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Heterogeneous Major Preferences for Extrinsic Incentives: The Effects of Wage Information on the Gender Gap in STEM Major Choice

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Abstract

Despite the growing evidence of informational interventions on college and major choices, we know little about how such light-touch interventions affect the gender gap in STEM majors. Linking survey data to administrative records of Chinese college applicants, we conducted a large-scale randomized experiment to examine the STEM gender gap in the major preference beliefs, application behaviors, and admissions outcomes. We find that female students are less likely to prefer, apply to, and enroll in STEM majors, particularly Engineering majors. In a school-level cluster randomized controlled trial, we provided treated students with major-specific wage information. Students' major preferences are easily malleable that 39% of treated students updated their preferences after receiving the wage informational intervention. The wage informational intervention has no statistically significant impacts on female students' STEM-related major applications and admissions. In contrast, those male students in rural areas who likely lack such information are largely shifted into STEM majors as a result of the intervention. We provide supporting evidence of heterogeneous major preferences for extrinsic incentives: even among those students who are most likely to be affected by the wage information (prefer high paying majors and lack the wage information), female students are less responsive to the informational intervention.

Keywords College application · Major choice · STEM gender gap · Informational intervention · Preference heterogeneity · Randomized experiment

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Introduction

The gender gap in STEM majors (science, technology, engineering, and mathematics) remains a persistent policy problem in higher education (Ganley et al., 2018; Griffith, 2010; Kugler et al., 2017; Rask, 2010). Governments and higher education institutions all around the world have enacted numerous policies designed to increase the number of students majoring in STEM, especially among women and racial and ethnic minorities (Crisp et al., 2009; Melguizo & Wolniak, 2012; Soldner et al., 2012). However, these efforts to expand female participation in STEM, especially in technology and engineering, are not achieving their goals (Kesar, 2017). In 2013, 28.4% of researchers in scientific fields were female and, in most countries, less than 30% of the post-secondary graduates in engineering were female (UNESCO, 2015)

Factors steering women away from STEM majors are complex and yet to be fully explained, though they have long been studied (Bobbitt-Zeher, 2007; Chipman & Thomas, 1987; Gemici & Wiswall, 2014; Mann & DiPrete, 2013; Simpson, 2001; Speer, 2017; Turner & Bowen, 1999; Zafar, 2013). Kanny et al. (2014) has reviewed 324 papers spanning 40 years of STEM-related literature. They summarize five main explanations of the persistent STEM gender gaps: individual background characteristics, structural barriers in K-12 education, psychological factors, values, and preferences; family influences and expectations; and perceptions of STEM fields. In a more recent literature review, McNally (2020) concludes that educational preparedness (e.g., prior achievement, comparative advantage, coursetaking), personal attributes (e.g., confidence, self-efficacy, competitiveness), and preferences are the key determinants of the gender gap in STEM education. However, educational preparedness and personal attributes do not fully explain the gender gap (Cheryan et al., 2017; Griffith, 2010; Riegle-Crumb & King, 2010; Speer, 2020; Wang, 2013; Watt et al., 2012). In particular, while there are on average no gender gaps in science achievement at the primary or secondary level and girls often outperform boys (Mostafa, 2019), a stark gender gap in enrollment and completion emerges for STEM education at the post-secondary level despite the overall higher rates of college enrollment and graduation for female students in higher education (World Bank, 2019).

The emergence of gender gap in STEM at higher levels of education between "STEM-ready" female and male students indicates that differences in preference for college-major choices are a driving factor of the gender gap in STEM major choice (Patnaik et al., 2020). The preferences for STEM majors might be relevant to the home/work-centered lifestyle, the perceived importance of money, the weighted value of extrinsic and intrinsic rewards of work, and working environment and objects (Mann & DiPrete, 2013; McNally, 2020). Of these preferences, future earnings are highly related to student college-major choices (Acton, 2020; Arcidiacono et al., 2012; Han & Winters, 2020; Hurwitz & Smith, 2018), but many students underestimate the benefits of education (Hastings et al., 2015; Jensen, 2010). Existing research finds that female students are less responsive to wage information (Freeman & Hirsch, 2008; Long et al., 2015; Montmarquette et al., 2002; Sloane et al., 2019); instead, they value intrinsic incentives and prefer work that is altruistic and people-oriented, compared with men's preferences for thing-oriented work and monetary rewards (Bobbitt-Zeher, 2007; Cheryan et al., 2017; Gemici & Wiswall, 2014).

In choosing college majors and occupations, female students are more willing to give up substantial amounts of earnings by not choosing their highest-paying options (Arcidiacono et al., 2020; Beffy et al., 2012), which is largely driven by that female have a higher willingness to pay for non-pecuniary factors including work flexibility, job stability, and marriage outcomes (Wiswall & Zafar, 2018, 2020). This gender gap might be from two sources: students have different predictions of future earnings due to lack of information (Page & Scott-Clayton, 2016; Wiswall & Zafar, 2015), students have heterogeneous preferences for different majors (Arcidiacono, 2004; Gemici & Wiswall, 2014; Reuben et al., 2017; Zafar, 2013). However, little is known about whether such preferences can be updated by external information and how preference heterogeneity affects college-major choices and outcomes.

In this paper, we provide compelling empirical evidence on the STEM gender gap in the major preference beliefs, application behaviors, and admissions outcomes in centralized admissions where students make major choices when they apply for college, and how light-tough wage information would affect the gender gap in STEM major choices. Linking large-scale survey data to administrative records of Chinese college applicants, we conducted a school-level cluster randomized experiment to study how major-specific wage information affects the gender gap of STEM major choice in both subjectively reported preferences and actual behaviors in college-major applications. Specifically, we answer three research questions. First, are there gender gaps in STEM (particularly Engineering) college-major choices under a centralized admissions system where students choose a STEM track as early as in the first year of high school and apply for college-and-major at the end of grade 12? Second, does information about the expected returns to each major alter students' major preferences, college-major application behaviors, and admissions results? Third, does the informational intervention mitigate the gender gap in STEM college-major choices?

Using administrative data from college entrance exams, applications, and admissions of the high school graduation class 2016 in one of the Chinese poorest provinces (Ningxia), we identify the gender gap in STEM major choices in the centralized college admissions system. All else equal, we find that female students are 13 percentage points less likely to apply to a STEM major and 20 percentage points less likely to enroll at a STEM major. The gender gap is particularly concentrated in Engineering majors. To elicit students' major-preferences, we conducted an in-school survey in May 2016 before students took the College Entrance Exam (CEE). On average, female students expressed less preference for a STEM major than male students. This ranking was consistent with their actual choices and admissions results in late June. The gender gap in students' intention to choose a STEM major before the exam nearly explains the gender gap in their actual choices.

Next, we examined whether and how receiving major-specific wage information affected the college-major choices of low-income students. In a randomized experimental design, we conducted a survey in 17 randomly selected high schools. We measured students' major preferences by asking them to rank eight major categories from the most preferred to the least preferred. After the initial preferences were collected, students were presented with information about the first-year post-graduation average wage in each category of majors for Chinese four-year college graduates in 2014. Students were then asked to report their updated major preferences.

We find that student major preference is easily malleable. Students responded strongly to the wage informational intervention that lasted for about one minute and updated their preferences accordingly. Among the students who completed the survey, 39% changed their first-choice major preference. There was no gender difference in the propensity to change majors after being given the wage informational intervention. However, female students were more than 50 percent less likely than male students to switch their top-ranked major from a non-STEM/Engineering major to a STEM/Engineering major. We explored the potential mechanisms of this STEM gender gap using the rich set of variables in both the administrative and survey data. We find that school environment, absolute and comparative ability, subject choice in high school, college choice behaviors, and family background do not explain the gender difference in the responses to the wage information intervention.

Finally, we estimate the causal impacts of the wage informational intervention on students' college application behaviors and admissions outcomes one month after the intervention. We estimate the intent-to-treat effects by comparing the average difference between students in randomly assigned treatment schools and those in control schools. The average null effect of the wage information on college-major choice is completely masked by the gender gap in the treatment effects. The probability of shifting into the STEM/Engineering majors for male students statistically significantly increased by 2.5 percentage points in applications and increased by 3 percentage points in admissions. In contrast, female students' STEM/Engineering-related college-major choice behaviors and admissions outcomes did not change at all.

These experimental results are consistent with the descriptive evidence that the gender gap in STEM and Engineering major choices is mainly from the differences in major-specific preferences between female and male students. While students' major-specific preferences were easily malleable by simple wage information, only male students shifted into STEM/Engineering majors as a response to the information and updated beliefs. We also find that the information impacts only existed in the subsample of rural students who were more likely to lack such information. Using survey data from various sources, we provided additional evidence suggesting that female students were less likely to be motivated by extrinsic incentives than male students in STEM major preferences; while the wage information only affected those who prefer high-paying majors, female students with such preference were still less responsive to the wage information than male students.

