Field of Study and Earnings: The Role of (Self-)Selection by Individual Characteristics

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Abstract

The choice of a field of study at university is an important part of students' career decisions and is commonly influenced by expected future earnings. However, when investigating the role of field of study for earnings, researchers often rely on descriptive data with only a few control variables. The present study goes beyond such estimates by investigating the effects of field of study on earnings, distinguishing between (self-)selection into fields by pre-existing individual characteristics and actual earnings effects of the field. The analyses are based on a unique longitudinal dataset of high school graduates in Germany followed for 14 years, which includes measures of abilities, personality, and family background assessed at the end of high school. We first find significant selection effects by various outset characteristics, including ability, personality, and family background measures. Then, propensity score matching reveals that, when accounting for these selection patterns, STEM and business/economics graduates receive significantly higher monthly earnings than similar social sciences/humanities graduates. Overall, accounting for (self-)selection only slightly reduces the estimated field of study effects compared to descriptive findings.

Keywords: field of study, earnings, self-selection

Supplemental materials and analysis code:

https://osf.io/9zwx3/?view_only=44aaed8b8a774877844abd44bb5b3220

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Field of Study and Earnings: The Role of (Self-)Selection by Individual Characteristics

The choice of a university-level field of study is an important part of students' career decisions. Among other factors, the field of study choice is commonly influenced by expected later earnings (e.g., Abramitzky et al., 2019; Arcidiacono et al., 2020; Ersoy, 2020; Long et al., 2015; Patnaik et al., 2020; Wiswall & Zafar, 2015; Xia, 2016). It is therefore an important question how the field of study at university affects later earnings.

However, researchers mostly rely on descriptive data with only a few control variables when estimating field of study effects on earnings (see the review by Altonji, Arcidiacono, & Maurel, 2016). It has therefore remained largely unclear to what extent the relationships between field of study and earnings actually reflect effects of the field and to what extent these associations are driven by selection effects that occur because students with different pre-existing individual characteristics tend to enter and graduate from different fields (e.g., Altonji, Arcidiacono, & Maurel, 2016; Grave & Görlitz, 2012; Hamermesh & Donald, 2008; Kinsler & Pavan, 2015).

In the present study, we investigate the effects of field of study on earnings and disentangle field effects and selection effects. We argue that, although it is likely that field of study affects earnings, many individual characteristics might predict the field of study choice and later earnings, therefore biasing the estimated field of study effects on earnings if these individual characteristics are not accounted for. Plausible candidates for such individual characteristics are, for example, abilities (cognitive abilities and educational achievement), personality traits, and family background (socioeconomic background and migration background).

Our empirical analysis is based on a unique, rich dataset from a cohort study in which high school graduates from 2002 in Germany are observed over 14 following years. This study includes measures of various individual characteristics, many of which are typically not observed

in the research field, assessed before students enter university. These individual characteristics include cognitive abilities, educational achievement (high school grade point average (GPA)), personality (Big Five traits), socioeconomic background (parental education level and parental occupational status), and migration background. We first apply multivariate logistic regressions to investigate how students self-select into different fields of study. On this basis, we then use propensity score matching (PSM) to investigate the effects of field of study on later earnings while accounting for the (self-)selection effects: The PSM analysis estimates earnings differences between graduates from different fields who are similar in their outset characteristics. We finally compare these results to the descriptive findings on the relationships between field of study and earnings, which allows us to estimate the bias that occurs when not accounting for selection effects.

The present research contributes to the existing literature on the relationships between field of study and earnings in several ways. First, although many studies have investigated how field of study is associated with later earnings, only few studies were able to determine whether field of study actually affects earnings (Altonji, Arcidiacono, & Maurel, 2016; Andrews et al., 2017; Hastings et al., 2013; Ketel et al., 2016; Kirkeboen et al., 2016). Using our unique longitudinal data source and a PSM approach, we are able to estimate the effects of field of study on earnings when graduates with similar pre-existing characteristics are compared.

We secondly contribute to the interpretation of descriptive evidence on the relationships between field of study and earnings. Due to data limitations, available information on the relationships between field of study and earnings is often descriptive with only few control variables. It is therefore important to know how such results should be interpreted: i.e., to what extent they reflect selection effects because students with different outset characteristics tend to

self-select into different fields, and to what extent they reflect effects of the field of study at university. By comparing the results of the PSM analysis—that does account for selection effects—to descriptive findings on the relationships between field of study and earnings, we are able to estimate to what extent these relationships are driven by selection rather than field effects.

Third, this is one of the first studies to investigate the effects of field of study on earnings in Germany. Grave & Görlitz (2012) investigated field of study effects in Germany but did not include measures of cognitive abilities, personality traits, or family background. Since field of study effects on earnings are likely to differ between countries due to different labor markets and institutions, it is important to investigate the effects in different countries.

Literature on Field of Study and Earnings

A large body of studies has investigated how the university-level field of study predicts future earnings (see the review by Altonji, Arcidiacono, & Maurel, 2016). Findings primarily suggest that the fields of STEM (science, technology, engineering, and mathematics) and business/economics are generally associated with higher earnings than social sciences/humanities (e.g., Altonji, Kahn, & Speer, 2016; Altonji & Zhong, 2021; Chevalier, 2011; Grave & Görlitz, 2012; Hamermesh & Donald, 2008; Kim et al., 2015; Kinsler & Pavan, 2015).

However, the mechanisms that lead to the associations between field of study and earnings have remained largely unclear. On the one hand, it is plausible that field of study affects earnings for several reasons: Graduating with a degree in particular fields might signal specific pre-existing abilities to the labor market, in line with signaling theory (Spence, 1973); students acquire specific knowledge and skills in study programs that enhance their productivity in the labor market, in line with human capital theory (G. Becker, 1962; Mincer, 1974); the relationship

between the labor supply and demand varies systematically across fields; and specific earnings levels in organizations are restricted to those with particular qualifications via fixed wages and collective agreements (the phenomenon of “closure”).

But estimated relationships between field of study and earnings may also reflect (self-)selection effects—rather than effects of the chosen field—if students who enter and graduate from different fields tend to differ from each other with respect to pre-existing individual characteristics that are also relevant to earnings. For example, the inclusion of control variables, such as educational achievement measures at college entry, can change the estimated earnings effects of field of study substantially (Grave & Görlitz, 2012; Hamermesh & Donald, 2008; Kinsler & Pavan, 2015). This suggests that students in different fields might differ from each other, on average, in pre-existing characteristics that are relevant to the labor market (Altonji, Arcidiacono, & Maurel, 2016).

