Sorting into Career Paths on Personality and Preferences*

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Abstract

We comprehensively study sorting into career paths on personality and preferences. To do so, we leverage a unique combination of survey and administrative data of several cohorts of students at a large German university. We find extensive sorting along 16 personality and preference measures that persists when controlling for expectations about earnings, own ability, and amenities. This sorting is productive: students whose personality is misaligned with their average peer have a higher likelihood of not completing their degree. Across fields over time, student personality seems rather stable. The sorting into fields of study foreshadows differences in worker personality by occupation.

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"There's nothing hidden in your head
the Sorting Hat can't see,
so try me on and I will tell you
where you ought to be."

The Sorting Hat, Harry Potter and the Philosopher's Stone, by J.K. Rowling

1 Introduction

Why do individuals choose certain career paths over others? The question of occupational sorting has long been a central topic in economics, particularly as it relates to human capital formation, labor market efficiency, and social mobility (e.g., Becker, 1964; Roy, 1951; Murphy et al., 1991; Hsieh et al., 2019; Haeck and Laliberté, 2025). While economic incentives such as wages and amenities play an important and well-studied role in shaping career decisions (e.g., Altonji et al., 2012, 2016; Lovenheim and Smith, 2023), a growing body of evidence suggests that individual personality traits and economic preferences substantially contribute to these choices (Dohmen and Falk, 2010; Friebel et al., 2019; Gill et al., 2023). A comprehensive understanding of how these factors influence individuals' choices of fields of study - and ultimately their occupations - is crucial for evaluating labor market outcomes, designing effective education policies, and enhancing workforce productivity.

This paper provides a comprehensive analysis of sorting into career paths based on personality and economic preferences. We leverage a unique combination of tailored survey and administrative data covering multiple cohorts of students $(N = 9,171)$ at a large German university. Our analysis reveals extensive sorting along 16 personality and preference dimensions, with significant implications for education and labor market outcomes.[1] Notably, we document that personality-based sorting persists even after accounting for traditional determinants of career choice, such as expected earnings, perceived ability, and job amenities. Moreover, we show that this sorting is consequential: students who are misaligned with their peers in terms of personality are significantly more likely to drop out or switch fields, highlighting the economic costs of poor personality-career fit. Finally, we provide suggestive evidence on the stability of students' personality by re-surveying the students close to graduation.

Our setting offers several unique advantages. First, as in most other OECD countries, students in tertiary education in Germany enroll in a specific field of study. Credits earned are field-specific, making field choice a consequential decision to be made right at the beginning of tertiary education. We run the initial survey when students are in the second week of their university studies. This ensures that

[1] From now on we refer to this set of measures as the students' "personality".

the university environment as such and specifically the sorting into different study fields has not yet affected the students' personality. We can thus rule out that the personality measures we elicit in our initial survey are contaminated by any imprint the field of study (via course contents or peers' personality) might have on the students' personality in the longer term. Second, conditional on having a university entrance qualification, students in our setting can almost freely choose between fields of study. This allows us to interpret the observed differences in personality across fields as pure sorting (as opposed to labor market entry or later occupational choices, where sorting on personality is confounded by demand factors).[2] Third, because students mostly choose between three-year degrees, our setting is particularly well suited for studying how the (mis)alignment between own and peers' personality impacts well-defined measures of selecting out of an initially chosen career path. Moreover, the students enter university at the same time, making sure that all subjects had the same length of exposure to their field-specific environment when we re-survey them towards the end of their third year.

Using the linked survey and administrative data, we document extensive sorting into career paths on personality and economic preferences. Immediately after starting their undergraduate degree, students differ substantially across fields in important personality and preference features. For example, students in teacher training are not only more risk averse, more trusting, and less negatively reciprocal than the average student (as suggested by Dohmen and Falk, 2010), but also more agreeable, more altruistic, more extroverted, and much less competitive. Law students, by contrast, are more negatively reciprocal and thus more willing to punish unfair behavior (similar to Friebel et al., 2019), but also less agreeable, much less trusting, and more competitive than the average student and thus show opposite patterns to students in teacher training in several personality dimensions. Students in business and economics are much more willing to take risks and significantly more competitive than their peers. They also reveal higher levels of extraversion and self-esteem, but score lower on trust, agreeableness, and altruism. Comparing variation in personality across fields and measures reveals that the largest differences emerge in competitiveness, suggesting an outsized role of competitiveness for occupational choice (Buser et al., 2014, 2024b).

To further study the extent of sorting, we derive each students' distance across all personality measures from the average student in each field (Mahalanobis, 1936) and, akin to Arcidiacono et al. (2020), regress actual field of study on these distances. We find that similarity to potential peers' average personality is indeed highly predictive

[2]The only study programs with binding entry barriers (based mostly on high school GPA) are psychology, pharmacy, and (dental) medicine, of which only medicine forms a separate field of study in our analysis. Controlling for high school GPA leaves our results on sorting unaffected, albeit making some of the differences between medicine and the other fields somewhat less pronounced.

for actual field of study choice, a finding that is robust to controlling for earnings expectations and beliefs about non-wage amenities across fields. The two primary mediators of the relationship between field of study and personality in our data are beliefs about own ability and about how much students would enjoy their future work, suggesting that these dimensions are driven by student personality and economic preferences. The extensive sorting on personality in our data complements earlier work that has identified expected earnings and perceived ability as drivers of college major choice, but also found that a heterogeneous taste component is the dominant factor in the choice of field of study (e.g., Wiswall and Zafar, 2015).

Using again the distance to peer personality, we also demonstrate that sorting on personality and preferences is consequential. Specifically, a larger distance in personality from the average student in the same field is associated with a lower likelihood of students finishing their degree, suggesting that misalignment between own personality and average peer personality hinders academic progress in higher education. Exploiting the feature that we re-survey students in their third year, we furthermore investigate to what extent initial sorting on personality predicts endline differences in personality across fields before students graduate and enter the labor market. We find that endline differences in personality are very similar to initial differences, suggesting that relative to field-specific changes in personality during higher education, initial sorting is the dominant factor in explaining differences in personality by field of study when university graduates enter the labor market. Finally, using fields that clearly correspond to an occupation (like, for instance, medicine and teacher training), we demonstrate that the sorting patterns in our data are well in line with personality differences between subjects working in the respective occupations. This finding suggests that the extensive sorting on personality observed in our data is indeed predictive of personality differences by occupation in the labor market.

Our paper contributes to two major strands of research. First, we contribute to the literature on personality and the labor market. A small, but growing part of this literature studies labor market sorting on personality and economic preferences. Similar in spirit to Dohmen and Falk (2010) on teachers and Friebel et al. (2019) on police officers, Gill et al. (2023) track a cohort of business students at a large German university over time and show that workers sorting into the financial industry are less trustworthy than their peers. Li et al. (2017) and Li et al. (2022) study social preferences of medicine students and physicians and highlight differences in altruism. Fisman et al. (2015) elicit social preferences of prospective lawyers at an elite institution in the US, finding higher selfishness and efficiency preferences than in the general population. Most papers in this literature focus on one occupation and consider a small set of specific personality features, but ignore whether sorting on personality is

a broader phenomenon. The closest paper to ours is Buser et al. (2023), who show that personality, preferences, and behaviors associated with genetic endowments differ between occupations and fields of study. In comparison to their paper, we focus on a setting where we can convincingly isolate sorting from other potential channels such as demand for specific skills. We also use direct measures of preferences and personality, and our coverage of personality and preference features is much broader. In addition, the student setting allows us to study individuals who sort into distinct, well-defined career paths within one integrated framework. This allows us to uncover mechanisms around personality-based sorting that are otherwise difficult to observe, including how misalignment between own and peer personality after initial sorting leads individuals to adjust their choices. This literature has also discussed the role of personality in education and the labor market more generally. This body of work has found that economic preferences and personality matter for outcomes (see, e.g., Heineck and Anger, 2010; Lundberg, 2013; Buser et al., 2014; Izadi and Tuhkuri, forthcoming).[3] We add to this literature a comprehensive analysis of sorting into career paths on personality and preferences.

Second, our paper speaks to the literature on field of study choice. One strand of this literature investigates college major choice using survey information and survey experiments in the US, where students only choose majors after some time at college.[4] For example, Wiswall and Zafar (2015) show that expected earnings and perceived ability are important for major choice, but that heterogeneous tastes are the dominant driver.[5] Our paper contributes to this literature by providing evidence suggesting that students sort into fields of study on personality and economic preferences. We show that students' personality systematically differs by field on average already at the very beginning of their studies. This holds true even conditional on high-stakes measures of cognitive skills and other observable characteristics. Because universities in Germany typically admit all eligible students (and eligibility, if anything, is restricted by minimum high school GPAs, our measure of cognitive ability), these differences arguably reflect student self-selection.[6] We also advance the literature by showing that students' mean distance in personality is highly predictive of actual field of study choice, following in spirit an approach of Arcidiacono et al. (2020), even conditional on earnings expectations, beliefs about own ability, and beliefs about non-wage amenities.

[3] In recent work, Buser et al. (2024a) show that differences in twins' genes associated with cognitive and non-cognitive skills are predictive of education and labor market outcomes.

