. Business & Law as the base category, we were unable to discuss how choosing Social Sciences & Humanities instead of STEM (or vice versa) would affect wages and overqualification. Therefore, in order to discuss how choosing STEM versus Social Sciences & Humanities and STEM versus Business & Law affects wages and overqualification, we have to choose STEM as the base category.

model the probabilities of choosing Business & Law versus STEM resp. Social Sciences & Humanities versus STEM as individual linear probability models (LPMs).[10] Based on these, we apply two-stage least squares (2SLS) approaches for estimating the effects of the choice of subjects on wages and the risk of overqualification (with a LPM-specification for overqualification).

We compare these implementations to other specifications to check the robustness of our results. First, we compare our results to the approach proposed by Deb and Trivedi (2006, 2009), where the correlation of the error terms of the multinomial treatment equation (subject choice) and the outcome equation (overqualification resp. wages) is modeled by introducing a latent variable which enters both parts of the model (henceforth DT). Second, for wages we apply the two-step procedure proposed by Wooldridge (2010, p.939), where we use the predicted probabilities from separate probit models for the subject choices (Busines & Law versus STEM and Social Sciences & Humanities versus STEM) as instruments in the outcome equation.[11] The advantage of this IV estimator (henceforth ATEIV) is that it is more efficient than the standard 2SLS, if the probit model is a better approximation for the first stage than the linear model (Newey, 1990).

4 Data and descriptive statistics

4.1 Data source and key variables

The sample used is drawn from the German Socio–Economic Panel (GSOEP), a panel data set for the years 1984-2011 consisting of about 20,000 individuals living in Germany (see Kroh (2012), for details). We focus on highly educated males surveyed in the years 2001 to 2011, for whom there is information about the subject of their tertiary degree. We restrict the analysis to male graduates, since female labour market participation in Germany is strongly influenced by child care and family responsibilities. The investigation of females therefore requires a different econometric approach that takes into account selection out of the labour market. On the contrary, more than 96% of male graduates under 55 in

[10] In addition to the strong assumptions implied by the LPM, this specification further treats the two subject choices as independent processes. Therefore, this implementation does not take into account the correlation of the two subject choice equations.

[11] This implementation, just like the LPM models from above, does not take into account the correlation of the two subject choice equations.

our SOEP sample are employed.[12] The 11 GSOEP waves include 4,081 male adults aged between 26 and 65 with a university degree (including universities of applied studies) and for 2,252 there is information on the field of study.[13] Of these, 2,064 are employed in one of the 11 waves. We select one observation per individual such that the time since graduation is minimized, but is at least 5 years. Moreover we drop individuals graduating before the age of 20 or after the age of 35, because the likelihood to obtain a university degree at a later stage of life might be higher for particular subject groups and we want to hinder that this could possibly affect our results. We end up with a sample of 896 individuals, for whom we have information on all variables relevant for our analysis. Most of the reduction of the sample is due to missing values for high school grades, which are available for about 75% of employed graduates.[14]

To analyze differences across fields of study, we divide graduates into three broad groups: STEM, Business & Law and Social Sciences & Humanities. Graduates in the fields of medicine and education (or teaching) are omitted from the analysis, because of the specificity of the link between education and occupation.[15] We consider as STEM fields mathematics, natural sciences (physics, chemistry and biology), computing, engineering and architecture.[16] The Business & Law group comprises law, management, public management, managerial engineering and economics. All other subjects including other social sciences, arts and humanities are grouped in the Social Sciences & Humanities category. Table 5 provides a detailed overview of the fields of study included in each subject group category.

Overqualification is measured based on workers' self–assessment about the educational requirement of the job. More precisely, the following question is asked in the GSOEP

[12]Of these, less than 2% are respectively unemployed and non–employed and the shares differ only slightly across the three subject groups considered. Because of early retirement provisions, the share of employed workers is lower for male graduates aged 55 to 65. Table 10 shows that our main results are not driven by this age group.

[13]Note that the high number of lost observation is mainly due to the fact that this type of information was not asked in the biography questionnaire before 2001

[14]Again, this is because this information was only asked in the biography questionnaire starting in 2001. Therefore, we do not have information for individuals entering the GSOEP before 2001 if they already completed high school.

[15]In Germany, students graduating in medicine and teaching have to take a state examination at the end of their studies. For each discipline, these state examinations are a prerequisite for holding a civil service job or a job regulated by the state. Since graduates of these subjects cannot be overqualified if they act within their profession, they face a very low overqualification risk.

[16]We follow the classification provided by the German Institute for Employment Research (IAB) for MINT subjects (the German acronym for STEM). See for example, IAB (2010). Re-defining architecture as a Social Sciences & Humanities field does not qualitatively alter the results.

questionnaire: "what type of education or training is usually necessary for this type of work?" We consider an individual to be overqualified if a graduate reports that her job requires a vocational degree or a no degree at all.[17] The measure, which is widespread in the overeducation literature, has the drawback of relying on the subjective individual self–assessment. Nevertheless, several authors have claimed that the measurement errors are probably less severe for this measure than for measures based on the distribution of educational qualification within occupations – i.e. "realized matches" on the qualification required by the job. This is because the latter is the result of demand and supply forces and it ignores variation in required schooling across jobs within an occupation (Leuven and Oosterbeek, 2011).

Hourly wages are measured through the self-reported monthly gross income divided by monthly working hours. We calculate real wages based on the CPI deflator using 2010 as the base year. In order to ensure that outliers are not driving the main results we trim wages excluding the 1st and the 99th percentile (individuals receiving a hourly wage lower than EUR 5 or higher than EUR 100) and we employ the standard logarithmic form for the wage regressions.