The role of (self-)selection by individual characteristics has not sufficiently been investigated and accounted for in previous empirical research on the relationships between field of study and earnings, since this research was mainly based on labor market data where psychological and sociological constructs were not extensively considered. For example, to our knowledge, no existing study on this topic has included measures of cognitive abilities (in terms of solving new cognitive tasks, or “fluid intelligence”). Results on educational achievement are likely to be relevant but are only imperfect proxies for cognitive abilities (e.g., Borghans et al., 2016; Frey & Detterman, 2004; R. D. Roberts et al., 2000). Moreover, existing literature on the relationships between field of study and earnings has not included a comprehensive measure of personality, such as the Big Five traits (Costa & McCrae, 1992). Most of the empirical literature has either not considered socioeconomic background (e.g., Grave & Görlitz, 2012; Kinsler & Pavan, 2015)

or has included only an imperfect proxy for socioeconomic background, such as the average income in the high school area (e.g., Hamermesh & Donald, 2008). Whereas some studies have controlled for race or ethnicity (e.g., Altonji, Kahn, & Speer, 2016; Altonji & Zhong, 2021; Chevalier, 2011; Kinsler & Pavan, 2015), migration background was mostly not considered (an exception being Kinsler & Pavan, 2015). As we describe in the following section, these measures of abilities, personality, and family background are likely to be relevant to field of study and earnings. Thus, it is important to consider and account for these factors when investigating field of study effects on earnings and the role of (self-)selection.

Some studies have used quasi-experimental designs for estimating field of study effects on earnings. These studies have either applied an instrumental variable or regression discontinuity approach on the basis of admission cutoffs (Andrews et al., 2017; Hastings et al., 2013; Kirkeboen et al., 2016) or exploited an admission lottery that created exogenous variation in the admission to one particular field of study (Ketel et al., 2016). However, these identification strategies are only feasible in specific contexts, i.e., specific countries or specific fields of study. Moreover, regression discontinuity designs in this research area are restricted to marginal students who score near the admission cutoff.

The approach that we follow in this study is estimating the effects of field of study on earnings with a PSM approach that accounts for selection effects into fields of study. Our unique data source allows us to consider a large set of individual characteristics, including measures of cognitive abilities, educational achievement, personality traits, socioeconomic background, and migration background. We analyze selection into fields of study by individual characteristics and the earnings effects of field of study when accounting for this selection. We also compare the

PSM results to descriptive findings that do not account for selection in order to estimate the importance of (self-)selection for estimated field of study effects on earnings.

Theoretical Perspectives on the Role of (Self-)Selection by Individual Characteristics

Various outset characteristics (i.e., individual characteristics that hold before studying the respective field) might influence the field of study choice and future earnings, thus potentially biasing the estimated effects of field of study on earnings if those characteristics are not accounted for. An obvious example is gender: On average, females choose other fields of study (Charles & Bradley, 2009; Charles & Grusky, 2005) and receive lower earnings in (parts of) the labor market (e.g., Mandel & Semyonov, 2005). Individuals' age at the time of high school graduation might influence their field of study choice, and age is also a well-known predictor of earnings (e.g., Murphy & Welch, 1990). The type of high school that students have attended (academic or vocational focus) might likewise influence the field choice and might affect earnings, e.g., due to a different form of human capital that students have accumulated.

Cognitive ability measures (in terms of “fluid intelligence”) aim to capture the ability to solve cognitive tasks that one has not been educated or trained for. As the ability to deal with new, cognitively demanding situations is important for academic performance (Kuncel et al., 2004), cognitive abilities might increase the probability of studying subjects that are perceived to be more challenging, such as the STEM or business/economics field (Päßler & Hell, 2012). At the same time, because cognitive abilities are relevant for job performance (Kuncel et al., 2004; Schmidt & Hunter, 2004), they might contribute to higher future earnings (M. Becker et al., 2019; Gottfredson, 2002; Spengler et al., 2015; Spengler et al., 2018; Strenze, 2007).

High school GPA is a measure of educational achievement. In contrast to cognitive abilities, educational achievement reflects the ability to solve problems that one has been educated and

trained for. High school GPA is important in the present context because admission to some study programs (e.g., medicine, pharmacy, and psychology) is highly restrictive in Germany and is typically based on the high school GPA. Moreover, individuals with higher achievement levels may have a greater tendency to choose and graduate from more quantitative subjects, such as the STEM field (e.g., Arcidiacono, 2004; Kinsler & Pavan, 2015; Wille et al., 2020). At the same time, educational achievement might be positively related to productivity in the labor market and might therefore predict higher earnings (Borghans et al., 2016; Heckman et al., 2006; Jencks et al., 1983; Kinsler & Pavan, 2015; Stoll et al., 2017).

Personality traits capture general and relatively stable patterns of thinking, feeling, and acting (Cervone & Pervin, 2018; B. W. Roberts, 2009). The Big Five model of personality (Costa & McCrae, 1992) distinguishes five broad traits: openness, conscientiousness, extraversion, agreeableness, and neuroticism. Personality traits may predict field of study because of the way in which different study programs and associated occupations are organized. For example, individuals with a higher level of openness might have a preference for programs whose curriculum offers more free choices, such as the humanities, and more extraverted individuals might have a preference for programs that might lead to jobs with more social interaction, such as business/economics and the social sciences (e.g., Humburg, 2017; Vedel, 2016). Because personality traits are related to job performance (Barrick & Mount, 1991), they are also likely to impact earnings (e.g., Gensowski, 2018; Müller & Plug, 2006; Nyhus & Pons, 2005; Ozer & Benet-Martínez, 2006; B. W. Roberts et al., 2007; Spengler, 2020; Sutin et al., 2009).

It is plausible that socioeconomic background might be relevant for the choice of a field of study and for future earnings. For example, individuals from a more educated background might choose humanities more often because of a higher expected success and direct enjoyment gained

from studying cultural subjects (Duru-Bellat et al., 2008; Van De Werfhorst et al., 2003), whereas students from a more prestigious occupational background might choose financially more promising fields to maintain their economic status (P. D. Parker et al., 2012; Van De Werfhorst et al., 2003). At the same time, because socioeconomic background might influence one's expectations, aspirations, and networks (Sewell et al., 1969) and the economic support during higher education and the beginning of an occupational career (McGue et al., 2017), socioeconomic background might positively predict earnings (e.g., Rumberger, 2010).

