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Preference-choice mismatch and university dropout[☆]

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ABSTRACT

Drawing on data from the German National Educational Panel Study (NEPS), we show that students who select majors that do not match their occupational preferences prior to enrolling in university are more likely to drop out than those who do choose majors that match their occupational preferences. Our findings suggest that this gap cannot be explained by institutional obstacles to entering a major. Instead, the primary mechanisms behind this phenomenon are indecisiveness and preference changes.

1. Introduction

Policy-makers have widely recognized the importance of evaluating the effectiveness of higher education using metrics such as costs per student and graduation rates. However, despite an average spending of $10,351 per full-time student in 2017 by OECD countries (OECD, 2020, pp. 208 and 275), only two out of three students graduate within three years of their expected graduation date. The direct costs of dropping out, both to individuals and society, are substantial, compounded by indirect costs such as lost tax revenues for the state and delayed entry into the labor market for students. For example, in the Netherlands, the annual total cost of dropping out and study switching has been estimated to be 5.7 billion euros (Borghans and Golsteyn, 2006).

Given these significant costs, there is a pressing need to identify and address the factors that contribute to low graduation rates. While extensive research has been conducted on the drivers of university dropout rates, including uncertainty in educational decision-making (e.g., Manski, 1989), personal characteristics (e.g., Almås et al., 2016), socio-economic background (e.g., Aina, 2013), financial pressure (e.g., Castex, 2017), peer effects (e.g., Arulampalam et al., 2005), cognitive and non-cognitive skills (e.g., Hanushek and Woessmann, 2008; Heckman and Rubinstein, 2001), learning about one's own abilities (e.g., Stinebrickner and Stinebrickner, 2013), and a lack of information (Conlon, 2021; Wiswall and Zafar, 2015b), our understanding of the specific preferences that drive voluntary dropout decisions remains limited.

Recent work by Conlon and Patel (2022) suggests that occupational preferences for the typical career associated with the major is often the driver of major choice. Additionally, students may overestimate the likelihood of achieving these careers after degree completion or misperceive the careers that a major can lead to, resulting in costly adjustments in human capital investments. However, empirical evidence on whether students revise their human capital investments when their chosen major is unlikely to lead to their aspired career is still lacking in the literature.

In this study, we utilize unique longitudinal data from the National Educational Panel Study (NEPS) in Germany to examine the impact of occupational preference-major mismatches on university dropout rates. By following upper secondary school students beyond their tertiary education choices, we can observe occupational preferences prior to university enrollment and the majors chosen upon enrollment, minimizing the risk of ex-post rationalization of occupational preferences. We develop a measure of mismatch by creating a crosswalk of majors to occupations using data from the German Graduate Panel (DZHW) and cohorts of graduates from 2009 and 2013. This measure allows us to determine the extent of the mismatch between occupational aspirations and chosen university majors.

Consistent with prior research (e.g., Dasgupta and Sharma, 2022; Wiswall and Zafar, 2015a), we find that male and female students tend to sort into different majors, with the dropout rate varying by gender-major combination (averaging 29%). We demonstrate that our measure of mismatch is highly predictive of dropout rates, with a 9-percentage-

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point increase in dropout likelihood for students with a mismatch, even after controlling for a student studying the preferred major and a range of personal characteristics and cognitive and non-cognitive skills. Notably, we observe a larger coefficients for female students, who are 13 percentage points more likely to drop out if they experience a mismatch, while no such relation is evident for male students.

We find that our results are highly robust across various specifications. First, we test the robustness of our findings by including older cohorts of graduates in the analysis. We use data from the DZHW for the cohorts of 2001 and 2005 and find that the results are quantitatively similar to those from the 2009 and 2013 cohorts. Additionally, we find similar results when we use older cohorts from the NEPS to generate major-occupation crosswalks instead of the DZHW data. Furthermore, we test the sensitivity of our measure of occupational mismatch by using an index of occupational similarity rather than a simple binary indicator of mismatch. We find that a one-point increase in the index of occupational similarity decreases the dropout rate by approximately 5 percentage points. Finally, we make a distinction between study switch and definitive drop out from university and show our findings really are driven by the relation between a major occupation mismatch and drop out.

In addition to examining the simple dropout decision, we also analyze the timing of dropout of students and find a gender difference in the timing of university dropout in relation to the mismatch between majors and occupational preferences. Specifically, we find that males with a mismatch tend to drop out in their first year than those without a mismatch, while no such pattern is observed for female dropouts. This suggests that female dropouts are more likely to make an early adjustment to their university program regardless of the mismatch, whereas males tend to drop out later in their study program but are more likely to make an early adjustment when they have a mismatch between their major and occupational preferences.

The observed pattern of findings can be attributed to three potential explanations, which we examine in our paper. First, we investigate the possibility of informational misperception, which refers to the lack of knowledge about which majors lead to which occupations. To test this, we use occupational preference-major preference match as a proxy for informational accuracy prior to university enrollment and only include students with a match in our analysis. We find that the estimates remain consistent with our main results. Furthermore, we provide compelling evidence that students who drop out and have a mismatch are less likely to switch to a major that aligns with their pre-university occupational preferences than students who drop out and have a match. These findings speak against informational misperceptions as a potential explanation as has been suggested in other related studies (e.g., Wiswall and Zafar, 2015b).

Second, it is possible that students enroll in university without a clear idea of their career preferences, hoping to use their time there to explore their options and eventually settle on a suitable major. Our analysis suggests that this indecisiveness is a common experience among students, as evidenced by our data. Interestingly, we find that the difference in dropout rates is not significant within gender-mismatch groups but rather between them. Moreover, the difference in dropout rates is particularly pronounced for females with and without a mismatch. To investigate possible coping strategies, we analyze whether selecting occupationally broad majors could reduce dropout incidence. We find that males benefit from choosing broad majors when they have a mismatch or no clear preferences, while females only seem to benefit from broad majors when they have not reported clear preferences. For both males and females, we find that dropping out is unrelated to the breadth of majors when their occupational preference matches their chosen major.

Third, it is possible that students modify their occupational preferences after enrolling in university, as their new environment and peers shape and influence their aspirations (e.g., Chevalier et al., 2020). Our analysis suggests that changes in occupational preferences can increase dropout rates if they result in a mismatch between the student's occupational preference and university major. Interestingly, we find significant gender differences in the impact of these changes. Females exhibit lower dropout rates when their occupational preference and major match both before and after enrolling in university. In contrast, males exhibit a lower dropout rate when their occupational preference and major match after enrolling in university, regardless of their prior mismatch status.

We make two contributions to the literature. First, our study contributes to the literature on university dropout decisions by exploring the connection between labor market preferences and educational choices. We take a novel approach by investigating the mismatch between occupational preferences and majors and how it relates to the decision to drop out, an aspect that has been overlooked in previous studies (see, e.g., Aina et al., 2018; Aina et al., 2022, for extensive summaries of the dropout literature). In particular, our study builds on recent research by Blom et al. (2021) and Acton (2021) which suggests that prospective students consider the current labour market situation when choosing their major, and argues that occupational preferences play a crucial role in shaping major choices (Conlon and Patel, 2022). Importantly, unlike previous studies that only surveyed students at the time of their enrollment (e.g., Conlon and Patel, 2022; Zafar, 2013), we capitalize on the longitudinal nature of our data to measure preferences before university enrollment, hereby eliminating any ex-post rationalization in preferences. By doing so, our study provides essential insights into the factors that influence the decision to drop out of university, filling a critical gap in the literature.

Second, our study contributes to the literature on gender differences in educational preferences and enrollment decisions (e.g., Wiswall and Zafar, 2018; Zafar, 2013). As shown by Croson and Gneezy (2009), significant differences exist between genders in risk preferences and competition behavior, which also influence gender differences in the choice of majors (Reuben et al., 2017). While we utilize a more generalized measure of preferences through stated occupational preferences, our study provides gender-specific evidence on the dropout behavior of students who experience a mismatch between their occupational preference and major choice. By focusing on this specific aspect, our study adds valuable insights to the literature and highlights the importance of considering gender differences in educational decision-making.

The remainder of this paper is structured as follows. Section 2 describes the data and empirical strategy. Section 3 provides the main results including some more descriptive statistics. Section 4 presents potential mechanisms and Section 5 concludes.