[4] A second strand studies major choice in observational data, highlighting econometric difficulties of identifying determinants of major choice because the second-best alternative is typically not known and because there are entry barriers to fields of study (e.g., Kirkeboen et al., 2016).

[5] In this literature, see also, e.g., Stinebrickner and Stinebrickner (2014); Wiswall and Zafar (2018); Delavande and Zafar (2019); Wiswall and Zafar (2021).

[6] This approach and interpretation follows research studying labor market sorting more broadly (e.g., Boehm and Watzinger, 2015; Shu, 2016; Friebel et al., 2019; Nagler et al., 2020).

More generally, we thus contribute to the literature on field of study choice and human capital formation. This literature typically models human capital and decisions on career paths as depending on three factors: returns, preferences, and constraints (Lovenheim and Smith, 2023). While there is extensive research on the roles of (expected) returns and constraints for human capital decisions, the literature has paid much less attention to factors that determine preferences for different career paths (for recent exceptions, see, e.g., Delavande and Zafar, 2019; Azmat and Kaufmann, 2024). We contribute to filling this gap by showing that student personality is a relevant determinant of preferences over fields of study, and that these effects exist even conditional on expected returns.

The remainder of this paper is as follows. Section 2 introduces the survey module and the data. Section 3 presents the evidence on sorting into career paths on personality and preferences and discusses implications and Section 4 concludes.

2 Institutional Setting and Survey Design

2.1 Institutional Setting

Our data cover undergraduate students at a large public university in Germany with about 40,000 students in total. The university offers a large variety of undergraduate programs from all academic disciplines, including teacher training, arts and humanities, social sciences, natural sciences, engineering, business and economics, law, and medicine. At undergraduate level, three-year degrees are most common, but there are also programs that take longer to complete (in particular in the fields of teacher training, law, and medicine).

The university is typical for non-elite schools in many OECD countries (Lovenheim and Smith, 2023). It offers tertiary education to students that have earned a university entrance qualification by completing a total of 12 or 13 years (depending on the school type) of primary and secondary school education. Because most larger cities in Germany host a university offering similar undergraduate programs broadly at the same level, the majority of students are from the region.[7] Importantly, students about to begin their undergraduate studies enroll in a specific field of study, as is typical at universities outside North America and Australia (Lovenheim and Smith, 2023). Credits earned are field-specific and usually cannot be transferred if a student changes to a different field. As a result, we consider a setting where students choose a field of study rather than a university only, and where field choice is a consequential

[7] More than 80 percent of the university's undergraduate students obtained their university entrance qualification in the federal state where the university is located. Around 70 percent are from places that are in commuting distance to the university.

decision to be made right at the beginning of tertiary education. At an individual level, there are few limitations on field choice. Notably, at this university, only degrees in Medicine, Psychology, and Pharmacy have entry barriers (mostly based on the GPA of the university entrance qualification) that materially restrict entry into these fields.

At the university we consider, the academic year comprises two semesters. Most study programs start in the fall semester, which begins in October and ends in February. The summer term begins in April and ends in July.

2.2 Survey Design

General Setup. Our data come from a set of surveys which we conducted among all first-year undergraduate students at the University under consideration. The surveys were conducted between 2020 and 2024. None of the students invited for the survey had studied at any university before. All of these eligible students were invited via e-mail to participate in the survey in the second week after they started their university studies, i.e., in October of each year. Students who completed the survey were paid €10 until 2021 and €15 since then; they could choose to receive their payment either via bank transfer or as a voucher for a large international online retailer.[8] The survey comprised several blocks, which were shown to the participants in semi–randomized order.

The survey elicited economic preferences and psychological personality measures in the first part, followed by study motives and questions related to the subjects' parental background in the second part. Finally, we asked students about their earnings expectations, perceived relative ability ranks, and expectations about non-wage amenities in their future job.

Most of our work relies on the data collected in the initial ("baseline") survey. To enable analyses of student personality by field of study shortly before students enter the labor market, we re-surveyed all students who participated in the initial survey when they were in their sixth term (i.e., in their third year). At this point, most students who had stayed enrolled in their initial field of study were close to graduation. In this endline survey, we elicited again the set of personality and preference items that formed part of the initial survey.[9]

We matched the survey data with registry data from the university comprising information on the students' entrance qualification GPA, grade, gender, nationality,

[8]The survey was implemented in oTree (Chen et al., 2016).

[9]Note that we currently have endline survey data only for two out of the five cohorts of students who took the initial survey (cohorts who started in 2020 and 2021). Analyses using the endline data therefore rely on smaller sample sizes than analyses based solely on survey data elicited when the students began their studies.

and the study program they enrolled in.[10] The data allow us to track students over their entire career at the university, including switches between study fields and dropout. We group students into eight fields of study according to the study program they enrolled in. The fields we consider in our analysis comprise Teacher Training, Humanities, Social Sciences, Natural Sciences, Engineering, Business & Economics, Law, and Medicine.

Survey Participation. Across the five waves, 48.4 percent of all eligible students took part in the initial survey, resulting in a sample of 9,171 students. Appendix Table A1 shows mean characteristics from the administrative data for baseline survey participants and non-participants (left panel). 58 percent of our sample are female, slightly more than among all students invited to the survey, and 6 percent are of non-German nationality. Students in our sample are on average 19.6 years of age. Regarding the university entrance qualification, survey participants are of slightly higher cognitive ability than survey non-participants. 16 percent of our sample are students in teacher training, 8 percent study arts and humanities, 9 percent social sciences, 13 percent natural sciences, 17 percent are in engineering, 20 percent in business and economics, 9 percent in law, and 8 percent in medicine. Overall, the sample of survey participants represents the student population reasonably well. Importantly, the survey also provides us with a fair representation of the student population regarding field of study.

Preferences. To measure economic preferences, we implemented the German version of the Global Preference Survey (Falk et al., 2023, 2018). This survey covers time and risk preferences, altruism, trust, and positive as well as negative reciprocity. It includes self-assessment questions that are answered on Likert scales as well as more involved tasks (e.g., choice lists to elicit time and risk preferences). Each preference measure except generalized trust is elicited using several items, usually comprising one or two self-assessment questions and one item involving a choice list or a hypothetical situation, i.e., qualitative as well as quantitative items. The final measures are then given by weighted averages of all preference-specific items.

Personality. Additionally, we elicited ten psychological personality features. We used a 15-item survey introduced by Gerlitz and Schupp (2005) to measure the Big 5 personality measures (openness, conscientiousness, extraversion, agreeableness, and neuroticism). We measure students' locus of control (i.e., the extent to which one

[10]We re-coded the GPA of the university entrance qualification such that higher numbers indicate better academic performance. In the German system, where school grades run from 1 to 4, 1 is the best outcome.

believes that certain events are the result of their own activities instead of someone else's or destiny) using a 4-item scale by Weinhardt and Schupp (2011) and Kantar Public (2019). We measure self-efficacy (i.e., the expectation to succeed in certain situations or tasks based on one's own competences and abilities) using a 3-item scale by Beierlein et al. (2012). We use a one-item scale to measure self-esteem, following Weinhardt and Schupp (2011). Furthermore, we elicit grit (passion and/or perseverance) following Fleckenstein et al. (2014) using a German 8-item version of Duckworth et al. (2007). Finally, we include two items on willingness to compete (Buser et al., 2024b; Niederle and Vesterlund, 2007).

Additional Measures. Apart from the preferences and personality features, we elicited a battery of additional measures. These include nine questions regarding students' motivation to choose their study program. These questions were answered on Likert scales and covered pecuniary as well as non-pecuniary motivations. We also elicited a proxy for students' socioeconomic status by asking for their parents' highest degrees. Next, we included a series of questions regarding one's beliefs about own ability in several study fields since these beliefs may be intertwined with students' personality (e.g., Lovenheim and Smith, 2023).[11] For each of the eight study fields, we asked participants to provide their expected rank in the ability distribution if they were to graduate in the given field. Thus, we have data on expected ability not only in students' actual field of study, but also for all remaining fields, yielding a comprehensive set of counterfactual ability measures. Using a similar approach, we elicited participants' expectations about their future earnings. We asked for their expected monthly gross wage at the age of 30 under the assumption that they would graduate in each out of the eight study fields. Lastly, we elicited expectations about several non-wage amenities in the same counterfactual manner to assess other aspects of compensation (Rosen, 1986). The non-wage amenities are leisure time, time for family, and enjoying work. For each dimension, participants were asked to indicate the probability at which they believed the amenity to be fulfilled given working full time at the age of 30 and having graduated in the respective (counterfactual) study field.

[11]We asked these questions for eight counterfactual study fields: Law, Medicine, Natural Sciences, Humanities, Social Sciences, Teacher Training, Engineering, and Business & Economics. For each study field, we provided examples of majors that fall into the respective category.

3 Personality and Preferences in Field of Study Choice

3.1 Sorting on Personality and Preferences Into Fields

Descriptive Evidence on Initial Sorting. To assess differences in personality and economic preferences across different fields of study due to sorting, we first plot the results of our initial surveys at the beginning of students' time at university. Here we exploit the fact that only very few fields have entry barriers. Thus, all other differences in personality and economic preferences are arguably driven by self-selection, in line with arguments in Friebel et al. (2019).