This paper contributes to three strands of literature. This paper provides one of the first evidence on the STEM gender gap and how high school students respond to earning information in a centralized college-and-major admissions system. Compared with choosing which college to go (e.g., Jacob et al., 2018; Long, 2004; Perna, 2006), the college-major choice is much closer to job market prospects since students specialize their human capital skills in college that vary across majors (Altonji et al., 2016; Kinsler & Pavan, 2015). The heterogeneous labor market returns to college-major types are a key factor for students making decisions in the field of study (Arcidiacono, 2004; Beffy et al., 2012; Berger, 1988; Jensen, 2010; Kim et al., 2015; Wiswall & Zafar, 2014; Xie & Shauman, 2003). However, nearly all the existing studies focus on students in decentralized systems and in situations that students declare majors after entering college (particularly in the US), little is known about whether the STEM gender gap persists in centralized systems (Bordón et al., 2020; Hastings et al., 2016). The college-and-major assignment widely adapted in centralized admissions all over the world requires students to make their major choices based on pre-college information and preferences, before learning about majors and update their major preferences in college (Bordón & Fu, 2015; Krussig & Neilson, 2021), where how students could be nudged into specific majors is of particular policy importance (Bordón et al., 2020). Using large-scale administrative data and survey data, we show that female students are less likely than male students to prefer, choose, and be admitted to STEM majors and one of the driving factors is the heterogenous preference for extrinsic incentives.

This paper closely relates to a small but growing strand of studies that focus on the effect of wage information on students' major choice. Motivated by the nudge theory proposed in Thaler and Sunstein (2008), in the past decade, behavioral interventions have been increasingly used to improve these educational decisions (e.g., see recent summaries in Page & Scott-Clayton, 2016). We contribute to fill two research gaps. First, the effect of wage information on major choice is still mixed. In the US, even students make major choice in college and information is generally accessible (e.g., the College Scorecard Data), they are substantially misinformed about mean salaries by major. Wiswall and Zafar (2014, 2015) find students revise their earnings beliefs and intended majors when being provided with information on the population distribution of earnings in an information experiment. Baker et al. (2018) find that the probability of choosing a specific category of majors is positively related to salary. Conlon (2019) is the first field-experimental study that provides salary information to US undergraduates and affects their actual choices of major. Students are more likely to prefer and eventually major in a field about which they received information correcting their beliefs about salaries. This effect of information may come from the change in the mean of the salary beliefs, or the reduction in uncertainty. In non-US context, Hastings et al. (2016) use a large-scale survey and field experiment in Chile and find that low-income students reduce their demand for low-return degrees and increase the likelihood of remaining in colleges after receiving the government-provided salary information. Kerr et al. (2020) provided high school students in Finland with labor market information associated with post-secondary programs but only a small subgroup updated their beliefs and choose higher paying programs. We show new evidence on the heterogeneous treatment effects that the wage information affects students who are from an economically disadvantaged background and lack have limited access to accurate information.

Furthermore, little work to date has thoroughly examined the gender gap in the wage information effects (particularly for STEM majors) and the underlying mechanisms. The paper uses a large-scale field experiment to investigate the gender difference in STEM major preference for extrinsic incentives. We find that the effect of wage information in major preference, application behavior, and admission result is largely different between female and male students. Using data from multiple sources, we also provide compelling evidence that females are less extrinsically incentivized; even among those who value extrinsic incentives, female students respond less to wage information than male students. Loewenstein et al. (2014) argue that disclosure of information of labor market is an effective and sustainable approach to help students to make educational choices. This paper provides important implications for such light-touch informational intervention designs that not all information intervention is effective: even for the group of students without sufficient information, females are much less responsive than male students to wage information because of heterogeneous preferences and motivations.

Research Question, Experimental Design, and Data

Research Questions and Conceptual Framework

This paper explores the gender gap in the belief preferences, application behaviors, and admissions outcomes related to STEM majors. We aim to answer three research questions: (1) Are there gender gaps in STEM (particularly Engineering) college-major choices under a centralized admissions system? (2) Do students update their major preferences and application behaviors as a result of an information intervention about the average wage? (3) How does the information intervention affect the gender gap in STEM majors?

We argue that differences in major preferences drive the gender gap in STEM major choices and admissions. Specifically, female students are less likely to choose STEM/Engineering majors for higher expected wages. However, since many factors contribute to the complex college-major choice, the estimated STEM gender gap from observational data might not be that female and male students prefer different majors but be due to the omitted variable bias of not being able to control for the confounding factors, such as admissions uncertainty and informational barriers.

We address this conceptual challenge in three ways. First, we study the college choice behaviors in a centralized admissions system that determines college-major admissions solely based on the entrance exam scores and student applications. By controlling for the CEE scores, any differences in the admissions outcomes are from the different application behaviors, not other unobservables during the admissions process. Therefore, the gender gap in admissions outcomes that remain after controlling for CEE scores must be due to the gender gap in different major preferences. Second, using rich information from the administrative and survey data, we rule out many alternative explanations, including individual demographics, absolute and comparative ability, subject choice before college, high school context, family background, or college-major preferences. Third, we conducted a large-scale randomized experiment that provided students with wage information to examine how the gender gap would persist in the response to the informational intervention. The experimental evidence, which will be discussed later, shows that the wage informational intervention did not affect female students' STEM/Engineering major choices, but substantially and statistically significantly altered male students' preferences, choices, and admissions. This finding is consistent with our framework as well as the descriptive evidence that female students less prefer wage as extrinsic incentives even if students have the same access to information.

Background: Chinese Centralized College Admissions

China's centralized college admissions system was established in 1978. Each year, on June 7 and 8, students take the National College Entrance Examination (CEE) in one of the two tracks: STEM or non-STEM. The tracks have three common exam subjects—Chinese, English, and math, and differ in track-specific subjects (physics, chemistry, and biology in the STEM track; history, geography, political science in the non-STEM track). Colleges allocate college-major admissions quotas to each province by tracks. Students are ranked within their province-track markets. Applications and admissions proceed by pre-designated college selectivity tiers. Students are eligible to apply to each tier if and only if their CEE scores are higher than the tier eligibility cutoff score.

Importantly, the choice of major is part of the Chinese college admissions process. This is a common practice in centralized college admissions (Krussig & Neilson, 2021) but is a substantial difference from decentralized systems in many other countries including the U.S. where students choose majors after exploring different options in college. In late June, students submit their college-and-major preference lists in each tier to apply simultaneously for colleges and the majors within each college. The undergraduate majors are divided into 13 categories: philosophy, economics, law, education, literature, history, science, engineering, agriculture, medical, management, art, and military. Students can apply to a limited number of different majors within a college application. Using a predetermined matching mechanism, college admissions are jointly determined by students' CEE scores and their applications (rank orders of the applied college-majors). A student is either admitted to one college-and-major program or they are declined admission. Admissions results are released in July and August.

Student Survey and Experimental Design

We partnered with the Department of Education in Ningxia Province, one of the least developed provinces of China, to conduct the survey and the randomized experiment. In 2016, the per capita disposable income of urban residents in Ningxia was less than $4000 (national average: $5000; Shanghai: $8000), and the per capita disposable income of its 65% population in rural areas was less than $1500 (national average: $2000; Shanghai: $3500). Each year, about 60,000 high school graduates in Ningxia—accounting for 60% of a birth cohort—take the CEE and submit their college-major applications. Of those who submit applications, 80% which receive college-major admissions.

The survey and experiment are part of a large project aiming to provide effective informational and behavioral interventions to improve low-income students' college access and match. As requested by the Ningxia Department of Education and following a stratified cluster randomization design, we first randomly selected three cities out of the total prefectural cities (31 out of 60 public high schools in the sample). Within strata defined by geographic location and school quality, we then randomly selected 17 schools to implement the survey and the experiment.

We designed the *Ningxia High School Graduation Survey* to collect data on students' college and major preferences and beliefs. At the end of May 2016, one week before high school seniors took the CEE and three weeks before they submitted college-major applications, the Ningxia Department of Education officially administered the survey in the 17 randomly selected high schools. As displayed in Online Appendix Figure 1, each school implemented the survey in a 20-min section in a similar manner to completing other high-stakes administrative forms. This formal implementation process ensured the quality of survey responses.

The survey collected student demographic information and college-major choice beliefs including their knowledge about the admissions mechanisms, preferences for different types of colleges and majors, and information sources. We measured student major preferences by asking them to rank eight major groups from the most preferred to the least preferred. We categorize the original thirteen major categories into eight major groups based on their similarities in the Chinese context: (1) Literature, History, and Philosophy; (2) Economics and Management; (3) Law (undergraduate) and Education; (4) Science; (5) Engineering; (6) Medical (undergraduate); (7) Agriculture; and (8) Art and Military. We focus in this paper on the first-choice major the students listed in this ranking.