2. Data and empirical strategy

2.1. The national educational panel study

The primary data source utilized in this paper is the representative cohort of upper secondary school students from the German National Educational Panel Study (NEPS), specifically, the Starting Cohort 4 (Blossfeld et al., 2011). The survey began in 2011 when the respondents were approximately 14–15 years old, and NEPS interviewed the students yearly throughout their upper secondary and tertiary education. Our study examines individual educational pathways into tertiary education using NEPS data until 2020, when the respondents were 23–24 years old.

Our study focuses on the main outcome of whether students discontinue their initial studies at their initial institution, which we define as dropping out. This includes students who have either stopped studying altogether or changed their majors or institutions. In addition, we analyze the timing of the dropout and whether it was a forced dropout due to failing exams. To ensure the accuracy of our analysis, we restrict our sample to students who have graduated from secondary school with a university entrance qualification and started attending university as their first vocational education.

After applying the restrictions, we are left with 3598 potential students. To refine our sample, we only consider students who participated in waves 1, 7 or 8 (depending on the year of graduation), and waves 10, 11, or 12, as these waves provide essential information for our estimations. As a result, our sample size decreases to 2851 students. We further exclude students without data on their dropout or their major, resulting in a final sample size of 2476.[1]

In the NEPS, students reported their preferences in wave 7 or 8, which is typically approximately half a year prior to their graduation, when they are 17 or 18 years old. The specific wave depends on whether the student attended the G8 or the G9 track (see Marcus and Zambre, 2019, for a brief description of the G8-reform.). After entering university, students report on their major and study progress, which we observe in wave 10 or later.

The importance of cognitive and non-cognitive abilities as strong predictors of educational achievements has been widely acknowledged (Hanushek and Woessmann, 2008; Heckman and Rubinstein, 2001; Stinebrickner and Stinebrickner, 2014; 2012).[2] To account for these skills, we correct for their measurements in wave 1, when students are 14 or 15 years old.[3] In this wave, the NEPS administered competency tests in mathematics, reading, information and communication technology (ICT), and natural sciences. We use weighted likelihood estimates (WLE) to reduce the impact of random errors for each competency domain (Pohl and Carstensen, 2012). Additionally, we capture non-cognitive skills by including the Big-5 personality traits in our analyses. We mean impute missing values for cognitive and non-cognitive skills for students who participated in the first wave and standardize them with a sample mean of 0 and a standard deviation of 1.

We use information on gender and age from the sampling information provided by schools to the NEPS before the survey began in 2011. Additionally, we use data on ethnicity and parental education from the survey of the children. We consider students to belong to an ethnic minority group if they or at least one of their parents migrated to Germany (Matthewes, 2020). Furthermore, we use parental education to determine whether the student's mother or the mother's partner[4] has a university degree. In cases where this information is missing, we create a separate category.

2.2. The German graduate panel

To link majors to likely occupations, we construct a major-occupation-map, which is a list of occupations that graduates of a particular major are likely to work in. We obtain data for this map from the German Graduate Panel, which conducts surveys every four years on university graduates. Specifically, we use the graduate cohorts from 2009 and 2013 Brandt et al. (2020); Briedis et al. (2021). The use of multiple cohorts offers two benefits. First, it reduces the impact of outliers in small majors. Second, it mitigates the influence of economic cycles on the occupations associated with each major.[5]

To construct the major-occupation-map, we followed a specific procedure. First, we identified the last major of the graduates and the occupation of their first job after graduation, which was started within 6 months after graduation and lasted for at least 6 months. Then, we aggregated this data to the major-occupation level and calculated the share of individuals per major-occupation combination. In our main specification, we excluded combinations in which less than 5 percent of the graduates of each major were sorted. For instance, Conlon and Patel (2022) used a 10 percent limit in one of their analyses. The major categories were based on the German classification of majors (Destatis, 2021), while the occupations were derived from the German classification of occupations (Bundesagentur für Arbeit, 2021). Appendix A provides further details on the methodology used to construct the major-occupation map and presents additional descriptive statistics related to the map (Table 8 and 9).

2.3. Major-occupational preference-mismatch

The primary aim of this study is to investigate how discrepancies between students' desired occupations and their actual majors can impact their decision to switch majors. To capture this phenomenon, we introduce a major-occupational preference-mismatch indicator, or MOM, which indicates whether a student's intended occupation before enrolling in university and their chosen major are aligned. For instance, if a student aspires to be a lawyer and enrolls in a law program, the MOM indicator would be 0. However, if a student aims to work in public administration but enrolls in an economics program, the MOM indicator would be 1.

In the German Higher Education System, admission to universities is typically based on students' GPAs and requires applications for specific major-university combinations. However, students are usually required to apply for a major before receiving their final GPA. Consequently, it is not uncommon for students to be unable to start their desired major because their GPA does not meet requirements. If such students sort into another major and drop out or switch majors systematically, this could potentially bias our results on the MOM indicator. To mitigate this, we introduced the major-major preference-mismatch (MMM) indicator. This indicator reflects whether the major a student eventually started at university aligns with the preference they expressed prior to enrollment. Specifically, if a student enrolled in their preferred major, the MMM indicator would be 0, while if they enrolled in a different major, the indicator would be 1. By controlling for MMM, we can account for factors such as eligibility and changes in preference that could impact a student's decision to switch majors, ultimately leading to a more accurate estimate of the coefficient for MOM.

To ensure the validity of our new MOM indicator, we conducted a correlation analysis with the reasons reported by students who dropped out of university, as shown in Table 1. The reasons considered were failed exams, loss of interest in the major, wrong expectations about the major and its content, financial problems, and no interest in occupations that can be achieved by graduating from the major. It is worth noting that these categories are not mutually exclusive, and a student may report one or more reasons for dropping out.

The results in Table 1 suggest that the MOM indicator is significantly correlated with dropping out due to a lack of interest in the occupations that can be pursued by graduates in the major, as indicated by a coefficient of 0.11. However, there is no significant correlation between the MOM indicator and any of the other reasons for dropping out. These findings suggest that our MOM measure is valid and can effectively capture the primary factor related to students' decision to drop out that we aim to investigate.

2.4. Sample description

To assess the representativeness of our sample, we conduct a comparison between our sample of freshmen and the actual population using

[1] Table 10 in Appendix B reports on the likelihood of attrition from the longitudinal sample we use. Our results indicate that there are no ethnic or socioeconomic status (SES) differences in the likelihood of being included in our sample. However, we did find that females are more likely to be in our analysis sample. However, this is a common phenomenon among panel studies (Zinn et al., 2020).

[2] Eegdeman et al., 2018 however find no relation between cognitive and non-cognitive skills and first-year dropout.

[3] Later competency tests are randomly allocated to students, such that some students have not performed some of the competency tests.

[4] The parents' interview asks for the interviewee's partner's education. Most of the interviewees are the children's mothers. The partner, however, is often not the biological father.

[5] In Appendix B, we conduct additional analyses using different data sources to test the robustness of our main findings. By examining the consistency of our results across multiple data sources, we can gain more confidence in the robustness of our conclusions.

Table 1
Correlates of MOM and reasons to drop out.

	Failed exams	No interest	Wrong expectations	Finances	Occupations
MOM	−0.015	0.026	−0.002	0.023	0.107***
	(0.034)	(0.041)	(0.043)	(0.018)	(0.041)
Observations	724	724	724	724	724

Dependent variables: Reasons to dropout (Yes/No; multiple reasons possible). This table shows results for simple correlations. Standard errors in parentheses are robust to heteroskedasticity. Source: NEPS SC4 12-0-0, own calculations. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.

