ANNENBERG
BROWN UNIVERSITY

EdWorkingPaper No. 21-395

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

Yanqing Ding
Peking University

Wei Li
University of Florida

Xin Li
UCLA

Yinduo Wu
Peking University

Jin Yang
Peking University

Xiaoyang Ye
Brown University

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.

VERSION: May 2021

Suggested citation: Ding, Yanqing, Wei Li, Xin Li, Yinduo Wu, Jin Yang, and Xiaoyang Ye. (2021). Heterogeneous Major Preference for Extrinsic Incentives: The Effects of Wage Information on the Gender Gap in STEM Major Choice. (EdWorkingPaper: 21-395). Retrieved from Annenberg Institute at Brown University: https://doi.org/10.26300/ffz9-4v57

Heterogeneous Major Preference for Extrinsic Incentives: The Effects of Wage Information on the Gender Gap in STEM Major Choice[1]

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

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: major choice; STEM gender gap; informational intervention; preference heterogeneity

---

[1] Please direct questions to Xiaoyang Ye, xiaoyang.ye@brown.edu, Annenberg Institute for School Reform, Brown University. We thank Will Doyle (the editor), two anonymous referees, Sarah Cannon, Di Xu, and participants at AEFP and China Education Finance Annual Meeting for their insightful comments, Wei Li (Ningxia University), Bingqing Dai and Wei Geng (Ningxia Department of Education) for their extraordinary effort in initiating the project, a team of research assistants (Si Chen, Honghui Li, Fengming Lu, Le Kang, Qiongqiong Wang) and partners for the Bright Future of China Project. We also thank the Institute of Economics of Education at Peking University and Ningxia Department of Education for providing the data used in this paper. This project would simply not have been possible without approval and collaboration from Ningxia Department of Education. Yan Zhang has been a great help with data. This research was made possible with generous funding from China NSF (71613013) and China Ministry of Education (16JJD880001). The research was approved by the University of Michigan IRB (HUM00127559). Equal authorship applies. All errors and omissions are our own.

Introduction

The gender gap in STEM majors (science, technology, engineering, and mathematics) remains a persistent policy problem in higher education (Griffith, 2010; Rask, 2010; Ganley et al., 2018; Kugler et al., 2017). 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 (Chipman & Thomas, 1987; Turner & Bowen, 1999; Simpson, 2001; Bobbitt-Zeher, 2007; Mann & DiPrete, 2013; Zafar, 2013; Gemici & Wiswall, 2014; Speer, 2017). 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 (Griffith, 2010; Riegle-Crumb & King, 2010; Wang, 2013; Watt et al., 2012; Cheryan et al., 2017; Speer, 2020). 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 (Arcidiacono et al., 2012; Acton, 2020; Hurwitz & Smith, 2018; Han & Winters, 2020), but many students underestimate the benefits of education (Jensen, 2010; Hastings et al., 2015). Existing research finds that female students are less responsive to wage information (Montmarquette et al., 2002; Freeman & Hirsch, 2008; Long et al., 2015; 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; Gemici & Wiswall, 2014; Cheryan et al., 2017).

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 (Beffy et al., 2012; Arcidiacono et al., 2020), 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; Wiswall & Zafar, 2021). This gender gap might be from two sources: students have different predictions of future earnings due to lack of information (Wiswall & Zafar, 2015; Page

& Scott-Clayton, 2016), students have heterogeneous preferences for different majors (Arcidiacono, 2004; Zafar, 2013; Gemici & Wiswall, 2014; Reuben et al., 2017). 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 if 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., Long, 2004; Perna, 2006; Jacob et al., 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 et al., 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 et al., 2012; Wiswall & Zafar, 2014; Kim et al., 2015). 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 (Hastings et al., 2016; Bordón et al., 2020). 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 & 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 $4,000 (national average: $5,000; Shanghai: $8,000), and the per capita disposable income of its 65% population in rural areas was less than $1,500 (national average: $2,000; Shanghai: $3,500). 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 Appendix Figure 1, each school implemented the survey in a 20-minute 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 (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 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 desing 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 (Wiswall & Zafar, 2015; Baker et al., 2018). Moreover, we ocused on a single factor of the labor market outcomes, students may respond to other labor market information such as employment rate, wage uncentatity, 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, 8,243 students responded to the survey. We excluded students with missing or incorrect student IDs that could not be matched to the administrative data (1,345), and those not in academic tracks (e.g., athletes or CTE; 1,214). 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 4,844 surveyed students who 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. Prior to the information intervention, Economics and Management were the most preferred majors while Agriculture was the least preferred major.

Students were more likely to choose Agriculture, Engineering, Economics and Management, Law and Education, and LHP, but less likely 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 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:

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

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, 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 (Mouganie & Wang, 2020; Card & Payne), 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), 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 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 (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 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 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 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 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 increase their preferences for Agriculture majors, which has the highest mean starting wage. Appendix Figure 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 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 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 (Kahn & Ginther, 2017; Kugler et al, 2017; Ganley et al, 2018).

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 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 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 equation (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.

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, Table 7 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. 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.