After students reported their initial major preferences, we implemented an information intervention for students in the survey. We presented them with information about the first-year post-graduation average wage in each major group. In the next part of the survey, we then measured the changes in students' major preferences by asking them to report their updated rankings of the eight major groups (Online Appendix Figure 2). We obtained the wage-by-major group data from the National Survey of College Graduate Employment conducted bi-annually by Peking University since 2003. This is the best available data that provides wage information by college-majors (see more survey descriptions in Yue, 2015). We used data from the 2014 graduation class, the then best available data that provides wage information by college-majors.

Table 1 presents the summary statistics of the wage information. There are large variations across individuals and college selectivity within each major group. But there are also large differences across majors. For example, the average wage of Agriculture

Table 1 First-year average wage of the 2014 graduation class Chinese college students

	N (Students)	Information	Mean	SD	Min	Max
A. By major group						
Agriculture	260	53,000	54,700	29,774	6000	240,000
Engineering	1379	51,000	50,865	36,648	6000	600,000
Econ & Mgt	1946	50,000	50,416	36,780	6000	600,000
Law & Edu	385	50,000	49,678	45,158	12,000	600,000
LHP	647	47,000	46,571	31,156	6000	600,000
Science	687	45,000	44,582	30,845	6000	240,000
Medical	140	42,000	41,644	24,816	10,200	180,000
Art & Military	305	39,000	39,175	23,765	6000	240,000
B. By college selectivity						
Most selective	747	77,000	76,895	35,767	6000	300,000
Selective	910	58,000	57,740	37,054	6000	600,000
Less selective	2889	44,000	44,441	33,632	6000	600,000
Non-selective	1387	36,000	35,548	27,725	6000	600,000

This table presents the summary statistics of first year average wage of the 2014 graduation class Chinese college students by major group and by college selectivity, using data from the nationally representative survey data conducted by Peking University. Data are censored by 6000–600,000. "Information" column presents the same numbers that we provided to the treated students, rounded to 1000 from the group mean values. Econ & Mgt includes majors in Economics and Management; Law & Edu includes majors in Law and Education; LHP includes majors in Literature, History, and Philosophy; Art & Military includes majors in Art and Military

majors (offered only in selective colleges) is more than 35 percent higher than that of Art or Military majors, regardless of college quality. Majors in Agriculture, Engineering, and social sciences have higher average first-year starting wages than the other majors.

There are limitations to the research design used in this paper. The beliefs about expected earnings may be correlated with unobserved factors were not analyzed in this paper, such as tastes and enjoyment that may also affect students' major choices (Baker et al., 2018). Ignoring this correlation may inflate the role of earnings in major choices (Baker et al., 2018; Wiswall & Zafar, 2015). Moreover, we focused on a single factor of the labor market outcomes, students may respond to other labor market information such as employment rate, wage uncertainty, work conditions, and long-term professional development. We hope to address these questions in the follow-up studies.

Data, Sample, and Summary Statistics

We linked the survey data to the administrative records provided by the Ningxia Department of Education. The latter include the registration information, CEE scores, college applications, and admissions information on every student in the 2016 high school graduation class in Ningxia. Importantly, we observe the college and major information in every student's applications as well as their admissions outcomes, which enables us to identify the impacts of the information intervention on both application behaviors and admissions outcomes. We code each major to one of the eight major groups according to the "China Four-Year College Major List" published by the Ministry of Education.

Additionally, we utilize the survey data to study students' major preferences and how students update their preferences in response to the wage information intervention in the survey. In the 17 treated schools, 8243 students responded to the survey. We excluded students with missing or incorrect student IDs that could not be matched to the administrative data (1345), and those not in academic tracks (e.g., athletes or CTE; 1214). We further excluded students who are not first-time high school seniors since they have experienced college applications and may have different beliefs (840). These sample restrictions result in an analytic sample of 4844 surveyed students who are matched to the administrative records.

Online Appendix Table 1 summarizes the share of students by major groups, using the sub-sample of students who were in the 2016 Ningxia Survey sample and were eligible to apply to four-year colleges with CEE scores higher than the eligibility cutoff. Prior to the information intervention, Economics and Management were the most preferred majors while Agriculture was the least preferred major.

Table 2 presents summary statistics on the main covariates and outcome variables, separately for the survey sample and the experimental sample. The survey sample includes students who were in the treatment schools and completed the survey. The experimental sample includes all students in either the treatment schools or control schools. The experimental sample has mechanically on average higher achieving students than the survey sample as we limit the analysis to four-year college eligible students. The survey sample shows that 39% of the treated students who were presented with the mean wage information changed their first-choice major preferences. Female students were less likely to prefer a STEM major (particularly an Engineering major) and also less likely to change their preference into a STEM major under the information intervention. However, the overall difference in college-major admissions outcomes between the treatment and control group is minimal.

To assess the balance across the treatment assignment on individual covariates, we first ran regressions of treatment assignment on each variable with strata fixed effects and school cluster standard errors. The results were summarized in Column (6). Only one significant difference was found (Minority). The joint F test statistic was 0.70 with a p value of 0.65, indicating the treatment group and the control group were well balanced on observable characteristics.

Results

Identifying the Gender Gap in STEM Major Choice

We first examine the gender gap in STEM major choice using actual college applications and admissions data. We limit the analysis to students who were eligible for four-year college applications and admissions. We estimate a Linear Probability Model:

$$Y_{ij} = \beta_0 + \beta_1 Female_{ij} + \mathbf{X_{ij}}\boldsymbol{\Gamma} + \delta_j + \varepsilon_{ij} \tag{1}$$

where Y_{ij} is the outcome—a binary indicator whether student i in high school j was admitted by a STEM major or applied to a STEM major; $Female_{ij}$ is a binary gender indicator coded as one for female students and zero for male students; $\mathbf{X_{ij}}$ is a vector of student characteristics, including a binary indicator of minority student, a binary indicator of

Table 2 Sample summary statistics

	Survey sample			Experimental sample		
	All	Female	Male	All	Control	T–C diff
	(1)	(2)	(3)	(4)	(5)	(6)
N	4844	2711	2133	11,114	5065	(6)
Treatment (= 1)				0.544	0	
				[0.498]		
A. Covariates						
Female (= 1)	0.560	1	0	0.547	0.539	0.014
	[0.496]			[0.498]	[0.499]	(0.017)
Minority (= 1)	0.225	0.237	0.209	0.273	0.385	− 0.146**
	[0.417]	[0.425]	[0.407]	[0.446]	[0.487]	(0.067)
Rural (= 1)	0.623	0.634	0.610	0.502	0.518	− 0.143
	[0.485]	[0.482]	[0.488]	[0.500]	[0.500]	(0.151)
Age (> 18-year old)	0.850	0.836	0.869	0.792	0.793	− 0.005
	[0.357]	[0.371]	[0.338]	[0.406]	[0.405]	(0.034)
STEM (= 1)	0.706	0.605	0.836	0.731	0.742	− 0.028
	[0.455]	[0.489]	[0.371]	[0.444]	[0.437]	(0.042)
CEE score (s.d.)	0.072	0.093	0.044	0.857	0.872	0.082
	[0.928]	[0.874]	[0.992]	[0.631]	[0.604]	(0.072)
Math score (s.d.)	0.126	0.083	0.180			
	[0.940]	[0.895]	[0.991]			
Science score (s.d.)	0.086	0.014	0.179			
	[0.959]	[0.893]	[1.030]			
B. College-major preferences and admissions						
STEM major (= 1)	0.156	0.081	0.252	0.478	0.480	0.000

Table 2 (continued)

	Survey sample			Experimental sample		
	All	Female	Male	All	Control	T–C diff
	(1)	(2)	(3)	(4)	(5)	(6)
	[0.363]	[0.273]	[0.434]	[0.500]	[0.500]	(0.023)
Engineering major (= 1)	0.071	0.034	0.118	0.397	0.394	0.008
	[0.257]	[0.182]	[0.322]	[0.489]	[0.489]	(0.017)
High-pay major (= 1)	0.470	0.494	0.441	0.738	0.734	0.009
	[0.499]	[0.500]	[0.497]	[0.440]	[0.442]	(0.013)
Mean salary (= 1)	46,551.191	46,632.523	46,446.273	49,170.621	49,116.078	98.418
	[4427.266]	[4327.464]	[4551.750]	[2810.662]	[2879.189]	(115.919)
Change major (= 1)	0.388	0.386	0.391			
	[0.487]	[0.487]	[0.488]			
Change STEM (= 1)	0.088	0.049	0.138			
	[0.284]	[0.217]	[0.345]			
Change engineering (= 1)	0.027	0.018	0.038			
	[0.162]	[0.132]	[0.192]			

The other samples (e.g., non-experimental sample or the applicant sample used in Table 3) have very similar mean and standard deviation values on these variables. Panel A shows the covariates. Panel B shows the main outcomes: those in the survey are student's self-reported preferences; and those in the experimental estimates are students' admissions results from the administrative data. Column 6 reports the treatment–control mean difference of each baseline variable and the corresponding standard errors, controlling for strata fixed effects. The F test p value for the joint significance test that the baseline covariates listed in column 4 of Panel A are jointly unrelated to the treatment assignment is 0.651, which is obtained from a linear regression of the treatment indicator on the baseline covariates and strata fixed effects. Standard deviations are in square parentheses, and standard errors clustered at schools are in parentheses

*Significant at 10%, ** significant at 5%, *** significant at 1%

rural student, age, CEE scores, and a binary indicator of STEM track students; δ_j controls for high school fixed effects; and ε_{ij} is the error term. We cluster standard errors at high schools.