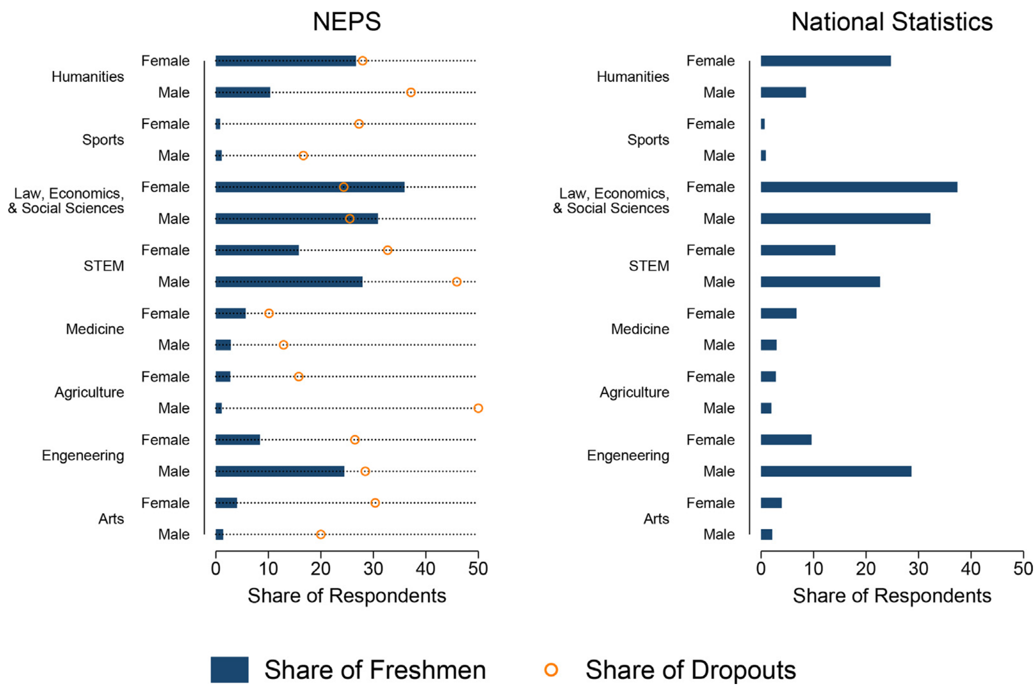

Fig. 1. Enrollment and dropout rates by major and gender for the NEPS and national statistics.

national statistics (destatis Table 21311-0012). We examine the sorting of students into major categories by gender, as shown in Fig. 1. The figure also includes information on dropout rates from the NEPS data.

Figure 1 illustrates the enrollment rates for each gender in both the national statistics and our sample, where the numbers add up to 100. Our analysis indicates a high level of similarity between our sample and the national statistics, with the only observable difference being a slightly higher proportion of humanities students in our sample. This discrepancy can be attributed to our focus on a student's self-assessed primary study program.

Our analysis of the gender distribution of majors in our sample compared to the national statistics has uncovered significant gender disparities. Specifically, we have found that a substantially larger proportion of females choose to study humanities, while a correspondingly higher percentage of males opt for STEM and engineering programs. Given the well-documented variability of dropout rates across both genders and majors (Isphording and Qendrai, 2019; Severiens and ten Dam, 2011), these gender-based differences in major selection may have important implications for our findings. Thus, it is essential to account for these disparities in our estimation strategy. To this end, we plotted the corresponding dropout rates by major and gender alongside the enrollment rates to demonstrate the presence of such differences in our data.

There is considerable variation in the dropout rates across different majors, with STEM subjects exhibiting an above-average dropout rate of approximately 38%, while medicine displays a lower-than-average rate of approximately 12%. Moreover, we note gender-based differences in dropout rates, with males having a higher rate of dropout in subjects such as STEM and agriculture, and females having a correspondingly higher rate of dropout in disciplines such as sports and arts. These findings emphasize the need to account for major-by-gender differences when estimating the potential impact of preference-choice mismatches on dropout rates.

Table 2 depicts a range of summary statistics regarding the 2476 students who comprise our sample. Previous literature has documented notable gender differences in both preferences (see, e.g., Wiswall and Zafar, 2015a) and skills (see, e.g., Stinebrickner and Stinebrickner, 2014), in addition to the observed gender differences in dropout rates mentioned before. Hence, we report the sample means of the model variables for the overall sample and the male (Column II) and female (Column III) subgroups. To investigate the presence of significant differences between the means of the male and female subgroups, we employ a two-sided *t*-test and provide both the standard errors and indications of statistical significance.

Table 2 presents key statistics of our sample. We find that 29% of students discontinued their initial university program, with males exhibiting a 6.8-percentage-point greater likelihood of dropping out than females. However, males had a 14-percentage-point lower likelihood of dropping out during their first year. We also observe that 64% of the sample reported some occupational preferences, with male students less likely to report their preferences. This finding is consistent with prior research, such as Wiswall and Zafar (2018), which shows that women tend to focus more on occupational characteristics than men. The majority of

Table 2
Summary statistics.

	I	II	III	Difference III - II	
	Total	Male	Female	b	se
Outcomes					
Dropout	0.29	0.33	0.26	0.068***	0.018
First-Year Dropout	0.62	0.55	0.68	−0.137***	0.036
Preferences					
Reported Occupational Preferences	0.64	0.61	0.66	−0.048**	0.019
MOM	0.71	0.72	0.70	0.021	0.018
MMM	0.68	0.64	0.71	−0.076***	0.019
Demographics					
Female	0.56				
Ethnic Minority	0.11	0.12	0.11	0.005	0.013
Mother has University Degree	0.28	0.28	0.27	0.014	0.018
Partner has University Degree	0.25	0.27	0.25	0.018	0.018
Age at Enrollment	19.53	19.56	19.51	0.045	0.037
Cognitive Skills					
Science Score	−0.00	0.16	−0.13	0.281***	0.040
Math Score	0.00	0.26	−0.20	0.468***	0.039
ICT Score	0.00	0.05	−0.04	0.096**	0.041
Reading Score	−0.00	−0.13	0.10	−0.232***	0.040
Non-cognitive Skills					
Openness	−0.00	−0.30	0.24	−0.537***	0.039
Neuroticism	−0.00	−0.24	0.18	−0.417***	0.040
Conscientiousness	−0.00	−0.25	0.19	−0.435***	0.040
Agreeableness	−0.00	−0.17	0.13	−0.293***	0.040
Extraversion	−0.00	−0.11	0.09	−0.201***	0.040
Observations	2476	1086	1390	2476	

This table reports summary statistics for the analysis sample. Column 1 reports averages for the total sample, columns 2 and 3 report averages for male and female samples, respectively. Column 4 reports differences and statistical significance of these differences from a two-sided t-test. Column 5 reports standard errors thereof. Source: NEPS SC4 12-0-0, own calculations. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.

the sample, 71%, have a MOM, and 68% have an MMM. While this could be due to the 36% of students who have not reported any occupational preferences, among the students who have reported occupational preferences, 54% have a MOM and 61% have an MMM.

Furthermore, the presented table reveals that approximately 56% of the sample is female. Notably, national statistics indicate a slightly lower proportion of females, with a weighted average of approximately 50.5% of females across the academic years 2014/15 to 2016/17 (see Table F3-1web Bildungsberichterstattung, 2020). The proportion of students belonging to an ethnic minority group was found to be 11%. Moreover, 28% of the students had a mother with a university degree, while the mother's partner of 25% of the students had a university degree. The average age of enrollment in the university was 19.53 years. In comparison, the national educational report cites a median age of 19.4 to 19.7 years for the semesters from 2014/15 to 2016/17 (see Table F3-3web Bildungsberichterstattung, 2020). In all demographic categories, gender differences were minor.

Amador-Hidalgo et al. (2021) show that lower cognitive skills correlate with inconsistent choices, which could add to the classical argument that low cognitive skills themselves cause dropout. Thus, we also show gender differences in cognitive and non-cognitive skills. Males showed higher cognitive proficiency in science, mathematics, and ICT, while females exhibited greater proficiency in reading. As Aucejo and James (2021) show, a female advantage in verbal skills may explain a large share of the gender-enrollment gap, which could also explain the gender-enrollment gap in our sample. Conversely, males consistently scored lower than females in non-cognitive skills, such as openness, conscientiousness, agreeableness, and extroversion, but exhibited lower levels of neuroticism.