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=1,555) 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 Table 4 and Table 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: 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:

$$Post\_STEM_{ij} = \beta_0 + \beta_1 Female_{ij} + \beta_2 Belief_{ij} * + \beta_3 Female_{ij} * Belief_{ij}$$

$$+ \pi Pre\_STEM_{ij} + \mathrm{X_{ij}}\Gamma + \delta_j + \varepsilon_{ij}, \qquad (3)$$

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 $\mathrm{X_{ij}}$, 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).

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 (Denning & Turley, 2017; Evans, 2017; Castleman et al., 2018; Fricke et al., 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.

References

Acton, R. (2020). Community college program choices in the wake of local job losses. *Journal of Labor Economics*.

Altonji, J. G., Arcidiacono, P., & Maurel, A. (2016). The analysis of field choice in college and graduate school: Determinants and wage effects. In *Handbook of the Economics of Education* (Vol. 5, pp. 305-396). Elsevier.

Arcidiacono, P. (2004). Ability sorting and the returns to college major. *Journal of Econometrics, 121*(1-2), 343-375.

Arcidiacono, P., Hotz, V. J., & Kang, S. (2012). Modeling college major choices using elicited measures of expectations and counterfactuals. *Journal of Econometrics*, *166*(1), 3-16.

Arcidiacono, P., Hotz, V. J., Maurel, A., & Romano, T. (2020). Ex ante returns and occupational choice. *Journal of Political Economy*, *128*(12), 4475-4522.

Baker, R., Bettinger, E., Jacob, B., & Marinescu, I. (2018). The effect of labor market information on community college students' major choice. *Economics of Education Review*, *65*, 18-30.

Beffy, M., Fougere, D., & Maurel, A. (2012). Choosing the field of study in postsecondary education: Do expected earnings matter?. *Review of Economics and Statistics, 94*(1), 334-347.

Berger, M. C. (1988). Predicted future earnings and choice of college major. *ILR Review, 41*(3), 418-429.

Blagg, K., Chingos, M. M., Graves, C., & Nicotera, A. (2017). *Rethinking consumer information in higher education.* Urban Institute.

Bobbitt-Zeher, D. (2007). The gender income gap and the role of education. *Sociology of Education, 80*(1), 1-22.

Bordón, P., & Fu, C. (2015). College-major choice to college-then-major choice. *Review of Economic Studies, 82*(4), 1247-1288.

Bordón, P., Canals, C., & Mizala, A. (2020). The gender gap in college major choice in Chile. *Economics of Education Review, 77*, 102011.

Breske, S., Koedel, C., & Parsons, E. (2019). Field interest and the choice of college major. *Working Paper*.

Buckles, K. (2019). Fixing the leaky pipeline: Strategies for making Economics work for women at every stage. *Journal of Economic Perspectives, 33*(1), 43-60.

Card, D., & Payne, A. A. (2021). High school choices and the gender gap in STEM. *Economic Inquiry*, *59*(1), 9-28.

Castleman, B. L., Long, B. T., & Mabel, Z. (2018). Can financial aid help to address the growing need for stem education? The effects of need-based grants on the completion of Science, Technology, Engineering, and Math courses and degrees. *Journal of Policy Analysis and Management*, *37*(1), 136-166.

Cheryan, S., Ziegler, S. A., Montoya, A. K., & Jiang, L. (2017). Why are some STEM fields more gender balanced than others?. *Psychological bulletin*, *143*(1), 1-35.

Chipman, S. F., & Thomas, V. G. (1987). The participation of women and minorities in mathematical, scientific, and technical fields. *Review of Research in Education, 14*(1), 387-430.

Conlon, J. J. (2019). Major malfunction: A field experiment correcting undergraduates' beliefs about salaries. *Journal of Human Resources*, 0317-8599R2.

Crisp, G., Nora, A., & Taggart, A. (2009). Student characteristics, pre-college, college, and environmental factors as predictors of majoring in and earning a STEM degree: An analysis of students attending a Hispanic Serving Institution. *American Educational Research Journal*, *46*(4), 924.

Denning, J. T., & Turley, P. (2017). Was that SMART? Institutional financial incentives and field of study. *Journal of Human Resources*, *52*(1), 152-186.

Evans, B. J. (2017). SMART money: Do financial incentives encourage college students to study science?. *Education Finance and Policy*, *12*(3), 342-368.

Freeman, J. A., & Hirsch, B. T. (2008). College majors and the knowledge content of jobs. *Economics of Education Review*, *27*(5), 517-535.

Fricke, H., Grogger, J., & Steinmayr, A. (2018). Exposure to academic fields and college major choice. *Economics of Education Review, 64*, 199-213.

Ganley, C. M., George, C. E., Cimpian, J. R., & Makowski, M. B. (2018). Gender equity in college majors: Looking beyond the STEM/non-STEM dichotomy for answers regarding female participation. *American Educational Research Journal, 55*(3), 453-487.

Gemici, A., & Wiswall, M. (2014). Evolution of gender differences in post-secondary human capital investments: College majors. *International Economic Review, 55*(1), 23-56.

Griffith, A. L. (2010). Persistence of women and minorities in STEM field majors: Is it the school that matters?. *Economics of Education Review, 29*(6), 911-922.