Concerning high school grades, we have data on the mathematics and the verbal (German) score from the last school report. These two subjects are the only compulsory courses for the high school diploma in most federal states in Germany. Grades are measured using the 6 points scale typical for the German system. We reverse the order of the grades in order to ease the interpretation of the regression results, so that 6 is the highest grade and 1 the lowest. We construct the variable *Grade:average*, which equals the individual average of the two grades, and the variable *Grade:difference*, resulting from subtracting math grades from verbal ones. The latter will be positive for students with a comparative advantage in math, negative for those better in German and equal to zero for students receiving the same grade for both subjects.

The school grades play an important role for the entrance of pupils into the university system in Germany. At the end of school education in the upper secondary level, pupils can earn the Abitur or Fachabitur, which qualifies them for general (Abitur) or subject-specific (Fachabitur) higher education entrance. University students typically have a general higher education entrance qualification, whereas the share of subject-specific higher

[17]Note that we do not distinguish between university and university of applied science (*Fachhochschule*) degrees, although the variable allows such a distinction.

education entrance qualification is higher for students at universities of applied sciences (Fachhochschule). In specific subjects where the number of applicants typically exceeds the number of available places at universities, the allocation of places to applicants is centrally organized at the national level and based on the final grade of the Abitur. Students whose final Abitur grade is not sufficient can queue for a place at a university whereas their queuing time depends on their grade. Universities also have individual university-specific entrance limitations for other subjects, which are typically based on the final Abitur grade and which are specific to the subjects. In these subjects, individuals require a minimum grade (numerus clausus) for registering as a student. For many subjects, however, no entrance limitation exists and anyone with a higher education entrance qualification can register as a student.

4.2 Descriptive results

Table 1 presents the mean and standard deviation for relevant variables. STEM subjects represent the largest field of study group (53%) followed by Business & Law (31%) and Social Sciences & Humanities (16%). The sample composition across fields of study reflects the fact that the STEM subjects are typically male-dominated subjects, differently from subjects of the other fields. 34% of the sample studied at an university of applied science (*Fachhochschule*, abbr. *FH*) for their highest degree. More than two thirds of graduates have an 'Abitur' high-school degree, which allows direct access to university. The great majority of those who don't have such a degree graduated then from an university of applied science (meaning that the variables 'Abitur' and 'FH degree' are negatively correlated). About 16% have a high-school degree providing direct access only to universities of applied sciences (Fachhochschulreife). Almost 30% of graduates did a professional apprenticeship, which is done in general before starting university. FH graduates are more likely to have done such an apprenticeship. Instead of actual experience we include potential experience, specifically time since graduation, which is independent from the unemployment spells. The average time since graduation is 19 years, while the average age is 46 years. The majority of the individuals was born in the 50s and the 60s.

Table 2 shows summary statistics of the dependent variables and other main variables by the three field of study groups employed. In our sample graduates from the Business & Law group earn on average slightly more than STEM graduates. Graduates from Social

Table 1: Summary statistics

	mean	sd	min	max
Subject group				
STEM fields	0.53	0.50	0	1
Business & Law	0.31	0.46	0	1
Social Sciences & Humanities	0.16	0.36	0	1
Dependent variables and other main variables				
Real hourly wage (log)	3.15	0.45	1.55	4.54
Overqualified	0.14	0.35	0	1
Grade: average	4.68	0.72	2.5	6
Grade: difference	0.26	1.08	-4	4
Played music in youth	0.37	0.48	0	1
Demographic characteristics				
Christian	0.60	0.49	0	1
Migration background	0.07	0.25	0	1
Parental education and employment				
Father: higher educ.	0.28	0.45	0	1
Mother: higher educ.	0.09	0.29	0	1
Mother non employed (age 15)	0.45	0.50	0	1
Pre-graduation characteristics				
FH degree	0.34	0.48	0	1
Apprenticeship	0.27	0.44	0	1
University access (Abitur)	0.69	0.46	0	1
FH access (Fachhochschulreife)	0.16	0.36	0	1
Birth year				
Born before 1950	0.19	0.40	0	1
Born in the 1950s	0.32	0.47	0	1
Born in the 1960s	0.29	0.46	0	1
Born in 1970 or after	0.19	0.39	0	1
High school federal state				
Schleswig-Holstein & Lower Saxony	0.11	0.3	0	1
Hamburg & Bremen	0.03	0.18	0	1
North Rhine-Westphalia	0.21	0.41	0	1
Hesse, Rhinel.-Palatinate & Saarl.	0.13	0.34	0	1
Baden-Wuerttemberg	0.14	0.34	0	1
Bavaria	0.14	0.34	0	1
Berlin	0.02	0.12	0	1
East Germany or outside Germany	0.22	0.41	0	1
Post-graduation characteristics				
Married	0.90	0.29	0	1
Urban region	0.56	0.50	0	1
Job in West Germany	0.70	0.46	0	1
Time since graduation	19.15	9.92	5	43
Time since grad. squared	465.3	404.3	25	1849
Survey year				
Surveyed in 2001 or 2002	0.27	0.44	0	1
Surveyed in 2003, 2004 or 2005	0.33	0.47	0	1
Surveyed in 2006, 2007 or 2008	0.15	0.36	0	1
Surveyed in 2009, 2010 or 2011	0.25	0.43	0	1

The summary statistics refer to the final sample of 896 observations.