2.5. Empirical strategy

This section outlines our empirical approach for examining the relation between preference mismatches and dropout behavior. Specifically, we estimate the following equation:

$$dropout_i = \alpha + \beta_1 MOM_i + \beta_2 MMM_i + \beta_3 X_i + \mu_{m,g} + \epsilon_i, \quad (1)$$

where $dropout_i$ represents an indicator variable for whether individual i dropped out of their university program. The mismatch indicators, MOM and MMM, take the value of 1 if there is a mismatch between the student's preferences and their chosen major and 0 otherwise. The main coefficient of interest, β_1, estimates the relation between preference mismatches and dropout behavior. We include a wide range of potential confounding factors in X_i, such as demographics, parental education, and cognitive and non-cognitive skills. Additionally, to account for gender-major-specific differences in dropout rates and potential gender-specific sorting probabilities across majors, we include major-by-gender fixed effects, denoted as $\mu_{m,g}$. Finally, ϵ_i represents the idiosyncratic error term. The coefficients we report are based on a Linear Probability Model (LPM). We estimated the main model using conditional logit model and found the marginal effects to be qualitatively the same and, if anything, even larger in size for females, compared to the LPM coefficients we report in Table 5.

In the NEPS, students were required to report a major. If their major was not listed in the German classification of majors, they were assigned to a "category 0" major, which we always considered to be a mismatch between their occupational preferences and their major. Also students who do not report their occupational preferences, are included, but we assign them to be mismatched. To control for these imputations, we include dummy variables in all regressions to account for missing information.

While we aim to account for all potential confounding variables that may affect the dropout decision through the use of a MOM, it is important to note that our estimation approach does not establish causality due to the absence of exogenous variation. Our findings can only be interpreted causally if the decision to drop out and the treatment assignment (i.e., mismatch) are not simultaneously influenced by the same unobserved factors. Stated differently, the occurrence of a mismatch must be *as good as random* conditional on our controls, that is, $Y_i \perp MOM_i | X_i, \mu_{m,g}$.

However, we have little knowledge about whether this is a sensible assumption. MOM might be influenced by several factors and may deviate for different subgroups depending on gender and the social context. Therefore, we show determinants of having a MOM for the total sample, by gender, and SES defined by parental education.

The table reveals that only a few model variables are significant predictors of having a MOM. Notably, gender and ethnicity are not significant predictors of having a MOM. Similarly, cognitive and most non-cognitive scores are not associated with having a MOM. Instead, maternal education, age at enrollment, and conscientiousness are significant predictors of a mismatch. Students with a mother holding a university degree and those who are older at enrollment are more likely to have a mismatch, regardless of gender and SES. Furthermore, higher levels of conscientiousness are negatively associated with having a mismatch, particularly among female students and those from higher SES backgrounds.

Prior research has established that certain factors, such as parental education (Aina, 2013), age at enrollment (Aina et al., 2022), and conscientiousness (Alarcon and Edwards, 2013), are associated with dropout rates. Our study examines the relation between these factors and the occurrence of a major-occupation mismatch (MOM), which can also affect dropout rates. However, we acknowledge the possibility of endogeneity issues arising from these correlations. For example, students may choose a major that does not match their occupational preferences due to parental pressure, potentially leading to a higher likelihood of dropout. To mitigate this concern, we restrict our analysis to students who are enrolled in their preferred major. Similarly, older students may have more time to consider their preferences, but they may also face academic challenges that could limit their options. Again, we address this by limiting our sample to students in their preferred major.

Conscientiousness is a personality trait that can incorporate various underlying preferences and motivations (Alarcon and Edwards, 2013), which may influence both having a mismatch and being a future dropout. Unfortunately, we cannot control for these underlying factors directly. For instance, conscientious individuals might be more stable in their preferences and tend to plan ahead, which could reduce the likelihood of a mismatch and dropping out. However, we can condition our analysis on students who have a match between their occupational and major preferences. By doing so, we include only those who have already made up their minds and are less likely to change their preferences or drop out due to indecisiveness.

While we have taken measures to close several sources of endogeneity by conditioning on students who study their preferred major, students with a match between occupational and major preferences, and using a large set of control variables that include often unobserved factors such as cognitive and non-cognitive skills that are predictors of human capital outcomes (Borghans et al., 2008), we cannot rule out that other unobserved factors influence both having a mismatch and university dropout. Therefore, our findings cannot be interpreted as causal.

3. Results

3.1. Main results

This section presents the main findings of our study. Table 4 reports the results obtained from estimating Eq. (1), which examines the relation between preference-choice mismatches and the decision to drop out of university. We estimate two specifications of Eq. (1): Panel A reports the results for a specification without MMM, while the results from Panel B include the MMM indicator. In each column, we progressively add a different set of control variables. Specifically, Column I shows the raw correlations without any control variables, while Column II includes demographic variables. Parental education is included in Column III, and cognitive skills are added in Column IV. Finally, Column V adds non-cognitive skills to the model. All the models include major-gender fixed effects.

In our baseline specification (Panel A, Column I), we find that students with a MOM are 12.5 percentage points more likely to drop out than those without a MOM. This result holds true even after controlling for various demographic, parental education, cognitive, and non-cognitive factors in Columns II-V. Panel B reports results of our preferred specification where we additionally control for MMM. As expected, the results show that the correlation between MOM and university dropout is slightly lower in specifications I to IV at between 9.3 and 9.5 percentage points. The coefficient remains virtually unchanged in the full model (Column V) at 9.1 percentage points, indicating that students with MOM are still significantly more likely to drop out than those without MOM. In accordance with the results from Table 3, the results show that the model variables do not mediate our mismatch indicator.

A natural question that arises from our main results is whether having a MOM leads to higher dropout rates only when the desired occupation cannot be reached or whether students accept some degree of occupational similarity to their preferred occupation to avoid dropping out. To address this question, we use a similarity index between the occupations that a major can lead to and the occupational preferences of the students. The index ranges from -1 to 1, with -1 indicating no occupational mobility between the two occupations and 1 indicating that the two occupations are the same (Neffke et al., 2017). Figure 6 presents the relation between the dropout rate and the similarity index, which shows a clear negative correlation, indicating that a closer match between a major's careers and a student's preferences reduces dropout rates.

We further investigate the effects of having a MOM and MMM on the dropout decision by gender in Table 5. We estimate the specifications from Eq. (1), where Columns I and III show the estimates with no controls, and Columns II and IV show the estimates with the full set of control variables. All models use major-gender fixed effects. Panel A presents results for the entire sample, while Panel B shows results for a subsample of students who study their preferred major. Panel C shows the results for a subsample of students whose occupational preference matches their major preferences[6].

Table 5, Panel A, suggests a strong positive association between having a MOM and the probability of dropping out of university. However, this association seems to be gender-specific, as only females show a significant increase in the likelihood of dropping out (between 13.3 and 13.8 percentage points) when they have a MOM, while the corresponding estimates for males are only between 2.5 and 2.8 percentage points. Furthermore, not studying the preferred major (i.e., having an MMM) increases the probability of dropping out by 5.2 to 6.8 percentage points, albeit with marginal statistical significance. Nevertheless, these results could be driven by students who study their preferred major, as the presence of a MOM may mediate the impact of an MMM. To investigate this potential mediation, we estimate the same model but restrict the sample to students who study their preferred major, as presented in Table 5, Panel B.

The findings from Table 5, Panel B, suggest that the relation between a MOM and dropout rates is larger among students who study their preferred major. In the case of males, the coefficients are still not significant at conventional levels, but they are between 4.6 and 7 percentage points more likely to drop out if they have a MOM and study their preferred major. For females, the coefficient is larger, between 19.4 and 21.3 percentage points, which is a significant difference. While the larger coefficients reported in Panel B come with higher standard errors, they do provide reassurance that the effects are not driven by students who were not able to study their preferred major and, for example, start another major to look for a real alternative to the preferred major. Table 5, Panel C shows similar results for the subgroup of students who had a match

[6] Table 11 shows results using different data sources to create the mismatch indicators.

Table 3
Correlates of MOM.

