Heterogeneous Preference for Extrinsic Incentives:

The Effects of Wage Information on the Gender Gap in STEM Major Choice

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Yanqing Ding[1], Wei Li[2], Xin Li[3], Yinduo Wu[1], Jin Yang[1], Xiaoyang Ye[4]

1. Peking University
2. University of Florida
3. UCLA
4. Brown University

Corresponding author:
Xiaoyang Ye, Annenberg Institute for School Reform, Brown University. Box 1985, Providence, RI 02912. Email: xiaoyang.ye@brown.edu.

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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, after ruling out alternative explanations including demographics, family background, school context, absolute and comparative ability, subject choice in high school, and preference heterogeneity. 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. While there is no gender difference in the propensity of changing stated major preferences, female students are less likely to switch their preferences into STEM majors. Consistent with the preference heterogeneity framework, the wage informational intervention has zero impacts on female students' STEM-related major applications and admissions. In contrast, male students are largely shifted into STEM majors as a result of the intervention.

Keywords: college application; major choice; STEM gender gap; informational intervention; preference heterogeneity; randomized experiment

Introduction

The gender gap in STEM majors (science, technology, engineering, and mathematics) remains as a persistent policy problem in higher education (Griffith, 2010; Rask, 2010; Ganley, George, Cimpian, & Makowski, 2018; Kugler, Tinsley, & Ukhaneva, 2017). Governments and higher education institutions all around the world have been enacting numerous policies designed to increase the number of students majoring in STEM, especially among women and racial and ethnic minorities (Crisp, Nora, & Taggart, 2009; Melguizo & Wolniak, 2012; Soldner, Rowan-Kenyon, Inkelas, Garvey, & Robbins, 2012). Nevertheless, these efforts to expand female participation in STEM, especially in technology and engineering, are not working as well as intended (Kesar, 2017). The share of female researchers in the field of science is 28.4% in 2013, and the percentages of female tertiary graduates in engineering are lower than 30% in most countries (UNESCO, 2015).

Factors steering women away from STEM majors are complex and yet to be fully explained, though they have long been studied (Chipman & Thomas, 1987; Turner & Bowen, 1999; Simpson, 2001; Bobbitt-Zeher, 2007; Mann & DiPrete, 2013; Zafar, 2013; Gemici & Wiswall, 2014). Kanny, Sax, & Riggers-Piehl (2014) has reviewed 324 papers spanning forty 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. Performance and confidence in mathematics and science may meaningfully affect a student's STEM major choice, but they are not able to explain the gender STEM gap (Griffith, 2010; Riegle-Crumb & King, 2010; Wang, 2013; Watt et al., 2012). In particular, there are on average no gender gaps in science achievement at the primary or secondary level and girls often outperform boys (Mostafa, 2019); however, 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).

To this end, the differences in preferences and behaviors of college-major choice between female and male students are one crucial driving factor of the gender gap in STEM major choice. Preference 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, working environment and objects (Mann & DiPrete, 2013). For instance, women are less work-centered while preferring flexible work and attach a lower value to monetary income while think highly of intrinsic rewards (Bobbitt-Zeher, 2007). Males, as income maximizers, are more responsive to the increase of relative prices of science and business skills, which widens the gender gap in major choice (Gemici & Wiswall, 2014). Zafar (2013) finds that the gender gap in college major choice is mainly due to gender differences in preferences and tastes, and not because females are under-confident about their academic ability or fear of monetary discrimination. Wiswall and Zafar (2018) find that women prefer jobs with greater work flexibility and job stability, and men prefer jobs with higher earnings growth. These job preferences relate to college major choices and actual job choices. 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, 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 impacts the gender gap of STEM major choice in both subjectively reported preferences and real behaviors in college-major applications. Specifically, we answer three research questions. First, are there gender gaps in STEM (particularly Engineering) college-major choices under centralized admissions where students choose a STEM track as early as in grade 9 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 on college entrance exam, 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. 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. Consistent with their actual choices and admissions results in late June, female students less preferred a STEM major or an Engineering major than male students. The gender gap in STEM major preference nearly explains the gender gap in STEM major choice.

Next, we provided major-specific wage information to help these low-income students make better college-major choices. In a randomized experimental design, we conducted the survey in 17 randomly selected high schools. We measured students' initial and updated major preferences by asking them to rank eight major groups from the most preferred to the least preferred, before and after students were presented with information about the first-year post-graduation average wage in each major group of Chinese four-year college graduates in 2014. We obtained the wage by major group data from the National Survey of College Graduate Employment, the best available data that provides wage information by college-majors.

While major preference is one of the most important factors in college-major choice, it is very malleable. Students strongly responded to the wage informational intervention that lasted for about one minute and accordingly updated their preferences. Among the students who completed the survey, 39% changed their first-choice major preferences. There is no gender difference in the propensity of changing majors given the wage informational intervention. However, female students were more than 50 percent less likely to switch 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 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.

Finally, we estimate the causal impacts of the wage informational intervention on students' real college applications and admissions 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 were 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 are easily malleable by simple wage information, only male students shift into STEM/Engineering majors as a response to the updated information and beliefs. We provided additional evidence suggesting that female students were less likely to be motivated by extrinsic incentives than male students in STEM major preference.

This paper contributes new evidence to three strands of literature. First, compared with choosing which college to go (e.g., Long, 2004; Perna, 2006; Jacob, McCall, & Stange, 2018), the college-major choice is much closer to job market prospects since students specialize their human capital skills in college that vary across majors (Kinsler & Pavan, 2015; Altonji, Arcidiacono, & Maurel, 2016). The heterogeneous labor market returns to college-major types are a key factor for students making decisions in the field of study (Berger, 1988; Arcidiacono, 2004; Xie & Shauman, 2003; Jensen, 2010; Beffy, Fougere, & Maurel, 2012; Wiswall & Zafar, 2014; Kim, Tamborini, & Sakamoto, 2015). However, there is little research about how different types of students respond to the labor market returns. One example is that Hastings, Neilson, Ramirez, & Zimmerman (2016) find that students in low-income families tend to be the vast majority in low-income majors. We find that female students are less likely to prefer, choose, and be admitted to high potential income majors, which primarily consist of Engineering majors. We also provide evidence that heterogeneity preference matters in this gender gap as we rule out a set of alternative explanations.

Second, we consider light-touch informational interventions according to the Nudge Theory as proposed by Thaler and Sunstein (2008). Traditional rational choice theory assumes that individuals make educational decisions in line with the principle of utility maximization. However, they often face behavioral issues such as insufficient information, present bias, and choice overload that prevent them to make optimal choices. 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). Existing literature has shown that students underestimate the benefits of education (Jensen, 2010; Hastings, Neilson, & Zimmerman, 2015). Loewenstein, Sunstein, & Golman (2014) argue that disclosure of information of labor market is an effective and sustainable approach to help students to make educational choices. In this paper, we provide clear experimental evidence that male students are much more likely to be shifted into STEM majors by wage information, but there is only a small change in female students' STEM preference, and no changes in their applications and admissions.