Gurantz, O., Howell, J., Hurwitz, M., Larson, C., Pender, M., & White, B. (2020). A national-level informational experiment to promote enrollment in selective colleges. *Journal of Policy Analysis and Management*.

Han, L., & Winters, J. V. (2020). Industry fluctuations and college major choices: Evidence from an energy boom and bust. *Economics of Education Review*, *77*, 101996.
Hastings, J., Neilson, C. A., & Zimmerman, S. D. (2015). *The effects of earnings disclosure on college enrollment decisions* (No. w21300). National Bureau of Economic Research.
Hastings, J. S., Neilson, C. A., Ramirez, A., & Zimmerman, S. D. (2016). (Un) informed college and major choice: Evidence from linked survey and administrative data. *Economics of Education Review, 51*, 136-151.
Hurwitz, M., & Smith, J. (2018). Student responsiveness to earnings data in the College Scorecard. *Economic Inquiry*, *56*(2), 1220-1243.
Jacob, B., McCall, B., & Stange, K. (2018). College as country club: Do colleges cater to students' preferences for consumption?. *Journal of Labor Economics, 36*(2), 309-348.
Jensen, R. (2010). The (perceived) returns to education and the demand for schooling. *The Quarterly Journal of Economics, 125*(2), 515-548.
Kahn, S., & Ginther, D. (2017). *Women and STEM* (No. w23525). National Bureau of Economic Research.
Kanny, M. A., Sax, L. J., & Riggers-Piehl, T. A. (2014). Investigating forty years of STEM research: How explanations for the gender gap have evolved over time. *Journal of Women and Minorities in Science and Engineering, 20*(2), 127-148.
Kerr, S. P., Pekkarinen, T., Sarvimäki, M., & Uusitalo, R. (2020). Post-secondary education and information on labor market prospects: A randomized field experiment. *Labour Economics*, *66*, 101888.
Kesar, S. (2017). *Closing the STEM Gap: Why STEM Classes and Career Still Lack Girls and What We Can Do About it*. Microsoft.
Kim, C., Tamborini, C. R., & Sakamoto, A. (2015). Field of study in college and lifetime earnings in the United States. *Sociology of Education, 88*(4), 320-339.
Kinsler, J., & Pavan, R. (2015). The specificity of general human capital: Evidence from college major choice. *Journal of Labor Economics, 33*(4), 933-972.
Krussig, T., & Neilson, C. (2021). The rise of centralized choice and assignment mechanisms in education markets around the world. *Working paper.*
Kugler, A. D., Tinsley, C. H., and Ukhaneva, O. (2017). *Choice of majors: Are women really different from men?* (No. w23735). National Bureau of Economic Research.
Loewenstein, G., Sunstein, C. R., & Golman, R. (2014). Disclosure: Psychology changes everything. *Annual Review of Economics, 6*(1), 391-419.
Long, B. T. (2004). How have college decisions changed over time? An application of the conditional logistic choice model. *Journal of Econometrics, 121*(1-2), 271-296.
Long, M. C., Goldhaber, D., & Huntington-Klein, N. (2015). Do completed college majors respond to changes in wages?. *Economics of Education Review*, *49*, 1-14.
Mabel, Z., Libassi, C. J., & Hurwitz, M. (2020). The value of using early-career earnings data in the College Scorecard to guide college choices. *Economics of Education Review*, *75*, 101958.
Mann, A., & DiPrete, T. A. (2013). Trends in gender segregation in the choice of science and engineering majors. *Social Science Research, 42*(6), 1519-1541.
McNally, S. (2020). Gender differences in tertiary education: what explains STEM participation. *IZA Policy Paper No. 165.*
Melguizo, T., & Wolniak, G. C. (2012). The earnings benefits of majoring in STEM fields among high achieving minority students. *Research in Higher Education, 53*(4), 383-405.
Montmarquette, C., Cannings, K., & Mahseredjian, S. (2002). How do young people choose college majors?. *Economics of Education Review*, *21*(6), 543-556.
Mostafa, T. (2019). Why don't more girls choose to pursue a science career?. *PISA in Focus, No. 93*, OECD Publishing, Paris, https://doi.org/10.1787/02bd2b68-en.
Mouganie, P., & Wang, Y. (2020). High-performing peers and female STEM choices in school. *Journal of Labor Economics*, *38*(3), 805-841.
Page, L. C., & Scott-Clayton, J. (2016). Improving college access in the United States: Barriers and policy responses. *Economics of Education Review, 51*, 4-22.
Rask, K. (2010). Attrition in STEM fields at a liberal arts college: The importance of grades and pre-collegiate preferences. *Economics of Education Review, 29*(6), 892-900.
Patnaik, A., Wiswall, M. J., & Zafar, B. (2020). College majors. *NBER Working Paper w27645.*
Perna, L. W. (2006). Studying college access and choice: A proposed conceptual model. In Higher Education (pp. 99-157). Springer, Dordrecht.