	Total	Male	Female	Low SES	High SES
Female	0.034			0.021	0.042
	(0.029)			(0.034)	(0.036)
Ethnic Minority	0.010	0.001	0.005	0.004	0.008
	(0.024)	(0.037)	(0.037)	(0.029)	(0.073)
Mother has University Degree	0.065***	0.051*	0.062**		0.062*
	(0.016)	(0.026)	(0.030)		(0.034)
Partner has University Degree	0.026	0.033	0.019		0.007
	(0.030)	(0.042)	(0.035)		(0.038)
Age at Enrollment	0.053***	0.074***	0.032**	0.043***	0.067***
	(0.013)	(0.025)	(0.013)	(0.014)	(0.019)
Squared Age at Enrollment	−0.001	−0.003	−0.001	0.001	0.000
	(0.006)	(0.006)	(0.015)	(0.007)	(0.010)
Science Score	−0.012	−0.028*	0.006	−0.016	−0.006
	(0.014)	(0.016)	(0.017)	(0.021)	(0.019)
Math Score	−0.011	−0.009	−0.015	−0.017	0.009
	(0.013)	(0.021)	(0.017)	(0.016)	(0.020)
ICT Score	−0.007	0.003	−0.015	−0.003	−0.020
	(0.012)	(0.022)	(0.014)	(0.015)	(0.015)
Reading Score	0.011	0.011	0.007	−0.003	0.035*
	(0.012)	(0.013)	(0.016)	(0.016)	(0.020)
Extraversion	0.009	0.011	0.009	0.006	0.010
	(0.010)	(0.015)	(0.014)	(0.013)	(0.015)
Agreeableness	0.005	0.017	−0.011	−0.001	0.013
	(0.009)	(0.013)	(0.012)	(0.011)	(0.012)
Conscientiousness	−0.026**	−0.023	−0.031*	−0.018	−0.048***
	(0.010)	(0.015)	(0.016)	(0.012)	(0.016)
Neuroticism	−0.002	−0.013	0.015	0.005	−0.018
	(0.013)	(0.016)	(0.015)	(0.018)	(0.016)
Openness	−0.011	−0.011	−0.013	−0.009	−0.022
	(0.008)	(0.016)	(0.009)	(0.012)	(0.014)
Constant	0.646***	0.675***	0.671***	0.650***	0.655***
	(0.028)	(0.021)	(0.028)	(0.030)	(0.050)
Observations	2476	1086	1390	1534	937

Note: Dependent variable: major-occupational preference-mismatch (Yes/No). We control for missing values in cognitive and non-cognitive skills and create a dummy for when ethnic minority, or parental education is missing. All models use major fixed effects. Standard errors in parentheses are clustered on the major level. Source: NEPS SC4 12-0-0, own calculations. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.

Table 4
Relation between MOM and the dropout decision.

	I	II	III	IV	V
Panel A					
MOM	0.125***	0.127***	0.127***	0.122***	0.120***
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
Panel B					
MOM	0.093***	0.095***	0.095***	0.093***	0.091***
	(0.025)	(0.026)	(0.026)	(0.025)	(0.025)
MMM	0.061***	0.063***	0.064***	0.060***	0.059***
	(0.023)	(0.022)	(0.022)	(0.021)	(0.022)
Demographics	No	Yes	Yes	Yes	Yes
Parental education	No	No	Yes	Yes	Yes
Cognitive skills	No	No	No	Yes	Yes
Non-cognitive skills	No	No	No	No	Yes
Observations	2476	2476	2476	2476	2476

Dependent variable: Dropout (Yes/No). This Table shows estimates for different models iteratively increasing the number of control variables. All models include MOM indicators and indicators of whether occupational preferences were missing. Panel B additionally reports the results for a specification with MMM indicators and indicators of whether major preferences were missing. Demographics included dummy variables for gender and migration background and quadratic interactions for age at enrollment. Parental Education includes the mother's education and the mother's partner education. Cognitive Skills include standardized test scores for science, math, ICT, and reading. Non-cognitive skills include the standardized Big-5 personality traits. All models use major-gender fixed effects. Standard errors in parentheses are clustered on the major level. Source: NEPS SC4 12.0.0, own calculations. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.

between occupational preferences and major preferences prior to university enrollment.

While our previous analysis has shown a positive correlation between having a MOM and the likelihood of dropping out of university, we have not yet explored the timing of dropping out. It is important to understand whether students with a mismatch drop out earlier than those with a match, and whether there are gender differences in this pattern. Additionally, it is possible that the different dropout rates between men and women with a MOM are due to different reasons, such as persistent males who adapt to their situation of not studying a major that leads to their preferred occupation. Moreover, a recent study on German vocational graduates using the same data as ours shows it matters to distinguish study switcher from dropouts who do not return to the education system (Holtmann and Solga, 2023). The different dropout rates between men and women could stem from such different coping strategies to a MOM leading to study switches or leaving university altogether. To address these questions, we present the results of our estimations using the month of dropout, an indicator for first-year dropout, whether the dropout was forced, and whether the students switched the program / university or left university altogether in Table 6. Panel A of the table reports the estimates for the full sample, while Panels B and C report the estimates for males and females, respectively.

The findings in Table 6 suggest that students with a MOM are not more likely to drop out earlier (Column I) or to have a higher probability of dropping out in their first year of university (Column II). They are also more prone to dropping out due to failed exams (Column III for extensive margin results), but the results does not hold at the intensive margin (Column IV). We do not find that a MOM is related to study

Table 5
Estimated relation between MOM and the dropout decision by gender.

	I Male	II Male	III Female	IV Female
Panel A - All students				
MOM	0.028	0.025	0.138***	0.133***
	(0.052)	(0.052)	(0.046)	(0.044)
MMM	0.068*	0.065*	0.052	0.055
	(0.040)	(0.036)	(0.032)	(0.034)
Controls	No	Yes	No	Yes
Observations	1086	1086	1390	1390
Panel B - Students who study preferred major				
MOM	0.070	0.046	0.213***	0.194**
	(0.108)	(0.097)	(0.076)	(0.072)
Controls	No	Yes	No	Yes
Observations	391	391	391	391
Panel C - Students with a preference match prior to university enrollment				
MOM	−0.073	−0.027	0.217***	0.199***
	(0.105)	(0.129)	(0.062)	(0.055)
MMM	0.143	0.065	0.022	0.049
	(0.097)	(0.107)	(0.055)	(0.045)
Controls	No	Yes	No	Yes
Observations	373	373	534	534

Dependent variable: Dropout (Yes/No). This Table shows results for models with a different set of control variables. All models include the MOM indicator. Models from Panel A and Panel C additionally include the MMM indicator as well as indicators of whether the students had occupational or subject preferences missing. The models from columns II and IV additionally control for the full set of control variables as described in Eq. (1). Columns I and II show results for the male sample only, while columns III and IV show results for the female sample only. Panel A shows the results for all students in our sample, while Panel B shows results for a subsample of students who study their preferred subject only. Panel C shows the results for a subsample of students with a match between occupational preferences and major preferences prior to university enrollment. All models use major-gender fixed effects. Standard errors in parentheses are clustered on the major level. Source: NEPS SC4 12.0.0, own calculations. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

switch (Column V). Students with a MOM are, however, significantly more likely to dropout of university altogether (Column VI).

Examining the results for males, we find that those with a MOM tend to drop out in the first year, with a significant increase of 19.5 percentage points. When we distinguish between study switch and drop out from university, we find that males, just like females are more likely to drop out of university altogether, but at low levels of significance. These findings suggest that there is significant heterogeneity in the dropout behavior between men with a match and those with a mismatch. For females, we find that those with a MOM are more likely to switch study programs / university as well as more likely to drop out of university altogether.

The presence of these gender differences in the dropout behavior aligns with existing literature, which highlights substantial disparities between boys and girls in shaping their educational paths (Gati et al., 2010). The process of making educational decisions involves gathering, processing, and evaluating relevant information (Solomon et al., 2010). However, in practice, students often adopt a more intuitive approach (Dijksterhuis and Nordgren, 2006; Tversky and Kahneman, 1974), particularly males, while females tend to be better prepared on average (Meyers-Levy and Loken, 2015).

On one hand, males who choose fields that are in higher demand in the labor market (Wiswall and Zafar, 2018) may struggle to adapt. On the other hand, relying on intuition for study choices can pose problems since intuition is susceptible to biases, leading to the systematic neglect of certain information (Kahneman, 2003). Consequently, males might disregard relevant signals and fail to adjust when faced with setbacks, while females tend to be more adaptive. This could potentially explain why males experience more regret regarding their choice of field of study compared to females (Borghans and Golsteyn, 2006). Alternatively, it is possible that males exhibit higher levels of overconfidence than females (Reuben et al., 2017), which could account for their diminished response to MOM. In any case, the gender difference observed in dropout rates related to MOM warrants further investigation.