Lastly but most importantly, this paper closely relates to a small but growing strand of studies that focus on the effect of wage information on students' major choice. Wiswall & Zafar (2014, 2015) find students' expected earnings and perceived ability are significant determinants of major choice, while heterogeneous tastes are the dominant factor. Students revise their earnings beliefs and intended majors when being provided with information on the population distribution of earnings in an information experiment. This intervention nudges students to majors with higher earnings and leads to positive average welfare gains. 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. It is because the disclosure of wage information in the treatment reduces the earnings uncertainty, but this effect is limited by the preference for non-pecuniary degree attributes. Baker, Bettinger, Jacob, & Marinescu (2018) utilize survey and experimental data to estimate the impact of expected labor market outcomes on community college students' major choices. They find that the probability of choosing a specific category of majors is positively related to salary, but less than 40% of a sample of community college students could rank major categories accurately in terms of labor market outcomes. Conlon (2019) find that 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. This paper provides new evidence from a centralized college admissions system that is very different from the U.S. decentralized college-then-major system or the open admissions system in community colleges. The college-and-major assignment in the widely adapted centralized admissions all over the world requires students to make their major choices before learning about majors in college (Bordon & Fu, 2015), in which how preferences could be nudged into specific majors is of particular policy importance.

Research question, experimental design, and data

Research question and theoretical framework

This paper explores the gender gap in the belief preferences, application behaviors, and admissions outcomes related to STEM/Engineering majors. We argue that the heterogeneous major preferences drive the gender gap in STEM/Engineering major choices and admissions. Since many factors contribute to the complex college-major choice, the estimated STEM gender gap might not be the preference heterogeneity, but due to the omitted variable bias of not being able to control for the confounding factors.

We address this conceptual challenge in three ways. First, the centralized admission system validates the identification of the gender differences in college-major choice because college admissions are only based on CEE scores and applications. By controlling for CEE scores, any differences in the admissions outcomes are from the different application behaviors, not other unobservables during the admission process. 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, and college-major preferences. Third, we conducted a large-scale randomized experiment that provided 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 does not affect female students' STEM/Engineering major choices, but substantially and statistically significantly alters 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 information as extrinsic incentives.

Background: Chinese centralized college admissions

China's college admission system was established in 1978. On June 7 and 8 each year, students take one of the two tracks tests in the National College Entrance Examination (CEE): STEM and non-STEM, which differ in track-specific subjects and have the other three common subjects in Chinese, English, and math. Colleges allocate admissions quotas to each province by tracks and students are only ranked within the province-track market. 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, unlike in many other countries that students choose majors after exploring different options in college, students submit their college-and-major preference lists in each tier to apply 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 different types of majors within a college application. Using a pre-selected matching mechanism, college admissions are jointly determined by students' CEE scores and their applications (rank orders of the applied college-majors). A student is at most admitted to one college-and-major offer.

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 experiment. In 2016, the per capita disposable income of urban residents in Ningxia is less than $4000 (national average: $5000; Shanghai: $8000), and that of its 65% population in rural areas is less than $1500 (national average: $2000; Shanghai: $3500). Each year, about 60,000 high school graduates - accounting for 60% of a birth cohort - take the CEE and submit their college-major applications, 80% of which receive college admissions.

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 17 randomly selected (by the research team) high schools. As displayed in Appendix Figure 1, each school implemented the survey in a 20-minute section in a similar manner of completing other high-stakes administrative forms. This formal implementation process ensured the quality of survey responses.

We surveyed 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. To answer the research questions in this paper, we measured student major preference by asking them to rank eight major groups from the most preferred (first-choice) to the least preferred. We categorize the original thirteen major groups 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. After students reported their initial major preferences, we presented them with information about the first-year post-graduation average wage in each major group, **the information intervention component**. We then measured the changes in students' major preferences by asking them to report their updated rankings of the eight major groups (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 most recent data by the time of the intervention. 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 majors (offered only in selective colleges) is more than 35 percent higher than that of Art or Military majors, regardless of college quality heterogeneity. Majors in Agriculture, Engineering, and social sciences have higher average first-year starting wages than the other majors.

The student survey is 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, we first randomly selected three out of the total prefectural cities (31 out of 60 public high schools in the sample). Then we randomly selected 17 schools to implement the survey.

We acknowledge research design limitations in the paper. The beliefs about expected earnings may be correlated with unobserved factors were not analyzed in this paper, such as tastes that may also affect students' major choices. Ignoring this correlation may inflate the role of earnings in major choices (Wiswall & Zafar, 2015; Baker et al., 2018). Moreover, we only focused on one single factor of the labor market outcomes, female students may respond to other labor market information such as employment rate, heterogeneous returns, 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 eventual admissions, which enables us to identify the information intervention impacts on their 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. On top of that, 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.

Across the 17 experimental schools, 8,243 students responded to the survey. We exclude those with missing or incorrect student IDs that cannot be matched to the administrative data (1,345), and those not in academic tracks (e.g., athletes or CTE; 1,214). We further exclude students who are not first-time high school seniors (repeaters) since they have experienced college applications and may have different beliefs (840). This sample restriction results in an analytic sample of 4,844 students that are matched to the administrative records.

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. Without the information intervention, Economics and Management were the most preferred majors while agriculture was the least preferred major. Students became more preferred to choose Agriculture, Engineering, Economics and Management, Law and Education, and LHP, but less preferred to choose Science, Medical, and Art and Military after the intervention. More than 40% students applied to and were admitted by an Engineering major, and around one-quarter of students applied to and admitted by Economics and Management majors. The difference between preference and real applications/admissions is primarily due to the fact that students form their beliefs without the admissions quota constraints. Appendix Table 2 shows similar patterns using all students in either the survey sample or administrative samples.

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 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:

$$Y_{ij} = \beta_0 + \beta_1 Female_{ij} + \mathbf{X_{ij}\Gamma} + \delta_j + \varepsilon_{ij}, \qquad (1)$$

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 rural student, age, GEE 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) shows that, holding race and family residence, 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 does not change from Column (2) to Column (3). 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), Appendix Table 4 presents the gender gap in Engineering major choice using the same identification as shown in model (1). Estimates in 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 Table 4 presents estimates from a separate regression, controlling for covariates and school fixed effects (as in Column 3 of Table 4). 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 (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 (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 5, we estimate the same Linear Probability Model as in Table 3, controlling for differences in demographics, absolute and comparative ability, high school contexts. 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 close 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 5) 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 5) explains 34% of the gender gap in Engineering major choice (-0.179 in Column 10 of Appendix Table 4). The preference gap is smaller among students with higher science scores. This difference 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 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 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. Appendix Figure 3 compares STEM majors with non-STEM majors. In aggregation, there is not a systematic pattern that students are shifted to one the two groups. Results are similar when we examine the top three preferred majors in Appendix Figure 4.

In Figure 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 take-way 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 increased their preferences over Agriculture majors, which has the highest mean starting wage.

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 6 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 used a Linear Probability Model similar to those in Table 6 with additional controls constructed using the survey responses. Columns (1) and (5) of Appendix Table 5 control for high school class fixed 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.

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. The final analysis is to estimate the impacts 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:

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

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 equation (2) as we did in equation (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 regression because we would like to report the treatment effects as the percentage 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 7) or whether a student was admitted to a STEM/Engineering major (Panel B). Columns (1) and (3) report the estimates from Model (2). The average treatment effects show that the wage information increased applications to a STEM major by 0.4 percentage point and to an Engineering major by 0.7 percentage point, both are statistically insignificant. Their improved college applications helped increase admissions to a STEM major by 1.7 percentage points and to an Engineering major by 1.5 percentage points, but not statistically significant as well. Female students in the experimental sample were consistently less likely to apply and to attend the STEM/Engineering majors.