In addition, migration background (i.e., whether the student has at least one immigrant parent) might be relevant for the field choice and earnings. For example, some individuals with a migration background might lack helpful networks in the country of residence and therefore prefer “safer” occupational choices such as STEM (Kinsler & Pavan, 2015). Even when accounting for educational achievement, both direct migration background and indirect migration background (i.e., through parents only) might have a negative effect on earnings (e.g., Algan et al., 2010), possibly due to discrimination by some employers (e.g., Drydakis, 2017; Kaas & Manger, 2012).

Finally, the year in which students start studying their (last completed) field of study might obviously influence earnings, because individuals who started studying later were probably less advanced in their career at the time when earnings were measured (i.e., in 2016). This factor is relevant for the relationship between field of study and earnings if students in some fields tend to start studying earlier than students in other fields.

Method

Sample

The present research was based on the TOSCA study (Köller et al., 2004; Trautwein et al., 2010), an ongoing multi-cohort longitudinal study of high school students and young adults. We used data from TOSCA Cohort 1 (TOSCA-2002), which tracked high school graduates from the German state of Baden-Württemberg over a 14-year period (2002–2016). Data from wave 1 (year 2002), wave 6 (2012), and wave 7 (2016) were used.

In 2002, students were observed in their final year of high school and shortly before high school graduation; in 2016, participants were typically settled in the labor market. The TOSCA-2002 study only includes graduates from upper secondary schools (*Gymnasiums*), a school track that contains schools with an academic focus and schools with a more vocational focus. Graduates from both types of upper secondary schools have direct access to university degree programs in Germany, although admission to some fields and programs can require additional criteria—such as a specific GPA—dependent on university-specific regulations. Academic upper secondary schools and vocational upper secondary schools had been randomly selected in the state of Baden-Württemberg, Germany, with a total number of 149 selected schools.

Originally, the questionnaire was distributed to 5,897 students in their high schools in 2002, and 4,730 filled it out. Most of the students (approximately 3,000) also provided their address and agreed to continue participating in the study. In 2012, when detailed information on study programs (including the year they began studying a particular program) was collected, answers from 1,428 individuals were received. Finally, in 2016, when earnings and the last completed field of study were collected, answers from 1,390 individuals were received.

We performed an attrition analysis to test the effects of the considerable attrition from the first wave to the most current wave included in this study. There were some small to moderate differences in observed individual characteristics—including gender, type of high school,

abilities, personality, and family background—between those who remained in the sample and those who did not (see online supplemental materials for the detailed results of the attrition analysis). Overall, individuals who remained in the sample had properties that may be associated with higher achievement. Therefore, we note that they were somewhat “positively” selected.

We added the relevant variables from 2002 and 2012 to the data from 2016. After dropping cases with missing values, the final sample included $N = 622$ individuals, with one observation per individual.

Measures

Earnings (observed in 2016): Participants reported their gross monthly earnings (i.e., monthly earnings before taxes and social security payments) from the current occupation in Euro in open response format in 2016. Individuals were asked to report earnings from their last employment in the case that they were currently not employed. Of all individuals in the final sample, 15.3% were not employed at the time when earnings were reported (2016), the most common reason being parental leave status (9.5% of the final sample).

Field of study (observed in 2016): We distinguished the following fields of study: STEM, business/economics, and social sciences/humanities. Table 1 shows the fields of study with example subjects and their number of observations.

[TABLE 1 ABOUT HERE]

Our study focused on the last completed field of study: For each individual, a study subject was considered only if it was completed and if the completion was later than the completion of any other reported subject. We included the PhD program in this procedure. Therefore, if someone had a master’s degree in the STEM field and later obtained a PhD in business/economics, then that individual was assigned to business/economics. The assumption

was that the last finished program would be most relevant to the labor market. Further details on the field of study variable are described in the online supplemental materials.

Female (observed in 2002): We considered the students' gender with a dummy variable (1 = female, 0 = male).

Age (observed in 2002): We included students' age in years.

Vocational high school (observed in 2002): We considered the type of upper secondary school from which the student achieved a university entrance qualification (1 = vocational, 0 = academic).

Cognitive abilities (observed in 2002): The TOSCA study includes two subscales of the revised cognitive abilities test for students in grades four to twelve (KFT 4–12+ R; Heller & Perleth, 2000): figural analogies and verbal analogies. These two subscales can be considered good markers of fluid intelligence (Brunner, 2008). In total, the included short test has 45 items. The dataset included a combined score of cognitive abilities, which was built as the sum score of these items, standardized to have a mean of 100 and a standard deviation of 15 in the original sample of last-year high school students in 2002.

High school GPA (observed in 2002): The dataset included the average grade of the high school degree (high school GPA), which can range from the lowest (4.0) to the highest (1.0) grade in Germany.

Personality traits (observed in 2002): The German version (Borkenau & Ostendorf, 1991) of the NEO-Five-Factor Inventory (NEO-FFI) was used to assess personality traits (Costa & McCrae, 1992). The inventory consists of 60 items in total, each on a Likert scale from 1 (*does not apply at all*) to 4 (*applies completely*). The following five scales were distinguished (with

internal consistencies as measured by Cronbach's alpha): openness ($\alpha = .73$), conscientiousness ($\alpha = .83$), extraversion ($\alpha = .77$), agreeableness ($\alpha = .73$), and neuroticism ($\alpha = .83$).

Parental education level (observed in 2002): As a first measure of socioeconomic background, we considered parental education level. This variable was defined as the highest educational degree held by the parents (i.e., the degree held by that parent holding the highest degree). The scale ranged from 1 (*no secondary school degree or lower secondary school degree without further education*) to 7 (*university degree from a traditional, research-based university*).

Parental occupational status (observed in 2002): As a second measure of socioeconomic background, we considered parental occupational status, which was defined as the highest occupational status of the parents. Occupational status was assessed with the International Socio-Economic Index (ISEI), which takes on values from 16 (e.g., farmhands, laborers, and cleaners) to 90 (judges); it assesses the "prestige" of occupations, mainly based on the education level and income of individuals who are employed in specific occupations (Ganzeboom et al., 1992; Ganzeboom & Treiman, 1996).

