



DISCUSSION PAPER SERIES

045/26

Stephen versus Stephanie? Does Gender Matter for Peer-to-Peer Career Advice

Warn N. Lekfuangfu, Grace Lordan

Stephen versus Stephanie? Does Gender Matter for Peer-to-Peer Career Advice

Authors

Warn N. Lekfuangfu, Grace Lordan

Reference

JEL Codes: I2, J16, J24

Keywords: Occupational choice, College major choice, Vignette design, Gender, Gender Stereotype, Sorting

Recommended Citation: Warn N. Lekfuangfu, Grace Lordan (2026): Stephen versus Stephanie? Does Gender Matter for Peer-to-Peer Career Advice. RFBerlin Discussion Paper No. 045/26

Access

Papers can be downloaded free of charge from the RFBerlin website: <https://www.rfberlin.com/discussion-papers>

Discussion Papers of RFBerlin are indexed on RePEc: <https://ideas.repec.org/s/crm/wpaper.html>

Disclaimer

Opinions and views expressed in this paper are those of the author(s) and not those of RFBerlin. Research disseminated in this discussion paper series may include views on policy, but RFBerlin takes no institutional policy positions. RFBerlin is an independent research institute.

RFBerlin Discussion Papers often represent preliminary or incomplete work and have not been peer-reviewed. Citation and use of research disseminated in this series should take into account the provisional nature of the work. Discussion papers are shared to encourage feedback and foster academic discussion.

All materials were provided by the authors, who are responsible for proper attribution and rights clearance. While every effort has been made to ensure proper attribution and accuracy, should any issues arise regarding authorship, citation, or rights, please contact RFBerlin to request a correction.

These materials may not be used for the development or training of artificial intelligence systems.

Imprint

RFBerlin

ROCKWOOL Foundation Berlin –
Institute for the Economy
and the Future of Work

Gormannstrasse 22, 10119 Berlin
Tel: +49 (0) 151 143 444 67
E-mail: info@rfberlin.com
Web: www.rfberlin.com



Stephen versus Stephanie? Does Gender Matter for Peer-to-Peer Career Advice

Warn N. Lekfuangfu

Universidad Carlos III de Madrid, IZA, J-PAL, RFBerlin

Grace Lordan

London School of Economics and Political Science

This version: December 2025

Abstract:

Occupational segregation is one of the major causes of the gender pay gap. We probe the possibility that individual beliefs regarding gender stereotypes established in childhood contribute to gendered sorting. Using an experiment with two vignette designs, which was carried out in schools in the UK, we consider whether students aged 15-16 years recommend that a fictitious peer pursue different college majors and career paths simply because of their gender. We find strong evidence that this is the case. The within-majors treatment design shows that our respondents are 11 percentage points more likely to recommend corporate law to a male peer. The across-majors design reveals that students presented with a male fictitious peer tend to recommend degrees that have lower shares of females to males.

Keywords: Vignette design, Gender, Gender Stereotype, Sorting, Occupational choice, College major choice

Acknowledgement: This study received ethical approval from the London School of Economics ethics committee. We thank the editor, Isaac Ehrlich, for useful comments on the manuscript. Lekfuangfu acknowledges financial support by Spanish Ministry of the Economy (grant MDM 2014-0431); Spanish Ministry of Science and Innovation (CEX2021-001181-M; MICIU/AEI/10.13039/501100011033; and RYC2023-043730-I); Comunidad de Madrid (grant numbers S2015/HUM-3444; EPUC3M11 (V PRICIT); H2019/HUM-589).

I. Introduction

Since the 1960s, women have made great progress in the labour market, converging into many occupations that were historically male-dominated; such as law, medicine and accountancy. Despite this convergence, a stubborn gender pay gap remains whereby occupational segregation by gender is a known major cause (Goldin 2014, Bayard et al. 2003, Blau and Kahn 2016). Notably, gender segregation is the most obvious across occupations, for instance, technology and engineering have low shares of women (Zafar 2013, Altonji et al. 2016).¹ Additionally, the sexes remain segregated *within* broad occupational groupings (Goldin and Katz 2011, Goldin 2014, Azmat and Ferrer 2017). For instance, in law, females are more likely to choose civil rights law over corporate; in medicine, females more regularly choose paediatrics over plastic surgery; and in economics, females more commonly pursue health economics as compared to game theory.

Segregation into professional jobs can be partly explained by gender sorting in academic choices (Arcidiacono et al. 2020, Barres, 2006) – including choices over fields of study, and college majors.² Gender differences in earnings expectations, risk preferences, competitiveness, and overconfidence are offered as explanations by economists for why college major choices differ greatly between men and women (Arcidiacono et al. 2020, Reuben, Wiswall and Zafar 2017, Murphy and Weinhardt 2020, Goldin 2014, Zafar 2013).

Separately, several studies have demonstrated that the peer environment in school plays an important role in determining a child's educational choices and future career decisions.³ It follows that if personal beliefs matter for own career choices, then the beliefs held by peers in the school environment can be contagious. That is, it is likely that peers influence each other's beliefs. Previous work in economics suggests this conjecture is true. For instance, Dahl, Løken

¹ In addition, based on the US 2010 sample of the National Survey of College Graduate (NSCG10), gender sorting into different bachelor degree is highly reflective of field of study at advanced degree. Women are more highly represented in education or psychology and less than business, medical, mathematic and STEM advanced degrees (Altonji et al. 2016)

² For a recent review of existing studies on the determinants of college major choices on occupational choices, see Altonji, Arcidiacono and Mural (2016) and Patnaik, Wiswall and Zafar (2020).

³ For literature on educational choices, see Sacerdote (2011) for a review of the evidence of peer effects in education. Selected studies on peer effect on educational choices based on UK data are Battiston et al (2020), Mendolia et al. (2018), Levy et al. (2012), Gibbons and Telhaj (2016) and De Giorgi et al. (2010). For literature on occupational choices, early studies by Solnick (1995) and Billger (2009) exploited the across-school variation (single-sex versus coed) to evaluate the effect of peer's gender composition on college majors. Recent works have exploited idiosyncratic assignment of gender composition in classroom and analyse the peer effect on major choices and labour market outcomes (see e.g., Anelli and Peri (2019) for Italy, Schneeweis and Zweimüller (2012) for Austria, Feld and Zolitz (2017) for the Netherland. In addition, Lavy and Schlosser (2011) look at the effect of gender composition of peer on academic gains and behavioural outcomes among Israeli students.

and Mogstad (2014) provide compelling evidence that social norms, including attitudes towards gender roles, are strongly determined by peer groups.

In this study, we provide further evidence that individual beliefs regarding gender stereotypes matter to high schoolers' perceptions about their academic and career decisions. We achieve this by probing the possibility that children hold a belief that certain college choices – *across* college major choices and *within* college major choices (professional specialties) suit females and suit males differently, holding all else equal. Our approach is to conduct a randomised controlled experiment with high school students. The experiment contains two bundled vignette designs where we assign a random, fictitious friend to each participant and we asked the participants to give advice on the fictitious peer's future career path. In detail, each student is randomly presented with either a male or a female peer who otherwise shares an exactly identical set of characteristics. Our experiment considers the advice given to this fictitious peer on (i) sorting *within* college majors (the first vignette), and (ii) sorting *across* college majors (the second vignette). The random assignment of a fictitious peer allows us to deal with a key estimation challenge in the peer effect literature concerning peer group selection bias. Specifically, we consider whether a sample of UK students aged 15-16 years recommend that a fictitious peer pursue different career paths simply because of their gender. We expect our approach with a non-incentivised, stated belief elicitation method to capture a noisy signal of the true advice these students would give if engaging with a real peer (e.g., Ameriks et al. 2020, Wiswall and Zafar 2018, Mas and Pallais 2017).⁴

For the *within-majors* vignette design, we ask students to make a recommendation between two legal specialities (corporate law and civil rights law). Our focus on the legal profession is driven by the fact that upon entry to the law degrees as well as at graduation, there is an equal representation of males and females in the UK. Therefore, there is no apparent gender sorting across college major choices. Moreover, the choice of specialties allows us to understand better the role that individual beliefs regarding gender stereotypes may play in driving the pay gaps among law graduates thereafter. Notably, corporate law has significantly higher earnings and a larger gender pay gap than civil law, but there is no strong over-representation of men or

⁴ The validity of methods of preference elicitation strongly relies upon the assumption that there is a strong correlation between pre-labour market job preferences and later actual job characteristics. Growing evidence points to the fact that the two approaches of using stated choices or actual choices yield similar preference estimates in a variety of contexts, especially when the hypothetical scenarios are realistic and relevant for the respondents. Wiswall and Zafar (2018, 2021) and Giannola (2022) provide evidence that there is a correlation between stated beliefs and later actual actions, which supports the credibility of our elicitation design.

women in either speciality (UK Solicitor Regulation Authority 2022, Azmat and Ferrer 2017).⁵ This vignette design implies that any gender differences identified in our experiment will reflect an ascribed individual belief regarding gender stereotypes that men belong more in corporate law environments, as it does not reflect the actual gender composition in these legal fields. Thus, our within-majors design seeks to add a potential explanation of gender gaps in career outcomes for a highly educated workforce (see Bertrand, Goldin and Katz 2010, Azmat and Ferrer 2017) as our student participants are less likely to assign a fictitious female peer to corporate law.⁶ The effects captured by our within-majors design reflects the *within-majors* margin of appropriate occupational sorting along the gender lines.

Next, we implemented the *across-majors* vignette design in the second part of the experiment to trace out individual beliefs regarding gender stereotypes that manifest in a peer's recommendation of college major choices. Paired with a fictitious peer who differs only by gender, we elicited the students' advice on an appropriate college major choice for the peer. We derive the outcome variable from translating the college major recommendation into the actual ratio of females to males enrolled in the UK universities that the peer would be exposed to in their college degree.