We examine the heterogeneous treatment effects by adding the interactions between the treatment and female indicators in Columns (2) and (4). The null average treatment effects are largely driven by the gender heterogeneity. Male students were statistically significantly shifted into the STEM/Engineering majors by a 2.5 percentage points increase in applications and more than a 3 percentage points increase in admissions. In contrast, female students' college-major choice behaviors and admissions outcomes did not change: the point estimates are smaller than 1 percentage points and they are not statistically significant (joint test p-value>0.1).

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 admissions probability of 9.6 percentage points (*p*-value=0.047) and female students had only 1.4 percentage points (*p*-value=0.782).

Explaining the gender gap in the wage information effects

In the final analysis, we seek to further understand the gender gap in the wage information effects on STEM major choice. In columns 2-3 of Table 8, we decompose the heterogeneous treatment effects by student socioeconomic background. Economically disadvantaged students from rural families are more responsive. Female, rural students who received the wage information intervention were 1.6 percentage points more likely to be admitted to a STEM major; but this positive effect was not statistically significant ($p=0.247$). 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.

Using two large-scale national surveys among college students and high school students, Table 8 shows that female students and students from rural areas were less likely to prefer expected salaries in major choice, particularly choosing a STEM major. This result confirms 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 might still value extrinsic incentives, for example, returns to family considerations in marriage, spousal earnings, and fertility (Wiswall & Zafar, 2020).

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. Females students less prefer STEM (particularly Engineering) majors, and thus they 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 as well as wage as extrinsic incentives for STEM majors, the wage informational intervention does not alter their college-major applications and admissions. In contrast, male students are largely shifted into STEM majors by the wage information.

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. One important channel is stereotype. Female students may have exposed to gender stereotypes at home or in school in early grades (Kahn & Ginther, 2017; Ganley et al, 2018). They may also less prefer male-dominated professions (Ganley et al, 2018; Kugler et al, 2017). Lack of role models also reinforces the dearth of women in STEM (Kesar, 2017; Kahn & Ginther, 2017). The other channel is psychological taste that female students may attach greater value to risk aversion, more people-oriented (than thing-oriented) and less-competitive environment, and intrinsic rewards (Zafar, 2013; Mann & DiPrete, 2013; Reuben, Wiswall, & Zafar, 2017; Kahn & Ginther, 2017). Lastly, some other factors may also contribute to the heterogeneous preferences, such as curriculum enjoyment, study climate and environment, parental occupation and expectations (Zafar, 2013; Kanny et al. 2014, Kahn & Ginther, 2017; Baker et al., 2018).

Clearly, there is much to be done to understand how female students form the STEM major related preferences differently from their male counterparts and to explore effective policy interventions that can have real impacts on improving the supply of women in STEM (particularly Engineering) majors and professions. To attract and retain female students in STEM fields, 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 (Denning & Turley, 2017; Evans, 2017; Castleman, Long, & Mabel, 2018; Fricke, Grogger, & Steinmayr, 2018; Buckles, 2019). 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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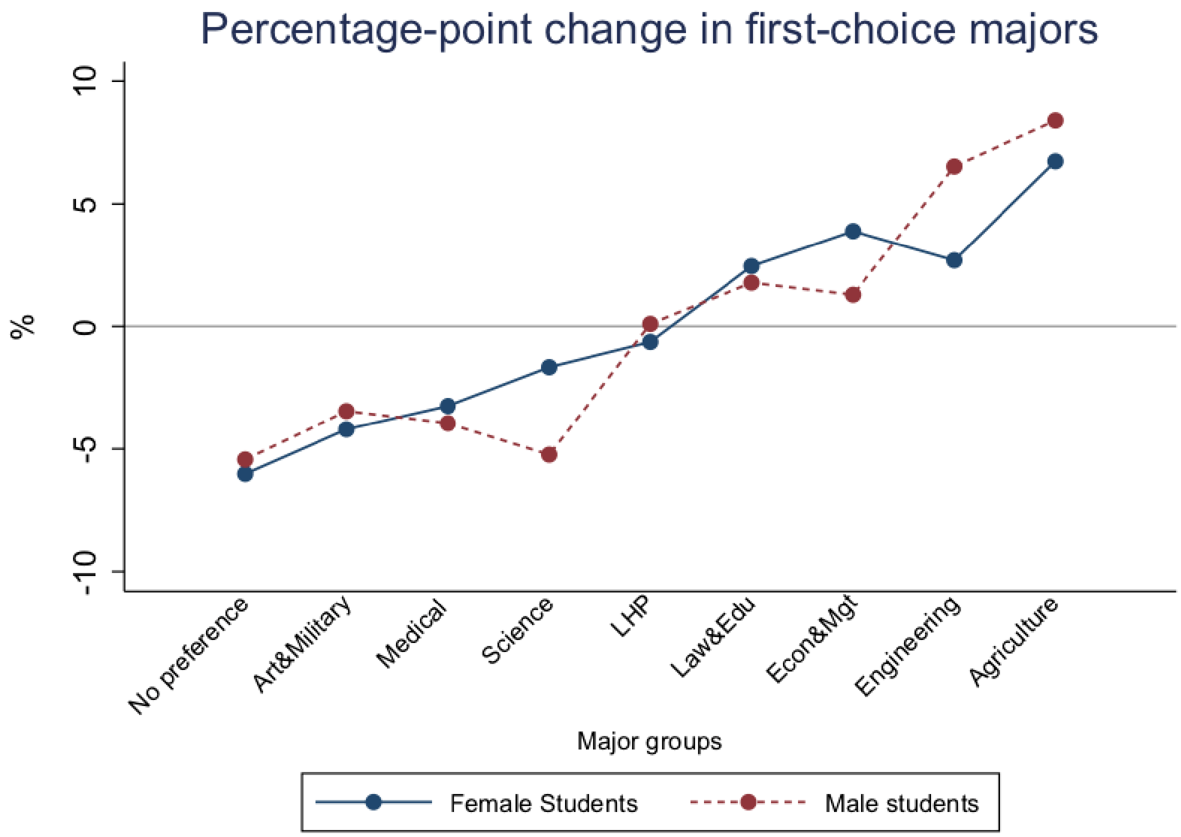


Figure 1: Changes in the share of students with different first-choice major preferences

Notes: 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 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.