Sciences & Humanities have on average the lowest earnings. Concerning overqualification, STEM graduates face a lower risk of being mismatched (12%) followed by the Social Sciences & Humanities (14%) and Business & Law (18%). As regards average grades from the last school report, STEM graduates received on average better grades than the other two groups. This supports our hypothesis that STEM graduates might have on average higher ability, meaning that there is some ability sorting into fields of study. The figures on the difference between math and German grades anticipate the results of the first stage regressions. STEM graduates had a comparative advantage in math at school, while Social Sciences & Humanities graduates had a comparative advantage in German. Graduates of the Business & Law group had on average very similar German and math school grades. The Social Sciences & Humanities group presents the highest share of individuals playing an instrument or being involved in other music activities in youth (47%), followed by STEM and Business & Law graduates (37% and 33% respectively).

Table 2: Relevant variables by field of study

	STEM		Business & Law		Social Sciences & Humanities	
	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.
Real hourly wage (log)	3.16	0.44	3.24	0.47	2.94	0.43
Overqualified	0.12	0.33	0.18	0.38	0.14	0.35
School grade: average[a]	4.82	0.7	4.54	0.73	4.54	0.73
School grade: difference	0.56	0.99	0.01	1.1	-0.27	1.05
Played music in youth	0.37	0.48	0.33	0.47	0.47	0.5

[a]Note that we reverse the order of grades typical to the German system, so that 6 is the highest and 1 the lowest grade.

5 Results

5.1 Impact of university subjects on overqualification

Our first aim is to investigate the impact of the field of study on the probability of being overqualified. To do so, we explicitly model the subject choice to address the selection into the three broad subject groups considered. We include the difference in math and German high school grades and whether the individual played a musical instrument in youth as instrumental variables for the subject dummies (see Section 3). In order to highlight the relevance of modeling the sorting into subjects, we compare the results of the instrumental variable model with a simple linear probability model and a probit model for the probability of overqualification where we do not account for sorting.

The results from the overqualification regressions are shown in Table 3. The first two columns present the results of the linear probability model, where the overqualification dummy is regressed on the fields of study dummies and a large set of demographic, family background, pre-graduate education and geographic control variables. We show the coefficients for the subject groups Business & Law and Social Sciences & Humanities, leaving STEM fields as the comparison group. While the specification in column 2 includes the average of math and German grades from the last school report, this variable is omitted in the model of column 1. Graduates in STEM fields appear to be less likely to be overqualified than graduates in other fields. According to the first specification the coefficient is of about 8% for Business & Law graduates (significant at the 99% confidence level) and of about 6% for Social Sciences & Humanities graduates (significant at the 90% confidence level). The point estimates decrease by about 1 percentage point in the second specification, when we control for school grades. High school grades have a negative and significant effect on the overqualification probability and appear to be an important omitted variable in the first specification. Since graduates in STEM fields had on average better grades at school, the difference in the overqualification risk with respect to other graduates decreases when grades are controlled for.

Column 3 of Table 3 shows the results of the instrumental variable model with a linear probability model for the overqualification equation. Panel A shows again the coefficients for the main variables from the overqualification equation. Panel B shows the coefficients of the instrumental variables and the average school grades for the subject choice equation. The coefficients in Panel B are average marginal effects. In Section 4 we already anticipated the relationship between the instrumental variables and the subject dummies. Panel B shows that this relationship is strong also in the model including control variables (i.e. the other instruments). First of all, the coefficients for the difference in grades are negative and strongly significant for both Business & Law and Social Sciences & Humanities. This means that individuals with a comparative advantage in mathematics are more likely to choose STEM subjects than the other two subject groups. Second, the coefficient for playing music in youth is negative and significant for Business & Law and

Table 3: Effect of fields of study on the risk of overqualification

	LPM		MP LPM[a]	Probit	MP Probit[b]
	(1)	(2)	(3)	(4)	(5)
Panel A: Overqualification equation					
Business & Law	0.084***	0.075***	0.021	0.068***	-0.075
	(0.027)	(0.027)	(0.035)	(0.025)	(0.081)
Social Sc. & Humanities	0.057*	0.046	0.500***	0.045	0.210*
	(0.034)	(0.034)	(0.034)	(0.033)	(0.114)
Grade: average		-0.045**	-0.026	-0.048***	-0.051***
		(0.018)	(0.020)	(0.016)	(0.019)
Demographic charact.	Yes	Yes	Yes	Yes	Yes
Parental education	Yes	Yes	Yes	Yes	Yes
Pre-graduation charact.	Yes	Yes	Yes	Yes	Yes
Post-graduation charact.	Yes	Yes	Yes	Yes	Yes
School state dummies	Yes	Yes	Yes	Yes	Yes
Panel B: Subject choice equation					
Business & Law fields					
Grade: difference			-0.120***		-0.122***
			(0.017)		(0.017)
Played music in youth			-0.084**		-0.086**
			(0.040)		(0.039)
Grade: average			-0.074**		-0.076***
			(0.029)		(0.028)
Social Sc. & Humanities					
Grade: difference			-0.098***		-0.116***
			(0.015)		(0.015)
Played music in youth			0.048		0.043
			(0.032)		(0.034)
Grade: average			-0.075***		-0.076***
			(0.024)		(0.023)
Control variables					
Demographic charact.			Yes		Yes
Parental education			Yes		Yes
Pre-graduation charact.			Yes		Yes
Post-graduation charact.			Yes		Yes
School state dummies			Yes		Yes
Observations	896	896	896	896	896
R-sq.	0.111	0.118			

Standard errors in parentheses; * p<0.10, ** p<0.05, *** p<0.01. The coefficients in Panel B and in columns (4) and (5) are average marginal effects. [a] MP model with linear specification for the overqualification equation; [b] MP model with probit specification for the overqualification equation.

positve but not significant for Social Sciences & Humanities, meaning that individuals playing music in youth are less likely to choose Business & Law subjects and are more likely to choose other Social Sciences & Humanities subjects. Third, the average of mathematics and German high-school grades has a strong impact on the field of study chosen. Students with higher grades select themselves into STEM fields. We test the two instruments for joint significance in the multinomial probit model using the likelihood ratio (LR) statistic. The test statistic is of 81, which is much larger than the 99 % critical values for $\chi^2(4)$. Thus the result confirms that the instruments are relevant.[18]