Specifically, we estimate the differences in personality and preference measure p between field j and all others for all $P \times J$ combinations, for students i at the beginning of their studies:

$$item_i^p = \alpha + \beta^{pj} field_i^j + \epsilon_i \;\; \forall \, p, j \tag{1}$$

In this equation, $item_i^p$ is a measure of personality or preferences $p = 1, \ldots, P$ of individual i and $field_i^j$ is an indicator for i's study field $j = 1, \ldots, J$. We adjust standard errors for multiple hypothesis testing using the Westfall-Young approach.

Figure 1 shows the estimates from Equation 1, each cell representing the coefficient from a separate regression that uses the personality measure as the dependent variable and an indicator for field of study as the independent variable, using all other fields as the comparison group. Orange cells reflect positive, blue cells reflect negative coefficients, while gray cells show that an estimate is insignificantly different from zero at the five percent level. We also test for row-wise and column-wise joint significance of coefficients using seemingly unrelated regressions.

The figure shows that differences in personality and economic preferences are not confined to specific occupations and items, but that sorting is a broad phenomenon. For example, students in business and economics are not only more risk loving and less trusting than other students (similar to Gill et al. 2023), they are also less agreeable, less altruistic, less open and more extroverted, have higher grit, self-esteem, and are substantially more competitive. Students aspiring to become teachers are not only more risk averse than other students (similar to Dohmen and Falk 2010), but also show less negative reciprocity, grit, and competitiveness and are more agreeable and extroverted. Our findings also show that students in medicine are more altruistic (as in Li et al. 2022 and Attema et al. 2023 and in line with professional norms (Arrow, 1963), but in contrast to Li et al. 2017), more conscientious, more patient, and have somewhat higher positive reciprocity, while showing lower negative reciprocity than other students.[12]

[12]As noted before, medicine is the main study field where entry barriers play a role, typically requiring a very good GPA of the university entrance qualification. After recoding (such that higher

We also expand prior research by including study fields that have not yet been studied. For example, engineers are less altruistic, less extroverted, less neurotic, and less open, and are more risk-loving, more patient, and more competitive than other students. In contrast, students in the humanities are less conscientious, less patient, less competitive, and have lower self-esteem, but are more open than other students.

All in all, the row-wise joint significance tests indicate that students in each field seem quite different to other students, while the column-wise significance tests suggest that all personality and preference items differ significantly across fields of study. These results substantially broaden the evidence that the recent literature has produced, with most papers' main results representing specific cells in the matrix. Importantly, our approach of comprehensively documenting sorting into fields of study successfully replicates a number of these earlier contributions and generally leads to very plausible patterns.[13]

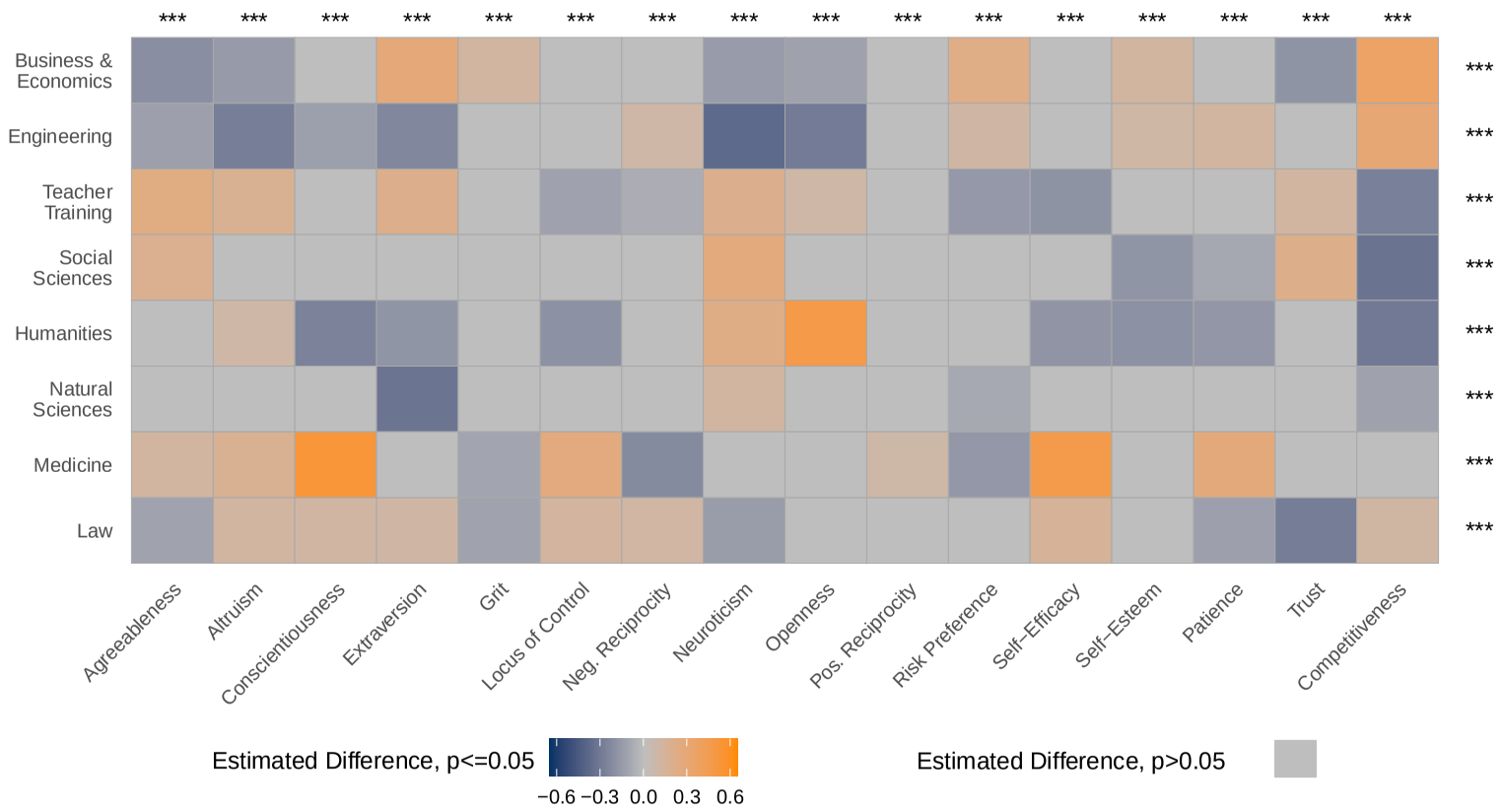
Our interpretation of these estimates as reflecting sorting on personality and preferences is corroborated by the high degree of correlation in the differences across distinct subsamples (i.e., the cell values in Figure 1). For example, the correlations are above 0.8 when comparing students with excellent university qualification exams (the top 25% in our data) who face almost no constraints in choosing fields of study in any university to all other students, when comparing men and women, and when comparing specifications without (as in Figure 1) and with controls (for gender, migration background, FiF status, and the university entrance qualification degree).

Finally, previous work on sorting on personality in the labor market has often focused on a small set of personality measures. One concern regarding this literature could be that other, correlated and unobserved personality measures could equally well drive the observed associations. Given the comprehensive set of personality and preference measures in our data, we can address this concern and assess which dimensions of personality are the likely drivers of field of study choice. We therefore determine in the following those dimensions of personality that differ most strongly across fields, following the idea that these dimensions of personality are most likely to drive sorting into career paths.

grades indicate better academic performance, with a GPA of 4 being the highest possible value), the average GPA of survey respondents in medicine is 3.51, relative to 2.81 among all survey participants. This could explain some of the findings, for example that medicine students are highly conscientious.

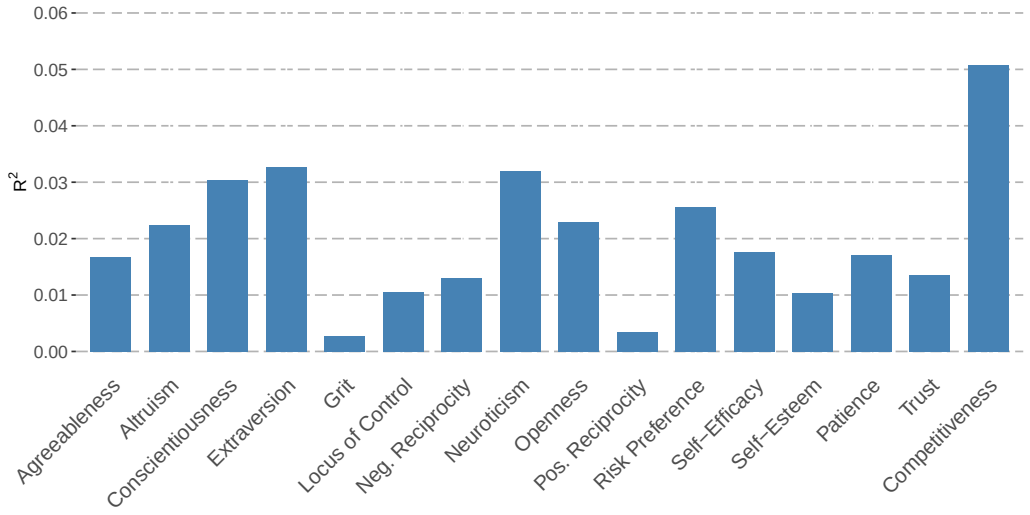
[13]One example for this is teacher training, with a clearly predictable career path leading most graduates to become civil servants. This makes it a very reasonable career choice for risk-averse individuals.