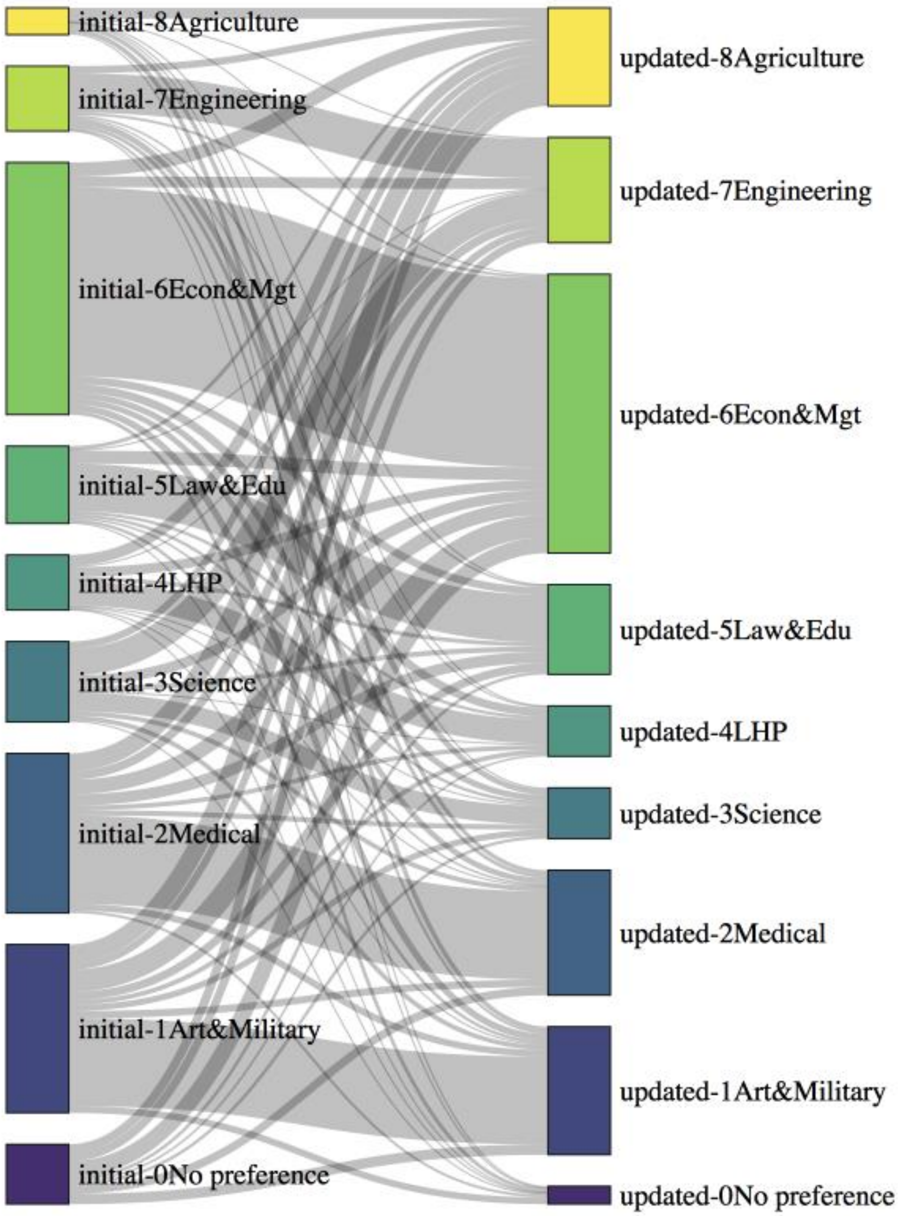


Figure 2: Network flows of the changes in first-choice major preferences

Notes: Lines are weighted by the number of students. Bars are scaled by the share of students in each major group.

A. Female

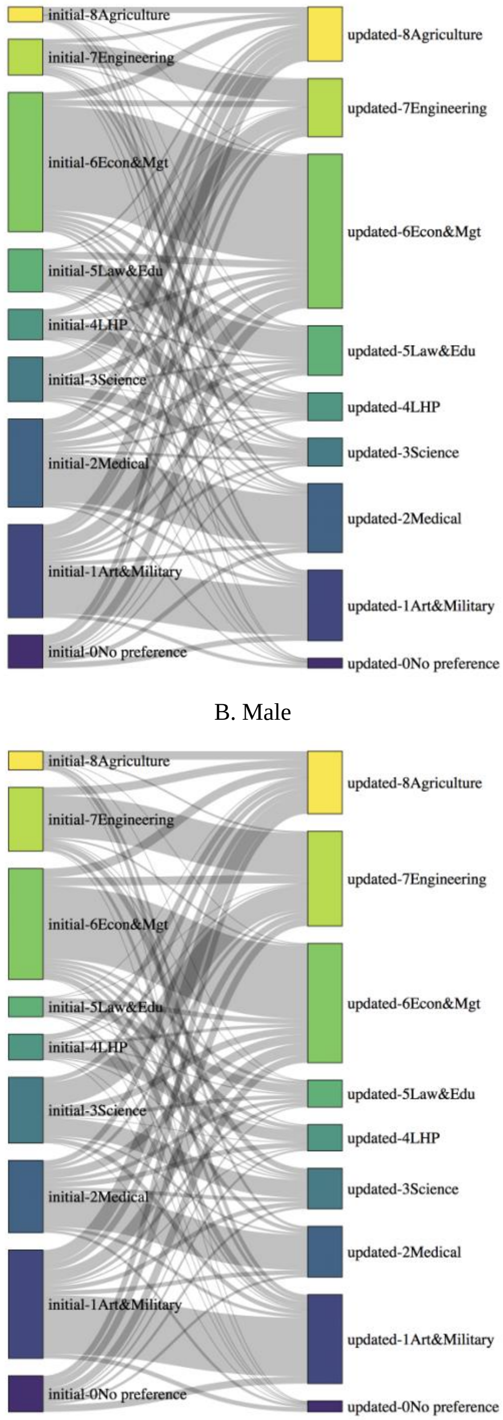


Figure 3: Gender difference in the network flows of the changes in first-choice major preferences

Notes: Lines are weighted by the number of students. Bars are scaled by the share of students in each major group.

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	53000	54700	29774	6000	240000
Engineering	1379	51000	50865	36648	6000	600000
Econ & Mgt	1946	50000	50416	36780	6000	600000
Law & Edu	385	50000	49678	45158	12000	600000
LHP	647	47000	46571	31156	6000	600000
Science	687	45000	44582	30845	6000	240000
Medical	140	42000	41644	24816	10200	180000
Art & Military	305	39000	39175	23765	6000	240000
			B. By college selectivity			
Most selective	747	77000	76895	35767	6000	300000
Selective	910	58000	57740	37054	6000	600000
Less selective	2889	44000	44441	33632	6000	600000
Non-selective	1387	36000	35548	27725	6000	600000

Notes: 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 6000-600000. “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.

Table 2: Sample summary statistics

	Survey sample			Experimental sample		
	All	Female	Male	All	Control	T-C
	(1)	(2)	(3)	(4)	(5)	(6)
N	4844	2711	2133	11114	5065	
Treatment (=1)				0.544	0	
				[0.498]		
A. Demographics						
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
	[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
	[4,427.266]	[4,327.464]	[4,551.750]	[2,810.662]	[2,879.189]	(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]			

Notes: 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. Standard deviations are in square parentheses, and standard errors clustered at schools are in parentheses. * significant at 10%, ** significant at 5%, *** significant at 1%.

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
Observations	7,627	7,627	7,627	7,627	7,627	5,874	5,874	5,874	5,874	5,874
R-squared	0.131	0.292	0.297	0.297	0.297	0.298	0.560	0.568	0.574	0.575

Notes: 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%.