In addition to analyzing dropout behavior, and further digging into the differences we report in Columns V and VI of Table 6, it would also be interesting to explore what students with and without a MOM do after dropping out of university. To shed light on this, we present evidence on the post-dropout behavior of male and female students with and without a MOM using the second vocational education spell that lies within one year after dropout from the first vocational education spell. Specifically, we distinguish between five categories, including whether the student left university altogether and entered an apprenticeship in their second vocational education spell. Students enter the second category if they switched study programs and their new major aligns with the occupa-

Table 6
Relation between MOM and various measures of dropout.

	I Month of dropout	II First-year dropout	III Forced dropout (extens. Margin)	IV Forced dropout (intens. Margin)	V Study switch	VI Full dropout
Panel A: All						
MOM	−0.736	0.076	0.023*	0.025	0.037	0.053***
	(1.033)	(0.051)	(0.014)	(0.053)	(0.024)	(0.018)
Observations	711	711	2476	711	2476	2476
Panel B: Males						
MOM	−2.040	0.195***	0.015	0.005	−0.024	0.043*
	(1.331)	(0.058)	(0.021)	(0.068)	(0.049)	(0.022)
Observations	352	352	1086	352	1086	1086
Panel C: Females						
MOM	0.334	−0.036	0.030	0.054	0.084**	0.055**
	(1.568)	(0.065)	(0.019)	(0.061)	(0.037)	(0.026)
Observations	359	359	1390	359	1390	1390

Dependent variables: month of dropout, a dummy for first-year dropout, forced dropout on the intensive and extensive margin, an indicator for switching study programs / university, and an indicator for leaving the university altogether. All results show estimates of our preferred specification with the different outcomes specified above. Panel A reports results for the whole sample, while Panel B and Panel C report results for the subsample of males and females, respectively. All models use major-gender fixed effects. Standard errors in parentheses are clustered on the major level. Source: NEPS SC4 12.0.0, own calculations. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.

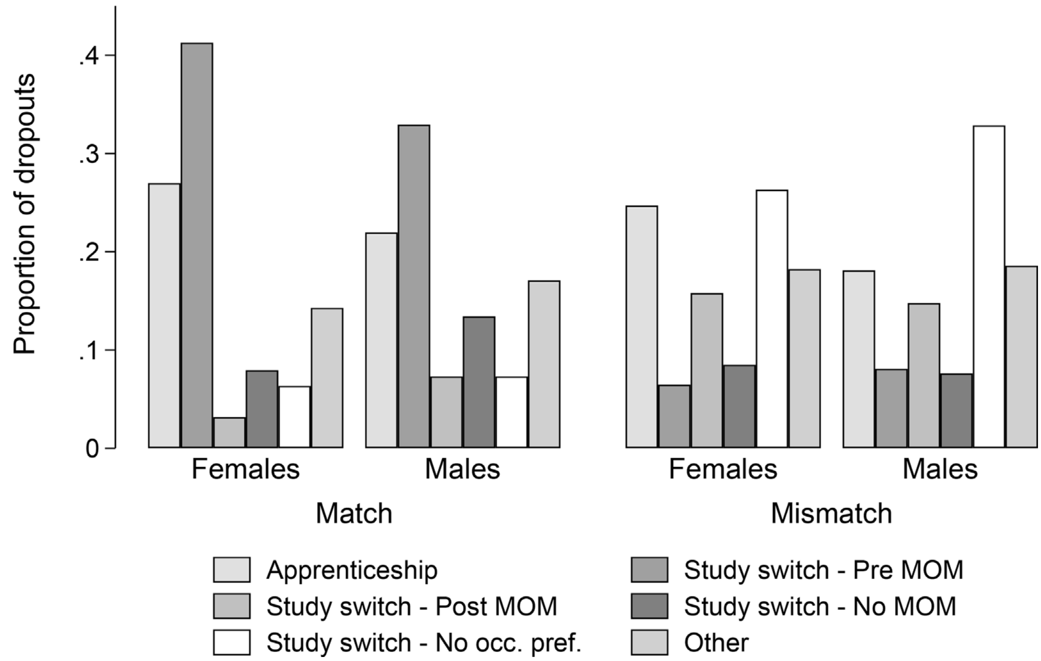

Fig. 2. Educational sorting of dropouts after dropping out by MOM and gender.

tional preferences they reported prior to enrolling in university (Study Switch - Pre MOM). Students enter the third category if they switched study programs and their new major aligns with their occupational preferences they reported after enrolling in university (Study Switch - Post MOM). Students enter the fourth category if they switched study programs and their new major aligns with neither the occupational preferences before or after enrolling in university. The fifth category includes all students who have switched study programs but have not reported occupational preferences after enrolling in university. Lastly, the sixth category includes all students for which we do not have information on the second spell. The numbers in Fig. 2 add up to 1 in each gender-mismatch combination.

Figure 2 shows that of the female students with a match, around 27% start an apprenticeship, while still 42% change program or institution to match their original occupational preferences. For male dropouts with a match, the picture is similar to that for female dropouts, although they are more likely to change to a study program that does not match their stated occupational preferences before or after enrollment.

Dropouts with a mismatch are only slightly more likely to change to a study program that is in line with their stated occupational preferences prior to enrollment. In addition, they are more likely than dropouts with a match to change to a study program that corresponds to their stated occupational preferences after enrollment. A large group of students with a mismatch and no occupational preference have never expressed an occupational preference.

The results presented in Fig. 2 do not support the idea that information deficits are the main mechanism of the higher dropout rates for students with a MOM. If this were the case, we would expect to see more dropouts with a mismatch eventually finding a major that aligns with their occupational preferences reported prior to university enrollment. However, we do observe that a greater proportion of dropouts with a MOM never report their occupational preferences at all. Moreover, previous analyses revealed that students who have a match in their occupational and major preferences exhibit similar results to the entire sample, which provides further evidence that information deficits are not the primary driver of the higher dropout rates for students with a MOM. As a result, in the next section we explore two alternative explanations for our findings.

4. Mechanisms

Having explored the factors influencing the dropout decision and the relation between students' preferences and their subsequent choices, we now aim to identify the drivers of our findings. Our econometric model is designed to already account for various potential mechanisms that may drive our results. For instance, we have ruled out the possibility that differences in major-gender combinations are the main driving force of our findings, thanks to the inclusion of major-by-gender fixed effects. Similarly, we have controlled for not reporting occupational preferences in our main specifications, which also eliminates this factor as an explanation for our results.

Nonetheless, our previous analysis of dropout behavior after leaving university suggests that indecisiveness prior to choosing a major and changing preference may be important factors that contribute to higher dropout rates among students with MOM. We offer additional evidence to support this claim in the following section.

4.1. Indecisiveness prior to major choice

The literature on decision-making has devoted some attention to the phenomenon of indecisiveness (Manski, 1989; Milla, 2017). In the context of our study, uncertainty arises when students are unsure about the occupation they aspire to, which is more likely to happen to students with a MOM. To shed light on this issue, we consider two different dimensions of uncertainty. First, we investigate whether dropout rates vary across groups of students who reported having clarity about their future occupation, disaggregated by gender and MOM. Figure 3 presents the results and reveals only marginal differences in the dropout rates within the groups of gender and MOM, but it displays a pronounced difference between the groups. Specifically, it highlights that females without a MOM are significantly less likely to drop out than any other group.