Figure 1: Differences in Personality and Economic Preferences Across Fields of Study



Note: This figure visualizes results from separate regressions of 16 personality and preference items on eight study field dummies (128 regressions). Each cell represents the coefficient of the field dummy in the respective regression. The data cover five cohorts of students (2020 to 2024) who participated in the initial survey and contain observations from 9,171 subjects in total. Due to missing values in personality and preference measures, the individual coefficients are based on slightly smaller samples. Cells containing a coefficient with a p-value$>$ 0.05 are gray, positive (negative) significant coefficients are shown in orange (blue). p-values are adjusted for multiple hypothesis testing using the Westfall-Young method. The more intense the color, the larger the absolute value of the respective coefficient. Stars at the row and column margins show the results of joint coefficient tests originating from estimating seemingly unrelated regressions. * $p<0.1$ ** $p<0.05$ *** $p<0.01$.

Figure 2: Explanatory Power of Fields of Study for Personality



Note: This figure shows the R^2 of separate regressions of each personality measure on a comprehensive set of eight field of study dummies.

Figure 2 shows the results from this exercise. It depicts the R^2 of regressions of each personality and preference measure in our data on field of study fixed effects. We find that the average R^2 of field of study fixed effects is around 0.02. The highest value results from the regression using competitiveness as the dependent variable ($R^2 = 0.05$). For comparison, this is around half of the explanatory power of gender for competitiveness in our data. Thus, field of study differences in personality do seem to matter. Our finding that the largest differences in personality across fields emerge in competitiveness also suggest an outsized role of competitiveness for occupational choice (in line with, e.g., Buser et al., 2014, 2024b).

Within-Student Regressions. To investigate in more depth whether sorting into fields of study on personality is important, we subsequently estimate within-student regressions of field of study choice on the distance in personality to other students in a field. Our measure of a student's distance in personality to other students in a field is the leave-one-out Mahalanobis distance. The Mahalanobis distance is a unitless measure and indicates how far away a particular observation is from its distribution (Mahalanobis, 1936).[14] The greater the distance, the further a point is from the mean of the distribution or, put differently, the more dissimilar an individual is from their peers. Stronger dissimilarity in personality could, e.g., lead to students having a

[14]In the univariate case, the Mahalanobis distance is equal to the z-score.

harder time finding friends or could imply that a student's personality is further away from a profile that predicts success in this field.[15]

To study sorting on personality, we relate a student's actual field of study choice to this distance. Specifically, we estimate the following regression:

$$y_{is} = \psi_i + \gamma Distance_{is} + \delta X_{is} + \xi_{is}, \tag{2}$$

where y_{is} is an indicator taking the value one for student i's actual field of study and zero for all counterfactual fields s. We regress this indicator on the Mahalanobis distance of a student's personality to the average personality of all other students by field, using all personality items and economic preferences we elicited in our survey and treating all measures as equally important. The vector X_{is} potentially includes individual beliefs about own ability by study field. In our preferred specification, it is empty because these beliefs may be an outcome of having a personality that "fits the field". However, we leave this assessment to the reader. In a subset of student cohorts, we additionally elicited expectations about earnings at age 30 across fields as well as beliefs about non-wage amenities, which we additionally include in X_{is} in subsequent regressions. Note, however, that these beliefs may again be outcomes of personality fit. We also include an individual fixed effect ψ_i. We compute standard errors allowing for the clustering at the student level. Given our estimation equation, we can interpret our coefficient of interest γ as the increase in the likelihood of a given field being the student's actual field given a one standard deviation increase in the Mahalanobis distance in personality to other students in the field. If there is sorting into fields of study on personality, we would expect this relationship to be negative.

This exercise is similar in spirit to Arcidiacono et al. (2020), who estimate ex-ante treatment effects of study fields on earnings and relate these to major choice at Duke University. We believe this exercise to be useful in our setting even though the sorting into fields of study has already happened because the survey took place at the very beginning of the students' time at university. We are confident that the timing of the initial survey makes it very unlikely that students' survey responses were affected by their field of study environment.[16]

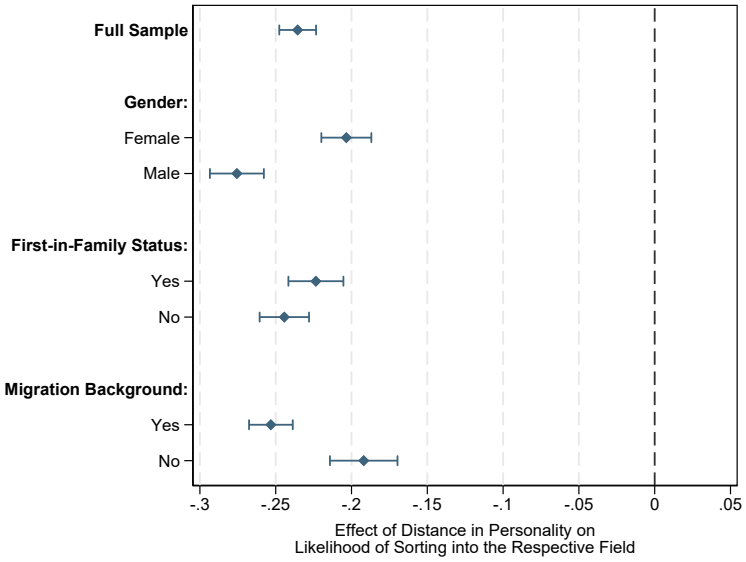
Figure 3 shows the results from our analysis along with heterogeneity analyses. The figure shows that on average, a one standard deviation increase in the Mahalanobis distance is associated with a 24 percentage points lower likelihood of actually studying

[15]Note that the Mahalanobis distance is already a unitless measure. We nevertheless standardize it for the regressions to ensure interpretability of effects in standard deviations.

[16]In line with this, only 22% of students are in a field that minimizes their Mahalanobis distance across fields. This suggests that reverse causality, in the sense that students' field of study choice influences their survey responses to make them appear like a fitting type for the field, is not much of a concern in our setting.

this field. The subsequent estimates show that this relationship is stronger for men than for women, somewhat stronger for students who are not first in their family (FiF) to attend university (Adler et al., 2024), and more pronounced for students that (additionally) speak a language other than German at home than for students whose only native language is German. All in all, these results suggest a strong impact of student personality on field of study choice. Note again that, at the same time, only a minority of students study the field that for the respective student has the smallest Mahalanobis distance across all fields. This suggests that other features of fields of study, most prominently earnings and non-wage amenity expectations, may also play a role.

Figure 3: Selection into Study Fields on Mahalanobis Distance



Note: This figure reports coefficients of the standardized Mahalanobis distance in regressions of study field choice on the distance. We estimate an individual fixed-effects model with an artificial panel data created from our survey data set by calculating counterfactual Mahalanobis distances for each student in every study field. We cluster standard errors at the student level and display 95% confidence bands. The uppermost panel reports the coefficient for the whole sample; each coefficient below results from splitting the sample either by gender, first-in-family (FiF) status, or by migration background (defined as the individual speaking a second mother tongue).

To test whether these other features influence the relationship between field of study choice and personality distance, we again estimate Equation 2 using the subset of student cohorts in which we elicited expectations about future earnings and beliefs about non-wage amenities across fields. Next to these beliefs, we also add beliefs about own ability since, for example, common models of field of study choice assume that preferences and ability may be intertwined (e.g., Lovenheim and Smith, 2023). The first coefficient in Figure 4 shows that in these waves, the relationship between personality

distance and field of study choice is similar to that in the overall sample. The remaining estimates depicted in Figure 4 show sorting on the personality distance if we gradually add controls for expectations about earnings at age 30, as well as beliefs about own ability by field and about the degree to which non-wage aspects of work are met, conditional on graduating in each field. The estimates show that expected earnings do not moderate the relationship between personality distance and field of study choice. Beliefs about own ability by field instead do affect this relationship, suggesting that personality distance drives beliefs about own ability. Among the beliefs about future non-wage amenities by field, only students' belief about how much they would enjoy work affects the relationship between personality distance and field of study choice. Nevertheless, even conditional on all counterfactual expectations we elicited, a one-standard-deviation increase in the Mahalanobis distance is associated with a 10 percentage points decrease in the likelihood of studying this field, highlighting the important role that personality and preferences have for field of study choice. Overall, Figure 4 suggests that student personality is an independent determinant of field of study choice beyond purely economic incentives and that personality drives students' taste for and perceived own fit to fields (e.g., Wiswall and Zafar, 2015).