Table 4: Gender gap in STEM major choice (alternative outcomes and samples)

	STEM major (1)	Engineering major (2)	High-paying major (3)	Major mean wage (4)
		A. All students, college-major admissions		
Female	-0.206***	-0.238***	-0.148***	-902.199***
	(0.014)	(0.016)	(0.017)	(88.576)
		B. STEM-track students, college-major admissions		
Female	-0.258***	-0.303***	-0.141***	-1,038.178***
	(0.014)	(0.015)	(0.015)	(102.907)
		C. All students, college-major applications (all)		
Female	-0.203***	-0.241***	-0.125***	-1,086.866***
	(0.018)	(0.020)	(0.011)	(84.909)
		D. STEM-track students, college-major applications (all)		
Female	-0.254***	-0.304***	-0.139***	-1,295.513***
	(0.014)	(0.015)	(0.013)	(95.048)
		E. All students, college-major applications (first major)		
Female	-0.228***	-0.266***	-0.136***	-1,247.345***
	(0.023)	(0.025)	(0.014)	(109.473)
		F. STEM-track students, college-major applications (first major)		
Female	-0.287***	-0.336***	-0.146***	-1,455.413***
	(0.020)	(0.020)	(0.015)	(124.354)

Notes: This table estimates the gender gap in STEM major choice using Linear Probability Model with alternative outcomes and samples. Each cell presents estimates from a separate regression, controlling for covariates and school fixed effects (as in Column 3 of Table 4). Standard errors are clustered at high schools. * significant at 10%, ** significant at 5%, *** significant at 1%.

Table 5: 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	4,844	4,844	4,844	4,844	3,421	3,421	3,421	3,421
R-squared	0.057	0.167	0.028	0.106	0.052	0.147	0.027	0.101

Notes: 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%.

Table 6: 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	4,844	4,844	4,844	4,844	4,844	4,844
R-squared	0.003	0.131	0.024	0.101	0.004	0.043

Notes: Standard errors are clustered at high school classes. * significant at 10%, ** significant at 5%, *** significant at 1%.

Table 7: Experimental estimates of the wage information intervention on college-major applications and admissions

	STEM major (=1)		Engineering major (=1)	
	(1)	(2)	(5)	(6)
		A. Applications (Obs=10,458)		
Treatment	0.004	0.025*	0.007	0.025
	(0.014)	(0.015)	(0.015)	(0.016)
Treatment*Female		-0.036***		-0.031***
		(0.009)		(0.009)
Female	-0.220***	-0.202***	-0.272***	-0.256***
	(0.005)	(0.007)	(0.005)	(0.006)
Prob(Treatment effect for female=0)		*0.429*		*0.711*
		B. Admissions (Obs=11,114)		
Treatment	0.017	0.034**	0.015	0.031*
	(0.011)	（0.014）	(0.014)	(0.017)
Treatment*Female		-0.028*		-0.029*
		（0.016）		(0.016)
Female	-0.231***	-0.216***	-0.301***	-0.285***
	（0.008）	(0.012)	(0.008)	(0.012)
Prob(Treatment effect for female=0)		*0.695*		*0.874*

Notes: 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%.

Table 8: Heterogeneous treatment effects and evidence on the gender difference in major preferences

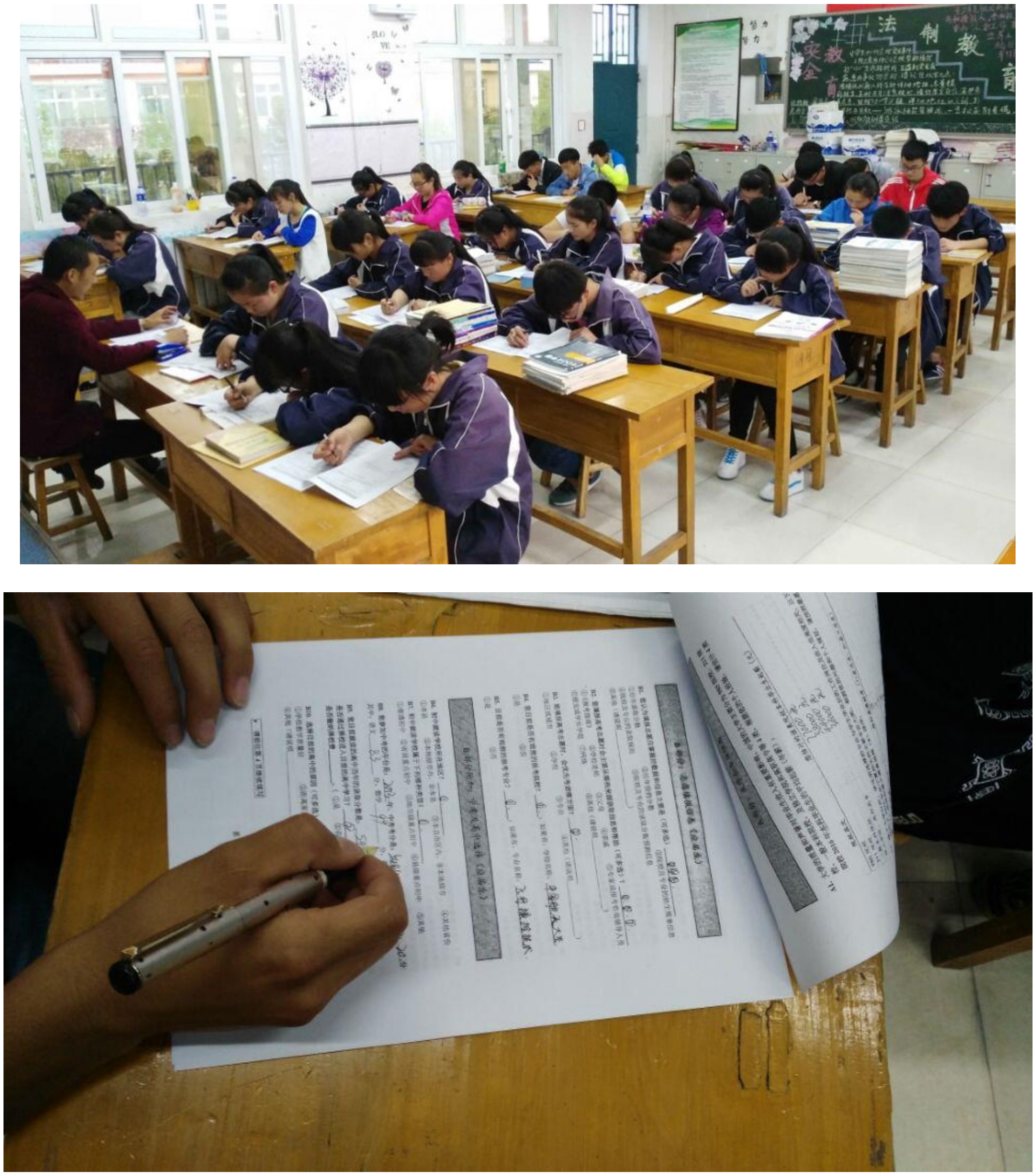
Outcome	Admissions to a STEM major (0/1)			Salary incentives for choosing a STEM major (s.d.)			Salary incentives for major choice (0/1)		
Sample	Ningxia experimental sample (2016)			National college student survey sample (2014)			National high school student survey sample (2017)		
Group	All	Urban	Rural	All	Urban	Rural	All	Urban	Rural
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment	0.034**	0.005	0.075***						
	(0.014)	(0.020)	(0.024)						
Treatment*Female	-0.028*	-0.006	-0.049**						
	(0.016)	(0.022)	(0.022)						
Female	-0.216***	-0.226***	-0.208***	-0.060***	-0.014	-0.088***	-0.02***	-0.02***	-0.03**
	(0.012)	(0.017)	(0.016)	(0.020)	(0.033)	(0.026)	(0.00)	(0.01)	(0.01)
Rural				-0.151***			-0.12***		
				(0.022)			(0.02)		
Prob(Treatment effect for female=0)	0.695	0.953	0.247						
Observations	11,114	5530	5584	15,092	6,140	8,952	16,479	12,469	4,010