Reuben, E., Wiswall, M., & Zafar, B. (2017). Preferences and biases in educational choices and labour market expectations: Shrinking the black box of gender. *The Economic Journal, 127*(604), 2153-2186.
Riegle-Crumb, C., & King, B. (2010). Questioning a white male advantage in STEM: Examining disparities in college major by gender and race/ethnicity. *Educational Researcher, 39*(9), 656-664.
Simpson, J. C. (2001). Segregated by subject: Racial differences in the factors influencing academic major between European Americans, Asian Americans, and African, Hispanic, and Native Americans*. Journal of Higher Education, 72*(1), 63-100.
Sloane, C., Hurst, E., & Black, D. (2019). A cross-cohort analysis of human capital specialization and the college gender wage gap (No. w26348). National Bureau of Economic Research.
Soldner, M., Rowan-Kenyon, H., Inkelas, K. K., Garvey, J., & Robbins, C. (2012). Supporting students' intentions to persist in STEM disciplines: The role of living-learning programs among other social-cognitive factors. *Journal of Higher Education, 83*(3), 311-336.
Speer, J. D. (2017). The gender gap in college major: Revisiting the role of pre-college factors. *Labour Economics*, *44*, 69-88.
Speer, J. D. (2020). Bye Bye Ms. American Sci: Women and the leaky STEM pipeline. *Working paper.*
Thaler, R. H., & Sunstein, C. R. (2008). *Nudge: Improving decisions about health, wealth, and happiness*. Yale University Press.
Turner, S. E., & Bowen, W. G. (1999). Choice of major: The changing (unchanging) gender gap. *ILR Review, 52*(2), 289-313.
United Nations Educational, Scientific and Cultural Organization. (2015). *UNESCO Science Report: Towards 2030.*
Wang, X. (2013). Why students choose STEM majors: Motivation, high school learning, and postsecondary context of support. *American Educational Research Journal, 50*(5), 1081-1121.
Watt, H. M., Shapka, J. D., Morris, Z. A., Durik, A. M., Keating, D. P., & Eccles, J. S. (2012). Gendered motivational processes affecting high school mathematics participation, educational aspirations, and career plans: A comparison of samples from Australia, Canada, and the United States. *Developmental psychology, 48*(6), 1594.
Wiswall, M., & Zafar, B. (2014). Determinants of college major choice: Identification using an information experiment. *The Review of Economic Studies, 82*(2), 791-824.
Wiswall, M., & Zafar, B. (2015). How do college students respond to public information about earnings?. *Journal of Human Capital, 9*(2), 117-169.
Wiswall, M., & Zafar, B. (2018). Preference for the workplace, investment in human capital, and gender. *The Quarterly Journal of Economics*, *133*(1), 457-507.
Wiswall, M., & Zafar, B. (2020). Human capital investments and expectations about career and family. *Journal of Political Economy.*
World Bank. (2019). *Improving the pathway from school to STEM careers for girls and women*. Retrieved from https://blogs.worldbank.org/opendata/improving-pathway-school-stem-careers-girls-and-women
Xie, Y., & Shauman, K. A. (2003). *Women in Science: Career Processes and Outcomes*. Harvard University Press,
Yue, C. (2015). Expansion and equality in Chinese higher education. *International Journal of Educational Development, 40*, 50-58.
Zafar, B. (2013). College major choice and the gender gap. *Journal of Human Resources, 48*(3), 545-595.