The results from model (1), identifying the gender gap in STEM major choice measured by their admissions (Columns 1 to 5) and applications (Columns 6 to 10) to a STEM major in the centralized college admissions process, are presented in Table 3. We primarily focus on students in the high schools that were not randomly selected in the experimental sample (either the treatment or the control samples). This sample choice follows the practice of a hold-out test in cross-validation. Those students were never exposed to the spill-over of our interventions because they were in prefectural cities other than those in the experimental sample. Results in Appendix Table 3 shows that including students who were in the control group in the experimental sample does not alter the results, which also validates the randomness of the experimental sample selection.

We find a substantially and statistically significant gender gap in college-major admissions. Column (1) of Table 3 shows that, holding race and family residence equal, female students are 32 percentage points (p-value <0.01) less likely than male students to study a STEM major in college. On average, 61% of all non-minority male students from urban families are admitted to a STEM major. This gender gap reduces to 20.7 percentage points when we control for age, College Entrance Exam score, and whether studying in the STEM track (Column 2). However, differences in high school contexts do not explain this gender gap and the coefficient only changes slightly from Column (2) to Column (3). While previous literature finds that high school choice affects the gender gap in STEM (Card & Payne, 2021; Mouganie & Wang, 2020;), our results show little variation in the impacts of high school conditional on students' track choice and college entrance exam performance. In Columns (4) and (5), we control for comparative ability, measured by STEM-track and math scores in the College Entrance Exam. The estimated gender gap in the probability of being admitted to a STEM major remains unchanged.

Since the centralized college admissions are solely based on students' CEE total scores and applications. The gender gap in college admissions is likely due to the gap in the college-major choices between female and male students. Results in Columns (6) to (10) confirm the gender gap in STEM major applications. Controlling for demographics, absolute (CEE total score) and comparative (math and science subject scores) ability measures, and high school fixed effects, female students are 13 percentage points (p value <0.01) less likely to apply to a STEM major.

Differentiating the majors in Engineering from those in Science (math and technology included), Online Appendix Table 4 presents the gender gap in Engineering major choice using the same identification as shown in model (1). Estimates in Online Appendix Table 4 suggest that the gender gap in STEM is particularly driven by the gap in Engineering major choice. All else in the mode equal, female students are 18 percentage points (p value <0.01) less likely to apply to an Engineering major, and 24 percentage points (p value <0.01) less likely to attend an Engineering major.

We conduct a set of robustness checks using alternative outcomes and samples. Each cell of Online Appendix Table 5 presents estimates from a separate regression, controlling for covariates and school fixed effects (as in Column 3 of Table 3). Each panel shows results from separate samples using either the whole sample or the STEM-track students only, as well as from different ways of measuring the outcomes: using the major that a student was admitted to, using all the majors that a student applied to, or using the first major within each college that a student applied to. Each column uses a different outcome: whether the major (in admissions or applications) is STEM (Column 1), Engineering

Table 3 Gender gap in STEM major choice

	Outcome: Admission to a STEM major					Outcome: Application to a STEM major				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Female	− 0.320***	− 0.207***	− 0.206***	− 0.209***	− 0.198***	− 0.306***	− 0.205***	− 0.203***	− 0.138***	− 0.130***
	(0.013)	(0.013)	(0.014)	(0.020)	(0.021)	(0.013)	(0.017)	(0.018)	(0.025)	(0.026)
Female × Science				0.010	0.014				− 0.062***	− 0.052***
				(0.015)	(0.018)				(0.018)	(0.013)
Science score				0.010	0.021				0.080***	0.079***
				(0.020)	(0.024)				(0.013)	(0.012)
Female × Math					− 0.007					− 0.015
					(0.018)					(0.019)
Math score					0.036**					0.023
					(0.016)					(0.015)
Minority	− 0.117***	− 0.085***	− 0.080***	− 0.077***	− 0.068***	− 0.187***	− 0.125***	− 0.112***	− 0.104***	− 0.101***
	(0.020)	(0.014)	(0.013)	(0.014)	(0.014)	(0.021)	(0.014)	(0.012)	(0.013)	(0.013)
Rural	− 0.038**	0.013	0.015	0.014	0.013	− 0.021	0.023**	0.025***	0.023***	0.023***
	(0.015)	(0.012)	(0.012)	(0.012)	(0.012)	(0.018)	(0.008)	(0.006)	(0.005)	(0.005)
Age		− 0.008	− 0.011	− 0.011	− 0.011		− 0.002	− 0.002	− 0.004	− 0.004
		(0.012)	(0.013)	(0.013)	(0.013)		(0.008)	(0.009)	(0.008)	(0.008)
CEE score		0.076***	0.079***	0.064**	0.024		0.076***	0.082***	0.035*	0.019
		(0.020)	(0.022)	(0.027)	(0.028)		(0.011)	(0.010)	(0.017)	(0.025)
STEM track		0.426***	0.434***	0.435***	0.436***		0.397***	0.405***	0.400***	0.401***
		(0.018)	(0.019)	(0.019)	(0.019)		(0.020)	(0.020)	(0.020)	(0.020)
Constant	0.609***	0.168***	0.160***	0.161***	0.151***	0.616***	0.161***	0.144***	0.111***	0.104***
	(0.019)	(0.017)	(0.025)	(0.029)	(0.029)	(0.019)	(0.017)	(0.022)	(0.026)	(0.024)
School FE	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes

Table 3 (continued)

	Outcome: Admission to a STEM major					Outcome: Application to a STEM major				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Observations	7627	7627	7627	7627	7627	5874	5874	5874	5874	5874
R-squared	0.131	0.292	0.297	0.297	0.297	0.298	0.560	0.568	0.574	0.575

This table estimates the gender gap in STEM major choice, measured by their applications and admissions to a STEM major in the centralized college admissions process, using a Linear Probability Model. The sample includes all first-time high school graduates who took the College Entrance Examination in Ningxia in 2016, applied to (in the first round) or were admitted to four-year colleges, and were not in our experimental sample. Some students were admitted through applications in later rounds, in which colleges still had open spots called for additional applications. Standard errors are clustered at high schools

*Significant at 10%, ** significant at 5%, *** significant at 1%

(Column 2), or high paying (Column 3; the top three majors in mean wage, Agriculture, Engineering, Economics & Management as shown in Table 3), or the mean wage by major as presented in the experiment (Column 4).

Results are very consistent across outcomes and samples. Compared with male students, female students are less likely to apply to and attend a STEM major, particularly an Engineering major. While female students may shift into other high-paying majors such as in Economics or Management, however, on average, they are about 15 percentage points less likely to choose a high-paying major. As welfare consequences, female students enroll in college-majors that are expected to have about 1000 RMB (2%; about 140 U.S. dollars) lower mean starting yearly wages; this gender gap is larger among students in the STEM track.

Eliciting the Gender Gap in STEM Major Preference

College-major choice can be affected by many factors that the difference in application behaviors and admissions might not reveal students' real major preferences. This is particularly true in centralized college admissions where the assignment mechanism rewards strategic play. For example, to maximize their chances of getting into higher quality colleges, students may trade off their preferred majors to other less popular majors. To address this question, we conducted the large-scale *Ningxia High School Graduation Survey* to elicit students' major-specific preferences. For simplicity, we focus on students' initial first-choice major preferences in the survey before the wage information intervention.

In Table 4, we estimate the same Linear Probability Model as in Table 3, controlling for differences in demographics, absolute and comparative ability, and high school contexts. In Online Appendix Table 5, we limit the analytical sample to students in the survey who were eligible for four-year college applications and find similar results. It should be noted that we use class fixed effects rather than school fixed effects because we could identify classroom for each student through the survey responses. Specifically, Columns (1) to (4) present the results for all first-time high school graduates who completed the survey, and Columns (5) to (8) present the results for STEM-track students only. Estimates are similar using the full sample or the STEM-track sample. This suggests that the gender gap in STEM/Engineering major preference does not concentrate on either STEM or non-STEM track students, which rules out the explanation that tracking early in high school drives the gender gap in college-major choice.