Together, both vignette designs help assess the extent to which one's attitudes and beliefs towards gender roles transmit to beliefs on how peer groups should behave. Overall, we find robust evidence that gendered recommendations are evoked by the gender of the peer presented. Within the law degree, the students are 11 percentage points (pp.) more likely to recommend corporate law to a fictitious male peer than to a female peer. Moreover, in the across-major design, students presented with a fictitious male peer also recommend degrees that have a share of females to males that is 0.195 units lower approximately (where a ratio =1 implies equal men and women). We also find robust evidence that an intrinsic justification is more likely to be mentioned if the peer is female, and an extrinsic justification if the peer is male. We view this as evidence that there are underlying beliefs among these students that men are better suited to jobs with extrinsic motivations while women are more suited to jobs with intrinsic motivations. Independently, the child's gender also matters when predicting their recommendations, with boys and girls choosing options that are in line with their traditional

⁵ Based on the statistics of regulated law firms in 2019 in England and Wales, 52% of lawyers are females. Women are strongly underrepresented in criminal work, where only 39% lawyers are female. For corporate law, women are slightly under-represented and they make up 46% of the workforce. By contrast, female lawyers are overrepresented in private client work (at 56%).

⁶ Previous experimental evidence for why women underperform and are under-represented in corporate and financial careers despite the equal representative at entry are, for instance, a lack of taste for competition (Niederle and Vesterlund 2007; lower willingness to negotiate for pay and promotion (Babcock and Laschever 2003).

gender roles. However, the interaction between the child's gender and the treatment is never significant and centred around zero, allowing us to conclude that there are no heterogenous treatment effects by gender. We also explore heterogeneity across several other dimensions and find evidence that children who have a father who works long hours are significantly less likely to recommend that a male fictitious peer (i.e., those presented with Stephen or John) pursued careers in corporate law or careers with high shares of men.

Recent contributions present evidence that individual beliefs regarding gender stereotypes likely play a significant role in causing gendered sorting. For example, if engineering and being a CEO are viewed as 'male roles', as argued by Akerlof and Kranton (2000), females experience a loss of identity should they work in one of these occupations.⁷ Studies by Lordan and Pischke (2022), Cortés and Pan (2018), Grove et al. (2011) and Su et al. (2009) emphasise the role of gendered preferences in occupational and college major choice. Preferences can be formed based on social expectations, again implying a role for individual beliefs regarding gender stereotypes in determining important labour market outcomes.

In addition, recent studies on the role of limited information, and subjective beliefs (Rueben et al. 2017, Wiswall and Zafar 2021, Azmat et al. 2020) provide causal evidence for why gender segregation in college major choices and occupational decisions persist. Besides individual beliefs regarding gender stereotypes and beliefs, alternative key explanations of work culture, such as discrimination (Altonji and Blank 1999) and work flexibility (Goldin 2014) are reasons why women avoid certain occupations.⁸ It is possible that children assess these characteristics when giving advice to a peer. For example, to the extent that children are aware of the available flexibility an occupation may give and simultaneously aware that women take on more of the childcare responsibilities, they may be less likely to recommend to a peer an environment where they are exposed to high shares of males.⁹ In sum, we acknowledge this limitation of

⁷ More recent contributions also give evidence that gender norms likely play a significant role in causing gendered sorting. For example, Lordan and Pischke (2022), Cortés and Pan (2018), Grove, Hussey and Jetter (2011) and Su, Rounds, and Armstrong (2009) provide empirical evidence that there is a role for gendered preferences in occupational and college major choice. Together these studies suggest that gender norms, either innate or constructed, determine gendered sorting.

⁸ We note that Becker (1985), Katz and Murphy (1992) and Goldin (2006) have suggested that the effects of gender discrimination are less relevant than other factors when it comes to explaining gender wage gaps and occupational segregation. This is further highlighted by a meta-analysis of the gender wage gap (Jarrell and Stanley, 2004). In addition, we note that firms can increase flexibility to make it easier for females to juggle work and home but a stable equilibrium which tackles the gender pay gap can truly only arise if males undertake a greater proportion of the home-making responsibilities or these are outsourced. Otherwise, males will remain on average more attractive in the labour market, as females will on average have lower attachments, assuming that work experience continues to garner increasing rewards.

⁹ A recent work by Gallen and Wasserman (2021) shows that professional advice given to college students focuses on the work/life balance aspect more when students are female.

our design. We are less able to disentangle own beliefs regarding gender stereotype from other factors embedded within the ‘gender’ (of the fictitious peer and of our participants).

The paper is outlined as follows. Section 2 discusses the experimental design and the procedures of the previous literature. Section 3 outlines the empirical strategy. Section 4 discusses the results, and Section 5 discusses other potential channels and concludes.

II. Study Design

2.1. Experiment Context

We set up an experiment with 2 bundled vignette designs to assess whether the gender of a peer alone would cause UK students to give differential career advice. Two vignette designs are distinct in that they consider the advice given to a peer on: (i) sorting within majors (the first vignette), and (ii) sorting across majors (the second vignette). We recruited two mixed-gender schools in the area of Hertfordshire in England. The students were in Year 11 (about ages 15 – 16). The survey satisfied the ethics committee at the author’s home institution at the London School of Economics and Political Science. Schools were advised of the survey two months ahead of time. The experiment took place in January 2018. The students completed the surveys in an assembly hall on a day when the authors visited the school, accompanied by research assistants. All students who were present on the day participated in both vignettes but were given the option to opt out (and sit silently) or skip any question they like. No identifiable information was gathered and the students were made aware of this before commencing the study. The study design did not offer incentives to the students to participate. Students were allocated 45 minutes to complete the survey.

The two schools produce students who are, on average, of higher ability in final examination results as compared to the average school in England. See Table 1 for a summary of the two school’s characteristics, as compared to the national average.¹⁰ Notice that the performance of students from School A is relatively close to the national average while those from School B

¹⁰ The information in Table 1 is derived from www.compare-school-performance.service.gov.uk. It shows school statistics for the 2019 academic year. *Ofsted rating* is a 4-point grading score used for inspection judgement. Grade 1 is outstanding, grade 2 is good, grade 3 is requiring improvement, and grade 4 is inadequate. In 2019, there were 20% of state-funded schools received grade 1, 66% with grade 2, 10% with grade 3, and 4% with the lowest grade. *Entering EBacc* measures the percentage share of pupils having entered for the English Baccalaureate if they entered for qualifications in English, maths, sciences, a language and either history or geography; *Attainment 8 score* is based on how well pupils have performed in up to 8 qualifications, which include English, maths. English Baccalaureate opens a new set of qualifications including sciences, computer science, history, geography and languages, and other additional approved qualifications. Staying in education or entering employment shows the number of pupils who either stayed in education or went into employment after finishing key stage 4 (after year 11, usually aged 16), covering any sustained education or employment destination.

have superior attainment. This was intentional as we wished to survey a cohort who had equal or a higher propensity to pursue the tertiary level of education as compared to the national average. The students we recruited were in their final General Certificate of Secondary Education (GCSE) year and were 15-16 years old. In England, students who finish their GCSEs either leave school or continue to Advanced Level qualifications (A-levels). Those that continue to A-levels are planning to go to university and will choose a maximum of four subjects to pursue the next year. These choices will affect the degree they can apply for later on.¹¹ Overall, we surveyed 307 students (188 students in School A and 119 students in School B), which is a relatively large subject pool for a controlled, laboratory-type experiment which allows for good confidence with respect to identifying effects. We collected a total of 3 blank questionnaires (which we deem as opt-outs) and we drop four responses who provided no sex information. In total 8 students were absent on the day of the survey. The resulting dataset contains 157 males and 150 females.

2.2. Vignette Design I: Stephen/Stephanie

To consider the potential role perceived gender identity can play in choices within college majors we designed a *Stephen/Stephanie* vignette, which describes a fictitious student who is finishing A-level in the UK (England's high school qualification). Specifically, the experiment describes a student who has focused their studies on Politics, Economics, and English literature. They expect to do very well in their high school exams and have decided to pursue a career in law. However, they do not yet know how they should specialise. The respondent student has been asked to provide guidance to this fictitious peer. The vignette provides a brief description of what both a civil rights and corporate lawyer does on a day-to-day basis, along with some other information on what the student's day-to-day life looks like.

There are two versions of the text which are randomly distributed to the students. The first name of the student is *Stephanie* Williams, and the second is *Stephen* Williams. In all other respects, the fictitious peer is identical (see Appendix A for the full text). This part of the experiment took about five minutes to read and was followed by several questions. Randomization allows us to identify the causal effect of gender identity on the recommended occupational choice given to a fictitious student named either Stephen or Stephanie. The

¹¹ Advanced level qualifications (known as A levels) are subject-based qualifications and it is a main school leaving qualification in England, Wales, Northern Ireland. Students can normally study three or more A levels over two years after the GCSE qualification. Applications to UK higher institutions and universities normally require specific A level subjects and grade achievement.

student is described in a way that makes them a peer of the responder, so we view the responses as advice the student may give to a peer. In addition to the choice elicitation, the respondents were asked to provide justifications for their recommendation in an opened-end statement, which we subsequently exploit in our estimation analysis (see details in the next section).

In deciding on the text to include in this vignette, we decided to include enough narrative to allow the student to visualize their fictitious peer. For instance, we provide short text descriptions of what both civil law and corporate law are about. We choose to focus on law as it has a couple of appealing characteristics. First, law is one of the major professional occupations that women have entered more regularly. Currently, in the UK about 50% of solicitors are female, and more than 60% of students studying law are female.¹² So, the purpose of our experiment is not overtly obvious. Second, within a law degree, there are big disparities in income that depend on speciality, with male lawyers being overrepresented in the highest earning specialties, and in progression to the highest ranks (Beioley 2014). In terms of career advancement in private practice in the UK, 40.2% of male solicitors with Practising Certificates (PCs) holders are partners versus only 29.5% of females, while 75% of males become partners versus 30% of females (Solicitor Regulation Authority 2017). Similarly, the 2014 Gender in the Law Survey (with a breakdown of gender by firm) shows a steady decline of females from trainees (nearly 60% are female) to partners (24% average).