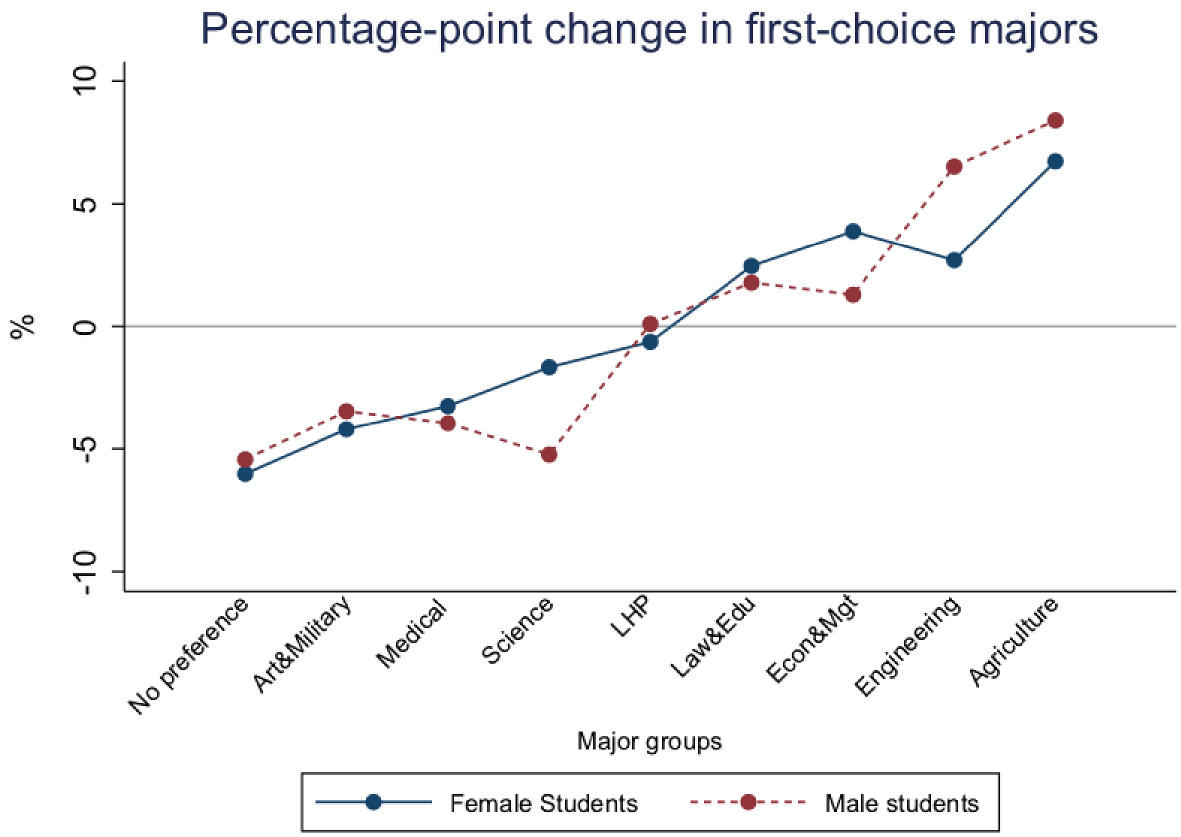


Figure 1: Changes in the share of students with different first-choice major preferences

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 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.

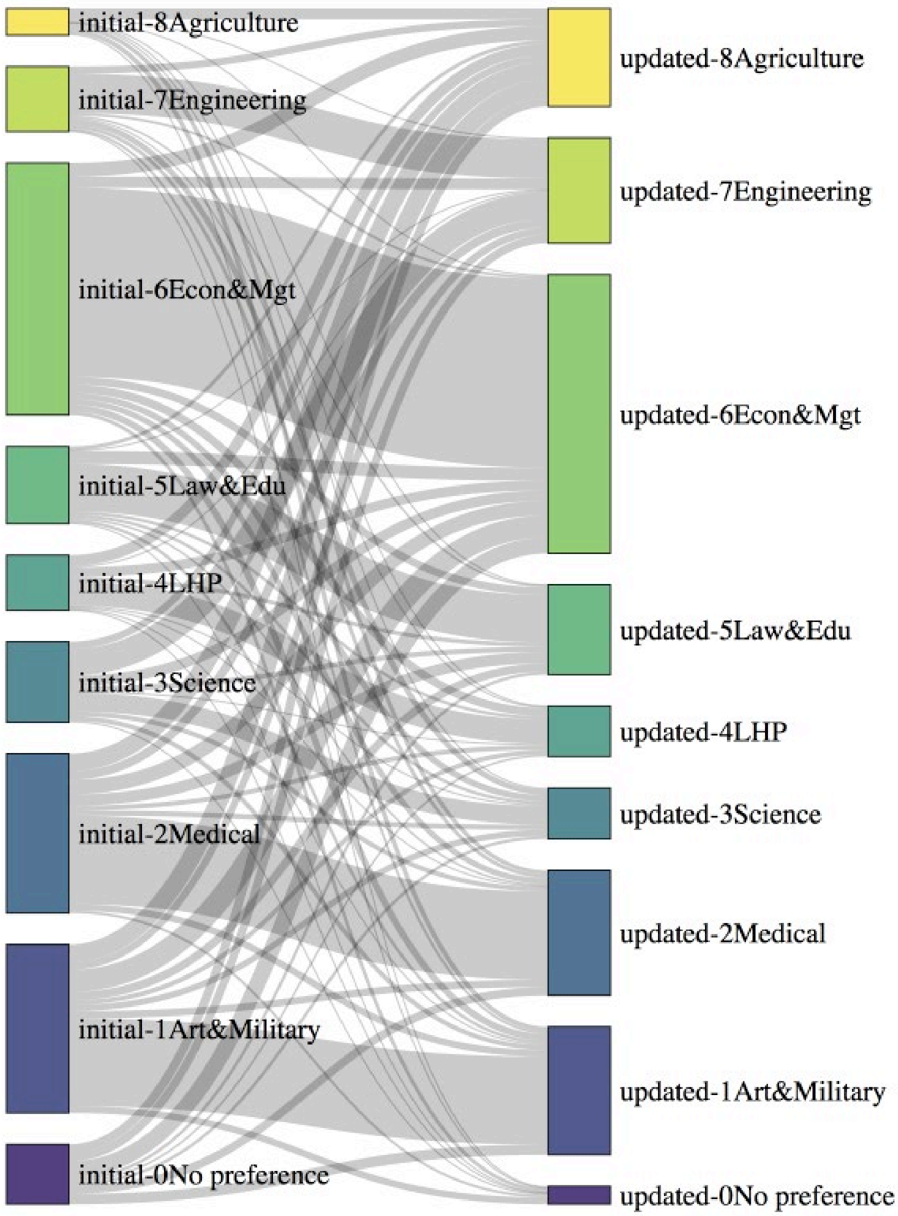
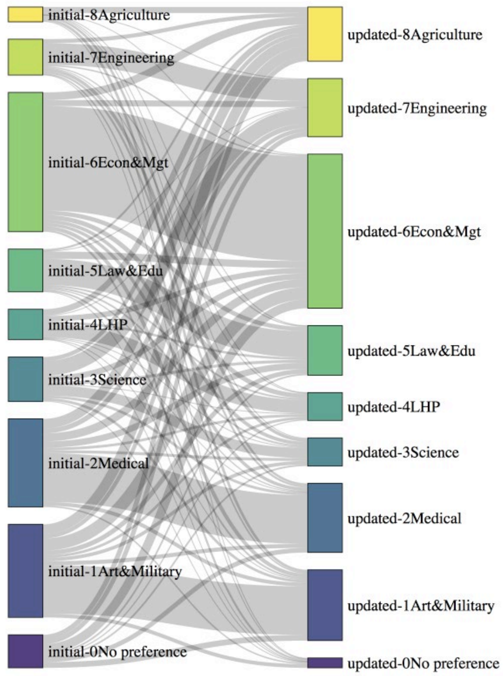