Second, Fig. 4 displays the relation between the dropout rates by MOM and the occupational breadth of majors, which we define as the number of occupations per major that occurred in our major-occupation-map without any restriction. This figure introduces a third category of not having any occupational preferences instead of being part of the group having a mismatch. The figure reveals that students who enroll

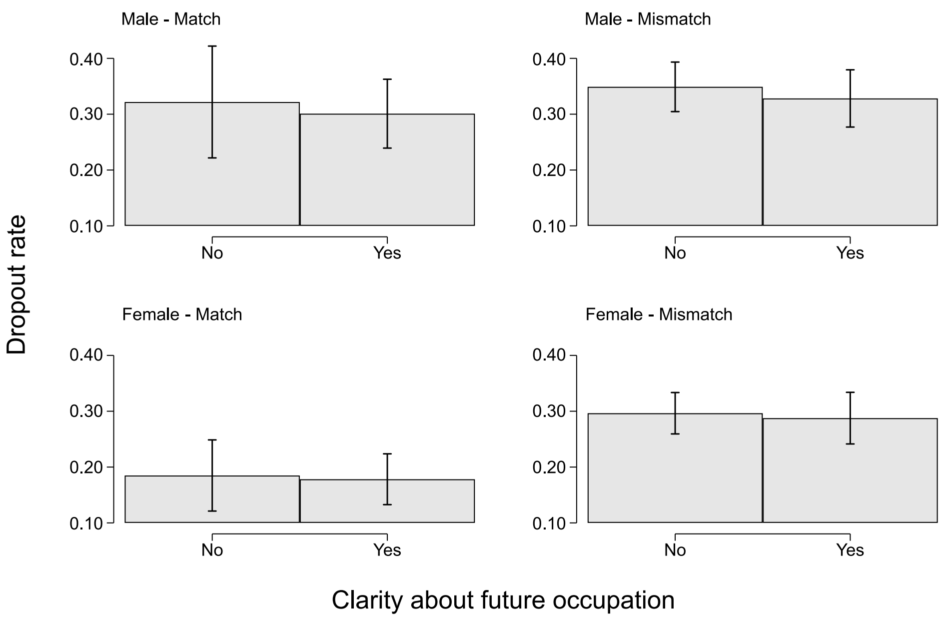

Fig. 3. Clarity of future occupation by MOM and gender.

in majors that provide more occupational options are less likely to drop out. This is especially true for males with a mismatch and those who did not report any preferences but not for males with a match. For females with a mismatch or a match, we do not observe that the dropout rates are associated to the occupational breadth of their major. Females without stated preferences, however, have a high dropout rate when sorting into narrow majors but clearly benefit from sorting into broad majors.

4.2. Changes in occupational preferences

In addition to being indecisive about their future careers, students may also change their occupational preferences after starting university. This channel is more relevant for students who have a match prior to university enrollment. Figure 5 presents the dropout rates for distinct flows of occupational preferences by gender. We plot flows from no MOM (pre-enrollment) to no MOM (post-enrollment), from MOM to no MOM, from no MOM to MOM, and from MOM to MOM.

In Fig. 5, we can see that females who maintain a match between their major and occupational preference throughout their university studies have a relatively low dropout rate of only 12%, compared to higher female dropout rates observed in other occupational preference flows and male dropout rates in the same flow. The highest female dropout rates are observed when they transition from having a mismatch to maintaining a mismatch. Conversely, males seem to have a lower dropout rate when their occupational preference after university enrollment matches their initial study choice. However, having a mismatch at university increases the risk of dropping out for males, while not having a mismatch before university enrollment does not appear to prevent males from dropping out. These findings help us to identify the key drivers of our main specification results. Specifically, we find that the relation with dropout among students with a mismatch is primarily driven by females who do not have a mismatch before or after enrolling in university.

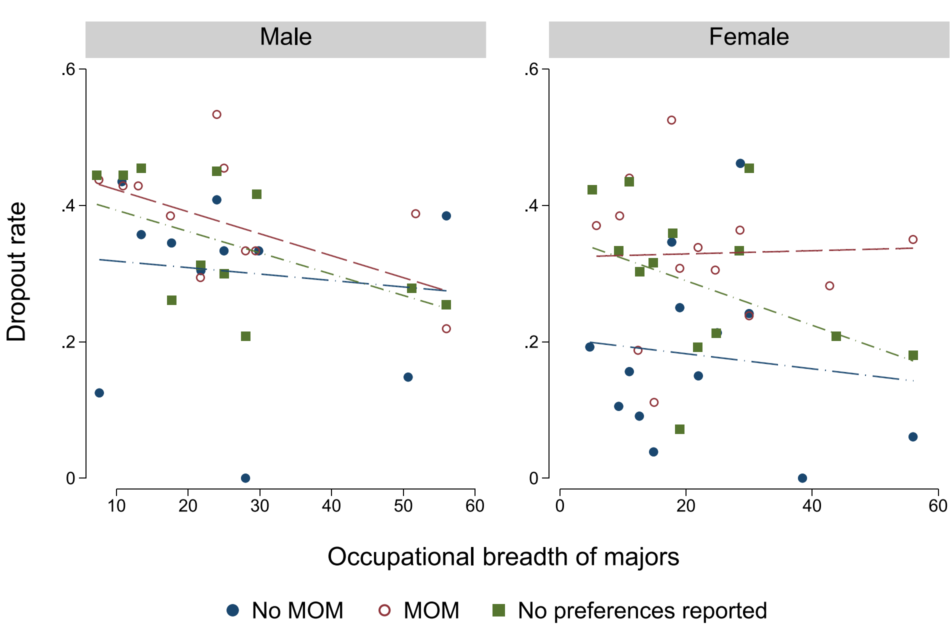

Fig. 4. Correlation of dropout rate and occupational breadth of majors by MOM and gender.

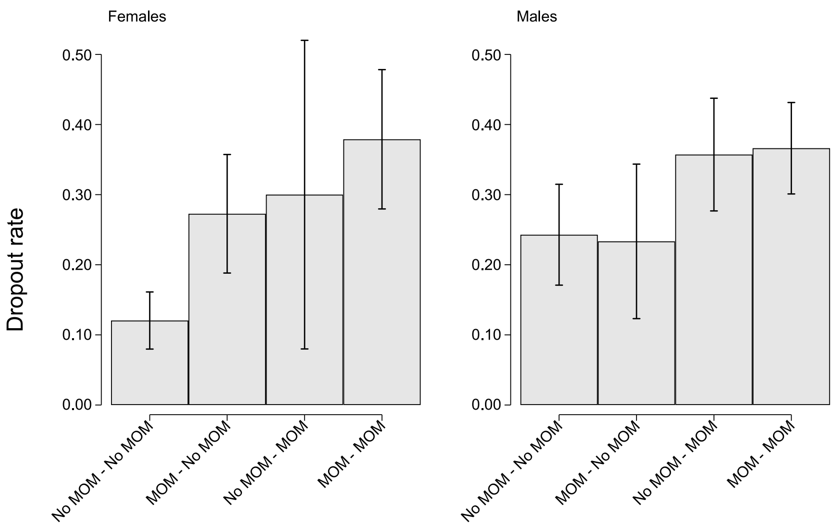

Fig. 5. Dropout rate by preference change (pre- and post-enrollment MOM) and gender.

5. Conclusion

This study provides compelling evidence of the correlation of occupational preferences on human capital investments and university dropout decisions. By analyzing data on students' preferences before enrollment and their chosen majors, we uncover a strong connection between mismatched preferences and the likelihood of dropping out. Our results reinforce recent findings, such as those by Conlon and Patel (2022), that emphasize the importance of occupational preferences in shaping educational outcomes. Notably, our study highlights the disproportionate impact of a mismatched occupational preference on female students, who are more likely to drop out if they have a mismatch. The results are highly significant and robust to various specifications, providing strong evidence of the link between occupational preferences and educational outcomes.

Overall, our results suggest that mismatches between students occupational preferences and their major choice are highly predictive of future dropout. Specifically, we find that having a MOM increases the likelihood of dropping out by 9.3 percentage points, a sizeable coefficient that represents approximately 30% of the baseline dropout rate of 29%. These findings emphasize the importance of considering occupational preferences when designing higher education policies, as mismatches can have significant consequences for student outcomes. Our study also sheds light on the mechanisms underlying this relation, showing that indecisiveness prior to enrollment and preference changes are likely factors contributing to dropping out. In contrast, we find that information deficits are not a significant driver. Interestingly, our study suggests that students who do not report occupational preferences may benefit from sorting into broad majors to reduce their likelihood of dropping out. Overall, our findings have important implications for policy-makers and educational institutions seeking to improve student outcomes and reduce dropout rates.

Our study suggests that the current institution-major admission system in Germany may contribute to high dropout rates, particularly for students who are indecisive or change their preferences in the first year of studies. We propose that a possibly effective approach to reduce dropout rates would be to adopt an institution admission system in which students choose their major after enrolling in the institution, as proposed by Bordon and Fu (2015). This would allow students to explore their interests and abilities in a broader range of fields before committing to a major, potentially reducing the likelihood of a mismatch between their preferences and their chosen field of study. By reducing this source of dissatisfaction and frustration, we believe that a change to the admission system could have a meaningful impact on dropout rates in Germany.