On average, corporate lawyers earn more than civil rights lawyers. In addition, corporate law has a larger gender pay gap as compared to civil rights law. Yet, in none of these cases can the gender pay gaps completely be explained by the area of law or billable hours (Azmat and Ferrer 2017). This raises the question of whether women are less accepted in corporate law in terms of ‘face not fitting’, and this contributes to the gender pay gap. Overall, this implies that any differences in peer recommendations cannot be rationally explained away by the children in the study having a true knowledge that women do not choose either law speciality regularly enough. Rather, it points to a simpler explanation of gender driving any differences in advice received by the fictitious peer.

In the Stephen/Stephanie vignette, we choose to highlight the difference in pay received by corporate lawyers as compared to civil rights lawyers (£100,000 versus £60,000). We also highlight that those who are corporate lawyers will help their company become more profitable. In contrast, we write in the civil rights vignette “Civil rights lawyers will have the personal

¹² <https://www.lawsociety.org.uk/Law-careers/Becoming-a-solicitor/Entry-trends/>

reward of knowing they are helping people who have been wronged.” This is a strategy to emphasise the extrinsic-intrinsic reward trade-off between both of these career choices for our respondents. We do acknowledge that some people might find corporate law personally gratifying, and as a result, experience some additional intrinsic reward.

The subjects we choose for Stephen/Stephanie are Politics, Economics, and English. This is primarily because none of these subjects points in the direction of a particular type of law. Moreover, we flag that Stephen/Stephanie are expected to do very well so that our respondents do not assume a lack of ability causing them to pick one type of law over the others.

In the background section of the instruction, we make Stephen/Stephanie relatable by having them share the same area of residence as the majority of our respondents.¹³ For the parent background for Stephen/Stephanie, their mother is a teacher, which is a profession that the students are naturally exposed to. For the father, we choose a tax lawyer - making it obvious that Stephen/Stephanie are choosing to follow in their father’s footsteps, and solidifying the intuition behind their career choice. In addition, tax law is an area of law that is not related strongly to civil or corporate law. Finally, we emphasise that Stephen/Stephanie hope for a life that aligns with UK society’s dominant narrative of what a successful adult life looks like: to be married with two children (Dolan 2019). We acknowledge that this means that we cannot disentangle a ‘male’ effect from the social norms of the man being a breadwinner in the *Stephen* treatment effects we obtain.

2.3. Vignette Design II: John/Jennifer

We complement the *Stephen/Stephanie* vignette with the *John/Jennifer* vignette, which considers choices *across college majors*. Our causal identification strategy is identical to the *Stephen/Stephanie* vignette, only that this time the respondent randomly meets a fictitious peer named John or Jennifer who are colleagues of Stephen/Stephanie. Note that the two vignette designs are bundled such that students who meet Stephanie in the first vignette will meet John in the second design; and students who meet Stephen in the first vignette will meet Jennifer. In sum, our bundled vignette design has two variations.

In the vignette design when the respondents meet *John*, they read the following text:

“John Collins is a colleague of Stephanie Williams at school. He is taking Economics, Maths, Physics and French for his A levels. He is a straight A student. His mother died when he was very young. His father is a very successful builder. John has many friends. He enjoys

¹³ We are confident in this claim as in England the schools we study have enrolments that are based on the location of the child’s house with respect to its distance to the school.

reading, listening to music and playing computer games. He does not know what to do in university and needs your help [to choose a field of study].”

Subsequently, they are asked two open-ended questions:

- i) State the university degree that they think *John* should consider.
- ii) Say why they recommended that specific degree to *John*.

We intentionally choose two subjects at A level which are STEM (i.e., Maths and Physics), so that students should choose a STEM degree if they are only taking subject choice into account STEM is currently male dominated in England (share of males >85% in all careers). We choose a subject that relates to business (Economics), which is closer to a 50:50 gender split on the entry level but does have a glass ceiling. Finally, French is included as an Arts subject, where college majors and main occupations in the UK (teaching and translating) that utilise this language have high shares of females (HESA 2021).

We let *John*'s father be a builder. This is contrary to the *Stephen/Stephanie* vignette. For this design, we want to minimise any influence from parental occupation on driving the intuition of the pathway that the respondent chooses for their fictitious peer. To remove any maternal role model, we choose for their mother to have died.

We note that the *John/Jennifer* vignette provides much less information to the respondent on their fictitious peer. This is intentional so as to contrast with the *Stephen/Stephanie* vignette, which gives out more details. We believe that this shorter description has two advantages. First, it makes the gender of the fictitious more salient as it is competing with less text. Second, by providing fewer texts, we, in return, provide fewer primes for the respondent, which can potentially disrupt their true response. Nonetheless, we note that this comes with the limitation that the respondent may find it harder to visualise their fictitious peer, and may subsequently put less thought into their response as compared to the *Stephen/Stephanie* vignette.

Table 2 documents the balancing test of observed characteristics of the respondent students across our randomised treatments. In detail, the t-tests assess the differences in means across several characteristics of the child, mainly the respondent's gender, employment status of their mother and a set of variables, which describes the nature of the dad's occupation (see Table notes and below). Overall, we do not find evidence for significance differences at the 5% level of significance. Note however that we find significant difference for the respondent's gender, but at p-value equals 0.054.

III. Empirical Approach

3.1. Data and variable construction

3.1.1. Main outcomes

The coding of the surveys was done independently by two coders hired by one of the authors of this work. They were given unique identifiers of the students, along with survey responses. They were not aware of the vignette bundle the respondent was exposed to when coding. The unique code identifier allowed the authors to map back later the data they produced.¹⁴

The *Stephen/Stephanie* vignette specifically asks the students to (i) choose between corporate law or civil rights law and (ii) justify their answer. Based on (i) we create a binary variable that is assigned equal to 1 if the student chooses corporate law and 0 otherwise. From the justification, we create four binary indicators, which we view as a proxy for the underlying belief that drives the student's choice between corporate and civil rights law. The first variable equals 1 if the justifications given are intrinsic in nature and zero otherwise. Examples of intrinsic responses mention caring, feeling good and happiness. The second variable equals 1 if the justifications given are extrinsic in nature and zero otherwise. Examples of extrinsic responses mention income or money. The third variable equals 1 if the justifications given relate to the fictitious peer's knowledge and skills. Examples of knowledge-skill responses relate to A levels or other hard skills. Finally, a fourth variable captures all 'other' justifications. The four indicators are mutually exclusive so we exclude 'other' from our analysis. As discussed, we enlisted two independent coders for this work. There was no occasion where both intrinsic and extrinsic motivation was given, or indeed any multiple categorisations were chosen by the coders. Discrepancies in categorisation arose on three occasions only, and the final categorisation was determined by an author of this paper.¹⁵

Figure 1 illustrates the unconditional share of responses that falls under each of the four justifications *within* each name (i.e., the combination of the vignette and the gender of a fictitious friend). An intrinsic justification is more likely to be given if the student meets Stephanie (45%) as compared to Stephen (30%). Conversely, an extrinsic justification is more likely to be given if the student meets Stephen (61%) as compared to Stephanie (44%). We view this as evidence that there are underlying beliefs among these students that men are better suited to jobs with extrinsic motivations, while women are more suited to jobs with intrinsic

¹⁴ One of the authors studied any discrepancies in coding classifications between the coders and thus decided on the correct code. This amounted to approximately 2.5% of the variables in a matrix of respondents crossed by individual variables.

¹⁵ In Appendix Table A.1 in the online appendix, we list the detail of how we classify the justifications into 4 groups for the Stephan/Stephanie vignette.

motivations. Figure 1 reveals no significant difference in the knowledge or ‘other’ justifications by the Stephen/Stephanie design.

For the John/Jennifer vignette design, the students recommend a variety of degrees to their fictitious peers.¹⁶ We rely on the mapping of the degree recommended by the respondent to their peer to the ratio of females to males enrolled in each subject (at Level 1 of the Common Aggregation Hierarchy, CAH-1) at the undergraduate level during the UK’s academic year of 2019/20. The statistics come from the UK’s Higher Education Statistics Agency’s administrative statistics of higher education student enrolments by subject and sex and are not available in 2018 (the year of the experiment). There are 24 broad subjects, with 13 and 11 subjects classified as science subjects, and non-science subjects, respectively.¹⁷ On average, the ratio of females to males is 1.286. The gender ratios for science and non-science subjects are at 1.526, and 1.062, respectively. Education and teaching exhibit the highest ratio (at 6.609) while computing has the lowest female-male ratio (at 0.234). The dependent variable is then the ratio of females to males, with a value of 1 implying an equal number of men and women enrolled.

Akin to the Stephen/Stephanie design, we create four binary indicators from the justification given by each respondent for their choice. These four mutually exclusive variables capture whether the justification given was intrinsic, extrinsic, knowledge-based, or ‘other’.¹⁸ As discussed, we rely on two independent coders for this work. Discrepancies in categorisation arose on two occasions only, and the final categorisation was determined by an author of this paper.

From Figure 1, an intrinsic justification is more likely to be given if the student meets Jennifer (29%) as compared to John (11%). Conversely, an extrinsic justification is more likely to be given if the student meets John (14%) as compared to Jennifer (5%). Slightly more

¹⁶ The top 20 responses are documented in Table A.1 of Appendix A, including the related share of the responses.