Turning to the results of the subject equation (Column 3, Panel A) the coefficient for Business & Law graduates decreases now to 2% and becomes insignificant. It appears thus that the differences between graduates of this group and STEM graduates are almost entirely explained by selection into subject groups. Conversely, the coefficient for Social Sciences & Humanities increases strongly suggesting that graduating in Social Sciences & Humanities increases the risk of overqualification relative to graduating in STEM disciplines. Thus the results point towards the presence of individual unobservable characteristics, which simultaneously increase the chance of studying Social Sciences & Humanities and lower the risk of overqualification. It remains unclear, which characteristics these might be. Nevertheless, the group of Social Sciences & Humanities is both small and heterogeneous, and this might affect the results. Columns 4 and 5 show the results for the simple probit regression and the instrumental variable model with a probit model for the overqualification equation, respectively. All the coefficients shown are average marginal effects, so that we can compare these to the coefficients of the previous models. Comparing the outcomes from the model in column 5 to the simple probit, we can find a similar pattern as the one found with the linear models (contrasting the linear probability model with the model in column 3). In the non-linear instrumental variable model (column 5) the Business & Law coefficient becomes even negative. The Social Sciences & Humanities coefficient increases, albeit to a lower extent than in the linear instrumental variable model (column 3). These results are robust with respect to the specification used, as the 2SLS and DT specifications lead qualitatively to the same results (Table 6).

[18] We also estimate a simple 2SLS model considering the two subject dummies as independent variables in order to compute the Angrist and Pischke multinomial F-test of excluded instruments (Angrist and Pischke, 2008). The test statistic equals 18.6 for Business & Law and 23.6 for Social Sciences & Humanities, much above the rule-of-thumb value of 10.

5.2 Impacts on wages

Our second aim is to investigate the effect of subjects on wages. The main model we estimate is the MP model following the procedure described in Section 3, which allows us to take into account the non-linearity of the first stage regression. The instruments used are the same as for the overqualification models and the model is analogous to the one presented in column 3 of Table 3. Again, we compare our main model to two OLS models with and without the inclusion of the average high-school grades.

Column 1 of Table 4 shows the results of the OLS regression when grades are omitted. Graduates in Business & Law subjects appear to receive hourly wages that are very similar to those of STEM graduates. The difference in earnings between the two groups of graduates found in the descriptive table thus disappears when we include control variables. Differently, graduates in Social Sciences & Humanities earn about 25% less than the above groups and the coefficient is highly significant. Column 2 shows the results of the same model when average grades are controlled for. As expected, the coefficient of school grades is positive, but is not significant at standard confidence levels. Nevertheless, it seems to be important to control for grades since the point estimates for the subject group dummies change slightly. Consistently with ability sorting into STEM fields, the negative coefficient of Social Sciences & Humanities decreases, while the Business & Law coefficient increases.

Column 3 of Table 4 shows the results of the MP model. Again, Panel B shows the coefficients of the instrumental variables and the average school grades for the subject choice equation. The coefficient shown in Panel B are average marginal effects. Since the subjects choice equations are the same as for the overqualification results, the coefficients are almost the same. Coefficients for the log wage equation are shown in Panel A. The coefficient for Business & Law subjects is larger compared to the OLS coefficient, but remains insignificant because of the larger standard errors of the IV model. The difference in hourly wages between Business & Law graduates and STEM graduates increases to about 10%. Similarly to the overqualification regressions, selection into subjects appears to play a role when we compare these two groups, although the effect is still insignificant. However, note that the effect becomes significant if we exclude self-employed individuals or individuals with migration background (see Table 10). Conversely, the coefficient for Social Sciences & Humanities decreases slightly in the MP model. Thus, selection does not seem to matter much for the difference between the STEM and the Social Sciences &

Table 4: Effect of fields of study on log hourly wages

	OLS		MP
	(1)	(2)	(3)
Panel A: Wage equation			
Business & Law	-0.003	0.002	0.102
	(0.029)	(0.030)	(0.105)
Social Sciences & Humanities	-0.249***	-0.243***	-0.245**
	(0.037)	(0.038)	(0.115)
Grade: average		0.025	0.031
		(0.020)	(0.021)
Demographic charact.	Yes	Yes	Yes
Parental education	Yes	Yes	Yes
Pre-graduation charact.	Yes	Yes	Yes
Post-graduation charact.	Yes	Yes	Yes
School state dummies	Yes	Yes	Yes
Panel B: Subject choice equation			
Business & Law fields			
Grade: difference			-0.122***
			(0.017)
Played music in youth			-0.088**
			(0.040)
Grade: average			-0.076***
			(0.029)
Social Sciences & Humanities			
Grade: difference			-0.117***
			(0.015)
Played music in youth			0.036
			(0.034)
Grade: average			-0.070***
			(0.024)
Control variables			
Demographic charact.			Yes
Parental education			Yes
Pre-graduation charact.			Yes
Post-graduation charact.			Yes
School state dummies			Yes
Observations	896	896	896
R-sq.	0.353	0.355	

Standard errors in parentheses; * p<0.10, ** p<0.05, *** p<0.01. The coefficients in Panel B are average marginal effects.

Humanities group. The results are robust with respect to the specification employed, as we get comparable results with the ATE IV, 2SLS and DT specifications (Table 7). The coefficient for Social Sciences & Humanities are larger in the ATE IV and DT compared to the MP specification and insignificant in the ATE IV and 2SLS specifications, but they again remain close to those of the OLS models, such that our interpretation remains unaffected.