Among the students who reported their major preferences in the survey, female students less preferred a STEM major or an Engineering major than male students. Comparing the estimated magnitudes in preferences and application behaviors, the gender gap in STEM major preference (− 0.118 in Column 2 of Table 4) nearly explains the gender gap in STEM major choice (− 0.130 in Column 10 of Table 3) for a student with average math and science scores. In contrast, the gender gap in Engineering major preference (− 0.061 in Column 4 of Table 4) explains 34% of the gender gap in Engineering major choice (− 0.179 in Column 10 of Online Appendix Table 4). The preference gap is smaller among students with higher science scores. This difference between Engineering majors and non-Engineering majors might be due to other factors that affect students' college choice behaviors. One explanation from our data is that students form their major preferences without considering the capacity limit by major. As shown in Online Appendix Table 1, Engineering majors have seats to enroll more than 35% of college freshmen either in Ningxia or nationally;

however, fewer than 10% of the students in the survey reported first-choice preference in Engineering. The proportion of students preferred in some other majors (e.g., Medical and Management) is much smaller than the share of available seats in those majors.

Information Matters in Major Preference Beliefs

The next question of interest is to examine whether students' major preferences belies respond to the wage information intervention. As shown in Table 2, 39% of the treated students who were presented with the mean wage information as summarized in Table 1 changed their first-choice major preferences. The gender gap in this change is small: 38.6% of female students and 39.1% of male students. Results are consistent when we examine the changes in all the rank orders of the eight major groups.

Figure 1 compares students' initial and updated first-choice major preferences that we elicited before and after we provided the wage information intervention. Each dot represents the changes in the share of students for each initial major group, separately for female and male students. Figure 1 provides clear evidence that students responded to the wage information in an expected direction: they were shifted from low paying majors to high paying majors. The wage information largely reduces the proportion of students without major preference. Male students are more likely to be shifted to Agriculture and Engineering majors by the wage information.

In Fig. 2, we present a complete picture of the network flows of the changes from initial major preferences to the wage information-induced updated major preferences. One takeway is that there are great heterogeneities in the changes of students' major preferences. While most students showed the pattern that being shifted from low paying majors to high paying majors, some students also moved from high-paying majors to low paying majors. The latter might be because that these students perceived the wage differentials between majors and updated their preferences. Within STEM, students were largely shifted from Science majors to Engineering majors. Figure 3 shows the differences between female and male students. Female students are less likely to choose Engineering than male students and are more likely to stay in the "outside option" Economics and Management majors. Both female and male students increase their preferences for Agriculture majors, which has the highest mean starting wage. Appendix Fig. 3 compares STEM majors with non-STEM majors. In aggregation, there is no systematic pattern that students are shifted to one of the two groups. Results are similar for the top three preferred majors in Online Appendix Figure 4

We then use the Linear Probability Model (1) to quantify the gender gaps in the changes of major preferences induced by the wage information intervention. Results from Table 5 indicate that, there is overall no gender difference in the propensity of changing first-choice major preference based on the wage information. Female students with average math and science scores were 2.8 percentage points less likely to change their first-choice major preference. Compared with the male mean of 39%, this difference (7 percent) is small. However, female students were much less likely than male students to change from a non-STEM major to a STEM major (7.1 percentage points, 51 percent) and to change from a non-Engineering major to an Engineering major (2.1 percentage points, 55 percent).

To explore the potential mechanisms of the gender gap in the changes of first-choice major preferences after the wage information intervention, we use a Linear Probability Model similar to those in Table 5 with additional controls constructed using the survey responses. Columns (1) and (5) of Appendix Table 7 control for high school class fixed

Table 4 Gender gap in major preference

	All students in the survey				STEM-track students in the survey			
	STEM major		Engineering major		STEM major		Engineering major	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	− 0.171***	− 0.118***	− 0.083***	− 0.061***	− 0.175***	− 0.135***	− 0.086***	− 0.073***
	(0.018)	(0.015)	(0.010)	(0.010)	(0.021)	(0.019)	(0.012)	(0.013)
Female × Science		0.081***		0.055***		0.116***		0.076***
		(0.023)		(0.018)		(0.029)		(0.025)
Science score		− 0.061***		− 0.045***		− 0.074***		− 0.064***
		(0.019)		(0.017)		(0.024)		(0.022)
Female × Math		0.002		− 0.006		0.006		− 0.011
		(0.017)		(0.015)		(0.020)		(0.019)
Math score		0.026		0.026*		0.035		0.043**
		(0.017)		(0.015)		(0.022)		(0.020)
Minority	− 0.022	0.006	− 0.008	0.004	− 0.018	0.017	− 0.004	0.014
	(0.014)	(0.015)	(0.009)	(0.011)	(0.019)	(0.021)	(0.012)	(0.016)
Rural	− 0.022	− 0.005	− 0.022**	− 0.009	− 0.040**	-0.011	− 0.035***	− 0.013
	(0.017)	(0.013)	(0.011)	(0.009)	(0.020)	(0.018)	(0.013)	(0.011)
Age		0.028*		0.019*		0.037**		0.026*
		(0.014)		(0.011)		(0.018)		(0.013)
CEE score		− 0.030		− 0.025		− 0.056		− 0.037
		(0.024)		(0.020)		(0.035)		(0.030)
STEM track		0.067***		0.056***				
		(0.021)		(0.012)				
Constant	0.270***	0.147***	0.133***	0.051***	0.313***	0.227***	0.154***	0.104***
	(0.024)	(0.025)	(0.015)	(0.018)	(0.026)	(0.021)	(0.017)	(0.016)
Class FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	4844	4844	4844	4844	3421	3421	3421	3421

Table 4 (continued)

	All students in the survey				STEM-track students in the survey			
	STEM major		Engineering major		STEM major		Engineering major	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
R-squared	0.057	0.167	0.028	0.106	0.052	0.147	0.027	0.101

The sample includes all first-time high school graduates who completed the survey. STEM-track students only include students who would take the STEM composite test (physics, chemistry, biology) in the College Entrance Examination. Non-STEM-track students would take the non-STEM composite (history, social studies, geography) and would not be eligible to apply to most of the STEM majors in college.Standard errors are clustered at high school classes

*Significant at 10%, ** significant at 5%, *** significant at 1%

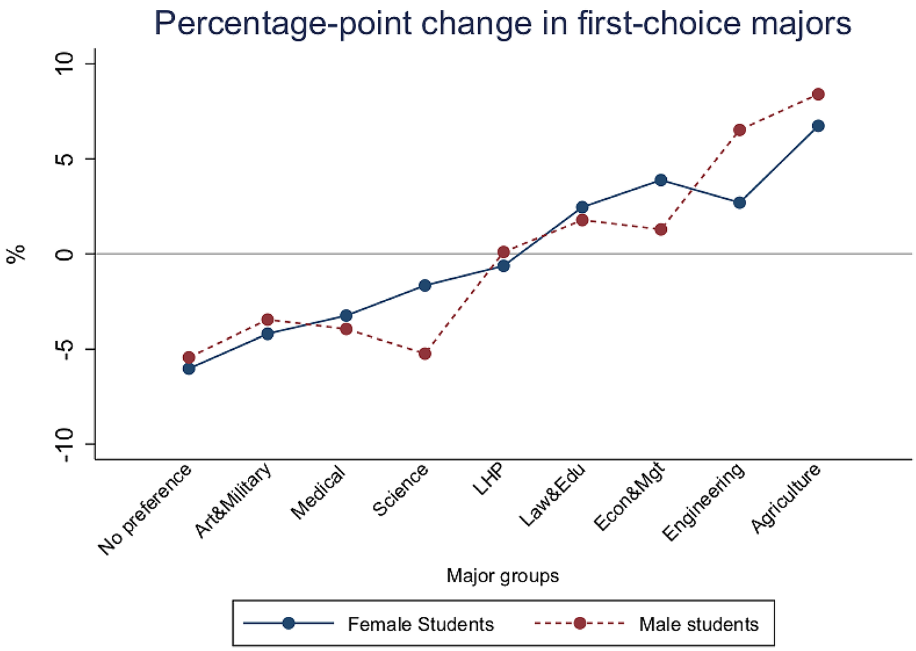

Fig. 1 Changes in the share of students with different first-choice major preferences. X-axis shows major groups from the lowest average first-year post-graduation wage (Art & Military) to the highest average wage (Agriculture); no wage data were available for the "No preference" group. Y-axis shows the percentage point change of the share of students in each major from their initial first choice to updated first choice after students were presented with the wage information

effects to rule out school contextual differences. Columns (2) and (6) control for comparative ability differences by adding math and STEM composite scores in the CEE. Columns (3) and (7) controls for additional preference heterogeneity: whether students thought major is the most important factor in college-major choice, whether they already had a target college or major. Columns (4) and (8) rules out family background differences by adding controls of "poor family" indicators and parental education (categorical variables). However, school impacts, absolute and comparative ability, subject choice in high school, preference heterogeneity, and family background do not explain the gender difference in the responses to the wage information intervention. While we rule out a number of alternative explanations why female students differ in STEM major preferences from male students, there are a few possible explanations that we cannot test using our data and need future work, including stereotype and psychological taste for occupations (Ganley et al, 2018; Kahn & Ginther, 2017; Kugler et al, 2017).