¹⁷ The CAH is a comprehensive aggregation of the entirety of the Higher Education Classification of Subjects (HECoS) at each of three hierarchical levels or tiers, where a *parent* group at a higher level of CAH always comprises the full set of HECoS codes represented by related *child* groups of CAH below it. See <https://www.hesa.ac.uk/support/documentation/hecos/cah> for more details. The subjects in CAH level 1 are: 01 Medicine and dentistry, 02 Subjects allied to medicine, 03 Biological and sport sciences, 04 Psychology, 05 Veterinary sciences, 06 Agriculture, food and related studies, 07 Physical sciences, 08 General and others in sciences, 09 Mathematical sciences, 10 Engineering and technology, 11 Computing, 12A Geographical and environmental studies (natural sciences), 12B Geographical and environmental studies (social sciences), 13 Architecture, building and planning, 14 Humanities and liberal arts (non-specific), 15 Social sciences, 16 Law, 17 Business and management, 18 Communications and media, 19 Language and area studies, 20 Historical, philosophical and religious studies, 21 Creative arts and design, 22 Education and teaching, 23 Combined and general studies.

¹⁸ We note that the ‘other’ category has a significant number of responses (31). The majority of these relate to ‘keeping options open’ for the fictitious peer, or are missing (including ‘I don’t know’). See Appendix A.3 for exact responses in the John/Jennifer vignette.

students from the John vignette choose knowledge as a motivation (52%) as compared to those from the Jennifer vignette (48%). Figure 1 also reveals that more students give the ‘other’ as a motivation if faced with the Jennifer vignette compared to the John vignette (18% versus 13%).

We also consider the robustness of our classification by developing an intuitive starting lexicon to capture intrinsic, extrinsic and knowledge motivations in the Stephen/Stephanie and John/Jennifer experiments. In particular, for *intrinsic motivation*, the starting lexicon is: caring, empathy, enjoy, fun, happy, likes, loves, help and wellbeing. For *extrinsic motivation*, the starting lexicon is: money, better pay, higher pay, income and salary. Finally, for *knowledge*, the starting lexicon is: ability, a level, a-level, economics, math, physics, politics, skills and talent. We augment each of these starting lexicons with a co-occurrence analysis that allows us to identify words that happen alongside this chosen starting lexicon in the survey responses which are added to our lexicon (see Table A.4). The final lexicon is then applied to the justifications given in both the Stephen/Stephanie and John/Jennifer experiments to assign whether a classification is intrinsic, extrinsic or knowledge based. The concordance between our human coders and the classifications derived by the algorithm is excellent with only 16 disagreements. These are documented in Table A.4. We note that the estimates in this paper are robust with precision to re-classifying responses in line with those extracted by the lexicon. However, we believe it is intuitive in all instances that the human coders made an appropriate assignment, so therefore stick to their classifications for our main analysis.

3.1.2. Heterogeneous treatment effects and control variables

When running our regressions, we rely on the underlying randomization of the fictitious peer’s name to establish causality. However, there may be heterogeneous treatment effects, in the sense that different types of students are more and less susceptible to individual beliefs regarding gender stereotypes. Therefore, we consider how these variables impact the main treatment effects retrieved from our regressions when, firstly, they are added as a control variable, and, secondly, when we use them to interact with our treatment variable.

We first consider a dummy variable, F_i , indicating whether the student respondent’s gender (equals 1 if the respondent is female, and zero otherwise). This is to account for potential gender differences in individuals’ sensitivity to their own beliefs regarding gender stereotypes. According to Polavieja and Platt (2014), girls are more subjected to sex-typicality in their occupational choices. They require higher motivation and self-esteem than boys to make choices that contradict the existing social norms.

Similarly, we are also interested in creating a set of proxies that capture well the norms that the respondent is exposed to in their home. For this, we choose to build a set of indicators that account for heterogeneous family environments that may influence the child's sensitivity to typical gender roles. Parental socioeconomic status may, for instance, capture the type of paternal role model that the child is exposed to, as well as the intra-family transmission of beliefs and values (Bisin and Verdier 2000, Min et al. 2012, Dohmen et al. 2012).

In addition, Polavieja and Platt (2014) show that girls with higher parental resources will be less likely to embrace gender roles and more likely to choose male-dominated occupations. Therefore, we expect that the students with father working in non-traditional jobs may hold a less traditional view regarding gender stereotypes, and thereby the treatments of our experiments. Therefore, we create a dummy variable that is equal to 1 if the child's mother is employed at the time of the survey and 0 otherwise. In addition, we follow Lordan and Pischke (2022) and construct three variables: 'people', 'brains' and 'brawn'. The measures capture the father's job content in terms of how much it requires people interactions, cognitive tasks, and physicality, respectively. Moreover, we construct more familiar occupation averages that relate to the father's occupation, namely averages of hourly wage, weekly hours, the proportion of college graduates, age for each occupation, and the share of males.¹⁹ Overall, our estimations make use of these additional variables in two ways. First, we use them as additional control variables in all treatments (see Section 3.2 below). Second, we will interact each of these variables with the treatment so as to detect heterogeneity of the treatment effect.

3.2. Analysis of the Stephen/Stephanie design

For the Stephen/Stephanie design, we are interested in whether having the Stephen treatment caused students to be more likely to recommend corporate law over civil rights law. Thus, we estimate Equation (1) here:

$$Y_i = S_i \delta' + F_i \pi' + X_i \beta' + \varepsilon_i \quad (1)$$

where Y_i is equal to 1 if the student chose corporate law as the recommended career for their fictitious peer, and zero if they chose civil rights law. The term S_i is then equal to 1 if the student was assigned to the *Stephen* treatment and zero if the student was assigned to the *Stephanie* treatment. The term F_i is equal to 1 if the student is female and 0 otherwise. We also

¹⁹ see Appendix D for the detail on the construction of these variables.

consider an alternate specification that adds the interaction between the *Stephen* treatment and the female dummy ($S_i * F_i$), with ψ' a coefficient to be estimated.

The baseline specification does not contain any additional controls, X_i . In subsequent specifications, we include a vector of control variables from different domains, including those previously described in Section 3.1.2. In details, the second variant of the estimations includes the school fixed effects. This allows us to control for heterogeneous attitudes towards gender blindness across schools. The third variant adds a dummy variable that is equal to 1 if the child's mother works and zero otherwise. The fourth variant adds the father's occupation content variables, and the fifth variant includes the child's father's occupation averages. Note that once the father's occupation controls are added, we lose almost 1/3 of our observations. More than 3/4 of the missing information is because the child's father is not at home or is not working. To address this issue and allow us to maintain the full sample size, we employ a standard practice of mean imputation with a missing value indicator (equals 1 if the observation has a missing value and zero otherwise) in the specifications that include father's characteristics.

If δ' is non-zero and significant, the estimates tell us that the fictitious peer's gender significantly determines the career that is being recommended. This is indicative that the respondents have internalised expectations about preferences for occupations which vary by gender. The coefficient π' is also interesting although we cannot put a causal interpretation on it. π' captures whether the gender of the respondent predicts occupational choice. Finally, if ψ' is positive and significant, it implies that female respondents hold beliefs that align with gender stereotypes more than their male peers.

We also hypothesize that students differ in their perceptions of how their peer's value intrinsic versus extrinsic motivation in their job. That is, perhaps there is an internalised belief that females are more intrinsically motivated, and conversely that males are more extrinsically motivated. To investigate this hypothesis, we utilise the free text question in our experiment that asked the student to 'give a reason for their recommendation', and create the following non-overlapping categories: (i) intrinsic, (ii) extrinsic, (iii) knowledge and (iv) 'other' (as described in Section 3.1). Given the approach outlined in Equation (1), we take each category of (i) to (iv) as dependent variables and explicitly test if students exposed to the *Stephen* vignette treatment give significantly different justifications as compared to those exposed to the *Stephanie* vignette.

3.3. John/Jennifer design

The analysis for the John/Jennifer vignette design is also based on Equation (1). The modification is that now S_i equals 1 if the student was assigned to the *John* treatment and zero if the student was assigned to the *Jennifer* treatment. The main difference here is that we relate the degree recommendation to the fictitious peer in the John/Jennifer treatment to the actual ratio of females to males enrolled in the degree as described in Section 3.1. Therefore, for the John/Jennifer analysis, Y_i is the ratio of females to males enrolled in the recommended graduate program. This ratio is equal to one if there are equal men and women usually enrolled in the recommended degree. A negative and significant δ in the John/Jennifer vignette design suggests that when presented with John (as compared to Jennifer), the gender of the fictitious peer determines the career pathway that is being recommended. Similarly, if ψ' is negative and significant, it implies that female respondents hold beliefs that align with gender stereotypes *more* than their male peers. In contrast, if ψ' is positive and significant, it implies that male respondents hold beliefs that align with gender stereotypes *more* than their female peers.

In an alternative specification, we also run the analysis with Y_i as a binary variable, which equals 1 if the share of males in a degree is ‘high’ (defined as a ratio of female-male enrolment that is <0.7), and zero otherwise. Alongside this cut-off matching well with the enrolment ratios in the highest share of male’s degrees, it also relates directly to the *tipping point theory*, which suggests we need a minimum of 30% of women in work environments to tip the persistence of occupational segregation along gendered lines (Pan 2015).

Analogous to the *Stephen/Stephanie design*, drawing on the free text responses in the John/Jennifer vignette design, we also investigate whether the justification given bifurcates between extrinsic and intrinsic motivation depending on whether the student is exposed to the John or Jennifer experiment respectively.