5.3 Robustness checks

In Section 3 we highlighted that there are studies showing that mathematics skills are particularly important for labour market outcomes (Murnane et al., 1995; Joensen and Nielsen, 2009). Therefore, there might be reasons to be suspicious about the validity of the difference in grades instrument. For example, if mathematics grades would have a larger positive effect on wages than German grades (other than through the field of study chosen), this might lead to biased IV estimates. Since the grade difference is negatively correlated with the Business & Law and Social Sciences & Humanities dummies, coefficients of the two subject dummies would be underestimated in the 2SLS wage equations. By the same token, if mathematics grades would matter more than German grades for overqualification, this would lead to an overestimation of the two subject dummies in the 2SLS overqualification equation. Therefore, if mathematics grades matter more than German grades for labour market outcomes, the IV models would underestimate the bias of a possible ability sorting into STEM subjects. We perform an informal test to investigate whether math and German grades have different impacts on the dependent variables. Table 8 shows the results of OLS regressions for overqualification and wages highlighting the impact of high school grades. For each dependent variable, we show the results from two specifications - with and without the inclusion of subject dummies. The coefficient for average grade is, as expected, negative for the overqualification regressions and positive for the wage regressions. Conversely, the coefficient of the difference in grades (i.e. of the instrumental variable) is never significant in any specification. When subject dummies are not controlled for, the coefficient is small and negative in the overqualification regression (column 1) and small and positive in the wage regression (column 3). From these regressions mathematics grades seem to be slightly more important than German grades for labour market outcomes, even if the effect is close to zero and far from being significant.

However, when we control for subject dummies the coefficient approaches zero in the overqualification regression (column 2) and reverses sign in the wage regression (column 4). We receive similar results when regressing wages (resp. overqualification) on math and German grades, i.e. both grades have effects of similar sizes on wages (resp. overqualification). This informal test suggest that the difference in grades does not directly affect labour market outcomes, i.e. that it is a valid instrument. This is in line with recent evidence, which shows that returns to mathematical and literacy skills are very similar in Germany (Hanushek et al., 2013).

The exogeneity of the other exclusion restriction i.e. playing music in youth could be also called into question. We believe that in our setting the potential concerns are minimized for the reasons outlined in section 3.2. Nevertheless, we perform the same informal test also with this second instrumental variable. The results are shown in Table 9. The coefficient for playing music in youth is never significant in any specification. The coefficient is positive in the overqualification equation and is about 2% in both specifications (with or without subject dummies). Conversely, it is negative and about 3% in the wage equation without subject control variables, but drops to the half (1.4%) when subject dummies are included. All coefficients are very small and far from being significant. Thus, playing music in youth does not seem to have a direct effect on overqualification and wages, i.e. we are confident that it is a valid instrument.

Since our model is just-identified, we cannot directly implement a test of overidentifying restrictions in our context. A simple solution is to drop one of the three subject categories, estimate a GMM IV model with the binary subject dummy as endogenous variable and test our overidentifying instruments. We first drop the Social Sciences & Humanities category and estimate a model comparing STEM fields to Business & Law fields. The test statistic of the Hansen-Sargan test equals 0.017 (p-value of 0.90). Similarly, dropping the Business & Law fields and comparing STEM to Social Sciences & Humanities, we get a test statistic of 0.635 (p-value of 0.43). Finally, if we drop STEM fields and follow the same procedure we get a test statistic of 2.44 (p-value of 0.12). Therefore, in none of the three cases we would reject the null hypothesis that the two instruments are valid. The conditions under which the overidentification test can fail to detect invalid instruments seem implausible in our case (c.f. appendix 7.1).

Although we restrict our sample to employed males with at least 5 years of potential experience (measured as time since graduation), our sample is still very heterogeneous. Ideally, we would like to look at potential heterogeneous effects by interacting the instrument with relevant individual characteristics. However, because of the small sample size and the many control variables, this is impracticable. A feasible alternative is to exclude small sub-samples of individuals and estimate the main specifications with a restricted sample. This can also ensure that our results are consistent for the whole sample and are not driven by large effects for very specific graduates. Table 10 shows the results for sub-samples excluding self-employed, part-time workers and older cohorts, respectively. We included self-employed workers in our main specification, because we consider self-employment to be an outcome of the university subject choice. However, individuals with a propensity towards self-employment might choose specific fields especially because they allow them the possibility to be self-employed. Moreover, self-employed workers might respond differently to the question regarding the qualifications required for the job and this can affect the overqualification variable.[19] Results for the sub-sample of employees are shown in Panel A of Table 10. If anything, we can observe larger differences to the main model for the wage regression than for overqualification regressions. While the point estimates in the OLS do not differ too much to the main specifications, the difference to the coefficients in the IV model gets larger. On the one hand, the coefficient for Business & Law increases to 0.22 and is now statistically significant (at the 90% confidence level). On the other hand, the coefficient for Social Sciences & Humanities is of -0.13 (about 9 percentage points larger than the estimate in the OLS case). Panel B shows the results when we exclude part-time workers. Again, we did not control for part-time jobs considering them more an outcome of the study choice than an individual attitude. This argument is especially valid for involuntary part-time. On the contrary, voluntary part-time might be the outcome of individual attitudes such as family orientation. The results for the sub-sample of full-time workers are very similar to the main results. This is not surprising since there are only 24 males in our sample that work in part-time jobs. Panel C shows the results for a younger sub-sample, namely if we exclude individuals born before 1950. Also in this case the results do not differ qualitatively. Nevertheless, it has to be pointed out that ability sorting (or other similar unobservable biases) seem to play

[19]A concern is that self-employed could underestimate the qualification required by the job. Indeed, self-employed workers are more likely to report to be overqualified in the job. The overqualification incidence is of 19% for self-employed and of 14% for other worker and this difference is significant (at the 99% confidence level) according to a simple t-test.

a smaller role for the difference in wages between STEM and Business & Law graduates when older cohorts are excluded.