Figure 2: Network flows of the changes in first-choice major preferences

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

A. Female



B. Male

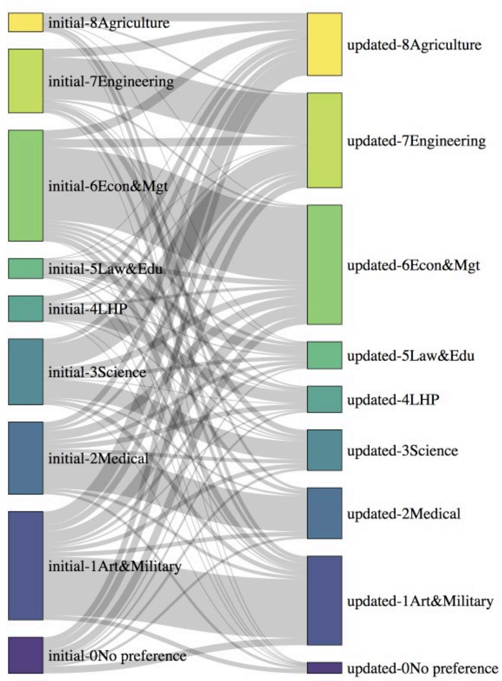


Figure 3: Gender difference in the network flows of the changes in first-choice major preferences

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 diff
	(1)	(2)	(3)	(4)	(5)	(6)
N	4,844	2,711	2,133	11,114	5,065	
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
	[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. 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%.

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

	STEM major (=1)				Engineering major (=1)			
Sample	All	All	Urban	Rural	All	All	Urban	Rural
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	A. Applications (N=11,114; Urban N=5,530; Rural N=5,584)							
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=5,530; Rural N=5,584)							
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*

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 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	4,548	5,763

Notes: 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%.

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

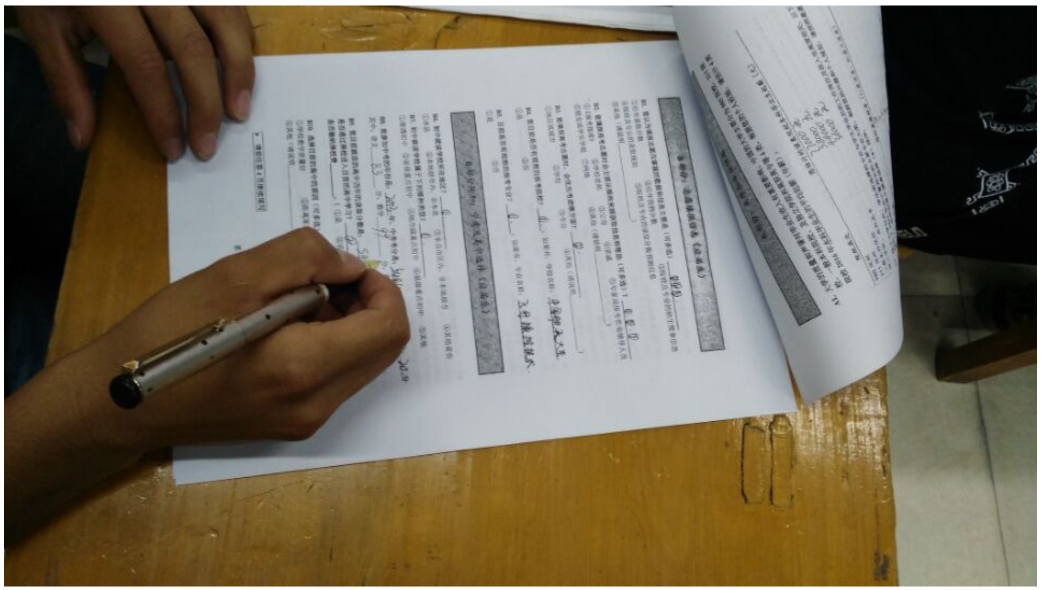
Outcome	Top preference for Engineering (Post) = 1						
Group	All					Lack info=1	Lack info=0
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Top preference for Engineering (Pre)	0.758***	0.728***	0.728***	0.731***	0.728***	0.731***	0.734***
	(0.023)	(0.025)	(0.025)	(0.025)	(0.025)	(0.028)	(0.051)
Female	-0.081***	-0.066***	-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)
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	1,555	1,555	1,555	1,555	1,138	417
R-squared	0.535	0.551	0.551	0.552	0.552	0.547	0.568

Notes: 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%.