Impacts of Wage Information on College-Major Choice

We have shown that students responded to the wage information and updated their major preferences and female students were about 50 percent less likely than male students to switch from a non-STEM major to a STEM major. This subsection estimates the impacts

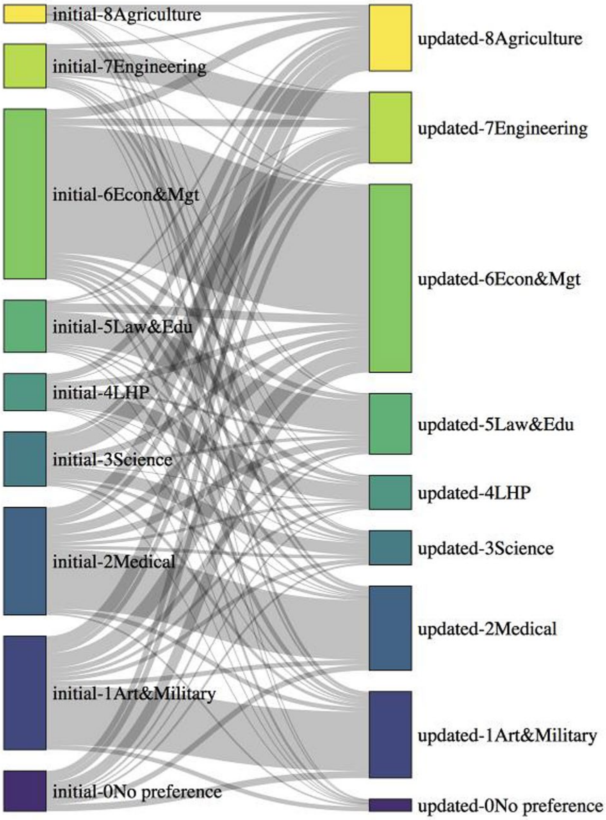

Fig. 2 Network flows of the changes in first-choice major preferences. Lines are weighted by the number of students. Bars are scaled by the share of students in each major group

of the wage information intervention on students' real college applications and admissions, one month after the survey intervention.

Using the experimental sample, we estimate a Linear Probability Model with school random effects to account for the clustering of student-level observations with school-level treatment:

$$Y_{ij} = \beta_0 + \beta_1 Treatment_j + \mathbf{X_{ij}}\Gamma + \mathbf{Strata_j}\Theta + \mu_j + \varepsilon_{ij} \quad (2)$$

where Y_{ij} is the outcome of interest for student i in school j; $Treatment_j$ is a binary treatment indicator coded as one for treatment schools and zero for control schools; β_1 estimates the average treatment effects of the wage information intervention; $\mathbf{Strata_j}$ are the randomization strata fixed effects; u_j represent school random effects (each school has a different intercept); and ε_{ij} is the error term. We control for the same vector of covariates as used in the previous analyses to improve the precision of the estimates, including gender, race, family residence, age, STEM-track indicator, and CEE score.

It should be noted that we cannot use school-fixed effects in Eq. (2) as we did in Eq. (1) because the school fixed-effects and the binary treatment indicator are perfectly collinear. We chose a Linear Probability Model with school random effects over a two-level logistic

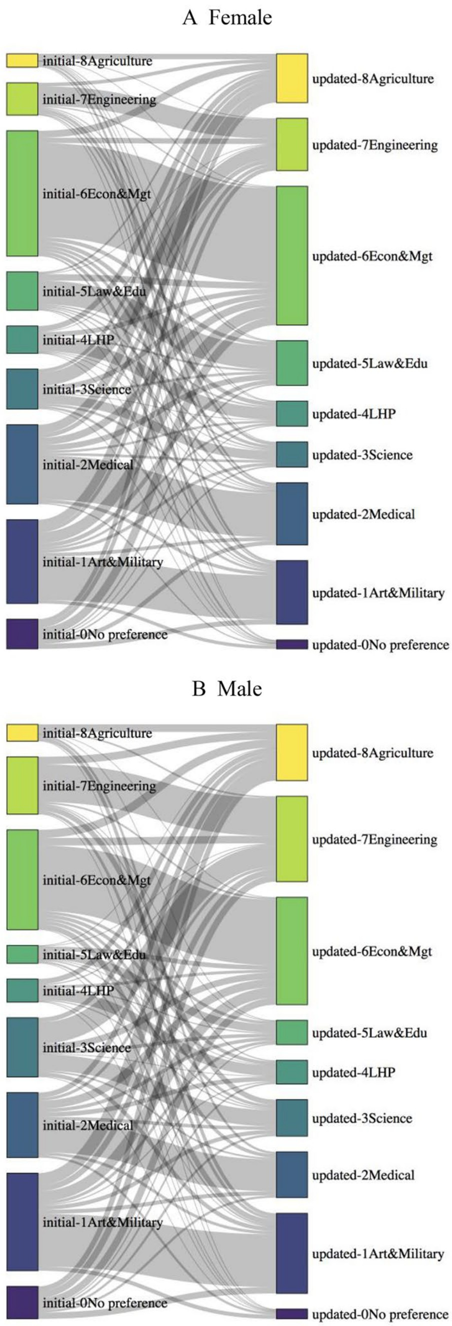

Fig. 3 Gender difference in the network flows of the changes in first-choice major preferences. Lines are weighted by the number of students. Bars are scaled by the share of students in each major group

Table 5 Changes in first-choice major preference

	Change major		Change to a STEM major		Change to an Engineering major	
	(1)	(2)	(3)	(4)	(5)	(6)
Female	− 0.008	− 0.028*	− 0.089***	− 0.071***	− 0.021***	− 0.021***
	(0.019)	(0.017)	(0.012)	(0.011)	(0.006)	(0.007)
Female × Science		0.032		− 0.048***		− 0.011
		(0.022)		(0.014)		(0.010)
Science score		− 0.020		0.056***		− 0.001
		(0.024)		(0.018)		(0.010)
Female × Math		− 0.056**		0.034**		0.006
		(0.026)		(0.015)		(0.009)
Math score		0.012		− 0.008		− 0.005
		(0.024)		(0.013)		(0.008)
Minority	0.052**	− 0.000	− 0.007	− 0.003	0.001	0.000
	(0.023)	(0.022)	(0.012)	(0.012)	(0.006)	(0.007)
Rural	0.028	0.026*	0.000	0.010	0.001	0.005
	(0.017)	(0.015)	(0.012)	(0.010)	(0.005)	(0.006)
Age		− 0.026		0.005		− 0.006
		(0.019)		(0.013)		(0.007)
CEE score		0.005		− 0.021		0.010
		(0.031)		(0.018)		(0.009)
STEM track		− 0.325***		− 0.032**		0.006
		(0.026)		(0.015)		(0.009)
Constant	0.364***	0.642***	0.139***	0.137***	0.038***	0.036***
	(0.022)	(0.033)	(0.016)	(0.019)	(0.006)	(0.013)
Class FE	No	Yes	No	Yes	No	Yes
Observations	4844	4844	4844	4844	4844	4844
R-squared	0.003	0.131	0.024	0.101	0.004	0.043

Standard errors are clustered at high school classes

*Significant at 10%, ** significant at 5%, *** significant at 1%

regression because we would like to report the treatment effects as the percentage point differences rather than the log odds ratio for simple interpretation. We also used pooled Linear Probability Model with cluster robust SEs and the results were very similar.

The primary outcomes are four binary measures of college-major choices and admissions: whether a student applied to a STEM/Engineering major (Panel A in Table 6) or whether a student was admitted to a STEM/Engineering major (Panel B). Columns (1) and (5) report the estimates from Eq. (2). The average treatment effects show that the wage information increased applications to a STEM major by 0.7 percentage point and to an Engineering major by 1 percentage point, both are statistically insignificant. Students' increased college-major applications helped increase admissions to a STEM major by 1.7 percentage points and to an Engineering major by 1.5 percentage points, still statistically insignificant. Female students in the experimental sample were consistently less likely to apply and to attend the STEM/Engineering majors.