6 Conclusions

In this paper, we analyze the effects of graduating in STEM fields and other subjects on wages and the risk of overqualification. Unobservable factors, such as for example ability, are likely to affect not only wages and the risk of overqualification, but also the probability of graduating in a specific subject. We therefore apply instrumental variable techniques to control for the selection into subjects.

We find that the risk of overqualification for Business & Law graduates is about 7-8% higher compared to STEM graduates, even when controlling for individual, family, and other characteristics. However, once we control for the selection into subjects, no significant differences in the risk of overqualification remain between these groups. This implies that differences in the risk of overqualification between these groups are driven by the selection of individuals into these fields of study. Further, controlling for individual, family and other characteristics we find almost no wage differences between Business & Law and STEM graduates. However, once we control for selection, we find that Business & Law graduates earn on average 10% more than STEM graduates.[20] This indicates that on average we observe only minor wage differences between STEM and Business & Law, because of the differences of the individuals that choose these subjects.

The results for Social Sciences & Humanities are less clear. Graduates in these subjects face a higher risk of overqualification, and it seems that this risk is even higher when controlling for selection into subjects. This would imply that studying Social Sciences & Humanities is associated with a higher risk of overqualification than studying STEM and that this is reduced on aggregate by the selection of students with favorable unobserved characteristics into Social Sciences & Humanities. Further, Social Sciences & Humanities graduates earn less than STEM graduates and controlling for selection into subjects does not significantly affect this wage gap. However, this group accounts for only 16% of the sample and contains very diverse subjects, so that these results could be influenced by the small sample size and the diversity of the subjects.

[20] The effect is only significant when individuals with migration background or self-employed individuals are excluded from the sample.

We apply several robustness checks in order to ensure the robustness of our results. Our results are robust with respect to different specifications, variations of the sample, and in- or exclusion of control variables. Further, we provide tests to confirm the credibility of our instruments.

Our results indicate that it is not sufficient to compare average wages and average risks of overqualification between fields of study when one is interested in the individual returns to subject choices. Moreover, the results are highly relevant for education policy. They suggest that policies promoting STEM over Business & Law subjects could negatively affect wages while having no effect on the risk of overqualification for pupils, who would otherwise have chosen Business & Law. This does not imply that such policies are ineffective. Assuming that there is a lack of STEM graduates, such policies could be an option to increase the aggregate supply of these graduates. The results, however, indicate that the individual level effects of such policies could be negative in terms of wages and that these policies might not reduce the incidence of overqualification. This negatively affects the efficiency of such policy measures with respect to their goal of increasing the supply of STEM graduates. Our results suggest that individual characteristics play an important role for the subject choice, as well as for labor market outcomes (i.e. overqualification and wages). This would imply that policy measures which aim at increasing the supply of adequate STEM graduates should additionally take into account individual characteristics by, for example, fostering the development of math skills early in school. In line with this, Stinebrickner and Stinebrickner (2014) argue that students' subject choices by and large fit their abilities, so that policies which aim at increasing the supply of science graduates should focus on providing pupils with the skills required by these subjects.

Our findings are based on a sample of German men born between 1940 and 1980. It would be very relevant from a policy perspective to check whether similar results are found for women and for younger cohorts. Moreover, further research is necessary to evaluate the role of policies promoting STEM fields for the aggregate supply of STEM graduates and to identify whether there is an excess demand for STEM graduates.

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7 Appendix

7.1 A Note on the Overidentification Test

Above we have reduced the sample to bivariate comparison of fields of study (for each potential comparison) so that we were able to apply overidentification tests. In non of the cases did the test reject the null hypothesis that the instruments are valid. However, an objection against the use of the overidentification test for detecting invalid instruments is that the test does not detect invalid instruments when the IV estimators using the full and the reduced set of instruments are similarly asymptotically biased (Wooldridge, 2010, p. 135). Parente and Santos Silva (2012) discuss this issue in the case of one endogenous explanatory variable and two instruments — as in the case of our bivariate comparison of fields of study — and argue that the overidentification test does not detect invalid instruments if $\gamma_2/\gamma_1 = \pi_2/\pi_1$, where π_1 and π_2 are the coefficients in the linear projection of the explanatory endogenous variable (field of study) on the instruments and γ_1 and γ_2 are the coefficients in the projection of the error of the outcome equation on the instruments. More generally, De Blander (2008) shows that the overidentification test does not detect invalid instruments if the instruments appear in the same linear combination in the linear projection of the error of the outcome equation on the instruments, as they appear in the linear projection of the endogenous explanatory variable (field of study) on the instruments.

In our case both instruments are negatively correlated with the Business & Law dummy, so that the test would fail if the instruments were directly linked to the error in the outcome equation and if the ratio of these effects would be about the same as for the instruments' effects on the endogenous explanatory variable. This requires that the instruments are linked with the same sign to the error in the outcome equation. For example, higher ability pupils might both have relative better math grades and might be more likely to play instruments, so that we would underestimate the wage-effect of the Business & Law dummy with both instruments, assuming that ability positively affects wages. Conversely, the first instrument is negatively and the second instrument is positively correlated to the Social Sciences & Humanities dummy, so that the test would fail if the instruments were directly linked to the error in the outcome equation and if the ratio of these effects would be about the same as for the instruments' effects on the endogenous explanatory variable. This requires that the instruments are linked with opposite signs to the error in the outcome equation. For example, higher ability pupils might have relative better math grades and might be less likely to play instruments, so that we would underestimate the wage-effect of the Social Sciences & Humanities dummy with both instruments. This implies that the test can fail in both cases only if the instruments are differently linked to the outcome equation for the two fields of study. In fact, in neither case the test rejects the null so that the test can only fail if the instruments differently directly affect wages (overqualification) for Business & Law vs. STEM than for Social Sciences & Humanities vs. STEM. This seems implausible and we are therefore confident that the test is reliable.