Heterogeneous major preferences 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

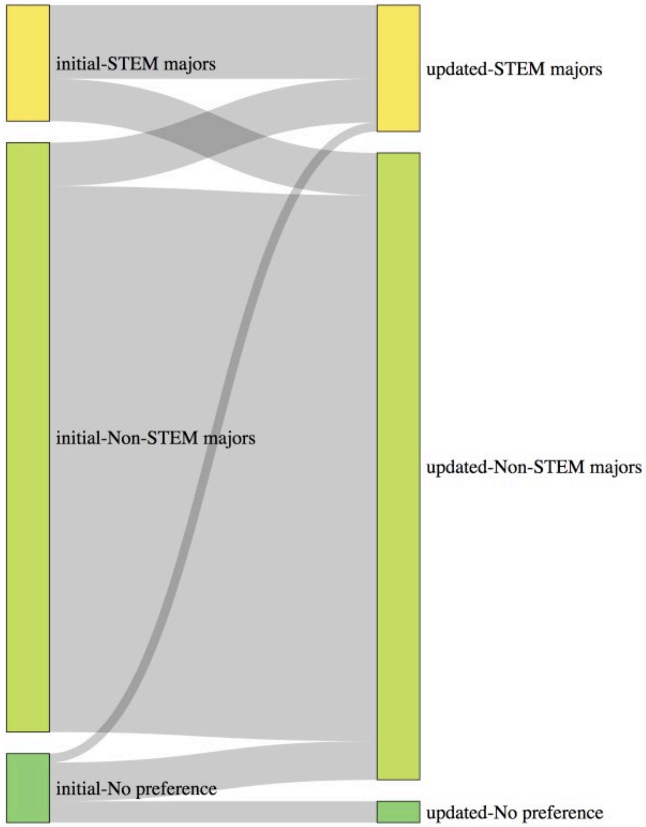
第 5 组：______________________________

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

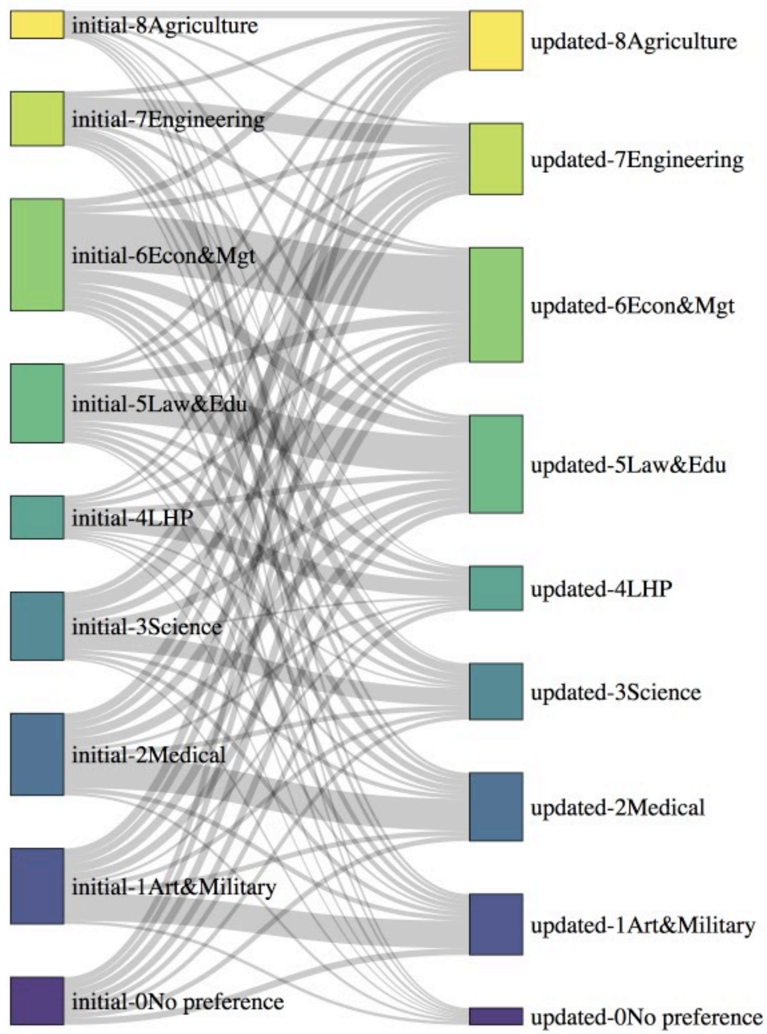
Appendix Figure 2: Screenshots of the survey (in Chinese)

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
Economics & Management	29.16	33.62	30.05	34.36	25.45	24.95
Law & Education	8.25	9.51	8.35	9.54	5.44	5.61
Literature, History, Philosophy	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
Economics & Management	28.68	34.19	29.76	34.81	26.57	27.97
Law & Education	8.46	10.09	8.96	10.48	6.24	5.62
Literature, History, Philosophy	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	4,844	4,065	4,844	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: 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%.