Table 6 Experimental estimates of the wage information intervention on college-major applications and admissions

Sample	STEM major (=1)				Engineering major (=1)			
	All	All	Urban	Rural	All	All	Urban	Rural
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. Applications (N = 11,114; Urban N = 5530; Rural N = 5584)								
Treatment	0.007	0.029*	− 0.001	0.081***	0.010	0.0295*	0.003	0.077***
	(0.015)	(0.016)	(0.018)	(0.017)	(0.016)	(0.017)	(0.018)	(0.021)
Treatment × Female		− 0.041***	− 0.026*	− 0.056***		− 0.034***	− 0.020	− 0.053***
		(0.10)	(0.014)	(0.013)		(0.009)	(0.014)	(0.013)
Female	− 0.234***	− 0.212***	− 0.209***	− 0.216***	− 0.288***	− 0.270***	− 0.248***	− 0.288***
	(0.005)	(0.007)	(0.011)	(0.009)	(0.005)	(0.007)	(0.011)	(0.009)
Prob (Treatment effect for female = 0)		0.460	0.133	0.135		0.776	0.323	0.238
B. Admissions (N = 11,114; Urban N = 5530; Rural N = 5584)								
Treatment	0.017	0.034**	0.005	0.075***	0.015	0.031*	0.005	0.062**
	(0.011)	(0.014)	(0.020)	(0.024)	(0.014)	(0.017)	(0.021)	(0.025)
Treatment × Female		− 0.028*	− 0.006	− 0.049**		− 0.029*	− 0.011	− 0.049**
		(0.016)	(0.022)	(0.022)		(0.016)	(0.022)	(0.022)
Female	− 0.231***	− 0.216***	− 0.226***	− 0.208***	− 0.301***	− 0.285***	− 0.274***	− 0.296***
	(0.008)	(0.012)	(0.017)	(0.016)	(0.008)	(0.012)	(0.017)	(0.017)
Prob (Treatment effect for female = 0)		0.695	0.953	0.247		0.874	0.753	0.578

All the models control for indicators for female, rural, minority, age, CEE score, and STEM, school random effects, as well as randomization strata fixed effects

*Significant at 10%, ** significant at 5%, *** significant at 1%

We examine the heterogeneous treatment effects by adding the interactions between the treatment and female indicators in Columns (2) and (6). The null average treatment effects were largely driven by the substantial differences in treatment effects between female and male students. Male students were statistically significantly shifted into the STEM/Engineering majors by about three percentage points increase in both applications and admissions. In contrast, female students' college-major choice behaviors and admissions outcomes did not change: the point estimates are smaller than one percentage point and they are not statistically significant (joint test p value >0.1).

The wage information intervention was designed to equalize the information gap in college-major choices between students from disadvantaged and advantaged families, with larger treatment effects for students with limited access to such information. In Columns (3) and (4), we decompose the heterogeneous treatment effects by student socioeconomic background. The wage information did not affect STEM major applications and admissions outcomes for urban students. Economically disadvantaged students from rural families were more responsive. The experimentally nudged male students in rural areas were about 8 percentage points more likely to apply for and enroll at STEM majors. Female, rural students who received the wage information intervention were 2.6 percentage points more likely to be admitted to a STEM major; but this positive effect was not statistically significant ($p=0.247$), suggesting that the gender gap persisted. Columns (7) and (8) present similar findings. We have also examined a wide array of additional heterogeneities between female and male students, including race, age, high school effects, CEE score distribution, and math and science score distribution. Consistently, we don't find these factors explain the gender gap in the treatment effect heterogeneity on STEM/Science major applications and admissions in the response to the wage information.

If we assume that all the major-choice effects are from the wage information intervention, we can approximately estimate the treatment-on-the-treated effects using an IV-2SLS model with the random assignments as the IV. As a first-stage estimate, about 36.7% of male students in the randomly selected treatment schools completed the survey (F test value of excluded instruments is 20.8). Female students were only 2.4 percentage points ($p$value $=0.169$) less likely to complete the survey. 2SLS-IV estimates show that providing the simple information of mean starting wage by major group would increase 10 percentage points (p value $=0.047$) enrollment in STEM majors among male students. Still, there was no change among female students (1.7 pp, p value $=0.741$). Admissions to Engineering majors were nearly the same that male students had an increased admission probability of 9.6 percentage points (p value $=0.047$) and female students had only 1.4 percentage points (p value $=0.782$).

Discussion: Explaining the Gender Gap in the Wage Information Effects

In this section, using various data sources, we show that the gender gap in the wage information effects on STEM major choice is driven by two underlying channels. First, on average, female students are less likely to value extrinsic incentives for major choice. Second, while the wage information only affects students who prefer high-paying majors, female students with such preference are still less responsive to the wage information than male students.

Female Students are Less Likely to Value Extrinsic Incentives for Major Choice

Using data from three large-scale national surveys among college students and high school students in China, shows that female students are less likely to prefer expected salaries in major choice, particularly choosing a STEM major. This is true across the surveys with different student samples in different cohorts. Results are also robust to controlling for a wide set of covariates, including demographics, College Entrance Exam scores, and high school or college fixed effects. Holding all else equal, female students are 1 to 2 percentage points less likely to choose majors based on salary incentives (Columns 1 and 7). While about 10 percent of male students in elite high schools reported that salary is the most important incentive for their college choices, female students were 2.4 percentage points (24 percent) less likely to have this extrinsic preference (Column 4). Furthermore, panel B suggests that, controlling for the full set of covariates, the gender gap in extrinsic preference was larger among economically disadvantaged students in rural areas.

The gender gap in extrinsic incentives might not be the driving factor of the female-male differences in the wage information effects on STEM major choice if the gender gap in extrinsic incentives exists in all college-majors. We replicated the analyses in Columns (1)-(3) of Table 7 for subsamples of students in different majors. Online Appendix Table 8 presents results for students in STEM majors and in economics-related majors. We find that, while there was no gender gap in salary preference among students in economics majors, female students were much less likely than their male peers to choose STEM majors because of expected monetary returns. The gender gap in extrinsic incentives did not exist in other non-STEM majors as well.

Online Appendix Table 9 provides descriptive evidence on the poverty gaps and the gender gaps in the access to information and guidance of college-major choice, which helps explain the differential treatment effects by student socioeconomic background. On average, rural students had less information about the college and major that they applied to and were less likely to receive assistance during college applications. Therefore, they were more likely to choose popular majors rather than those they were interested in. In practice, majors become popular among the public most likely due to their expected career benefits. There was little difference in the access to information and assistance (except for information about college) between female and male students in the rural areas. However, even under similar information and guidance constraints, female students were much more likely to choose their interested majors, providing additional support for the explanation that female students were less likely to be incentivized by salary information in their college-major choice decisions.

Extrinsically Incentivized Female Students are Still Less Responsive to the Wage Information

One limitation in the 2016 RCT as reported in the previous section is that we did not observe students' pre-intervention incentives for major choice. We replicated the same experimental design in 2017 with a random sample of high school graduates (N = 1555) in two provinces (Ningxia and Anhui), which provided students with the same wage information intervention during the college application week. Results on initial and updated preferences are identical to those in Tables 4 and 5. However, we are not able to replicate Table 6 as we do not have access to the administrative data on college applications and admissions.

We focus on understanding how students updated their major choices using the three pre-intervention incentive variables measured as dummy indicators in the 2017 replication:

Table 7 Descriptive evidence on the gender difference in extrinsic preferences for major choice

Outcome	Salary is one of the incentives for major choice (=1)			Salary is the most important incentive for major choice (=1)			Salary is one of the incentives for major choice (=1)		
Sample	National college student survey (2014)			National elite high school student survey (2017)			National high school graduate survey (2020)		
Group	All	Urban	Rural	All	Urban	Rural	All	Urban	Rural
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
A. Without additional controls									
Female	− 0.036***	− 0.037***	− 0.035***	− 0.012***	− 0.011**	− 0.014	− 0.023**	− 0.010	− 0.032**
	(0.007)	(0.009)	(0.008)	(0.004)	(0.005)	(0.010)	(0.011)	(0.017)	(0.012)
Constant	0.544***	0.592***	0.507***	0.100***	0.097***	0.111***	0.437***	0.451***	0.425***
	(0.007)	(0.009)	(0.007)	(0.005)	(0.005)	(0.012)	(0.014)	(0.016)	(0.015)
B. With additional controls									
Female	− 0.013**	− 0.005	− 0.017**	− 0.024***	− 0.016***	− 0.028**	− 0.023**	− 0.017	− 0.028**
	(0.006)	(0.010)	(0.008)	(0.005)	(0.005)	(0.013)	(0.010)	(0.015)	(0.013)
Demographics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
College Entrance Exam scores	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Elite high school dummy	Yes	Yes	Yes	No	No	No	No	No	No
High school fixed effects	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
College fixed effects	Yes	Yes	Yes	No	No	No	No	No	No
Observations	33,308	18,756	15,092	16,479	12,800	3,679	10,311	4548	5763