Information on parental education level and parental occupational status was reported by the parents and, where missing, was obtained from information provided by the students.

Migration background (observed in 2002): Based on the countries of birth of the student and of her or his parents (as reported by the student), we determined whether the student had a migration background. Specifically, we distinguished the following two types of migration background with dummy variables (1 = yes, 0 = no): direct migration background (the student and at least one parent were born outside of Germany) and indirect migration background (the student was born in Germany, but at least one parent was born outside of Germany). The reference category was no migration background (both parents were born in Germany).

Year of study start (observed in 2012): The year of study start was defined as the year in which the last finished study program was started. If the most recently finished program was a consecutive program (i.e., a master's or PhD/doctoral degree), then the start of the (last) preceding bachelor's, *Diplom*, or *Staatsexamen* program was considered.¹ In this way, the variable "year of study start" was comparable across degree types because it always captured the beginning of the study career in the final chosen field.

We did not include the year of the university degree, because this variable was likely influenced by field of study and might therefore be interpreted as a mediator between field of study and earnings. Since we were interested in the effects of field of study, we refrained from accounting for mediator variables; their influence belongs to the field of study effects and should therefore not be subtracted from them (see Kirkeboen et al., 2016 for a similar reasoning). An additional analysis of mediators between field of study and earnings was beyond the scope of the present study.

Analyses

First, we used descriptive statistics to analyze raw differences in earnings and individual characteristics between different fields of study. We intentionally did not account for these individual differences when investigating earnings differences at this point.

In the second step, we used multivariate logistic (logit) regressions to analyze patterns of selection into different fields of study by individual characteristics. In this analysis, we tested whether specific individual characteristics were conditionally predictive (i.e., predictive when

¹ *Diplom* and *Staatsexamen* are German university degrees that were more common in the past; the *Diplom* has now been fully replaced by the bachelor's and master's degree.

holding other individual characteristics constant) for studying and completing a particular field of study compared to another field. We used three separate logit models to predict (1) STEM vs. social sciences/humanities, (2) business/economics vs. social sciences/humanities, and (3) STEM vs. business/economics graduation. In each of these models, the dependent variable was the respective field of study indicator and the explanatory variables were the individual characteristics (gender, age, type of high school, cognitive abilities, high school GPA, personality traits, parental education level, parental occupational status, migration background, and year of study start).

In the third step, we used PSM to analyze the effects of field of study on earnings when accounting for the selection patterns. PSM is composed of two steps (Rosenbaum & Rubin, 1983). The first step is the treatment model, where the probability of a treatment is regressed on the explanatory variables. From the treatment model, a propensity score is obtained for each individual. The propensity score is the probability of the treatment conditional on the explanatory variables. In the second step of PSM, the effect of the treatment on the dependent variable is estimated. To this aim, PSM matches individuals who receive the treatment with otherwise similar individuals who do not receive the treatment (i.e., who are in the control group). Similarity is specified with the propensity score: Individuals from the treatment group are matched with individuals from the control group who have a similar propensity score. Then, differences in the dependent variable between matched individuals are calculated. In this way, PSM compares the outcomes of individuals with similar values on the explanatory variables and therefore accounts for selection effects.

In our PSM analysis, the treatment was a particular field of study (compared to a particular alternative field of study as the control condition), the explanatory variables were the individual

characteristics, and the dependent variable was the natural logarithm of earnings (log earnings; the logarithm was used to account for the non-normality of earnings residuals). We separately estimated the earnings effects of (A) STEM vs. social sciences/humanities, (B) business/economics vs. social sciences/humanities, and (C) STEM vs. business/economics graduation. In each of these parts of the analysis, the treatment model was a multivariate logit model in which the probability of completing the respective field of study (compared to the respective alternative field) was regressed on the individual characteristics, exactly as in the selection analysis described above. We included all individual characteristics in the treatment model, since all of them were theoretically motivated (see Theoretical Perspectives on the Role of (Self-)Selection by Individual Characteristics section above). The propensity scores were obtained from this treatment model. In the PSM analysis, we only included observations who had a propensity score that was within the common support region (i.e., the range of propensity scores that occur in both the treatment and the control group), as no causal effect is defined for observations outside this region (Thoemmes & Kim, 2011).

An important aim of PSM is to make groups comparable, i.e., to reduce differences in explanatory variables between treatment and control group. Therefore, we tested how successful different matching procedures were in balancing the covariates (i.e., how strongly they reduced standardized mean differences in the explanatory variables between treatment and control group). In particular, we tested matching with 1, 2, 5, 10, 20, 50, and 100 matches (“neighbors”) per observation as well as with the maximum number of matches per observation (the maximum number is the number of observations in the smaller group). Tables S1–3 in the online supplemental materials show the results of these tests. Across the different parts (A)–(C) of the PSM analysis, matching with 10 matches per observation minimized the absolute values of

standardized mean differences in explanatory variables between groups. Therefore, we used this matching procedure in the PSM analysis. We did not define a maximum distance between propensity scores (caliper), implying that all observations in the analysis sample were potential matches. It was possible that two or more observations had the same neighbor (matching with replacement).

We estimated the average treatment effect (ATE) of the respective field of study (compared to the respective alternative field) on earnings. Therefore, the earnings of individuals who completed different fields of study and had similar individual characteristics were compared, so that (self-)selection effects by individual characteristics were accounted for. Finally, we compared the results of the PSM analysis to the respective results of the descriptive analysis—which did not account for (self-)selection effects—in order to find evidence on the relevance of selection patterns for the relationship between field of study and earnings.

Results

Descriptive Statistics and Correlations

Table 2 shows the descriptive statistics (means and standard deviations for the different fields of study). Average monthly earnings 14 years after high school graduation were higher for STEM (€5,030) and business/economics (€5,111) than for social sciences/humanities graduates (€4,114). The standard deviations indicated that earnings were also very heterogeneous within fields. As *t*-tests showed, the differences in mean earnings between STEM and social sciences/humanities and between business/economics and social sciences/humanities were statistically significant at the 5% level ($p = .038$ and $.042$, respectively), while the difference between STEM and business/economics was not ($p = .722$). In relative terms, STEM graduates

had 23.3% higher earnings and business/economics graduates 24.2% higher earnings than social sciences/humanities graduates, on average.