IV. Empirical Results

4.1. Main Findings

The estimates from the Stephen/Stephanie design are documented in Table 3 where each column (1-6) differs only in the variables that they condition on. The top panel represents our baseline specification, while our bottom panel adds an interaction between the Stephen treatment and the child’s gender. Notably, adding control variables changes the magnitude of the treatment slightly, and the overall conclusion of an effect of around 12.2 percentage points is very robust. In addition, adding the interaction between the Stephen treatment and the child’s

gender does not change the treatment effect. The interaction effect itself is always centred around zero and not significant, allowing us to conclude that there are no heterogeneous treatment effects by gender. Overall, Table 3 points to internalised individual beliefs regarding gender stereotypes affecting the advice given by students to their fictitious peers. Table 3 also illustrates that the gender of the respondent significantly predicts whether corporate law is chosen independently of any treatment effect. From column (1), females are approximately 20 percentage points less likely to recommend that their peer pursued corporate law regardless of the peer's gender. This coefficient is attenuated when we add controls related to father's occupations, but it remains at 12.2 percentage points even in our fullest model. This suggests that the genders bifurcate in the advice they give along traditional lines. Adding an interaction between the Stephen treatment and the female dummy also does not change the point estimates in panel B of Table 3. The coefficient on the interaction is around zero.

Table 4 documents our second set of outcomes for the Stephen/Stephanie design. We are asking, does the Stephen treatment trigger the student to be more likely to give an intrinsic over extrinsic justification, as compared to Stephanie. From panels A and B, there is strong evidence that students bifurcate along the lines of extrinsic versus intrinsic justifications when faced with the Stephen versus Stephanie treatments respectively. From Appendix Table B.1, we note that the interaction between gender and the Stephen treatment is never significant and centred around zero. These conclusions are robust to a variety of controls which are sequentially added in columns (2) through (5) in Table 3 and Appendix Table B.1, respectively.

Specifically, looking at panel A of Table 4, column (1) implies that the student is 19 percentage points more likely to give an extrinsic motivation if faced with the Stephen treatment. Conversely, they are 13.7 percentage points less likely to give an intrinsic motivation if given the Stephen treatment. There are no significant differences in the propensity to give a justification based on knowledge if they were given the Stephen treatment, and the associated coefficients are around zero. Notably, females are more likely to give an intrinsic justification (a rise of 19.0 pp. in column (5)), and less likely to give an extrinsic justification (a decline of 18.3 pp.).

Table 5 documents the results from the John/Jennifer vignette. We present estimates for our baseline model, in addition to a model that also adds the interaction between gender and the John treatment. In panel A, the dependent variable is equal to the ratio of females to males being enrolled in undergraduate degrees. We note that the estimates in Table 5 are in line with what would be expected if individual beliefs regarding gender stereotypes were evoked. That is, being exposed to the John treatment causes respondents to recommend degrees that have a

share of females to males that is 0.175 units lower approximately (where a ratio =1 implies equal men and women). We note that adding an interaction between the John treatment and the female dummy changes the point estimates in Table 5 slightly (see panel C). Meanwhile, the coefficients of the interaction term are mostly around zero and never statistically significant.²⁰

Recall that, if the gender in our vignette experiment is ignored, the information in the experiment regarding A-levels leans most to the recommendation of a degree which is high in the share of males i.e., utilizes math and physics (the female-male UK enrolment ratio is 0.576 and 0.692, respectively). Therefore, we turn to an alternative estimation with the binary dependent variable indicating whether or not the degree is with a high share of female enrolment (equals to 1 if the ratio of female-male enrolment is higher than 0.7). The estimates in Table 5 panel B are in line with what would be expected if individual beliefs regarding gender stereotypes were evoked. Being exposed to the John treatment as compared to the Jennifer treatment causes respondents to be approximately 8 percentage points more likely to recommend a degree with high shares of males.

Additionally, we construct another outcome, STEM, which takes value of 1 if the respondent recommended that John/Jennifer studied a STEM major and 0 otherwise. Here, STEM majors are namely, math, engineering, architecture, physics, statistics, computer science, game design, programmer, or science (see also Appendix Table A.2). Panel A of Table 6 (columns 1-2) shows that a female respondent is 19.3 pp. less likely to recommend a STEM field than a male. When faced the John vignette, our students are 4 pp. more likely to recommend a STEM field to him than to Jennifer (at 10% significance level). When we add the interacted term (John*Female), both coefficients do not vary much in magnitude, but the John variable becomes statistically insignificant (column 4, panel A).

Of course, jobs and majors are bundles of attributes. It is very possible students are recommending majors to their peers based on other attributes of the major that are potentially correlated with occupational male share. We do not have any further information on the bundles of attributes that are associated with the college majors we have classified. We do however have information on the bundles of attributes of associated jobs. To map college majors to jobs, we gather information on knowledge from the O*NET database. Specifically, for each US Standard Occupational Classification 2000 (SOC00), the US' Occupational

²⁰ Per a suggestion by a referee, we also consider an alternative definition of the gender ratio and therefore compute the log of the ratio of female to male, instead of the raw ratio, as another outcome variable. The result is present in Appendix Table B.2. The 'John' effect remains relatively unchanged. The coefficient for Female becomes almost double in magnitude, but stays statistically insignificant from zero.

Information Network (O*NET) provides a level of knowledge for a subject area that is required.²¹ The level is provided on a scale of 1 to 7. We match the main knowledge category to the child's choice of degree for John/Jennifer. For example, a student who recommends an economics degree is matched with the economics and accounting knowledge category. For a French degree the match is foreign languages and so on. Based on the knowledge categories represented, we assume that all occupations that are in the top decile of this knowledge requirement are potential occupations given the degree recommended. This leaves us with a group of occupations for each degree choice. We match these groups of occupations based on their US SOC00 codes to the British SOC10 in the QLFS 2015-2018. For each of the occupations, we calculate the share of males, log of average income and log of average hours. We take an average of this over the respondent's choice group. For each degree choice we then have an associated average of each of these attributes that we can consider as dependent variables in Equation 1.

We also construct three additional variables that capture what a job is about. These variables follow an identical construction to the 'Father's Job Content' variables (see Appendix D) and to that described by Lordan and Pischke (2022). Three latent factors 'people,' 'brains,' and 'brawn' (PBB) are calculated using this data (measured in a standardized unit of mean 0 and standard deviation 1).²² We match these three factors for each occupation to the UK Standard Occupational Classification 2000 (SOC10) that represent those that map to the respondent's chosen college major. Panels B and C of Table 6 presents a set of analyses that considers these 6 additional dependent variables that capture several relevant attributes in jobs associated with the respondent's chosen college major. The John treatment effect is never significant and, for the most part, is at zero. This is highly suggestive evidence that the difference we observe in the John treatment in Table 5 is truly operating through differences in beliefs about the college majors that are suitable for women as compared to men, which are based on the current

²¹ It covers administration and management, biology, building and construction, chemistry, clerical, communication and media, computers and electronics, customer and personal service, design, economics and accounting, education and training, engineering and technology, English language, fine arts, food production, foreign language, geography, history and archaeology, law and government, mathematics, mechanical, medicine and dentistry, personnel and human resources, philosophy and theology, physics, production and processing, psychology, public safety and security, sales and marketing, sociology and anthropology, telecommunications, therapy and counselling and transportation.

²² Specifically, we retrieve from O*NET version 5 items relating to the activities and context of an individual's work. These items on activities and context are linked to US Standard Occupation Codes (SOC) 2000. These 79 items report the level at which an occupation has a particular characteristic from 1 to 7. The job content indices are derived from latent factors and they are measured in a standardised unit (mean 0, standard deviation 1). We match the US SOC00 codes in the O*NET data directly to the British SOC10 using an amended crosswalk, using an amended crosswalk of Lordan and Pischke (2022). We then match the O*NET items to the QLFS using the British SOC10 codes.

representation of women and men in these same roles. Notice that we do not observe strong effects of John on job attributes. On the other hand, we acknowledge that these measures could be rather noisy (due to how we converted college majors to jobs, as described earlier). In addition, to check why the metrics of female representation between college majors and jobs do not replicate, we look at their correlation. It turns out that the correlation between gender share in major and in occupation is 0.43. Therefore, we remain cautious with this conclusion. Having said that, panels B and C of Table 6 strongly point to the effect of gender of the participants along the traditional gender line. Female participants are less likely than their male counterparts to recommend a job if it comprises typical male attributes, namely, ‘brain’, ‘brawn’, jobs with high share of men, jobs with higher average income. On the contrary, female participants are more likely to recommend a job with high ‘people’ content.

Table 7 documents our second set of outcomes for the John/Jennifer design. We are asking to what extent the John treatment triggers the students to be more likely to give a particular type of justification for the degree choice they give as compared to the Jennifer treatment. From panel A, there is some evidence that students are more likely to give an extrinsic justification if faced with the John treatment. Note that we present estimates for a model that also includes an interaction between gender and the John treatment in Appendix Table B.3. Consistent with earlier estimates, the coefficient on the interaction is never significant and is approximately zero.

For example, in panel A in Table 7, the estimates imply an effect of 8.4 percentage points. A clearer picture is evident if we consider the estimates for intrinsic motivation (panel B). Across all specifications, students are at least 18 pp. less likely to give intrinsic motivation if faced with the John treatment. Similar to the Stephen/Stephanie design, there are no significant differences in the propensity to give a justification based on knowledge if given the John treatment. Consistent with the Stephen/Stephanie treatment, females are less likely to give an extrinsic motivation. There are no gender differences in the propensity to give an intrinsic motivation.

For robustness check, in Appendix C, we repeat our analyses from Tables 3 through 6, but restrict the samples to be balanced based on a child having a full set of data for the control variables. That is, we exclude children who do not (i) have both parents at home, and (ii) report on the variables that concern their mom and dad’s job. There is no change to our conclusions based on these robustness analyses (see Appendix Tables C.1 to C.4).