Notes: All the models include additional covariates. Column 1 replicates column 2 of Panel B in Table 8; columns 2 and 3 estimate the same model but separately for the urban and rural student subsamples. Columns 4-6 control for student STEM interest, STEM track, high school effects, and college entrance exam scores. Columns 7-9 control for STEM track, race, family SES. * significant at 10%, ** significant at 5%, *** significant at 1%.

Heterogeneous Preference for Extrinsic Incentives:

The Effects of Wage Information on the Gender Gap in STEM Major Choice

Online Appendix Only



Appendix Figure 1: Survey implementation

Notes: These two pictures who the implementation and administration of the student survey in 2016. The survey was officially conducted by the Ningxia Department of Education and was seriously implemented by each school in the survey sample in a similar manner of completing other administrative forms.

宁夏普通高中毕业生调查

（学生问卷）

二〇一六年

宁夏大学、北京大学联合课题组

◆◆

亲爱的同学：

您好！感谢您参加宁夏大学和北京大学联合组织的 2016 年"宁夏普通高中毕业生调查"。本次调查旨在全面了解宁夏学生高考及志愿填报状况，为学校管理和政府决策提供参考，以精准地帮助贫困地区学生更加科学地进行教育决策。

您是经由严格的科学抽样被选中的受访者，请您按照您的实际情况和想法作答。对您所提供的信息，我们将依照《统计法》严格保密。您的合作对科学研究和公共决策都有重要意义，感谢您的贡献！

1. 高中： 贺兰一中

2. 班级号： |__|__|

3. 姓名： |__|__|__|__|__|__|

4. 考生号：

|1|6|6|4|__|__|__|__|__|__|__|__|__|__|

5. 填写日期： |2|0|1|6| 年 |__| 月 |__|__| 日

C 部分：大学和专业信息（续）

- **课题组根据 2014 年全国大学生就业调查数据，计算了 4 类院校本科毕业生的平均起薪（年薪），供您参考。**

院校层次	2014 年该类院校本科毕业生起薪（年薪）
985 院校	77000 元
211 院校	58000 元
一般本科院校	44000 元
独立学院、高职高专	36000 元

C1. 课题组还计算了 8 类专业 2014 年本科毕业生的平均起薪（年薪），请见下表。根据上述信息，您的专业选择意愿是否有所变化__________

①是　　② 否

C2. 如果您的专业选择意愿有变化，请按照最愿意（1）选择到最不愿意选择（8）排序：

专业分类	2014 年该类专业本科毕业生起薪（年薪）	您的意愿排序（1=最愿意；8=最不愿意）
1. 文学、历史学、哲学	47000 元	
2. 经济学、管理学	50000 元	
3. 法学、教育学	50000 元	
4. 理学	45000 元	
5. 工学	51000 元	
6. 医学	42000 元	
7. 农学	55000 元	
8. 军事学、艺术学	40000 元	

C3. 下面的第 1、2 组高校位于福建省，第 3、4 组位于辽宁省，第 5 组位于宁夏回族自治区，你觉得它们中间哪些更好，请根据第一印象为它们排序（填写序号即可）：