There were also some significant differences in individual characteristics between fields of study. Compared to social sciences/humanities, STEM graduates were less often female, had (on average) higher cognitive abilities at the end of high school and a smaller (i.e., better) high school GPA, were less open and less extraverted at the end of high school, and had more often a direct migration background. Business/economics graduates, as compared to social sciences/humanities, were also less often female, were more likely to have attended a vocational high school, and were less open and more conscientious. When comparing STEM and business/economics graduates, the former turned out to have, on average, a smaller (better) high school GPA as well as higher openness and lower extraversion.

[TABLE 2 ABOUT HERE]

Figure 1 shows the earnings distributions and median earnings in each field of study. In line with Table 2, this figure indicates a substantial earnings dispersion within each field. While the distribution of earnings and median earnings were similar between STEM and business/economics graduates, earnings were typically substantially lower in the social sciences/humanities.

[FIGURE 1 ABOUT HERE]

Table 3 shows the correlations between the variables used in the analysis. In line with the descriptive results, social sciences/humanities was correlated with lower earnings as compared to the other fields of study ($r = -.11$, $p = .006$). Some other variables were also correlated with earnings (positively or negatively): being female ($r = -.20$, $p < .001$), conscientiousness ($r = .10$, $p = .014$), extraversion ($r = .09$, $p = .024$), agreeableness ($r = -.15$, $p < .001$), neuroticism ($r = -$

.14, $p < .001$), parental education level ($r = .08$, $p = .036$), and parental occupational status ($r = .08$, $p = .049$).

There were some medium correlations ($|r| \geq .20$) and only one large correlation ($|r| \geq .50$) between individual characteristics: Being female was, in the present sample, correlated with a lower score in the cognitive ability test used in the TOSCA study ($r = -.23$, $p < .001$) and with higher neuroticism ($r = .22$, $p < .001$). Age was positively correlated with direct migration background ($r = .26$, $p < .001$). Vocational high school was correlated with lower parental education level ($r = -.20$, $p < .001$) and lower parental occupational status ($r = -.20$, $p < .001$). Cognitive abilities were positively correlated with high school GPA ($r = .27$, $p < .001$; GPA was inverted, so that larger numbers reflect better grades). High school GPA was positively correlated with conscientiousness ($r = .26$, $p < .001$) and negatively correlated with year of study start ($r = -.21$, $p < .001$). Extraversion was positively correlated with agreeableness ($r = .21$, $p < .001$) and negatively correlated with neuroticism ($r = -.37$, $p < .001$). Finally, parental education level was positively correlated with parental occupational status ($r = .66$, $p < .001$).

[TABLE 3 ABOUT HERE]

Selection Into Fields of Study

Table 4 shows the results of a multivariate logit analysis, where field of study was regressed on all individual characteristics considered in the present study. In order to facilitate the interpretation of the findings, average marginal effects were calculated, which show how the individual characteristics were associated with the probability of a specific field of study (relative to a comparison field). Cognitive abilities, high school GPA, personality traits, parental education level, and parental occupational status were z-standardized to have a mean of 0 and a standard deviation of 1 in the final sample.

Model (1) predicted STEM vs. social sciences/humanities graduation. Holding the other individual characteristics constant, being female was associated with a lower probability of STEM (-26.9 percentage points, $p < .001$), a higher (better) high school GPA was a positive predictor (a one standard deviation higher GPA was associated with a 5.4 percentage points higher probability of STEM, $p = .026$), openness was a negative predictor (-5.3 percentage points, $p = .026$), extraversion was a negative predictor (-5.0 percentage points, $p = .036$), and direct migration background was a positive predictor (26.3 percentage points, $p = .029$) of STEM.

Model (2) predicted business/economics vs. social sciences/humanities graduation. All else being equal, female was a negative predictor (-23.1 percentage points, $p < .001$), cognitive abilities was a positive predictor (5.0 percentage points, $p = .047$), openness was a negative predictor (-11.3 percentage points, $p < .001$), parental occupational status was a positive predictor (6.4 percentage points, $p = .048$), and year of study start was a negative predictor (-3.0 percentage points, $p = .029$) of business/economics.

Finally, model (3) predicted STEM vs. business/economics graduation. *Ceteris paribus*, high school GPA was a positive predictor (6.2 percentage points, $p = .020$), openness was a positive predictor (8.1 percentage points, $p = .002$), and extraversion was a negative predictor (-10.6 percentage points, $p < .001$) of STEM.

[TABLE 4 ABOUT HERE]

Effects of Field of Study on Earnings

Table 5 shows the results of a PSM analysis that estimated the effects of field of study on earnings when accounting for the selection patterns shown in Table 4. ATEs of field of study on

log earnings were determined by calculating differences in log earnings between graduates from different fields whose propensity scores were as similar as possible.

Panel A of Table 5 compared STEM to social sciences/humanities. Figure S1 in the online supplemental materials shows the distribution of propensity scores in each of the two fields of study (before matching). There were four observations outside the common support region. After dropping these individuals, the analysis sample included 426 individuals (223 in STEM and 203 in social sciences/humanities). Each observation was successfully matched with 10 observations from the alternative field of study group. Table S1 in the online supplemental materials provides information on covariate balance, showing that the matching with 10 matches per observation successfully reduced standardized differences in explanatory variables between treatment and control group. As the results of the PSM analysis in Table 5 show, STEM had, on average, a positive effect on earnings compared to social sciences/humanities (0.207 higher log earnings, $p < .001$).

Panel B of Table 5 compared business/economics to social sciences/humanities. Figure S2 in the online supplemental materials shows the distribution of propensity scores in each of the two fields of study. After dropping the individuals outside the common support region (nine observations), the analysis sample included 389 individuals (186 in business/economics and 203 in social sciences/humanities). Each observation was successfully matched with 10 observations from the alternative group. Table S2 in the online supplemental materials shows that the matching with 10 matches per observation successfully balanced the covariates. As the results of the PSM analysis in Table 5 show, business/economics had a positive effect on earnings compared to social sciences/humanities (0.212 higher log earnings, $p < .001$).