We are also interested in exploring whether the differences given in the justification for responses in the bundled vignettes (i.e., intrinsic/extrinsic/knowledge justification) explain the

significant treatment effects documented in Tables 3 and 5. To empirically explore this potential relationship we extend the specification of Equation 1 for both vignette designs and add the three types of justification (extrinsic, intrinsic, knowledge) to our models (with ‘other’) being the omitted category. These results can be found in Table 8. We note that adding the justification variables does indeed attenuate the coefficients documented in Tables 3 and Tables 5. From Table 8, the extrinsic justification does most of the ‘heavy lifting’ in this regard, given it is significant and substantive across all regressions. It also carries the expected sign that aligns with gender stereotypes. That is, an extrinsic motivation justification is given for corporate law majors with a lower ratio of female to male students and majors with the highest shares of males. We note that the intrinsic motivation justification contributes significantly to explaining the variation in the regression that considers a dummy variable representing that the degree chosen in the John/Jennifer vignette has a high share of males. It again carries the expected positive sign that aligns with gender stereotypes.

4.2. Heterogeneous Treatment Effects

We wish to consider whether there are additional heterogeneous treatment effects beyond gender. We explore this in Appendix B where we present models that include interactions with the parent job variables we include as controls in earlier models. The full results from these analyses are documented in Tables B.4 to B.10. Mostly the interactions between the parent job variables and the Stephen and John treatments are not significant. An exception is the interaction between the variable that captures the number of hours worked by the child’s father and the Stephen and John treatment. Interestingly, we find a more negative effect on the likelihood of recommending a corporate law from being exposed to the treatments (Stephen and John) as father’s hours increase. Specifically, in Table B.4, the effect implies that when exposed to the Stephen treatment, those children who have fathers who work in occupations with average hours of 37.5 are 10 percentage points less likely to recommend a corporate law occupation (i.e., 0.276×0.375 as hours are scaled by division by 100). Here we can only speculate, but there seems to be some overlap with children whose fathers are in high average hours jobs and also whose mothers work in a professional job. So, this may be driven by an exposure to a professional mother, or an aversion to having a father who work relatively long hours. In addition, higher work hours of father also increase the negative effect of the treatment on the likelihood that they give an extrinsic motivation for their choice in the Stephen treatment (in Table B.5). It appears that those with fathers who work long hours are more averse to place monetary value of their job choices (for their peer). Table B.6 also supports that some of the

effect in Table B.5 is driven by a propensity to choose an intrinsic motivation. Moreover, when we look at Table B.7, we also notice the negative correlation between father's long work hours and the likelihood of recommending female-dominated degrees. Notice also that the higher father's income, the less likely that such degrees are recommended. Hence, we speculate that the students with fathers of more demanding jobs (long hours and better pays) are less influenced by the gender dimensions of university degrees. Nonetheless, looking at the data, the real driver is the children, in fact, pick out anticipated aspects of the job content that the peer would enjoy or a higher tendency to give a knowledge-based answer.

Overall, this is suggestive that children having experienced a father working long hours have had their preferences formed to prefer jobs that have lower shares of males and are less tied to extrinsic reward, as compared to those with fathers who work more moderate hours.

V. Final Remarks

5.1. Limitations

We acknowledge that certain aspects of the design of our vignette experiment can be improved. First, if family background of the fictitious peers could also influence the decision of our student participants, an alternative design could include a variation of gender norms in parental occupations and the family setting. Second, a strong assumption in the analysis is that our student participants' decisions are driven by gender-biased subjective beliefs. This assumption could have been tested by directly eliciting our students' subjective beliefs about the gender ratio in each occupation, which we did not do. Nevertheless, in reality, there is no obvious overrepresentation of any gender in either of the legal specialties in our vignette design. Yet, it is possible that there are some experimenter demand effects, which may lead some students to choose the option that is socially appropriate but may not truly reflect their true choices.

Third, on the one hand, our experiment presents that the different advice given to male and female peers are strongly driven by gendered stereotypical beliefs of our school-age participants regarding career options. On the other hand, our design does not allow us to further disentangle the multi-facet factors that shape the gendered beliefs, for instance, social norms regarding gender, individual beliefs on other unobservable traits and occupational attributes that we do not specify in our vignette designs, or expectations about future labour market

conditions.²³ Nonetheless, our design demonstrated that conditional on the given set of observed characteristics of our fictitious peer, the gender difference persists.

Note also that the setting of our experiment, particularly Vignette 1, is different from real-world situations whereby peer-to-peer advice on law specialization in the UK may take place much later than the high-school ages.²⁴ Moreover, instead of students advising from their own expertise and information set, our design provides this information to our participants. Therefore, we also have to maintain an assumption that our participants trust and process the information in the vignette.²⁵ For these reasons, we acknowledge that the external validity of our result may be more limited but not null as ages 15-16 are crucial ages (the end of the compulsory schooling age) when the students in our study need to make high-stake decisions about their educational and career choices.

Lastly, since the two vignettes are not independently assigned but presented as a bundle, spillover effects can possibly exist. In other words, seeing the description of the male/female character in the first vignette may influence the decision made in the subsequent vignette. Unfortunately, while we acknowledge this possibility, we cannot address or test this in our current design.

5.2. Conclusion

We present students aged 15-16 years with an experiment with two bundled vignette designs, which describe a fictitious peer who is in the process of making decisions regarding their future career path. We invite these students to consider the vignettes and offer advice to the fictitious peer. Crucially, we randomize the gender of the peer presented to the students, allowing us to test whether gender identity alone is enough to cause the students to give different advice to this peer, and hence highlighting that individual beliefs regarding gender stereotypes are playing a role in the recommendation given. In both vignettes, we find that gender alone significantly determines the advice given. In particular, the advice given follows a pattern of individual beliefs regarding gender stereotypes. However, the null result of the interaction of own gender and the treatment shows that there are no differences between boys and girls in the type of advice they give out when presented with the same vignette. However,

²³ The content in our Vignette 1 includes labour market information at the start of the legal career but it does not provide information about the future. However, Vignette 2 is absent in terms of labour market conditions (current and future).

²⁴ In Gallen and Wasserman (2021), they conduct a controlled experiment with real university students who also interact with real-life working professional.

²⁵ See Goldman, Hagmann and Loewenstein (2017) and Golman et al. (2021) for a review and discussion on individual's demand for and avoidance of information.

we find that, in both vignette designs, the justifications given to support the advice also follow individual beliefs regarding gender stereotypes, with the female fictitious peers being more likely to receive an intrinsic justification. Conversely, the justification was much more often extrinsic when students met the male peer. Conditional on the observable traits (ability, personal background, interest) of the fictitious peer that our experiment design keeps constant, the students who participated in our experiment likely have established gender stereotypes regarding degree and career choice advice which caused them to advise their fictitious peer to sort along gendered lines.

We note that our treatment effects imply that the fictitious peers Stephen and John are given different advice as compared to their counterfactuals, Stephanie and Jennifer. We also note that these treatment effects do not differ by the respondent's gender. That is, the interaction between the treatment effect and the gender dummy is never significant. We can therefore rule out that innate interests that differ by gender are driving the significant treatment effect, as advice to the fictitious peer is similar regardless of whether the respondent is a boy or a girl. We have no reason to believe that the boys and girls exposed to treatment are systematically different given that they are randomised to treatment. Therefore, our results are highly suggestive that the primary driving mechanism is in fact inefficient discrimination and/or social stereotypes. However, we cannot explicitly address this with our experimental design.

Learning whether individual beliefs regarding gender stereotypes can affect sorting (via preferences for specific occupations or skills accumulated since childhood) prior to labour market entry is important because the policy responses are different from dealing with the issue of constraints. To lift the constraints (e.g., discrimination, pay negotiation, work flexibility), firms can, for instance, send credible signals and women would subsequently sort into these firms. However, the persistence of individual beliefs regarding gender stereotypes in childhood reflects a more fundamental root that the sexes differ in what they perceive as appropriate jobs for males and females.²⁶ In the case of the UK, patterns towards gendered sorting are detected in choices of occupational aspirations stated at twelve years old by a recent sample of UK

²⁶ We interpret gender differences in perceptions regarding earnings expectations, career advancement, workplace discrimination, and promotion aspirations as examples of attitudes toward gender roles, which are socially constructed and unrelated to innate ability. A recent study on legal professionals by Azmat, Cunat and Henry (2025) demonstrate that career progress differs between female and male lawyers due to gender differences in partnership aspirations.

children (Lekfuangfu and Lordan 2022).²⁷ In such a case, removing the constraints will not cause an adjustment to happen quickly.

Our analyses reveal that children have established individual beliefs regarding gender stereotypes that cause them to give gendered advice to a fictitious peer. Under the assumption that peer interaction and advice to a real peer would follow the same patterns as demonstrated in our hypothetical scenario (see, for example, Wiswall and Zafar (2018, 2021), and Giannola (2022) who show that there is the high correlation between individuals' hypothetical choices and their actual decisions.) and that the influence of peers on a child's life path is considerable, our finding highlights the importance of policies that will tackle the socialisation aspect of gender norms. For example, at the firm level, changing the male-female ratios in highly visible jobs may serve to alter individual beliefs regarding gender stereotypes which rely on the gender composition of specific industries for signals of what jobs are and are not appropriate for females. Such policies could take a decade or more to see effects, given that gender norm aspirations have already been formed by the age of twelve years.²⁸ At the school level, there is an opportunity for experimentation with curriculum content and the presentation of role models to understand better how to cultivate an environment where children navigate towards careers that satisfy their interests (Ray 2006, Beaman et al. 2012, Riley 2022).

References

Akerlof, George, A., and Rachel E. Kranton. (2005). "Identity and the Economics of Organizations". *Journal of Economic Perspectives*, 19(1): 9-32.