Appendix Table 6: Gender gap in major preference among four-year college eligible students

	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	-0.090***	-0.190***	-0.070***	-0.050***	-0.101***	-0.272***	-0.078***	-0.057**
	(0.015)	(0.027)	(0.011)	(0.017)	(0.021)	(0.039)	(0.014)	(0.027)
Female*Science		-0.055***		-0.013		-0.113***		-0.034
		(0.019)		(0.017)		(0.036)		(0.032)
Science score		0.014		0.011		0.018		0.013
		(0.022)		(0.020)		(0.036)		(0.034)
Female*Math		-0.094***		0.023		-0.090***		0.057*
		(0.021)		(0.019)		(0.023)		(0.030)
Math score		0.069***		-0.014		0.051*		-0.030
		(0.021)		(0.019)		(0.027)		(0.026)
Covariates	No	Yes	No	Yes	No	Yes	No	Yes
Class FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	1,965	1,965	1,965	1,965	1,182	1,182	1,182	1,182
R-squared	0.048	0.290	0.024	0.098	0.061	0.314	0.027	0.097

Notes: The sample includes all first-time high school graduates who completed the survey and were eligible for four-year college applications. 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. Covariates include race, rural, age, CEE score, and STEM track indicator. Standard errors are clustered at high school classes. * significant at 10%, ** significant at 5%, *** significant at 1%.

Appendix Table 7: 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%.

Appendix Table 8: Gender difference in extrinsic preferences in STEM and economics major choices

Outcome	Salary is one of the incentives for major choice (=1)					
Sample	Students in STEM majors			Students in economics majors		
Group	All	Urban	Rural	All	Urban	Rural
	(1)	(2)	(3)	(4)	(5)	(6)
	A. Without additional controls					
Female	-0.037***	-0.020	-0.049***	0.011	0.011	0.014
	(0.011)	(0.016)	(0.013)	(0.013)	(0.018)	(0.017)
Constant	0.558***	0.610***	0.522***	0.569***	0.614***	0.528***
	(0.008)	(0.012)	(0.009)	(0.014)	(0.016)	(0.017)
	B. With additional controls					
Female	-0.025**	-0.005	-0.036**	0.016	0.019	0.021
	(0.010)	(0.017)	(0.014)	(0.012)	(0.021)	(0.018)
Demographics	Yes	Yes	Yes	Yes	Yes	Yes
College Entrance Exam scores	Yes	Yes	Yes	Yes	Yes	Yes
Elite high school dummy	Yes	Yes	Yes	Yes	Yes	Yes
College fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,092	6,140	8,952	7,752	3,610	4,143

Notes: This table replicates the analyses in columns (1)-(3) of Table 8 using the national college student survey in 2014, separably for the subsample of students in STEM majors and in economics-related majors. Demographics variables include race, age, parental education and occupation, and family SES. Standard errors are clustered at colleges. * significant at 10%, ** significant at 5%, *** significant at 1%.

Appendix Table 9: Poverty gaps in the access to information and guidance of college-major choice

	College information		Major information		Assistance in college choice		Choosing popular majors	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	0.000	-0.000	-0.010	-0.011	0.028***	0.030***	-0.091***	-0.090***
	(0.011)	(0.011)	(0.012)	(0.012)	(0.010)	(0.010)	(0.012)	(0.012)
Rural	-0.067***	-0.060***	-0.064***	-0.055***	-0.048***	-0.042***	0.072***	0.070***
	(0.013)	(0.014)	(0.012)	(0.011)	(0.018)	(0.014)	(0.013)	(0.015)
Female*Rural	0.041**	0.041**	0.027	0.026	0.009	0.010	-0.054***	-0.056***
	(0.019)	(0.020)	(0.016)	(0.017)	(0.017)	(0.016)	(0.017)	(0.018)
Constant	0.243***	0.240***	0.229***	0.225***	0.804***	0.800***	0.199***	0.200***
	(0.008)	(0.008)	(0.008)	(0.009)	(0.010)	(0.009)	(0.010)	(0.009)
Demographics	No	Yes	No	Yes	No	Yes	No	Yes
College Entrance Exam scores	No	Yes	No	Yes	No	Yes	No	Yes
High school fixed effects	No	Yes	No	Yes	No	Yes	No	Yes

Notes: This table shows the poverty gaps in the access to information and guidance of college-major choice between rural students and urban students in the 2020 national high school students survey (N=10,311). Students of class 2020 were asked about their college-major application experiences after they submitted the applications in August and September of 2020. All the outcome variables are dichotomous. “College information” indicates that students knew well about the colleges that they applied to. “Major information” indicates that students knew well about the majors that they applied to. “Choosing popular majors” indicates that students chose popular majors rather than those they were interested in. “Assistance in college choice” indicates that students received assistance from others, including parents, teachers, friends, and for-profit services. Standard errors are clustered at high schools. * significant at 10%, ** significant at 5%, *** significant at 1%.