Panel C compared STEM to business/economics. Figure S3 in the online supplemental materials shows the distribution of propensity scores in each of the two fields of study. After dropping the individuals outside the common support region (twelve observations), the analysis sample included 403 individuals (214 in STEM and 189 in business/economics). All observations were successfully matched with 10 observations from the alternative group. Table S3 in the online supplemental materials shows that the matching with 10 matches per observation successfully balanced the covariates. As the results in Table 5 show, STEM had no significant effect on earnings compared to business/economics (0.003 lower log earnings, $p = .947$).

When transforming the coefficients to relative differences in percent ($(e^{\beta} - 1) * 100 =$ relative difference in %), the results implied that STEM graduates had 23.0% higher earnings than social sciences/humanities graduates with similar outset characteristics and business/economics graduates had 23.6% higher earnings than similar social sciences/humanities graduates. Compared to the descriptive statistics described above, the estimated earnings effect of STEM (relative to social sciences/humanities) was 0.3 percentage points smaller and the earnings effect of business/economics (relative to social sciences/humanities) was 0.6 percentage points smaller than the descriptive statistics suggested.

[TABLE 5 ABOUT HERE]

Robustness Checks

We performed two checks to test the robustness of the main results. The detailed results of the robustness checks are shown in the online supplemental materials.

First, we added math and English competencies (according to standardized educational achievement tests) and vocational interests to the explanatory variables of the treatment model in the PSM analysis. Therefore, individuals who were similar in these domain-specific

competencies and in their vocational interests at the end of high school were compared (see Table S4 in the online supplemental materials). Second, we added the degree type (bachelor's, master's or equivalent, or PhD/doctoral) and the university type (e.g., research university or university of applied sciences) of the last finished study program to the explanatory variables of the treatment model used in the main PSM analysis (see Table S5 in the online supplemental materials).

The results of both robustness checks were similar to the main results shown above, with significant positive earnings effects for STEM and business/economics relative to social sciences/humanities. This indicates the robustness of our main results.

Discussion

Previous research on the relationships between the university-level field of study and later earnings was largely based on labor market data and did not sufficiently consider and account for the role of (self-)selection by individual characteristics such as abilities, personality, and family background. In the present study, we investigated the effects of field of study on earnings and disentangled selection effects and field effects. For this purpose, we made use of a unique, longitudinal dataset with upper secondary school graduates in Germany who were followed over 14 years since high school graduation. This dataset contained rich information on psychological and sociological conditions at the end of high school, including cognitive abilities, educational achievement, personality traits, socioeconomic background, and migration background. We analyzed selection into fields of study with multivariate logistic regressions and then applied PSM to account for these selection effects when estimating the effects of field of study on later earnings.

In the descriptive statistics, we found that STEM graduates had, on average, 23.3% higher earnings and business/economics graduates 24.2% higher earnings than social sciences/humanities graduates. However, students with different outset characteristics tended to self-select into different fields. Holding the other individual characteristics constant, male students, students with a higher (better) high school GPA, students with lower openness, students with lower extraversion, and students with a direct migration background were more likely to study and graduate from STEM compared to social sciences/humanities. And male students, students with higher cognitive abilities, students with lower openness, students with a higher parental occupational status, and students who started studying earlier were more likely to study and graduate from business/economics compared to social sciences/humanities. At least some of these individual characteristics were also relevant to earnings, as we found that being female was negatively correlated and extraversion and parental occupational status were positively correlated with earnings. When accounting for the selection patterns by comparing students with similar outset characteristics in the PSM analysis, STEM graduates turned out to have 23.0% higher earnings and business/economics graduates 23.6% higher earnings than similar social sciences/humanities graduates. Therefore, the effects of field of study decreased very slightly compared to the descriptive findings.

Interpretation and Explanations

Our results suggest that (self-)selection into fields of study has, overall, only a small influence on the relationships between field of study and earnings, as the estimated field of study effects barely changed when selection effects were accounted for. The main results remained consistent throughout the analyses: STEM and business/economics graduates received, on average, higher earnings than social sciences/humanities graduates, while there was no significant earnings

difference between STEM and business/economics. Therefore, the finding that specific fields are associated with higher earnings can apparently be attributed to the fields of study and is not only a consequence of selection by the individual characteristics included in the present study.

Various mechanisms may explain the remaining field of study effects. One plausible mechanism is signaling (Spence, 1973): By graduating from specific fields, individuals signal abilities and other desired characteristics to the labor market that were already present before studying the respective field. Another plausible explanation is human capital investment (G. Becker, 1962; Mincer, 1974): Particular skills that increase productivity in the labor market are learned more frequently or more intensively in some study programs than in others. Empirical evidence on the returns to higher education supports both the signaling and the human capital perspective (Arteaga, 2018; Barrera-Osorio & Bayona-Rodríguez, 2019). It is also plausible that the relationship between labor supply and demand systematically differs between fields and that sociological and negotiation processes have led to fixed wage schemes and collective agreements that offer high earnings only or mostly to workers with specific qualifications.

Comparison to Previous Literature

Our findings on (self-)selection patterns into the different fields of STEM, business/economics, and social sciences/humanities were very similar to the results of previous literature on determinants of the university-level field choice (e.g., Duru-Bellat et al., 2008; Humburg, 2017; Kinsler & Pavan, 2015; P. Parker et al., 2014; Päßler & Hell, 2012; Wille et al., 2020). Likewise, the relationships between individual characteristics and earnings found in our correlation analysis—with conscientiousness, extraversion, parental education level, and parental occupational status being positively related and being female, agreeableness, and neuroticism being negatively related to future earnings—largely resembled previous findings on individual

predictors of earnings (e.g., Müller & Plug, 2006; Murphy & Welch, 1990; Rumberger, 2010; Spengler, 2020).

Our main result that STEM and business/economics graduates received higher earnings than social sciences/humanities graduates was in line with results from the previous literature on field of study and earnings (Altonji, Arcidiacono, & Maurel, 2016), including data from—for example—the United States (e.g., Altonji & Zhong, 2021; Hamermesh & Donald, 2008; Kim et al., 2015; Kinsler & Pavan, 2015), the United Kingdom (e.g., Chevalier, 2011), Germany (Grave & Görlitz, 2012), Norway (Kirkeboen et al., 2016), and Chile (Hastings et al., 2013). Our finding that STEM graduates received similar earnings as business/economics graduates was also in line with previous studies (e.g., Grave & Görlitz, 2012; Kinsler & Pavan, 2015). Our study showed that these results were robust to accounting for (self-)selection by a large set of individual characteristics, many of which were not available in previous studies.