第 1 组：____________________

①福州大学 ②华东大学 ③福建学院 ④宁德大学 ⑤闽南学院 ⑥闽江大学

第 2 组：____________________

①华东理工学院 ②福州理工大学 ③宁德理工学院 ④福建理工大学 ⑤闽南理工大学 ⑥闽江理工学院

第 3 组：____________________

①辽东学院 ②大连大学 ③东北大学 ④沈阳大学 ⑤辽宁大学

第 4 组：____________________

①沈阳理工大学 ②营口理工学院 ③辽宁理工学院 ④大连理工大学

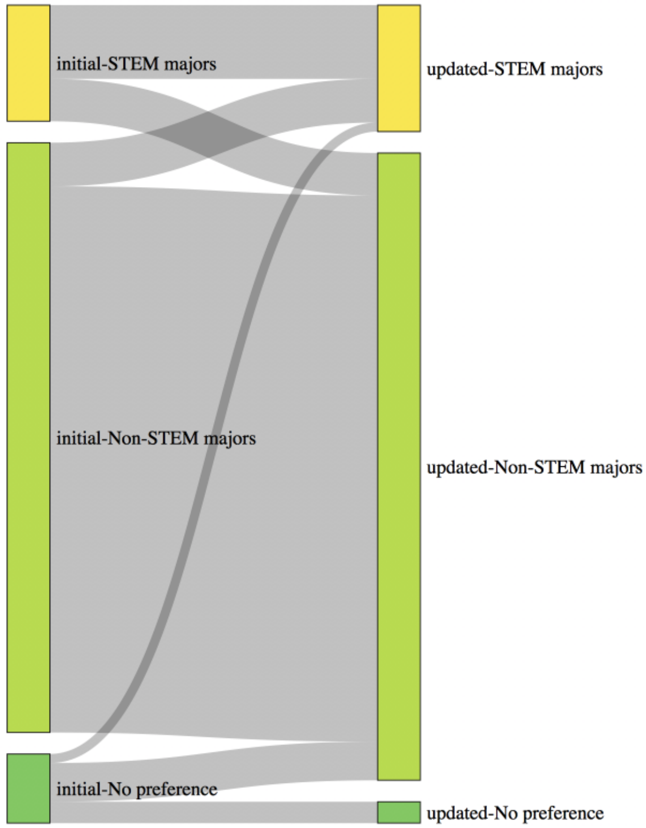
第 5 组：____________________

①宁夏大学 ②银川大学 ③宁夏医科大学 ④北方民族大学 ⑤宁夏理工学院

第 4 页

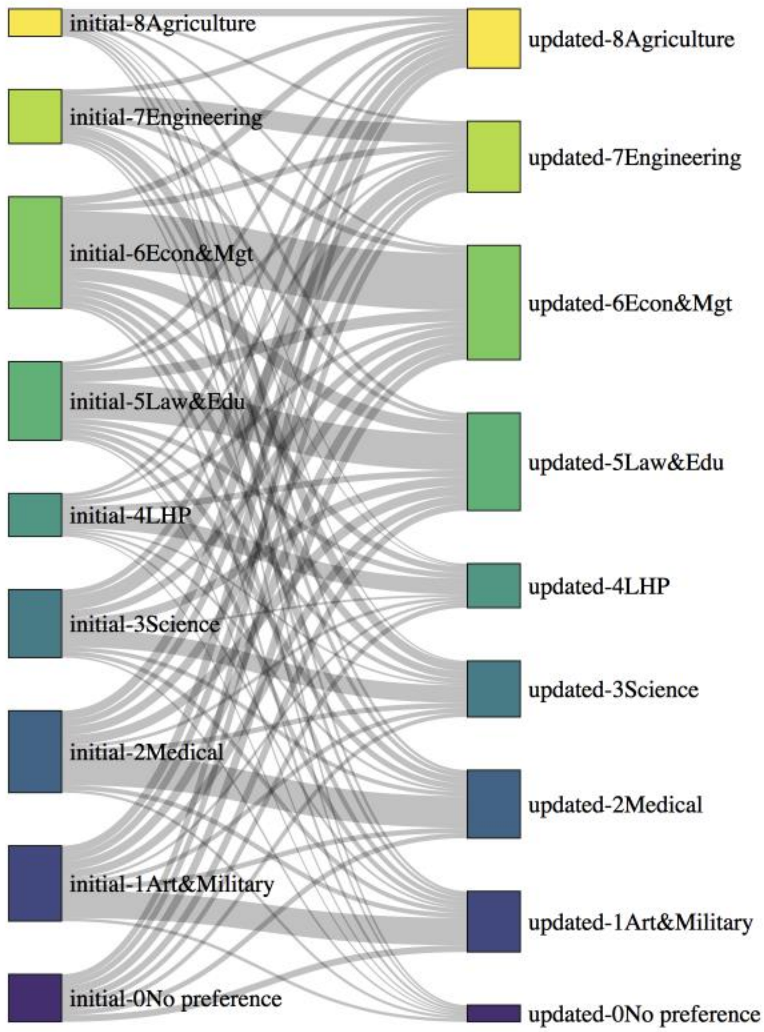
Appendix Figure 2: Screenshots of the survey (in Chinese)

Notes: The left picture shows the cover page of the survey that presents official information to validate the survey administration. The right picture shows how we presented the mean wage information by major and how students reported their updated references (the table in the middle page, by eight major groups).



Appendix Figure 3: Network flows of the changes in first-choice STEM major preferences

Notes: This figure shows the network flows of the changes in first-choice major preferences after the students were presented with the wage information in the survey, collapsed to STEM and non-STEM majors. Lines are weighted by the number of students. Bars are scaled by the share of students in each major group.



Appendix Figure 4: Network flows of the changes in top-3 choices major preferences

Notes: This figure shows the network flows of the changes in top three choices major preferences after the students were presented with the wage information in the survey. Lines are weighted by the number of students. Bars are scaled by the share of students in each major group.

Appendix Table 1: Share of students by major (four-year eligible students)

	Initial Preference		Updated preference		Applications	Admissions
	(1)	(2)	(3)	(4)	(5)	(6)
Agriculture	1.64	1.89	3.87	4.43	1.51	2.10
Engineering	9.64	11.11	12.12	13.86	42.31	43.79
Econ&Mgt	29.16	33.62	30.05	34.36	25.45	24.95
Law&Edu	8.25	9.51	8.35	9.54	5.44	5.61
LHP	5.32	6.13	5.46	6.25	6.40	8.57
Science	11.53	13.29	9.69	11.07	7.85	8.07
Medical	13.56	15.64	11.92	13.63	10.73	6.86
Art&Military	13.26	-	12.52	-	N/A	N/A
No preference	7.65	8.82	6.01	6.87	0.29	0.05
Total	2,013	1,761	2,013	1,746	2,013	1,996

Notes: This table 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. Initial and updated major preferences were measured in the survey, before and after students received the wage information intervention. Applications and Admissions data are from administrative data. Application data are from 50,038 student-college applications for the 2,013 students that each student could apply to about 8 colleges and 6 majors within each college for four-year colleges. Columns (1) and (3) include Art and Military; columns (2) and (4) exclude Art and Military to be consistent with the measures in columns (5) and (6), where we don't have access to data on students' applications and admissions to Art and Military majors. Each year, fewer than 10% of students apply to Art and Military majors through independent admissions channels.

Appendix Table 2: Share of students by major (all students)

	Survey sample preference				2016 Ningxia Admissions	2016 National Admissions
	Initial		Updated			
	(1)	(2)	(3)	(4)	(5)	(6)
Agriculture	2.81	3.35	5.65	6.61	2.21	2.19
Engineering	7.1	8.46	8.71	10.19	38.4	37.05
Econ&Mgt	28.68	34.19	29.76	34.81	26.57	27.97
Law&Edu	8.46	10.09	8.96	10.48	6.24	5.62
LHP	5.49	6.54	5.3	6.2	11.21	11.35
Science	8.52	10.16	7.35	8.59	8.29	7.42
Medical	14.73	17.56	13.35	15.62	6.75	8.28
Art&Military	16.12	-	14.51	-	N/A	0.13*
No preference	8.09	9.64	6.42	7.51	0.32	
Total	4,846	4,065	4,846	4,143	23,618	3,095,529

Notes: This table compares the share of students by major in the full 2016 Ningxia survey data (students may not be eligible to apply to four-year college) and in the total four-year college admissions in Ningxia and all over the country. Columns (1) and (3) include Art and Military; columns (2) and (4) exclude Art and Military to be consistent with the measures in columns (5) and (6), where we don't have access to data on students' applications and admissions to Art and Military majors. Each year, fewer than 10% of students apply to Art and Military majors through independent admissions channels. * only includes students in Art majors.

Appendix Table 3: Gender gap in STEM major choice using the non-treated sample

	Outcome: Admitted to a STEM major					Outcome: Choose a STEM major				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Female	-0.319***	-0.203***	-0.201***	-0.199***	-0.193***	-0.309***	-0.205***	-0.204***	-0.133***	-0.126***
	(0.012)	(0.011)	(0.011)	(0.015)	(0.016)	(0.008)	(0.009)	(0.010)	(0.014)	(0.015)
Female*Science				0.028*	0.045**				0.085***	0.088***
				(0.014)	(0.017)				(0.010)	(0.009)
Science score				0.008	0.003				-0.072***	-0.065***
				(0.011)	(0.013)				(0.013)	(0.010)
Female*Math					0.025**					0.023**
					(0.011)					(0.009)
Math score					0.008					-0.011
					(0.012)					(0.013)
Minority	-0.110***	-0.090***	-0.087***	-0.080***	-0.071***	-0.171***	-0.120***	-0.108***	-0.099***	-0.094***
	(0.011)	(0.009)	(0.010)	(0.010)	(0.010)	(0.014)	(0.008)	(0.006)	(0.007)	(0.007)
Rural	-0.008	0.000	0.002	0.000	0.000	0.000	0.007	0.017***	0.015***	0.015***
	(0.022)	(0.010)	(0.009)	(0.009)	(0.009)	(0.015)	(0.008)	(0.005)	(0.005)	(0.005)
Age		-0.010	-0.011	-0.011	-0.011		-0.005	-0.004	-0.005	-0.005
		(0.010)	(0.010)	(0.010)	(0.010)		(0.007)	(0.008)	(0.007)	(0.007)
CEE score		0.087***	0.095***	0.063***	0.025		0.082***	0.092***	0.043***	0.023
		(0.017)	(0.016)	(0.019)	(0.023)		(0.010)	(0.008)	(0.012)	(0.016)
STEM track		0.442***	0.448***	0.449***	0.451***		0.407***	0.415***	0.408***	0.409***
		(0.014)	(0.014)	(0.014)	(0.014)		(0.012)	(0.012)	(0.012)	(0.012)
Constant	0.609***	0.161***	0.148***	0.147***	0.139***	0.615***	0.158***	0.130***	0.098***	0.092***
	(0.013)	(0.016)	(0.018)	(0.021)	(0.022)	(0.014)	(0.012)	(0.015)	(0.016)	(0.016)
School FE	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes
Observations	13,718	13,718	13,718	13,718	13,718	10,886	10,886	10,886	10,886	10,886
R-squared	0.120	0.284	0.289	0.289	0.290	0.282	0.546	0.554	0.561	0.561

Notes: 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 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 did not receive any treatments 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%.