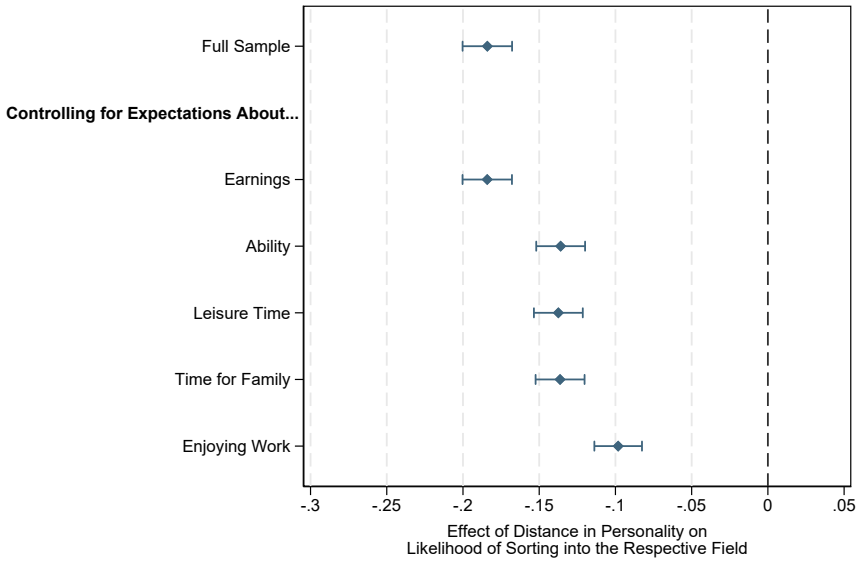
3.2 Personality Differences and Student Performance

In the previous subsection, we have shown that differences in personality end economic preferences are pronounced and in line with student sorting into fields of study on personality. One resulting question from an economics perspective is whether this sorting is productive or consequential. For example, we would like to know if the belief that own field-specific ability as a student is negatively related to the distance in personality to the average student in the field is correct on average. Specifically, are students who have sorted such that they do not fit their field's typical personality profile more likely to perform worse, switch to a different field, or drop out of university altogether?

In a next step, we therefore examine dropout or switching study field as a consequence of a misalignment in preferences and personality to one's own field. Our administrative data allow us to identify dropout and switching of fields since we observe all students' study fields in every term. If a student leaves the university, we no longer observe this student after their last term. However, the data provide information about the date at which the student left the university.

With this data structure, we define two outcomes: first, we define a binary variable equal to one if a student is no longer enrolled at the university after the end of the third year (i.e., in fall 2023 for wave 2020 and in fall 2024 for wave 2021, respectively). This is our dropout variable. Note that this includes students who dropped out of their

Figure 4: Selection into Study Fields on Mahalanobis Distance Controlling for Earnings and Amenity Expectations



Note: This figure reports coefficients of the standardized Mahalanobis distance in regressions of study field choice on the distance. We estimate an individual fixed-effects model with an artificial panel data created from our survey data set by calculating counterfactual Mahalanobis distances for each student in every study field. We cluster standard errors at the student level and display 95% confidence bands. The uppermost panel reports the coefficient for the whole sample. Each coefficient below results from including additional controls for different expectations (about earnings, own ability, and the non-wage amenities leisure time, time for family, and enjoying work). Note that this figure uses data from the baseline surveys of waves 2022 to 2024. This is because we only started eliciting earnings expectations in 2022.

course to enroll at a different university. Second, we define a variable that describes switching as a binary variable equal to one if a student switched study fields at some point in time between baseline and endline survey.[17] Additionally, we define a variable that combines dropout and switching and thus captures leaving one's initially chosen study field one way or another. Overall, around 24 percent of students in our sample leave their study field at some point in time, with 18 percent dropping out of our university and 8 percent switching fields within the university.

To study whether deviations from the average profile of preferences and personality predict leaving a study field, we again use the Mahalanobis distance for each individual in our sample. We then regress our indicators for dropping out, switching, or the combined indicator on the student's Mahalanobis distance across fields.

[17]Note that we only consider switches across broad study fields as defined in the data section. If a student, e.g., is enrolled in a philosophy degree at baseline and switches to history by the time of the endline survey, we do not consider this a switch since both programs are part of the study field of arts and humanities.

Table 1 shows the results of this exercise for the full sample. We see that a larger Mahalanobis distance is significantly related to both dropout and switching. A one standard deviation increase in the Mahalanobis distance is associated with an increase in the likelihood of dropout (switching) of 1 (1.4) percentage points. Column (3) of the same table shows that the same increase in the distance is associated with a 2 percentage points higher risk of either dropping out or switching fields. Given that on average 17.6 (8.4) percent of students in our sample drop out (switch), these effects are sizable, corresponding to an increase in dropout risk of almost six percent and more than a 16 percent increase in the risk of switching. Taken together, a one standard deviation increase in the Mahalanobis distance increases the risk of either dropping or switching by almost ten percent.

Table 1: Relation between Mahalanobis Distance and Dropout Measures

	(1) Dropout	(2) Switch	(3) Combined
Distance	0.010**	0.014***	0.020***
	(0.004)	(0.003)	(0.005)
Observations	8,033	8,033	8,033
Mean of Dependent Variable	0.176	0.084	0.242

Note: This table shows estimation results of regressing three dropout measures on the standardized Mahalanobis distance. The dependent variables in Columns (1), (2), and (3) are dropout from university, switch of study field, and a combined variable (dropout or switch), respectively. We consider an individual as having dropped out if the person is no longer enrolled at the university at the end of the third study year. Switches are defined as changes to a different study field between initial and endline survey. Robust standard errors in parentheses. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.

Appendix Table A2 takes a closer look at these patterns at the study field level. It documents hat a larger Mahalanobis distance is significantly related to the three measures in several study fields. Being different from one's peers in terms of preferences and personality is particularly strongly associated with a higher risk of dropping out or switching in natural sciences, teacher training, and engineering. The relative effect sizes correspond to around ten percent for all three fields.

3.3 Does Sorting on Personality Matter in the Long-Run?

We have documented that differences in personality and economic preferences immediately after students began their studies are already very pronounced (Figure 1). Whether this is relevant in the long run and especially in the labor market depends on whether these differences are stable. If study fields shape personality differentially to a large extent, the initial sorting may not matter much to understand differences in personality across occupations. To shed light on this question, we take two approaches. First, we leverage the student cohorts of 2020 and 2021 that we already re-surveyed in

their third year to study differences in personality across fields at endline and average changes in personality by field between enrollment and the end of the students' third year. Second, we compare our data patterns to differences in personality across occupations in the German Socio-Economic Panel (SOEP) for those fields that have closely corresponding occupations.

Descriptive Evidence on Endline Differences in Personality. In Figure 5, we show estimates analogous to Figure 1, but using data from the endline survey (rather than the initial survey) of the two student cohorts that we already re-surveyed in their third year (i.e., shortly before graduation).[18] The figure shows that differences in personality across fields after students' have studied their field for three years are very similar to the baseline differences shown in Figure 1. For example, students aspiring to become teachers are still more risk averse, agreeable, and extroverted and are still less negatively reciprocal and less competitive than other students. Students in medicine are still more altruistic, more conscientious, more patient, and have somewhat higher positive reciprocity, while showing lower negative reciprocity than other students. Students in the humanities are still less conscientious, less patient, less competitive, and have lower self-esteem, but are still more open than other students. In fact, the average correlation between each coefficient in Figure 1 and the corresponding coefficient in Figure 5 is around 0.8. In line with this, in Appendix Figure A3, we show that the individual-level correlations of personality measures between baseline and endline survey waves (i.e., over three years) are similar to short-run correlations for workers in the labor market estimated in the SOEP (Entringer et al., 2022).

Changes in Personality By Field. Our next step is to examine average changes in personality by field over the course of the students' time at university in more depth. For that purpose, we estimate separate regressions for each combination of personality and study field that follow a simple difference-in-difference (DiD) logic. Specifically, we estimate $P \times J$ coefficients from

$$item_{it}^{p} = \beta_0^{pj} + \beta_1^{pj} field_i^j + \beta_2^{pj} endline_t + \beta_{DiD}^{pj} (field_i^j \times endline_t) + \epsilon_{it} \; \forall \, p, j \qquad (3)$$

where $item_{it}^{p}$ denotes personality measure p of individual i at time t, $endline_t$ is an indicator for the endline survey, and $field_i^j$ is an indicator for i's study field j. Again, we derive standard errors that allow for clustering at the individual student level and are adjusted for multiple hypothesis testing via the Westfall-Young approach. Our

[18] Appendix Table A1 shows mean student characteristics from the administrative data for endline survey participants and non-participants (right panel).