7.2 Tables and Figures

Table 5: Fields of study groups

Subject group	Specific fields of study
STEM	Mathematics, Physics, Astronomy, Chemistry, Pharmacology, Biology, Geosciences, Computer Science, Engineering (incl. Civil, Mechanical, Electrical and Traffic Engineering), Mining and Metallurgy, Architecture and Interior Design, Regional Planning, Surveying and Mapping
Business & Law	Law, Business Administration, Public Management and Governance, Economics, Managerial Engineering
Social Sc. & Humanities	Philosophy, History, Literary Studies, Linguistics, Philology, Cultural Studies, Theology, Psychology, Political Science, Social Sciences, Social Work, Geography, Landscape Conservation, Agricultural Sciences, Forest Management, Fine Arts, Design, Performance, Film and Television, Theater, Sport Science, Music, Musicology

Note that Education, Medicine, Dentistry and other health sciences are excluded from the sample.

Table 6: Effect of fields of study on the risk of overqualification - Different specifications

	LPM	2SLS	DT
	(1)	(2)	(3)
Panel A: Overqualification equation			
Business & Law	0.075***	-0.096	0.019***
	(0.027)	(0.184)	(0.005)
Social Sc. & Humanities	0.046	0.203	0.262***
	(0.034)	(0.206)	(0.005)
Grade: average	-0.045**	-0.048**	-0.031***
	(0.018)	(0.021)	(0.002)
Demographic charact.	Yes	Yes	Yes
Parental education	Yes	Yes	Yes
Pre-graduation charact.	Yes	Yes	Yes
Post-graduation charact.	Yes	Yes	Yes
School state dummies	Yes	Yes	Yes
Panel B: Subject choice equation			
<u>Business & Law fields</u>			
Grade: difference		-0.061***	-0.562***
		(0.015)	(0.096)
Played music in youth		-0.091***	-0.424**
		(0.032)	(0.204)
Grade: average		-0.043*	-0.367**
		(0.024)	(0.143)
<u>Social Sciences & Humanities</u>			
Grade: difference		-0.061***	-0.738***
		(0.011)	(0.118)
Played music in youth		0.054**	0.294
		(0.026)	(0.223)
Grade: average		-0.038**	-0.453***
		(0.018)	(0.157)
<u>Control variables</u>			
Demographic charact.		Yes	Yes
Parental education		Yes	Yes
Pre-graduation charact.		Yes	Yes
Post-graduation charact.		Yes	Yes
School state dummies		Yes	Yes
Observations	896	896	896
R-sq.	0.118	0.023	

Standard errors in parentheses; * p<0.10, ** p<0.05, *** p<0.01. Note that the coefficients shown in column (3) and column (4) are not average marginal effects and cannot be directly compared to the coefficients of the other models.

Table 7: Effect of fields of study on log hourly wages - Different specifications

	OLS	2SLS	ATEIV	DT
	(1)	(2)	(3)	(4)
Panel A: Wage equation				
Business & Law	0.002	0.152	0.069	0.200***
	(0.030)	(0.200)	(0.164)	(0.050)
Social Sc. & Humanities	-0.243***	-0.271	-0.217	-0.229***
	(0.038)	(0.206)	(0.153)	(0.077)
Grade: average	0.025	0.032	0.030	0.036*
	(0.020)	(0.022)	(0.022)	(0.021)
Demographic charact.	Yes	Yes	Yes	Yes
Parental education	Yes	Yes	Yes	Yes
Pre-graduation charact.	Yes	Yes	Yes	Yes
Post-graduation charact.	Yes	Yes	Yes	Yes
School state dummies	Yes	Yes	Yes	Yes
Panel B: Subject choice equation				
Business & Law fields				
Grade: difference		-0.061***	-0.059***	-0.585***
		(0.015)	(0.014)	(0.098)
Played music in youth		-0.091***	-0.087***	-0.444**
		(0.032)	(0.031)	(0.209)
Grade: average		-0.043*	-0.037*	-0.371**
		(0.024)	(0.022)	(0.147)
F-test (excl. instr.)		18.6		
Social Sciences & Humanities				
Grade: difference		-0.061***	-0.058***	-0.825***
		(0.011)	(0.011)	(0.128)
Played music in youth		0.054**	0.052**	0.305
		(0.026)	(0.024)	(0.257)
Grade: average		-0.038**	-0.032*	-0.511***
		(0.018)	(0.016)	(0.179)
F-test (excl. instr.)		23.6		
Control variables				
Demographic charact.		Yes	Yes	Yes
Parental education		Yes	Yes	Yes
Pre-graduation charact.		Yes	Yes	Yes
Post-graduation charact.		Yes	Yes	Yes
School state dummies		Yes	Yes	Yes
Observations	896	896	896	896
R-sq.	0.355	0.330	0.351	

Standard errors in parentheses; * p<0.10, ** p<0.05, *** p<0.01. Note that the coefficients shown in Panel B of column (4) are not average marginal effects and cannot be directly compared to the coefficients of the other models.