Altonji, Joseph G. and Rebecca M. Blank (1999). "Race and Gender in the Labor Market." In: Orley Ashenfelter and David Card (eds.) *Handbook of Labor Economics*, volume 3C, Amsterdam: Elsevier, 3143-3259.

Altonji, Joseph G., Peter Arcidiacono, and Arnaud Maurel. (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.

Ameriks, John, Joseph Briggs, Andrew Caplin, Matthew D. Shapiro, and Christopher Tonetti. (2020) "Long-term-care utility and late-in-life saving." *Journal of Political Economy* 128 (6): 2375-2451.

Anelli, Massimo, and Giovanni Peri. (2019) "The effects of high school peers' gender on college major, college performance and income." *Economic Journal*, 129 (618): 553-602.

²⁷ By analysing the UK's Millennium Cohort Studies, they find that females born in the year 2000 plan to choose occupations with 33% lower share of males, almost £550 lower earnings a month and 2.7 hours less per week compared to their male peers.

²⁸ We note that Bertrand et al. (2019) found no impact on women in business of the Norway board quotas seven years after the policy came fully into effect.

Arcidiacono, Peter, V. Joseph Hotz, Arnaud Maurel, and Teresa Romano. (2020) "Ex ante returns and occupational choice." *Journal of Political Economy*, 128 (12): 4475-4522.

Azmat, Ghazala and Ferrer Rosa (2017) "Gender Gaps in Performance: Evidence from Young Lawyers," *Journal of Political Economy*, 125 (5): 1306-1355.

Azmat, Ghazala, Vicente Cuñat, and Emeric Henry. (2025) "Gender promotion gaps: Career aspirations and workplace discrimination." *Management Science*. 71 (3): 2127-41

Babcock, Linda, Sara Laschever, Michele Gelfand, and Deborah Small. (2003) "Nice girls don't ask." *Harvard Business Review*, 81 (10): 14-14.

Barres, Ben A. (2006) "Does gender matter?" *Nature*, 442 (7099): 133-136.

Battiston, Alice, Sophie Hedges, Thomas Lazarowicz, and Stefan Speckesser. (2020) "Peer Effects and Social Influence in Post-16 Educational Choice." *CVER Research Discussion Paper*, 25.

Bayard, Kimberly, Judith Hellerstein, David Neumark, and Kenneth Troske (2003). "New Evidence on Sex Segregation and Sex Differences in Wages from Matched Employee-Employer Data." *Journal of Labor Economics*, 21(4): 887-922.

Beaman, Lori, Esther Duflo, Rohini Pande, and Petia Topalova. (2012) "Female leadership raises aspirations and educational attainment for girls: A policy experiment in India." *Science*, 335 (6068): 582-586.

Becker, Gary S (1985), "Human Capital, Effort, and the Sexual Division of Labor", *Journal of Labor Economics*, 3 (1), S33-S80.

Beioley, Kate (2014). "Pinsent Masons targets 25 per cent female partnership by 2018", *The Lawyer Market Reports*. <https://www.thelawyer.com/pinsent-masons-targets-25-per-cent-female-partnership-by-2018/>

Bernard, Tanguy, Stefan Dercon, Kate Orkin, and Alemayehu Taffesse. (2014). *The future in mind: Aspirations and forward-looking behaviour in rural Ethiopia*. London: Centre for Economic Policy Research.

Bertrand, Marianne, Sandra E. Black, Sissel Jensen, and Adriana Lleras-Muney. (2019) "Breaking the glass ceiling? The effect of board quotas on female labour market outcomes in Norway." *Review of Economic Studies*, 86 (1): 191-239.

Bertrand, Marianne. (2010). "New Perspectives on Gender." In: Orley Ashenfelter and David Card (eds), *Handbook of Labor Economics*, volume 4B, Amsterdam: Elsevier, 1545-1592.

Billger, Sherrilyn M. (2009) "On reconstructing school segregation: The efficacy and equity of single-sex schooling." *Economics of Education Review*, 28 (3): 393-402.

Bisin, Alberto, and Thierry Verdier. (2000) "Beyond the melting pot": cultural transmission, marriage, and the evolution of ethnic and religious traits." *The Quarterly Journal of Economics*, 115 (3): 955-988.

Blau, Francine D. and Lawrence M. Kahn (2016). "The Gender Wage Gap: Extent, Trends, and Explanations." *NBER Working Paper*, 21913.

Cortés, Patricia, and Jessica Pan. (2018) "Occupation and gender." *The Oxford handbook of women and the economy*: 425-452.

Dahl, Gordon B., Katrine V. Løken, and Magne Mogstad. (2014) "Peer effects in program participation." *American Economic Review*, 104 (7): 2049-74.

De Giorgi, Giacomo, Michele Pellizzari, and Silvia Redaelli. (2010) "Identification of social interactions through partially overlapping peer groups." *American Economic Journal: Applied Economics*, 2 (2): 241-75.

Dohmen, Thomas, Armin Falk, David Huffman, and Uwe Sunde. (2012) "The intergenerational transmission of risk and trust attitudes." *Review of Economic Studies* 79 (2): 645-677.

Dolan, P. (2019) Happy Ever After: Escaping the Myth of the Perfect Life. London: Allen Lane.

Feld, Jan, and Ulf Zölitz. (2017) “Understanding peer effects: On the nature, estimation, and channels of peer effects.” *Journal of Labor Economics*, 35 (2): 387-428.

Gallen, Yana, and Melanie Wasserman. (2021) “Informed Choices: Gender Gaps in Career Advice.” *mimeo*

Giannola, Michele (2022). “Parental Investment, and Intra-household Inequality in Child Development: Theory, Measurement and Evidence from a Lab-in-the-field Experiment”. *IFS Working Paper no. 22/54, Inst. Fiscal Studies, London*

Gibbons, Stephen, and Shqiponja Telhaj (2016). Peer effects: Evidence from secondary school transition in England. *Oxford Bulletin of Economics and Statistics*, 78(4), 548-575.

Goldin Claudia (2006). “The Quiet Revolution That Transformed Women's Employment, Education, And Family,” *American Economic Review*, 96, 1-21.

Goldin, Claudia (2014). “A Grand Gender Convergence: Its Last Chapter.” *American Economic Review*, 104(4): 1091-1119.

Goldin, Claudia, and Lawrence F. Katz. (2011) “The cost of workplace flexibility for high-powered professionals.” *The Annals of the American Academy of Political and Social Science*, 638 (1): 45-67.

Golman, Russell, David Hagmann, and George Loewenstein. (2017) “Information avoidance.” *Journal of Economic Literature*, 55 (1): 96-135.

Golman, Russell, George Loewenstein, Andras Molnar, and Silvia Saccardo. (2021) “The demand for, and avoidance of, information.” *Management Science*.

Grove, Wayne, Hussey, Andrew, and Jetter, Michael. (2011). “The Gender Pay Gap Beyond Human Capital Heterogeneity in Noncognitive Skills and in Labor Market Tastes,” *Journal of Human Resources*. 46, 827-874.

Higher Education Statistics Agency (2021). the UK's Higher education graduate outcomes statistics. <https://www.hesa.ac.uk/data-and-analysis/students/outcomes>

Jarrell BS and Stanley DT (2004). Declining Bias and Gender Wage Discrimination? A Meta-Regression Analysis. *Journal of Human Resources*, 39.

Katz, Lawrence F., and Kevin M. Murphy. (1992) “Changes in relative wages, 1963–1987: supply and demand factors.” *Quarterly Journal of Economics*, 107 (1): 35-78.

Lavy, Victor, and Analia Schlosser. (2011) “Mechanisms and impacts of gender peer effects at school.” *American Economic Journal: Applied Economics*, 3 (2): 1-33.

Lavy, Victor, Olmo Silva, and Felix Weinhardt. (2012). “The good, the bad, and the average: Evidence on ability peer effects in schools.” *Journal of Labor Economics*, 30(2): 367-

Lekfuangfu, Warn N., and Grace Lordan. (2022). “Documenting occupational sorting by gender in the UK across three cohorts: does a grand convergence rely on societal movements?”. *Empirical Economics*, 1-42

Lordan, Grace and Jorn-Steffen Pischke. (2022). “Does Rosie like riveting? Male and female occupational choices.” *Economica*, 89 (353).

Mas, Alexandre, and Amanda Pallais. (2017) “Valuing alternative work arrangements.” *American Economic Review*, 107 (12): 3722-59.

Mendolia, S., Paloyo, A. R., & Walker, I. (2018). Heterogeneous effects of high school peers on educational outcomes. *Oxford Economic Papers*, 70(3), 613-634.

Min, Joohong, Merrill Silverstein, and Jessica P. Lendon. (2012) “Intergenerational transmission of values over the family life course.” *Advances in Life Course Research*, 17 (3): 112-120.

Murphy, Richard, and Felix Weinhardt. (2020) “Top of the class: The importance of ordinal rank.” *Review of Economic Studies*, 87 (6): 2777-2826.

Niederle, Muriel, and Lise Vesterlund. (2007) “Do women shy away from competition? Do men compete too much?” *Quarterly Journal of Economics*, 122 (3): 1067-1101.

Pan, Jessica. (2015). “Gender segregation in occupations: The role of tipping and social interactions.” *Journal of Labor Economics*, 33(2), 365-408.

Patnaik, Arpita, Matthew J. Wiswall, and Basit Zafar. (2020) “College majors.” *National Bureau of Economic Research Working Paper Series*, 27645.

Polavieja, Javier G., and Lucinda Platt (2014). “Nurse or mechanic? The role of parental socialization and children's personality in the formation of sex-typed occupational aspirations.” *Social Forces*, 93(1), 31-61.

Ray, Debraj. (2006) “Aspirations, poverty, and economic change.” *Understanding poverty* 1: 409-421.