Appendix Table 4: Gender gap in Engineering major choice

	Outcome: Admitted to an Engineering major					Outcome: Choose an Engineering major				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Female	-0.329***	-0.239***	-0.238***	-0.245***	-0.242***	-0.322***	-0.242***	-0.241***	-0.182***	-0.179***
	(0.015)	(0.016)	(0.016)	(0.020)	(0.020)	(0.017)	(0.020)	(0.020)	(0.028)	(0.028)
Female*Science				0.007	0.009				-0.059***	-0.047***
				(0.012)	(0.014)				(0.021)	(0.015)
Science score				-0.011	-0.009				0.060***	0.049***
				(0.016)	(0.017)				(0.012)	(0.012)
Female*Math					-0.003					-0.018
					(0.016)					(0.020)
Math score					0.010					0.003
					(0.016)					(0.014)
Minority	-0.097***	-0.072***	-0.067***	-0.069***	-0.067***	-0.153***	-0.100***	-0.087***	-0.083***	-0.086***
	(0.016)	(0.013)	(0.012)	(0.012)	(0.013)	(0.016)	(0.011)	(0.009)	(0.009)	(0.010)
Rural	-0.033**	0.002	0.011	0.011	0.011	-0.041**	0.001	0.007	0.007	0.007
	(0.014)	(0.012)	(0.012)	(0.012)	(0.012)	(0.016)	(0.007)	(0.004)	(0.004)	(0.004)
Age		-0.004	-0.008	-0.008	-0.008		-0.001	-0.002	-0.003	-0.003
		(0.011)	(0.011)	(0.011)	(0.011)		(0.009)	(0.008)	(0.008)	(0.008)
CEE score		0.048***	0.047**	0.054**	0.044*		0.080***	0.081***	0.052**	0.063**
		(0.016)	(0.018)	(0.022)	(0.022)		(0.012)	(0.012)	(0.019)	(0.025)
STEM track		0.338***	0.342***	0.342***	0.343***		0.318***	0.321***	0.317***	0.317***
		(0.020)	(0.022)	(0.022)	(0.022)		(0.021)	(0.023)	(0.023)	(0.023)
Constant	0.544***	0.205***	0.199***	0.203***	0.201***	0.555***	0.167***	0.157***	0.127***	0.127***
	(0.017)	(0.020)	(0.027)	(0.029)	(0.029)	(0.020)	(0.018)	(0.020)	(0.024)	(0.022)
School FE	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes
Observations	7,627	7,627	7,627	7,627	7,627	5,874	5,874	5,874	5,874	5,874
R-squared	0.143	0.253	0.258	0.258	0.258	0.335	0.529	0.537	0.542	0.542

Notes: This table estimates the gender gap in Engineering major choice, measured by their applications and admissions to an Engineering major in the centralized college admissions process, using 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%.

Appendix Table 5: Explaining the gender gap in the changes of first-choice major preferences

	Change first-choice major				Change to a STEM major			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	-0.029*	-0.028*	-0.028	-0.030*	-0.079***	-0.071***	-0.072***	-0.075***
	(0.016)	(0.017)	(0.017)	(0.017)	(0.012)	(0.011)	(0.012)	(0.012)
Female*Science		-0.020	-0.019	-0.019		0.056***	0.055***	0.057***
		(0.024)	(0.024)	(0.025)		(0.018)	(0.018)	(0.019)
Science score		0.032	0.030	0.026		-0.048***	-0.047***	-0.046***
		(0.022)	(0.022)	(0.023)		(0.014)	(0.014)	(0.016)
Female*Math		0.012	0.010	0.005		-0.008	-0.008	-0.006
		(0.024)	(0.024)	(0.025)		(0.013)	(0.013)	(0.015)
Math score		-0.056**	-0.055**	-0.059**		0.034**	0.034**	0.035**
		(0.026)	(0.026)	(0.027)		(0.015)	(0.015)	(0.016)
Minority	0.004	-0.000	0.000	-0.004	-0.014	-0.003	-0.003	0.004
	(0.021)	(0.022)	(0.022)	(0.025)	(0.012)	(0.012)	(0.013)	(0.014)
Rural	0.025	0.026*	0.026*	0.030*	0.011	0.010	0.010	0.011
	(0.016)	(0.015)	(0.015)	(0.018)	(0.010)	(0.010)	(0.010)	(0.011)
Age	-0.023	-0.026	-0.026	-0.027	0.006	0.005	0.004	0.002
	(0.019)	(0.019)	(0.019)	(0.022)	(0.013)	(0.013)	(0.013)	(0.014)
CEE score	-0.013	0.005	0.008	0.015	0.022***	-0.021	-0.018	-0.026
	(0.012)	(0.031)	(0.032)	(0.033)	(0.007)	(0.018)	(0.019)	(0.018)
STEM	-0.320***	-0.325***	-0.321***	-0.322***	-0.050***	-0.032**	-0.031*	-0.021
	(0.021)	(0.026)	(0.028)	(0.033)	(0.012)	(0.015)	(0.016)	(0.017)
Major is important			0.013	0.017			0.017*	0.020**
			(0.015)	(0.016)			(0.009)	(0.009)
Has a target college			-0.011	-0.007			-0.006	-0.006
			(0.015)	(0.016)			(0.010)	(0.010)
Has a target major			-0.014	-0.022			0.005	0.007
			(0.016)	(0.016)			(0.010)	(0.010)
Poor family				0.024				-0.027**
				(0.020)				(0.011)
Class FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Parental Edu	No	No	No	Yes	No	No	No	Yes
Constant	0.634***	0.642***	0.643***	0.688***	0.158***	0.137***	0.126***	0.115***
	(0.033)	(0.033)	(0.036)	(0.059)	(0.019)	(0.019)	(0.022)	(0.030)
Observations	4,844	4,844	4,844	4,424	4,844	4,844	4,844	4,424
R-squared	0.130	0.131	0.132	0.135	0.098	0.101	0.102	0.110

Notes: This table explores the potential mechanisms of the gender gap in the changes of first-choice major preferences, using a Linear Probability Model similar to that in Table 6, but with additional controls. Columns (1) and (5) control for high school class fixed effects to rule out school contextual differences. Columns (2) and (6) control for relative ability differences by adding math and STEM composite scores in the College Entrance Exam. 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, relative ability, preference heterogeneity, and family background do not explain the gender difference in the responses to the wage information intervention. Standard errors are clustered at high school classes. Results are robust to clustering at high schools. * significant at 10%, ** significant at 5%, *** significant at 1%.