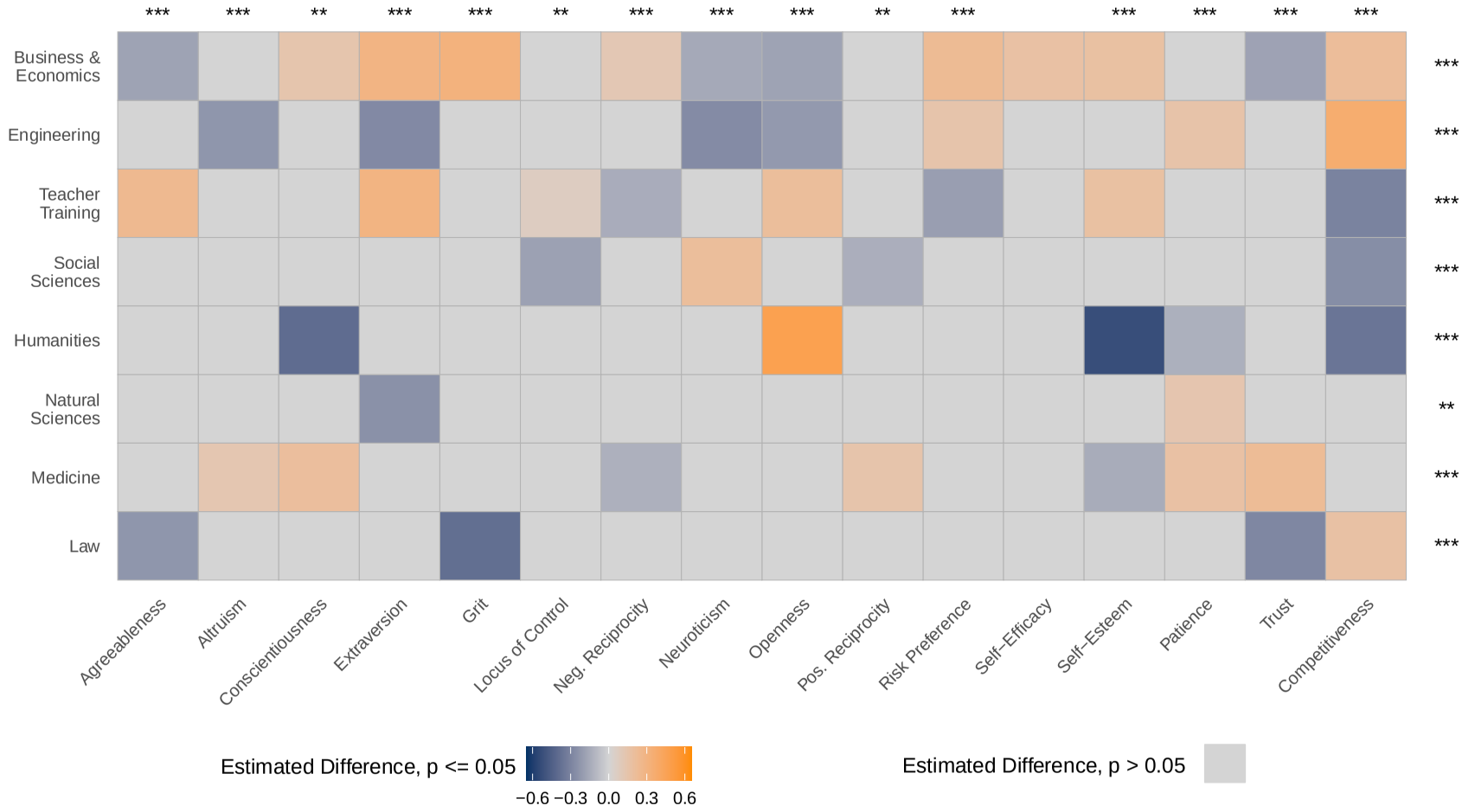
coefficients of interest are the β_{DiD}^{pj}s, reflecting changes in personality measure p if a student studies field j relative to students not studying j.

Figure 6 shows the results of these estimations and displays the estimated DiD coefficients. We see limited evidence for systematic changes of personality by field.[19] Some items change significantly in the same direction across subsets of fields, e.g., extraversion for teacher training students and students in the humanities field, for which we observe a positive DiD estimate. We also see that there is more change in some study fields than in others. For example, we observe no significant change in any personality or preference measure in social sciences, and almost none in natural sciences and law. Business & economics and medicine are the study fields where most items change: for business & economics, conscientiousness, grit, risk preferences, and self-efficacy all change significantly. In medicine, scores on altruism, conscientiousness, self-efficacy and competitiveness decrease. Apart from that, teacher training students become more extroverted, obtain a more internal locus of control, and become less positively reciprocal over time. The joint tests from seemingly unrelated regressions suggest that some items jointly change over time (e.g., conscientiousness or neuroticism) and that studying in some fields (e.g., business & econ or teacher training) significantly changes preferences and personality. Overall, these results show that personality does change on average in some fields. However, these changes seem to play a much smaller role in driving endline differences in personality by field of study than initial sorting.

Going beyond mean differences, in the appendix we compute Wasserstein distances within fields across waves for all items and study fields. The Wasserstein distance is a measure for dissimilarity between distributions and helps us examine differences between baseline and endline personality and economic preferences not only on average, but for entire distributions (Kantorovich, 1960; Villani, 2009). Thus, we can test whether the distributions of personality measures within fields changed meaningfully across waves even though the mean changes are limited. We do not find large differences between distributions, as shown in Appendix A.2.

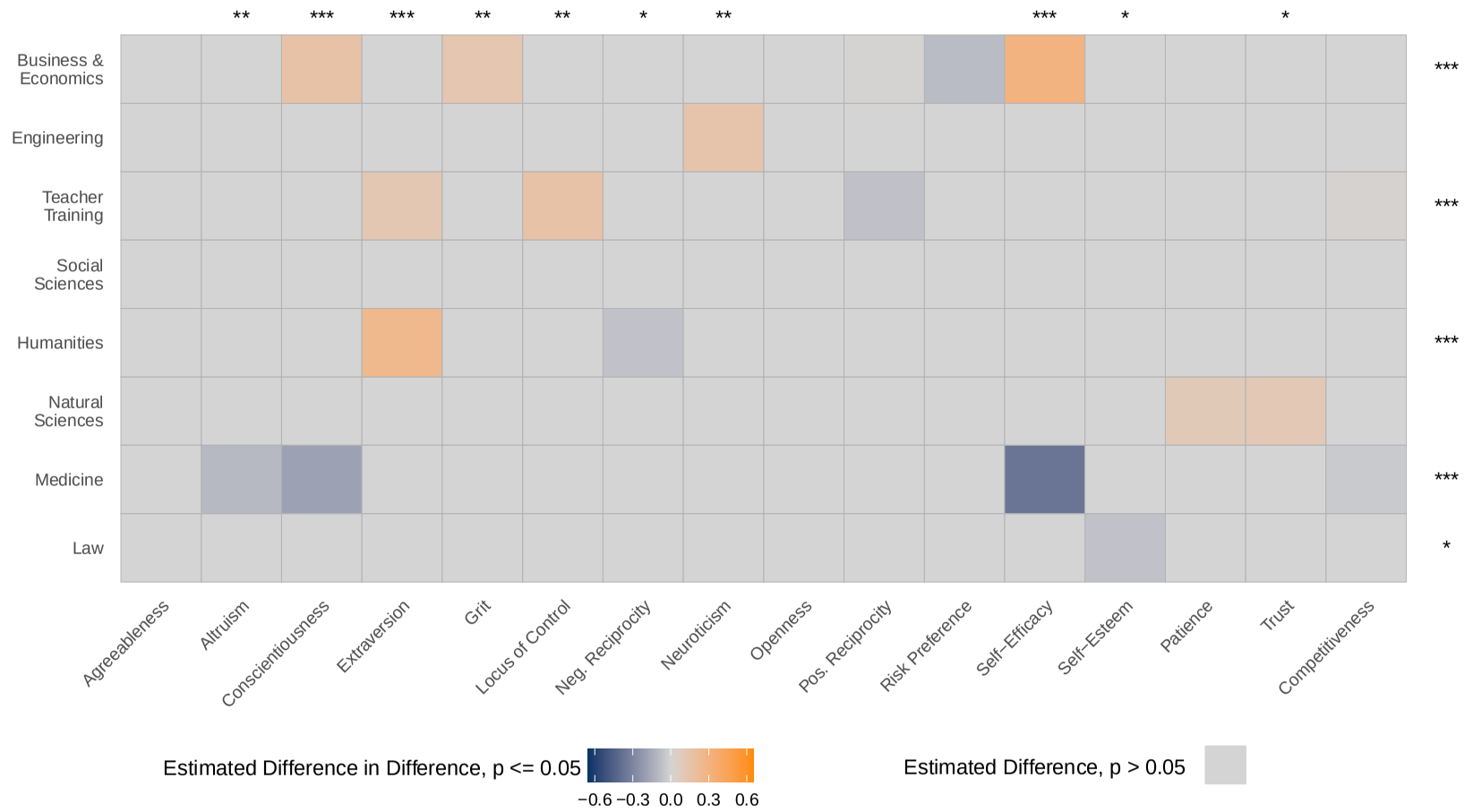
[19] Note that this is not driven by the smaller sample size. To show this, Appendix Figure A1 shows estimates analogously to Figure 1, but using only the survey responses of the baseline survey of students who took part in the endline survey as well. The results are qualitatively identical to those in Figure 1.

Figure 5: Endline Differences in Personality and Economic Preferences



Note: This figure shows results from separate regressions of 16 personality features and economic preferences on eight study field dummies (128 regressions). The sample consists of all students who participated in the endline survey (cohorts 2020 and 2021 only). We drop individuals who participated in the endline survey, but had changed their field of study during their studies. Cells containing a coefficient with a p-value>0.05 are gray, positive (negative) significant coefficients are shown in orange (blue). p-values are adjusted for multiple hypothesis testing using the Westfall-Young method. The more intense the color, the larger the absolute value of the respective coefficient. Stars at the row and column margins show the results of joint coefficient tests originating from estimating seemingly unrelated regressions. * $p<0.1$ ** $p<0.05$ *** $p<0.01$.