Data are from three national surveys of college students or high school students conducted by the Institute of Economics of Education at Peking University (with support from the Ministry of Education and the Chinese Society of Educational Development Strategy) in 2014, 2017, and 2020. The 2014 and 2020 surveys include two nationally representative samples of college students or high school graduates. The 2017 survey consists of a random sample of high school students from national elite high schools. All the three surveys asked about the impact factors of students' college and major choices. Demographics variables include race, age, parental education and occupation, and family SES. The 2017 survey controls for scores in a mock test of the College Entrance Exam. Results are qualitatively unchanged when controlling for additional variables including STEM interest, STEM track, individual beliefs in college and major choice, and educational expectations. Standard errors are clustered at colleges or high schools. * significant at 10%,

** significant at 5%, *** significant at 1%

whether students would only apply to majors that they were interested in (intrinsically incentivized), whether they would only apply to high-paying majors (extrinsically incentivized), and whether they lacked major wage information. We use the following linear regression to identify the gender gap in Engineering major preference with the wage intervention using the treated sample:

$$\begin{aligned} Post\_STEM_{ij} = \beta_0 + \beta_1 Female_{ij} + \beta_2 Belief_{ij} * + \beta_3 Female_{ij} * Belief_{ij} \\ + \pi Pre\_STEM_{ij} + \mathbf{X_{ij}} \Gamma + \delta_j + \varepsilon_{ij} \end{aligned} \tag{3}$$

where β_1 is the gender gap in the preference for Engineering major after receiving the major wage information among students whose $Belief_{ij}$ equals zero, controlling for pre-intervention preference Pre_STEM_{ij}, individual covariates $\mathbf{X_{ij}}$, and province fixed effects δ_j. β_3 represents the changes in the gender gap in the preference for Engineering major between students whose $Belief_{ij}$ equals zero and those whose $Belief_{ij}$ equals one.

Column (1) of Table 8 shows that the correlation between pre-intervention and post-intervention preferences for Engineering major is 75.8%, suggesting a substantial share of students changed their initial preferences after receiving the major wage information: 12.8% of male students switched from other majors into Engineering but only 4.7% female students did so. This gender gap persists after controlling for a set of covariates in Column (2). Columns (3)-(5) report how students' pre-intervention beliefs affected their preference changes. Neither female nor male students who were intrinsically incentivized to only apply to majors based on interest responded to the wage information. In contrast, male students who were extrinsically incentivized to only apply to high-paying majors were 5.2 percentage points more likely to choose Engineering but female students, even extrinsically incentivized, were only 1.9 percentage points more likely to choose Engineering ($p > 0.1$). The wage information increased the Engineering preference of those male students who lacked such information. However, those uninformed female students on average were not affected by the wage information. Finally, Columns (6) and (7) show that the wage information only affected female students who lack such information; still, female students were much less responsive to it.

To sum up, results in this section confirm that the heterogeneous preferences for wage—the main extrinsic incentive in job and major choice—drives the heterogeneous treatment effects of wage information on males and females. This explanation speaks to the recent literature on the gender difference in major choice. While women are much less likely than men to rank career salary highly in their major choice preferences (Breske et al., 2019), they often choose majors and occupations with lower potential wage (Sloane et al., 2019). In contrast, women are more likely to value extrinsic incentives, for example, returns to family considerations in marriage, spousal earnings, and fertility (Wiswall & Zafar, 2020). Furthermore, the intervention effects are validated by the fact that the light-touch wage information only affects students who lack such information, typically low-SES students (Hastings et al., 2015).

Table 8 Gender gap in Engineering major preference with the wage information intervention

Outcome	Top preference for Engineering (Post) = 1						
Group	All					Lack info = 1	Lack info = 0
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Top preference for Engineering (Pre)	0.758***	0.728***	0.728***	0.731***	0.728***	0.731***	0.734***
	(0.023)	(0.025)	(0.025)	(0.025)	(0.025)	(0.028)	(0.051)
Female	− 0.081***	− 0.066***	− 0.065***	− 0.052***	− 0.026	− 0.065**	− 0.033
	(0.016)	(0.015)	(0.021)	(0.019)	(0.025)	(0.026)	(0.028)
Prefer interested majors			0.013				
			(0.025)				
Female*Interested majors			− 0.002				
			(0.029)				
Prefer high-paying majors				0.052**		0.054*	0.021
				(0.025)		(0.030)	(0.049)
Female × High-paying majors				− 0.033		− 0.035	0.006
				(0.028)		(0.034)	(0.058)
Lack major wage information					0.057**		
					(0.026)		
Female × Lack wage information					− 0.058*		
					(0.030)		
Rural		0.006	0.006	0.006	0.005	0.005	0.012
		(0.015)	(0.015)	(0.015)	(0.015)	(0.018)	(0.026)
STEM track		0.092***	0.092***	0.091***	0.090***	0.097***	0.075***
		(0.013)	(0.013)	(0.013)	(0.013)	(0.015)	(0.025)
CEE score		0.001***	0.001***	0.001***	0.001***	0.001***	0.001
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Did not know CEE score		0.314***	0.313***	0.316***	0.312***	0.329***	0.260
		(0.093)	(0.093)	(0.093)	(0.093)	(0.112)	(0.168)

Table 8 (continued)

Outcome	Top preference for Engineering (Post) = 1						
Group	All					Lack info = 1	Lack info = 0
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ningxia		− 0.004	− 0.004	− 0.004	− 0.002	0.004	− 0.018
		(0.019)	(0.019)	(0.019)	(0.019)	(0.022)	(0.034)
Constant	0.128***	− 0.283***	− 0.284***	− 0.293***	− 0.303***	− 0.291**	− 0.217
	(0.014)	(0.101)	(0.101)	(0.102)	(0.101)	(0.125)	(0.166)
Prob (X + Female × X = 0)			*0.444*	*0.169*	*0.959*	*0.251*	*0.348*
Observations	1,555	1555	1555	1555	1555	1138	417
R-squared	0.535	0.551	0.551	0.552	0.552	0.547	0.568

This table shows the gender gap in Engineering major preference using a random sample of high school graduates in Ningxia and Anhui in June 2017, all of which were presented with the same wage information as the 2016 Ningxia RCT. The outcome variable measures whether students reported to list Engineering as their top major choice after the wage information was presented (sample means are 0.094 for female and 0.349 for male). All the covariates were measured before presenting the wage information. "Prefer interested majors" is a dummy variable indicating that students reported to choose their interested majors. "Prefer high-paying majors" is a dummy variable indicating that students reported to choose majors with high expected wages. "Lack major wage information" is a dummy variable indicating that students reported to not have information about each major's expected wage. *Prob (X + Female*X = 0)* reports the joint significance F test p-values in columns (3)-(5) for "Prefer interested majors," "Prefer high-paying majors," and "Lack major wage information." Robust standard errors are in parentheses

*Significant at 10%, ** significant at 5%, *** significant at 1%

Conclusion

In this paper, using unique survey and administrative data, we have shown compelling evidence that there is a large STEM gender gap of preferences, college-major choice, and admissions in the Chinese centralized college admissions system. Female students less prefer STEM (particularly Engineering) majors and are less likely to apply to and enroll in a STEM major. We conducted a large-scale randomized experiment of providing major-specific wage information to examine how students' major preferences would respond to additional information about the returns to different majors. The experimental results show that students' major preferences are easily malleable. However, as female students less prefer STEM majors and are less likely to value wage as extrinsic incentives for STEM major preferences, the wage informational intervention does not alter their college-major applications and admissions. In contrast, those male students who lack such information are largely shifted into STEM majors by the wage information.

Providing better information to guide students' informed college-major choices is a major focus of current higher education policy efforts but students may not always respond to such information as intended (Blagg et al., 2017; Gurantz et al., 2020; Mabel et al., 2020). As female students There is much more to be done to explore effective policy interventions to improve the supply of women in STEM (particularly Engineering) majors and professions. To attract and retain female students in the "leaky STEM pipeline" (Speer, 2020), we need to align their preferences for STEM disciplines. Strategies designed to reduce gender gaps like distribution of information about career prospects, exposure to female role models/mentoring, engagement with real-world experience, as well as targeted financial aid may arouse female students' interests and expectations in studying and working in STEM majors (Castleman et al., 2018; Denning & Turley, 2017; Evans, 2017; Fricke et al., 2018). Our paper provides promising results that even simple, light-touch may shape students' preferences for high-stakes decisions. But it also shows that the complex college-major choice problem, including college-major preference belief formation, application decision-making, and admissions, needs more research and policy efforts in closing the gender STEM gap and improving college and career opportunities for all.

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