Data availability

The authors do not have permission to share data.

Appendix A. Major-occupation-map

The full major-occupation-map consists of 59 distinct major categories and 36 distinct occupation categories. The major categories are

Table 7
Major-occupation-map: breadth and inequality within major.

Panel A: Top 5 majors with most occupations possible					
Without 5 percent restriction			With 5 percent restriction		
Major	Breadth	Inequality	Major	Breadth	Inequality
Arts, art sci. in general	19	0.61	Spatial Planning	11	0.27
Agricultural sci., food and beverage technology	14	0.58	Cultural studies (in narrow sense)	7	0.23
Nutrit. & domestic sci.	13	0.37	Nutrit. & domestic sci.	7	0.33
Geography	13	0.60	Health sciences	7	0.25
Earth sci.	13	0.72	Fine arts	6	0.36
Panel B: Top 5 Occupations with most majors possible					
Without 5 percent restriction			With 5 percent restriction		
Occupations	Breadth	Inequality	Occupations	Breadth	Inequality
Teaching and Training	58	0.46	Teaching and Training	50	0.40
Business Management	48	6 0.52	Business Management	28	0.39
Marketing	30	0.47	Marketing	18	0.28
Computer Sci, ICT	26	0.62	Medical Occupations	11	0.47
Tourism, Hotels, Restaurants	25	0.46	Computer Sci, ICT	8	0.34

Table 8
Top 4 occupations of top 4 majors.

Major	Occupation
Economics	Occupations in accounting, controlling and auditing
	Occupations in advertising and marketing
	Occupations in business organization and strategy
	Teachers and researcher at universities and colleges
Mechanical Engineering	Occupations in technical research and development
	Teachers and researcher at universities and colleges
	Occupations in machine-building and -operating
	Technical occupations in production planning and scheduling
Computer Science	Occupations in software development and programming
	Occ. in IT-system-analysis, IT-application-consulting and IT-sales
	Occupations in computer science
	Teachers and researcher at universities and colleges
Legal Studies	Occ. in legal services, jurisdiction, and other officers of the court
	Teachers and researcher at universities and colleges

Notes: The table displays the top 4 chosen 2-digit majors according to the NEPS data. The occupations are the top 4 occupations chosen by respondents of the DZHW data. Majors and occupations are sorted with the most frequent observations mentioned first.

Table 9
Top 3 mismatches of top 4 majors.

Major	Occupation
Economics	Managing directors and executive board members
	Teachers in schools of general education
	Occupations in event organization and management
Mechanical Engineering	Occ. in construction scheduling and supervision, and architecture
	Driver of vehicles in air traffic
	Teachers in schools of general education
Computer Science	Occupations in public administration
	Occupations in machine-building and -operating
	Occupations in business organization and strategy
Legal Studies	Teachers in schools of general education
	Occupations in editorial work and journalism
	Occupations in psychology and non-medical psychotherapy

Notes: The table displays the top 4 chosen 2-digit majors according to the NEPS data. The occupations are the top 3 occupations of students with a mismatch. Majors and occupations are sorted with the most frequent observations mentioned first.

based on the German classification of majors, whereas the occupations are based on the German classification of occupations. Table 7 presents some facts about the distribution of majors and occupations in the major-occupation-map. In more detail, it shows the 5 broadest major categories (Panel A) and 5 broadest occupations (Panel B) with and without 5 percent restriction.

In Table 7 Panel A, we observe that with the 1 percent restriction, Arts is the major with the broadest occupation possibilities after graduation. According to this result, studying Arts opens the door to 19 out of 36 different occupations. Inequality, measured by the Gini coefficient, lies at 0.61. Other majors in the top 5 are Agricultural science, Nutritional and domestic science, Geography, and Earth Sciences. Except for Nutritional and domestic science, each major has a Gini coefficient at or above 0.6. This indicates significant inequality of occupational sorting within majors. Indeed, less than a third of the Arts graduates sorted into 15 out of 19 (> 78 percent) different occupations. These 15 occupations include, e.g., occupations in construction, cleaning services, or occupations in tourism, that is, occupations without a direct link to the content of the major.

In contrast, when we restrict the map to major-occupation combinations with a share of at least 5 percent of graduates, we find largely different majors in the top 5 majors. The leading example is Spatial planning with 11 possible occupations after graduation. Cultural studies, Nutritional and domestic science, and Health sciences follow with 7 and Fine arts with 6 possible occupations after graduation. Comparing the inequality measure with and without the restriction shows a remarkable reduction in within major inequality within the broadest major categories while maintaining a reasonable range of different occupations.

Table 7 Panel B shows a slightly different picture than Panel A. The three broadest occupations stay the same with and without the 5 percent restriction. These occupations are Teaching and Training, Business Management, and Marketing. Remarkably, an occupation in Teaching and Training can be achieved with 58 out of 59 majors. Even with the 5 percent restriction, an occupation in Teaching and Training can be achieved by studying one of 50 different majors. On the one hand, the three broadest occupations with the 5 percent restriction are quite stable. On the other hand, the fourth and fifth broadest occupations lose a large share of majors that lead to this occupation. For example, ICT occupations can be achieved by studying one of 26 majors. With the 5 percent restriction, this can be achieved only by studying 6 majors (-77 percent). The majors drawn out with the restriction are largely broad majors where ICT occupations are not necessarily implausible. Occupations in Tourism, Hotels, and Restaurant, however, are often part of self-employment. Moreover, it could be an occupation to prevent post-graduation unemployment. Again, comparing the within-occupation inequality with and without the 5 percent restriction, the restriction significantly reduces the inequality again.

Appendix B. Additional figures & tables

Table 10
Predictors of attrition.

	Participation
Female	0.07***
	(0.03)
Migrant	−0.06
	(0.04)
Missing Info. Migrant	−1.03***
	(0.24)
Mother with University Degree	0.03
	(0.03)
Missing maternal education	−0.09*
	(0.05)
Partner with University Degree	−0.05
	(0.04)
Missing partner education	−0.01
	(0.04)
Constant	2.59***
	(0.03)
Observations	3598

Dependent variable: Sample participation. Source: NEPS SC4 12-0-0, own calculations. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.

Table 11
Relation between of MOM and dropout using different data.

	I Total	II Male	III Female
Panel A: DZHW 2001 and 2005			
MOM	−0.06**	0.01	−0.13***
	(0.03)	(0.04)	(0.04)
Panel B: NEPS			
MOM	−0.04*	0.01	−0.08**
	(0.02)	(0.03)	(0.03)
Observations	2476	1086	1390

Dependent variable: Dropout (Yes/No). This Table shows results for models using different data to create the major-occupation-map. All models include the MOM and MMM indicators as well as indicators of whether the students had occupational or major preferences missing and control for the full set of control variables as described in Eq. (1). Column I shows the results for the whole sample, Columns II and III show the results for males and females, respectively. All models use major-gender fixed effects. Standard errors in parentheses are clustered on the major level. Source: NEPS SC4 12-0-0, own calculations. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.

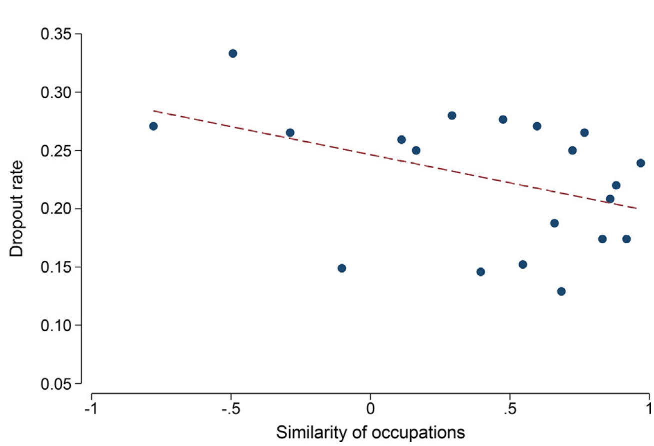

Fig. 6. Dropout rates and similarity of occupations.

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