Our finding that accounting for (self-)selection barely changed the estimated field of study effects on earnings was in line with previous studies that controlled for educational achievement (Hamermesh & Donald, 2008; Kinsler & Pavan, 2015). However, a previous study on field of study and earnings in Germany found that controlling for educational achievement and some other individual characteristics reduced the field of study effects more strongly (Grave & Görlitz, 2012). A potential explanation for this difference to the present study is that the present study accounted for psychological and sociological conditions—such as personality traits—that were not considered in the previous literature on this topic. For example, less extraverted high school graduates have a higher probability to choose STEM, and extraversion is a positive predictor of earnings, which creates a negative bias in the estimated earnings effect of STEM when the selection by personality is not accounted for.

Limitations and Potential for Future Research

One limitation of our study is that the consideration of (self-)selection effects was possibly imperfect. In the absence of an experiment or quasi-experiment, we could not of course calculate measures of field of study effects that were free of any potential selection bias. Nevertheless, we considered a rich set of individual characteristics, including psychological and sociological factors that were shown to be important for field of study and earnings, and accounted for these characteristics in the PSM analysis.

Another limitation arises from the fact that we aggregated subjects into relatively large field of study categories to ensure sufficient group sizes. For example, medicine was combined with all other STEM subjects. Previous literature found evidence for particularly high earnings among medicine graduates (e.g., Altonji & Zhong, 2021; Chevalier, 2011; Hastings et al., 2013; Kim et al., 2015; Kirkeboen et al., 2016).

It is also important to recognize that individuals in our study were observed no later than 14 years after high school graduation. Some effects of field of study on earnings might occur later in the career. For example, longitudinal data from the United States suggest that the earnings premium for medicine—a subject that requires long education—tends to increase with age (Kim et al., 2015). Thus, our results should be interpreted as early-career effects and do not necessarily reflect lifetime effects.

An interesting avenue for future research is the investigation of interactions between individual characteristics and field of study: Do individuals with certain characteristics receive higher earnings premia from certain fields than other individuals? Hastings et al. (2013) found evidence that the earnings gains from attending highly selective business schools depend on the

socioeconomic background. Future research might further investigate such interaction effects (which were beyond the scope of the present study).

Implications for Research and Practice

Our findings improve the understanding of the associations between university-level field of study and earnings: The results suggest that these associations mainly reflect actual effects of the field of study. Therefore, the results also suggest that descriptive evidence on the relationships between field of study and earnings is indeed informative about field of study effects, although accounting for (self-)selection might lead to more precise quantitative estimates.

Finally, our investigation has practical implications for students' choices: Since future earnings were found to be one of the determinants of the field choice at university (e.g., Abramitzky et al., 2019; Long et al., 2015; Wiswall & Zafar, 2015), our findings on the earnings effects of field of study might be informative for students' decision making. Nevertheless, we also found large earnings variances within fields (see Table 2 and Figure 1), so graduating from a particular field is by far no guarantee of a specific earnings level.

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Table 1*Fields of Study Distinguished in the Present Study*

Field of study	Included subjects (examples)	Number of individuals
STEM (science, technology, engineering, and mathematics)	Physics, chemistry, computer science, earth and environmental sciences, biology, medicine, pharmacy, sport sciences, veterinary medicine, biotechnology, civil engineering, electrical engineering, mechanical engineering, mathematics	224
Business/economics	Business administration, management, economics, business engineering, business informatics, business law	191
Social sciences/humanities	Sociology, political science, psychology, educational sciences, teacher education, public administration, (general) law, international law, tax law, philosophy, theology, languages, history, archaeology, architecture, arts	207

Note. $N = 622$.

Table 2*Descriptive Statistics: Means and Standard Deviations in Different Fields of Study*

Variables	(1) STEM ($n_1 = 224$)		(2) Business/ economics ($n_2 = 191$)		(3) Social sciences/ humanities ($n_3 = 207$)		<i>p</i> -value of mean difference (1)–(3)	<i>p</i> -value of mean difference (2)–(3)	<i>p</i> -value of mean difference (1)–(2)
	Mean	SD	Mean	SD	Mean	SD			
Earnings per month (€)	5030.36	1999.08	5110.96	2602.02	4113.84	6267.90	0.038	0.042	0.722
Female	0.39	0.49	0.48	0.50	0.73	0.45	0.000	0.000	0.069
Age	19.44	0.61	19.43	0.50	19.43	0.51	0.815	0.949	0.864
Vocational high school	0.33	0.47	0.38	0.49	0.27	0.45	0.177	0.017	0.272
Cognitive abilities	106.95	14.12	104.59	13.43	102.15	13.83	0.000	0.075	0.084
High school GPA	2.07	0.65	2.22	0.59	2.23	0.61	0.006	0.891	0.010
Openness	2.77	0.42	2.65	0.41	2.91	0.46	0.001	0.000	0.003
Conscientiousness	2.98	0.42	3.03	0.43	2.90	0.49	0.055	0.004	0.231
Extraversion	2.76	0.40	2.89	0.36	2.90	0.45	0.001	0.782	0.001
Agreeableness	2.91	0.33	2.90	0.37	2.95	0.34	0.323	0.172	0.620
Neuroticism	2.23	0.40	2.24	0.39	2.30	0.46	0.081	0.145	0.795
Parental education level	5.31	1.74	5.05	1.70	5.32	1.69	0.946	0.111	0.125
Parental occupational status	61.14	14.76	58.98	14.83	59.61	14.60	0.279	0.670	0.138
Direct migration background	0.07	0.26	0.04	0.20	0.02	0.15	0.023	0.321	0.200
Indirect migration background	0.09	0.29	0.12	0.32	0.13	0.33	0.290	0.751	0.476
Year of study start	2003.31	1.59	2003.20	1.61	2003.49	1.98	0.285	0.114	0.510

Note. $N = 622$. SD = standard deviation. Reported *p*-values resulted from two-tailed *t*-tests.