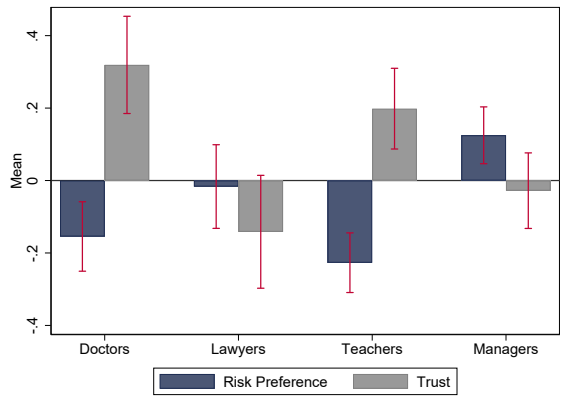
Figure 6: Changes in Personality by Field: Differences-in-Differences Estimations



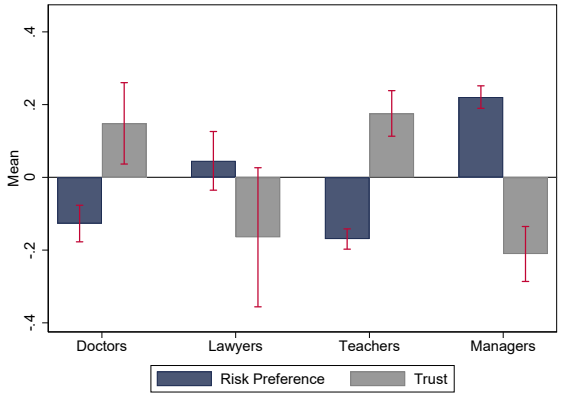
Note: This figure shows results from separate difference-in-difference (DiD) regressions of 16 personality and preference items on eight study field dummies, a dummy for the endline survey as well as the interaction of the two (128 regressions). Depicted are the coefficients of the interaction effects (i.e., the DiD estimates). The sample consists of all students who participated in both the initial and the endline survey (student cohorts 2020 and 2021 only). We drop individuals who participated in the endline survey, but had changed their field of study during their studies. Cells containing a coefficient with a p-value> 0.05 are gray, positive (negative) significant coefficients are shown in orange (blue). p-values are adjusted for multiple hypothesis testing using the Westfall-Young method. The more intense the color, the larger the absolute value of the respective coefficient. Stars at the row and column margins show the results of joint coefficient tests originating from estimating seemingly unrelated regressions. * $p<0.1$ ** $p<0.05$ *** $p<0.01$.

Figure 7: Students vs. Workers: Differences in Personality Across Career Paths

A: Student Survey Data



B: SOEP Data



Note: This figure shows differences in risk preference (blue bars) and trust (gray bars) across four occupational categories. The two measures are standardized to have mean zero and standard deviation one; afterwards, we plot the mean separately for each occupational category. 95%-confidence bands are shown in red. The left panel uses our own survey data at endline. The right panel is based on data from the German Socio-Economic Panel (SOEP). To keep the x-axes comparable, we use the same labels in both panels. In the left panel, the occupational categories doctors, lawyers, teachers, and managers correspond to the study fields medicine, law, teacher training, and business & economics, respectively.

Comparison of Student and Labor Market Data. To assess whether our findings matter beyond the higher education context, we also study whether the sorting patterns identified from our data are informative of occupational differences in personality. For that purpose, we select study fields that clearly correspond to an occupation: Medicine (where most students become doctors), law (with a major career path into law firms), teacher training (where almost all graduates become teachers), and business and economics (where many students later take on managerial positions). Figure 7 showcases how personality patterns of students in these study fields correspond to personality patterns of workers in the respective occupations, using risk preference and trust as examples. Panel A shows the patterns in our endline survey data by simply plotting field-specific means of the standardized personality measures separately for students on a career path to become doctors, lawyers, teachers, or managers, respectively. Panel A shows that students about to become medical doctors are more risk averse and more trusting, becoming lawyers are close to average in terms of risk preference, but less trusting, students in teacher training are substantially more risk averse and more trusting, and students on a career path to take over managerial positions are less risk averse and close to average in terms of trust. Panel B adds the respective means for workers actually employed as doctors, lawyers, teachers, and managers. To construct this panel, we use representative data from the German Socio-Economic Panel (SOEP). Comparing the two panels shows that the personality

patterns between students close to graduation and workers employed in the respective occupations are very similar, suggesting that differences in personality and economic preferences in our data are close to actual differences in the labor market. Moreover, the personality differences highlighted in Figure 7 also replicate some well-known patterns of occupational sorting on personality in the literature (e.g., Dohmen and Falk, 2010; Gill et al., 2023). Overall, we interpret Figure 7 as evidence that our estimates on sorting into fields of study on personality and preferences are informative of the broader question of workers sorting into career paths.

4 Conclusion

In this paper, we comprehensively examine sorting into fields of study and career paths on personality and preferences. Using a unique combination of survey and administrative data from a large university in Germany, we analyze how students sort into study fields and how the degree of alignment between the students' personality and their peers affects the students' progress in their studies. We re-survey the students when they are close to graduation, enabling us to assess the stability of students' personality over the course of their studies.

We replicate some well-established patterns of differences in personality across fields, but extend these findings by providing a very broad overview of how the personality profiles of students in higher education differ over prospective career paths. We find extensive sorting on a battery of 16 different personality and preference measures immediately after students have started into their studies. For example, students aspiring to become teachers are more risk averse, more trusting, more agreeable, more altruistic, more extroverted, less negatively reciprocal, and much less competitive than the average student. Law students, on average, have personalities that are opposite to those of students in teacher training in many dimensions: they are less trusting, less agreeable, more negatively reciprocal, and more competitive than the average student. Students on a career path leading to jobs in business and economics are much more willing to take risks and are significantly more competitive than their peers. They also reveal higher levels of extraversion and self-esteem, but lower levels of trust, agreeableness, and altruism.

We also show that having a personality that is similar to the field-specific average personality of other students is highly predictive for the field of study choice. The extensive sorting on personality in our data suggests that differences in personality and preference features are part of the heterogeneous taste component that Wiswall and Zafar (2015) identify as the dominant factor in the choice of field of study. Importantly, these patterns persist when controlling for expected returns and beliefs about own

ability (Lovenheim and Smith, 2023). Sorting on personality and preferences is not only very common, but also consequential at an individual level. A larger distance in personality from the average student in the same field predicts a significantly reduced likelihood of students finishing their degree, suggesting that one factor that hinders academic progress in higher education is misalignment between students' own personality and average peer personality.

Finally, using the sample of students who took both the initial and the endline survey administered close to graduation, we demonstrate that personality differences by field are rather stable during higher education. Hence, the differences in personality patters across fields of study immediately before the students enter the labor market are very similar to the sorting patterns we observe in the first days of the students' university life. Moreover, using selected fields of studies where career paths clearly lead to certain occupations, we show that the sorting patterns in our data are well in line with personality differences between subjects actually working in the respective occupations. We conclude that the extensive sorting on personality observed in our data is indeed predictive of personality differences by occupation in the labor market.

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A Appendix

A.1 Additional Tables and Figures

Table A1: Selection into Baseline and Endline Survey

	Baseline			Endline		
	Participants	Non-Part.	Diff.	Participants	Non-Part.	Diff.
Female	0.58	0.53	0.05***	0.60	0.56	0.04**
Entrance Qual. (GPA)	2.81	2.68	0.13***	2.93	2.86	0.72***
Foreign	0.06	0.08	-0.02***	0.06	0.09	-0.03***
Age	19.6	19.7	-0.03	22.6	22.6	0.00
Teacher Training	0.16	0.14	0.02***	0.18	0.18	0.00
Humanities	0.08	0.15	-0.07***	0.05	0.07	-0.02**
Social Sciences	0.09	0.06	0.02***	0.08	0.06	0.02**
Natural Sciences	0.13	0.17	-0.03***	0.13	0.13	0.00
Engineering	0.17	0.19	-0.02***	0.18	0.19	-0.01
Business & Econ.	0.20	0.15	0.05***	0.18	0.21	-0.02
Law	0.09	0.08	0.01*	0.09	0.09	0.00
Medicine	0.08	0.06	0.02***	0.12	0.09	0.03**
Observations	9,171	9,796	18,967	1,849	854	2,703

Note: This table describes selection into the baseline and endline survey by showing means of all variables by participation status, with asterisks denoting significant differences between the means (measured with a two-sided t-test). * $p<0.1$ ** $p<0.05$ *** $p<0.01$. The left panel covers participants and non-participants in the initial survey across five survey waves (student cohorts starting into their studies between 2020 and 2024). The right panel covers the endline survey, administered in the third year of the students' studies (cohorts 2020 and 2021 only). We invited to the endline survey all students who participated in the initial survey administered to their cohort.