Table 8: Effect of high-school grades on overqualification and wages

	Overqualification		Log hourly wages	
	LPM	LPM	OLS	OLS
	(1)	(2)	(3)	(4)
Grade: difference	-0.007	0.000	0.008	-0.008
	(0.012)	(0.013)	(0.012)	(0.012)
Grade: average	-0.051***	-0.046**	0.035*	0.026
	(0.018)	(0.018)	(0.020)	(0.020)
Business & Law		0.075***		-0.002
		(0.029)		(0.030)
Social Sc. & Humanities		0.046		-0.249***
		(0.035)		(0.039)
Demographic characteristics	Yes	Yes	Yes	Yes
Parental education	Yes	Yes	Yes	Yes
Pre-graduation charact.	Yes	Yes	Yes	Yes
Post-graduation charact.	Yes	Yes	Yes	Yes
School state dummies	Yes	Yes	Yes	Yes
Observations	896	896	896	896
R sq.	0.110	0.118	0.319	0.355

Standard errors in parentheses; * p<0.10, ** p<0.05, *** p<0.01

Table 9: Effect of playing music in youth on overqualification and wages

	Overqualification		Log hourly wages	
	LPM	LPM	OLS	OLS
	(1)	(2)	(3)	(4)
Played music in youth	0.021	0.024	-0.029	-0.014
	(0.024)	(0.024)	(0.027)	(0.026)
Grade: average	-0.053***	-0.046**	0.038*	0.025
	(0.018)	(0.019)	(0.019)	(0.019)
Business & Law		0.077***		0.001
		(0.028)		(0.030)
Social Sc. & Humanities		0.044		-0.242***
		(0.033)		(0.038)
Demographic characteristics	Yes	Yes	Yes	Yes
Parental education	Yes	Yes	Yes	Yes
Pre-graduation charact.	Yes	Yes	Yes	Yes
Post-graduation charact.	Yes	Yes	Yes	Yes
School state dummies	Yes	Yes	Yes	Yes
Observations	896	896	896	896
R sq.	0.110	0.119	0.320	0.355

Standard errors in parentheses; * p<0.10, ** p<0.05, *** p<0.01

Table 10: Results for restricted sample

	Overqualification		Log hourly wages	
	Probit	MP Probit	OLS	MP
	(1)	(2)	(3)	(4)
Panel A: Excluding self-employed workers				
Business & Law	0.067**	-0.074	-0.003	0.224*
	(0.026)	(0.087)	(0.028)	(0.121)
Social Sc. & Humanities	0.032	0.197	-0.220***	-0.132
	(0.035)	(0.152)	(0.038)	(0.099)
Grade: average	-0.044**	-0.048**	0.035*	0.056**
	(0.017)	(0.019)	(0.020)	(0.022)
Demographic characteristics	Yes	Yes	Yes	Yes
Parental education	Yes	Yes	Yes	Yes
Pre-graduation charact.	Yes	Yes	Yes	Yes
Post-graduation charact.	Yes	Yes	Yes	Yes
School state dummies	Yes	Yes	Yes	Yes
Observations	760	760	760	760
R sq.			0.401	
Panel B: Only full-time workers				
Business & Law	0.070***	-0.085	0.002	0.078
	(0.025)	(0.081)	(0.028)	(0.110)
Social Sc. & Humanities	0.045	0.253**	-0.260***	-0.297***
	(0.033)	(0.108)	(0.038)	(0.085)
Grade: average	-0.044***	-0.048**	0.021	0.024
	(0.016)	(0.019)	(0.019)	(0.020)
Demographic characteristics	Yes	Yes	Yes	Yes
Parental education	Yes	Yes	Yes	Yes
Pre-graduation charact.	Yes	Yes	Yes	Yes
Post-graduation charact.	Yes	Yes	Yes	Yes
School state dummies	Yes	Yes	Yes	Yes
Observations	872	872	872	872
R sq.			0.380	
Panel C: Younger cohorts				
Business & Law	0.071**	-0.090	-0.017	0.034
	(0.028)	(0.077)	(0.031)	(0.125)
Social Sc. & Humanities	0.067*	0.210*	-0.251***	-0.254***
	(0.036)	(0.109)	(0.042)	(0.108)
Grade: average	-0.047***	-0.049**	0.021	0.024
	(0.018)	(0.019)	(0.021)	(0.022)
Demographic characteristics	Yes	Yes	Yes	Yes
Parental education	Yes	Yes	Yes	Yes
Pre-graduation charact.	Yes	Yes	Yes	Yes
Post-graduation charact.	Yes	Yes	Yes	Yes
School state dummies	Yes	Yes	Yes	Yes
Observations	722	722	722	722
R sq.			0.357	

Standard errors in parentheses; * $p<0.10$, ** $p<0.05$, *** $p<0.01$;
The coefficients in columns (1) and (2) are average marginal effects.

Table 10: Results for restricted sample (continued)

	Overqualification		Log hourly wages	
	Probit	MP Probit	OLS	MP
	(1)	(2)	(3)	(4)
Panel D: Excluding individuals with migration background				
Business & Law	0.059**	-0.111	0.009	0.173*
	(0.026)	(0.079)	(0.030)	(0.096)
Social Sc. & Humanities	0.040	0.161	-0.248***	-0.265**
	(0.034)	(0.127)	(0.040)	(0.115)
Grade: average	-0.043**	-0.050**	0.010	0.020
	(0.017)	(0.020)	(0.020)	(0.022)
Demographic characteristics	Yes	Yes	Yes	Yes
Parental education	Yes	Yes	Yes	Yes
Pre-graduation charact.	Yes	Yes	Yes	Yes
Post-graduation charact.	Yes	Yes	Yes	Yes
School state dummies	Yes	Yes	Yes	Yes
Observations	837	837	837	837
R sq.			0.365	

Standard errors in parentheses; * p<0.10, ** p<0.05, *** p<0.01

The coefficients in columns (1) and (2) are average marginal effects.