Table 3*Correlations*

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
(1) Earnings	1.00																	
(2) STEM	.05	1.00																
(3) Business/economics	.06	-.50	1.00															
(4) Social sciences/humanities	-.11	-.53	-.47	1.00														
(5) Female	-.20	-.21	-.07	.28	1.00													
(6) Age	-.01	.01	.00	-.01	-.07	1.00												
(7) Vocational high school	.00	.01	.08	-.08	-.07	.15	1.00											
(8) Cognitive abilities	.02	.13	.00	-.13	-.23	-.10	-.17	1.00										
(9) High school GPA	.03	.13	-.06	-.07	.09	-.15	-.15	.27	1.00									
(10) Openness	.00	-.02	-.20	.21	.19	.04	-.13	.06	.16	1.00								
(11) Conscientiousness	.10	.02	.09	-.11	.05	.03	.01	-.03	.26	-.11	1.00							
(12) Extraversion	.09	-.16	.07	.09	.12	.04	-.06	-.18	-.10	.08	.08	1.00						
(13) Agreeableness	-.15	-.01	-.04	.05	.15	.00	-.02	-.04	-.03	.12	.00	.21	1.00					
(14) Neuroticism	-.14	-.05	-.03	.08	.22	-.03	.01	-.10	.01	.01	-.18	-.37	-.07	1.00				
(15) Parental education level	.08	.03	-.07	.04	.00	-.07	-.20	.09	.15	.13	-.06	.05	.07	-.03	1.00			
(16) Parental occupational status	.08	.06	-.04	-.02	.02	-.09	-.20	.03	.09	.10	-.01	.04	.07	-.09	.66	1.00		
(17) Direct migration background	.01	.09	-.01	-.08	-.02	.26	.09	-.10	-.03	-.04	-.01	-.04	-.08	.04	-.04	-.09	1.00	
(18) Indirect migration background	-.03	-.04	.01	.03	.07	.06	-.03	-.06	-.08	.10	.00	.05	.02	.01	-.06	-.03	-.08	1.00
(19) Year of study start	-.07	-.01	-.05	.06	-.14	.01	.03	-.02	-.21	.02	-.13	-.06	.06	.08	-.04	-.02	-.03	.04

Note. $N = 622$. Cognitive abilities, high school GPA, personality traits (openness, conscientiousness, extraversion, agreeableness, and

neuroticism), parental education level, and parental occupational status were z-standardized. GPA was inverted, so larger numbers reflect higher

(better) grades. Coefficients in bold were statistically significant ($p < .05$, two-tailed).

Table 4*Multivariate Logit Analysis of Selection Into Fields of Study*

Variables	(1) STEM			(2) Business/economics			(3) STEM		
	vs. social sciences/humanities			vs. social sciences/humanities			vs. business/economics		
	β	SE	p	β	SE	p	β	SE	p
Female	-0.269	0.043	0.000	-0.231	0.049	0.000	-0.100	0.052	0.053
Age	-0.014	0.041	0.733	-0.030	0.047	0.521	0.007	0.047	0.884
Vocational high school	0.048	0.051	0.343	0.092	0.051	0.070	-0.030	0.051	0.560
Cognitive abilities	0.029	0.025	0.234	0.050	0.025	0.047	-0.003	0.026	0.921
High school GPA	0.054	0.025	0.026	0.021	0.028	0.442	0.062	0.027	0.020
Openness	-0.053	0.024	0.026	-0.113	0.023	0.000	0.081	0.026	0.002
Conscientiousness	0.029	0.023	0.204	0.046	0.025	0.061	-0.040	0.027	0.146
Extraversion	-0.050	0.024	0.036	0.025	0.027	0.352	-0.106	0.028	0.000
Agreeableness	0.023	0.024	0.324	0.001	0.023	0.959	0.042	0.024	0.083
Neuroticism	-0.015	0.025	0.539	0.017	0.027	0.527	-0.034	0.028	0.223
Parental education level	-0.034	0.030	0.254	-0.063	0.032	0.053	0.007	0.031	0.813
Parental occupational status	0.055	0.030	0.064	0.064	0.032	0.048	0.022	0.031	0.486
Direct migration background	0.263	0.120	0.029	0.066	0.129	0.610	0.159	0.112	0.157
Indirect migration background	0.041	0.070	0.564	0.025	0.070	0.727	-0.045	0.078	0.564
Year of study start	-0.013	0.013	0.319	-0.030	0.014	0.029	0.013	0.016	0.417
Pseudo R-squared		0.145			0.137			0.076	
Observations		431			398			415	

Note. Average marginal effects from multivariate logit models. The dependent variable was the respective field of study. Model (1) was restricted to STEM and social sciences/humanities graduates, model (2) was restricted to business/economics and social sciences/humanities graduates, and model (3) was restricted to STEM and business/economics graduates. Cognitive abilities, high school GPA, personality traits (openness,

conscientiousness, extraversion, agreeableness, and neuroticism), parental education level, and parental occupational status were z-standardized. GPA was inverted, so larger numbers reflect higher (better) grades. β = coefficient. SE = standard error. Coefficients in bold were statistically significant ($p < .05$, two-tailed).

Table 5*Propensity Score Matching (PSM) Analysis of the Effects of Field of Study on Earnings*

Variables	Log earnings			
	β	SE	95% CI	p
Panel A				
STEM vs. social sciences/humanities	0.207	0.042	[0.124, 0.291]	0.000
Observations	426			
Panel B				
Business/economics vs. social sciences/humanities	0.212	0.058	[0.099, 0.326]	0.000
Observations	389			
Panel C				
STEM vs. business/economics	-0.003	0.044	[-0.088, 0.083]	0.947
Observations	403			

Note. Average treatment effects (ATEs) from a PSM analysis with 10 matches per observation. The dependent variable was the natural logarithm of gross monthly earnings. The treatment variable was the respective field of study. The explanatory variables of the treatment models (multivariate logit models) were the explanatory variables listed in Table 4 (gender, age, type of high school, cognitive abilities, high school GPA, personality traits, parental education level, parental occupational status, migration background, and year of study start). β = coefficient. SE = standard error. CI = confidence interval. Due to heteroscedasticity, robust standard errors were used. Coefficients in bold were statistically significant ($p < .05$, two-tailed).

Figure 1

Distributions and Median Values of Earnings for Different Fields of Study

Note. This figure shows density plots for gross monthly earnings up to €10,000. The vertical lines show the median earnings in the respective field.