Table A2: Distance in Personality to Peers and Dropout or Switching, By Field of Study

	Dropout or Switch							
	(1) Law	(2) Medicine	(3) Natural Sciences	(4) Humanities	(5) Social Sciences	(6) Teacher Training	(7) Engineering	(8) Business & Economics
Distance	0.024	0.005	0.028**	0.016	0.006	0.031***	0.041***	0.007
	(0.018)	(0.010)	(0.014)	(0.019)	(0.017)	(0.012)	(0.012)	(0.009)
Observations	710	698	1,084	673	691	1,263	1,312	1,602
Mean Dep. Var.	0.293	0.085	0.292	0.435	0.247	0.220	0.244	0.187

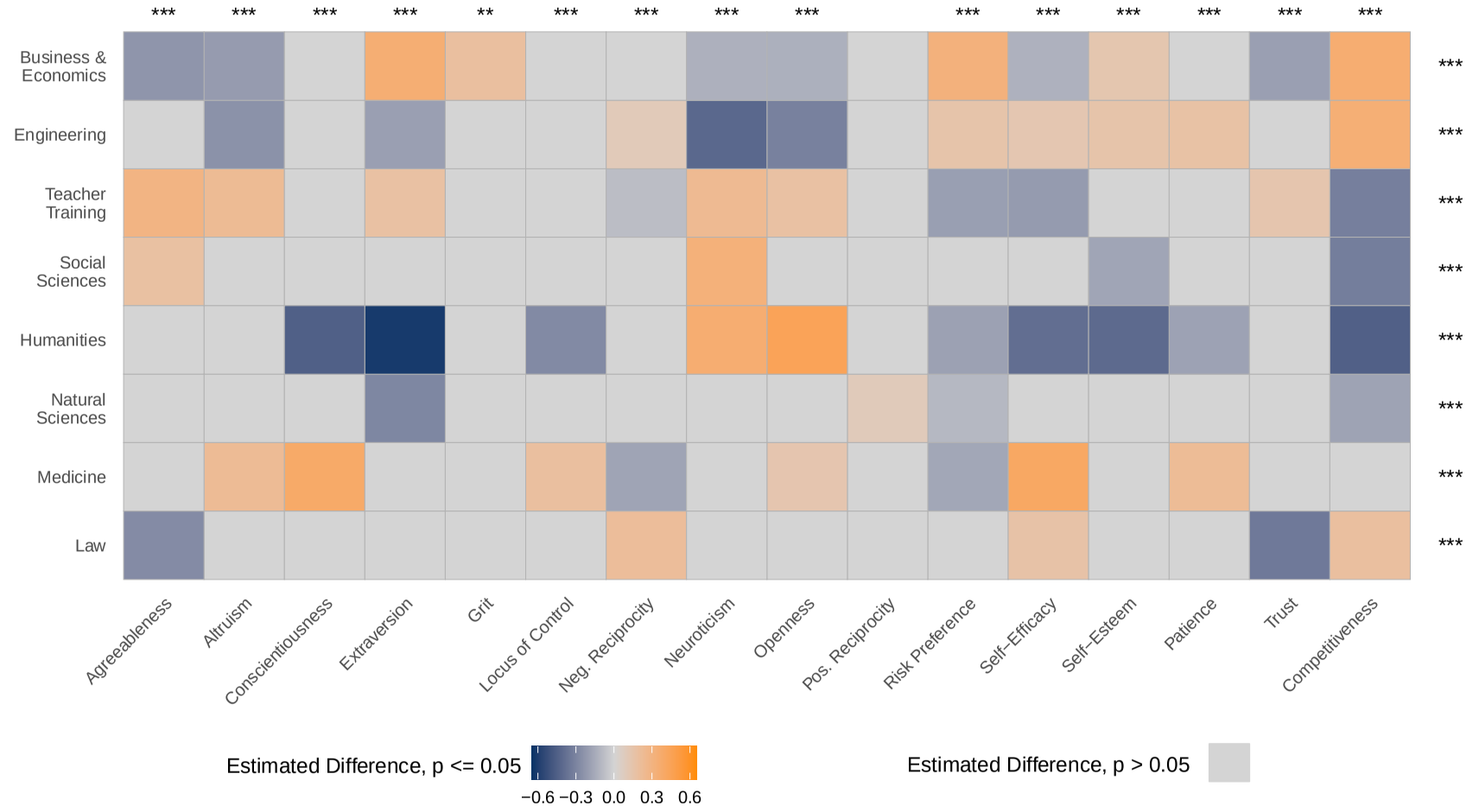
Note: This table shows results of regressions of a combined measure for not completing the initially selected field (switching to a different field or dropout) on the standardized Mahalanobis distance. In each column, we use a different field-specific subsample for the regression. We consider an individual as having dropped out if the person is no longer enrolled at the university at the end of the third study year. Switches are defined as changes to a different study field between initial and endline survey. Robust standard errors in parentheses. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Table A3: Stability in Personality Across Baseline and Endline Survey

	Correlation	Regression	
	ρ	β	R^2
Agreeableness	0.546	0.567***	0.298
	(0.00)	(0.00)	
Altruism	0.460	0.444***	0.212
	(0.00)	(0.00)	
Conscientiousness	0.611	0.631***	0.373
	(0.00)	(0.00)	
Extraversion	0.738	0.719***	0.544
	(0.00)	(0.00)	
Grit	0.384	0.398***	0.148
	(0.00)	(0.00)	
Locus of Control	0.430	0.461***	0.185
	(0.00)	(0.00)	
Neg. Recprocity	0.500	0.527***	0.250
	(0.00)	(0.00)	
Neuroticism	0.654	0.674***	0.427
	(0.00)	(0.00)	
Openness	0.632	0.638***	0.399
	(0.00)	(0.00)	
Pos. Reciprocity	0.392	0.401***	0.154
	(0.00)	(0.00)	
Risk Preference	0.512	0.503***	0.262
	(0.00)	(0.00)	
Self-Efficacy	0.435	0.475***	0.189
	(0.00)	(0.00)	
Self-Esteem	0.546	0.559***	0.298
	(0.00)	(0.00)	
Patience	0.481	0.490	0.231
	(0.00)	(0.00)	
Trust	0.496	0.499***	0.246
	(0.00)	(0.00)	
Competitiveness	0.539	0.551***	0.290
	(0.00)	(0.00)	

Note: This table describes correlations in personality and preference measures across baseline and endline survey. The sample consists of all students who participated in the baseline and the endline surveys (cohorts 2020 and 2021 only). * $p<0.1$ ** $p<0.05$ *** $p<0.01$.

Figure A1: Baseline Differences in Personality and Economic Preferences (Only Students Who also Participated in Endline Survey)



Note: This figure shows results from separate regressions of 16 personality and preference items on eight study field dummies (128 regressions). The personality and preference measures are those elicited in the initial survey. The sample consists of students who participated in both the initial and the endline survey and who did not drop out or switch their study field. Cells containing a coefficient with a p-value> 0.05 are gray, positive (negative) significant coefficients are shown in orange (blue). p-values are adjusted for multiple hypothesis testing using the Westfall-Young method. The more intense the color, the larger the absolute value of the respective coefficient. Stars at the row and column margins show the results of joint coefficient tests originating from estimating seemingly unrelated regressions. * $p<0.1$ ** $p<0.05$ *** $p<0.01$.

A.2 Wasserstein Distances

To study changes not only at the mean, but at a distributional level, we compute Wasserstein distances for all combinations of personality and preferences items and study fields and thus compare baseline with endline distributions. This distance metric gives a general impression about differences between two distributions and does not require assumptions, e.g., regarding normality of the underlying distributions.[20] Computing Wasserstein distances can be a very cumbersome exercise; two characteristics of our case, however, make calculations straightforward: first, we observe univariate distributions and second, both empirical distributions in each case (i.e., baseline and endline distributions for one personality measure in a given study field) are of the same length. In this case, the Wasserstein distance can be computed as follows (Ramdas et al., 2017):

$$W_p(P, Q) = \left(\sum_{i=1}^{n} \| X_{(i)} - Y_{(i)} \|^p \right)^{\frac{1}{p}},$$

with P and Q being the empirical distributions of two data sets $X_1, ..., X_n$ and $Y_1, ..., Y_n$, respectively, and $p = 2$.

The computed values are positive and greater values mean larger distance between the two distributions. Figure A2 shows the computed Wasserstein distances for all combinations of items and study fields. Darker cells imply larger distances, i.e., stronger dissimilarity between distributions. We see that overall, the computed distances are not exceptionally large. The small Wasserstein distances for many combinations of items and study field suggest little changes at the distributional level between baseline and endline. One measure for which some changes at the distributional level can be seen is self-efficacy. Here, we see the strongest difference between the baseline and the endline distribution in Business & Economics. This is also the largest Wasserstein distance we observe in the entire sample. Apart from that, Figure A2, similarly in spirit to Figure 6, suggests little evidence for adaptation at the distributional level.

[20] The concept of the Wasserstein distances originates from optimal transport theory. For more details, see, e.g, Kantorovich (1960) and Villani (2009).

Figure A2: Wasserstein Distances



Note: This figure shows Wasserstein distances (WD) calculated for all combinations of personality and preference measures and study fields. For each of these combinations, the respective cell shows the WD between the baseline and the endline distribution. The sample consists of all students who participated both in the baseline and the endline survey and who did not drop out or switch their study field. The more intense the color, the larger the WD.