Reuben, Ernesto, Matthew Wiswall, and Basit Zafar. (2017) “Preferences and biases in educational choices and labour market expectations: Shrinking the black box of gender.” *Economic Journal*, 127 (604): 2153-2186.

Riley, Emma (2022) “Role Models in Movies: The Impact of Queen of Katwe on Students' Educational Attainment.” *Review of Economics and Statistics*.

Sacerdote, Bruce (2011). “Peer effects in education: How might they work, how big are they and how much do we know thus far?.” In *Handbook of the Economics of Education* (Vol. 3, pp. 249-277). Elsevier.

Schneeweis, Nicole, and Martina Zweimüller. (2012) “Girls, girls, girls: Gender composition and female school choice.” *Economics of Education Review*, 31: 482-500.

Solicitor Regulation Authority (2017), *Annual Review 2017/18*

Solicitors Regulation Authority (2022) Population of solicitors in England and Wales. Available at: https://www.sra.org.uk/sra/research-publications/regulated-community-statistics/data/population_solicitors/

Solnick, Sara J. (1995) “Changes in women's majors from entrance to graduation at women's and coeducational colleges.” *ILR Review*, 48 (3): 505-514.

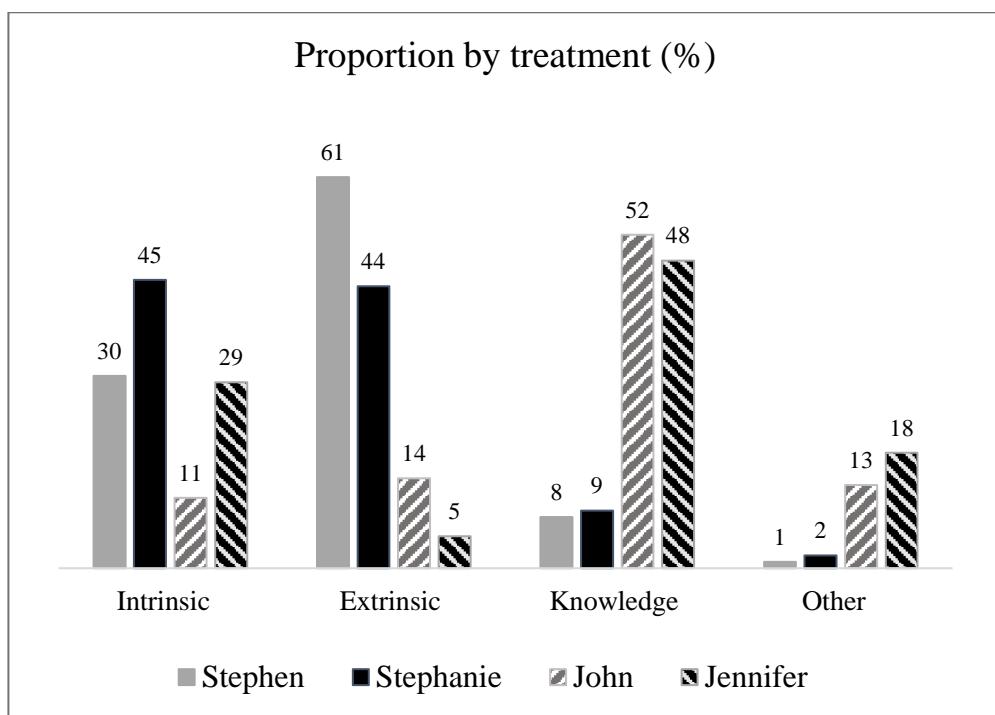
Su, Rong, James Rounds, and Patrick Ian Armstrong. (2009). “Men and Things, Women and People: A Meta-Analysis of Sex Differences in Interests.” *Psychological Bulletin*, 135(6): 859-884.

Wiswall, Matthew, and Basit Zafar. (2018). “Preference for the workplace, investment in human capital, and gender.” *Quarterly Journal of Economics*, 133(1), 457-507.

Wiswall, Matthew, and Basit Zafar. (2021). “Human capital investments and expectations about career and family.” *Journal of Political Economy*, 129 (5).

Zafar, Basit. (2013) “College major choice and the gender gap.” *Journal of Human Resources*, 48 (3): 545-595.

Figure 1. Justifications for recommending corporate law or civil rights law (*Stephen/Stephanie* vignette) and justification for recommending a college degree (*John/Jennifer* vignette).



Notes: The figure shows the unconditional share of responses (4 types: intrinsic, extrinsic, knowledge, 'other') within each 'name' of the fictitious peer. The first vignette design is the *Stephen/Stephanie*, and the second vignette design is the *John/Jennifer*. Examples of intrinsic responses mention caring, feeling good and happiness. Examples of extrinsic responses mention income or money. Examples of knowledge-skill responses relate to A levels or other hard skills. The four indicators are mutually exclusive. See Appendix Tables A.1 and A.3 for more detail of the classification. The total number of participants is 307.

Table 1. School Characteristics

	School A	School B	England Average
Age range	11-18	11-18	
Phase of education	Secondary	Secondary	
School type	Academy	Academy	
Gender entry	Mixed	Mixed	
Admission policy	Non-selective	Non-selective	
Enrolment	1000-1500	1000-1500	
Religious character	None	None	
Region	East of England	East of England	
<i>Academic performance measures</i>			
Ofsted rating (2011)	Good	Outstanding	
Pupils whose first language is not English	26-30 %	16-20 %	16.9%
% Children eligible for free school meals	11-15 %	6-10 %	27.7%
Pupil-to-teacher ratio	11-15	16-20	16.3
Attainment 8 score	41-45 %	66-70 %	47%
Entering EBacc	51-55 %	71-75 %	40%
Staying in education/entering employment	90-100 %	90-100 %	94%
% Grade 5+ in English and maths GCSEs	36-40 %	81-85 %	43%

Notes: The information is derived from www.compare-school-performance.service.gov.uk. It shows school statistics for the 2019 academic year. *Ofsted rating* is a 4-point grading score used for inspection judgement. Grade 1 is outstanding, grade 2 is good, grade 3 is requiring improvement, and grade 4 is inadequate. Here we compare those who received ‘good’ and ‘outstanding’ to the national average. *Entering EBacc* measures the percentage share of pupils having entered for the English Baccalaureate if they entered for qualifications in English, maths, sciences, a language and either history or geography; *Attainment 8 score* is based on how well pupils have performed in up to 8 qualifications, which include English, maths. English Baccalaureate opens a new set of qualifications including sciences, computer science, history, geography and languages, and other additional approved qualifications. *Staying in education or entering employment* shows the number of pupils who either stayed in education or went into employment after finishing key stage 4 (after year 11, usually aged 16), covering any sustained education or employment destination.

Table 2. Balancing test across the Stephen/Jennifer versus Stephanie/John vignettes

Vignette bundles:	Mean		Difference	p-values
	Stephen /Jennifer	Stephanie /John		
Female dummy	0.538	0.428	0.110	0.054
Mother is a homemaker dummy	0.172	0.123	0.048	0.239
Father's job content: Brains	0.280	0.380	-0.100	0.136
Father's job content: Brawn	0.144	0.014	0.131	0.354
Father's job content: People	-0.082	0.050	-0.132	0.233
Father's job: share of men	0.576	0.556	0.020	0.170
Father's job: average age	0.411	0.412	-0.001	0.894
Father's job: average hourly income	12.19	13.09	-0.894	0.151
Father's job: average hours	37.85	37.14	0.713	0.244
Father's job: % with a college degree	0.305	0.360	-0.056	0.146

Notes: Our experiment has two bundles of vignettes. For those who were assigned to Stephen in the first design, they were also assigned subsequently to Jennifer in the second design; vice versa, those who were given the Stephanie design also subsequently were given the John design. Mother is a homemaker is a dummy variable equal to 1 if the child's mother is employed at the time of the survey and 0 otherwise. The measures of father's job content (brains, brawn, people) and average occupation characteristics (share of men, average age, average hourly income, average hours, and share of workers with a college degree) are derived from the 2017–19 Quarterly Labour Force Survey data. See Appendix D for more details.

Table 3. The estimated effect of the *Stephen* treatment (Vignette 1) on the probability of recommending corporate law to a fictitious peer

	(1)	(2)	(3)	(4)	(5)
Panel A: Baseline Model					
<i>Stephen</i> Treatment	0.129** (0.056)	0.131** (0.056)	0.130** (0.057)	0.125** (0.059)	0.122** (0.059)
Female	-0.199*** (0.056)	-0.195*** (0.056)	-0.195*** (0.056)	-0.196*** (0.058)	-0.196*** (0.057)
Panel B: Adding Interaction Between <i>Stephen</i> Treatment and Female Dummy					
<i>Stephen</i> Treatment	0.129* (0.078)	0.130* (0.078)	0.129 * (0.078)	0.120* (0.073)	0.122* (0.073)
Female	-0.197** (0.084)	-0.196** (0.084)	-0.195** (0.084)	-0.195** (0.091)	-0.196** (0.091)
<i>Stephen</i> * Female	0.004 (0.112)	0.001 (0.113)	0.001 (0.058)	0.001 (0.118)	0.001 (0.110)
<i>Control Variables</i>					
School fixed effects	✗	✓	✓	✓	✓
Mother is a homemaker	✗	✗	✓	✓	✓
Father's job content	✗	✗	✗	✓	✓
Father's occupation averages	✗	✗	✗	✗	✓
Observations	307	307	307	307	307

Notes: Dependent variable is a binary variable that equals 1 if the students choose corporate law for their fictitious peer and 0 if they choose civil rights law. *Stephen* treatment is a dummy variable that equals 1 if participants were assigned to *Stephen* and 0 if they were assigned to *Stephanie*. Female equals 1 if the respondent is female. A vector of control variables contains a set of school fixed effects, a dummy variable that is equal to 1 if the child's mother works and 0 otherwise, father's occupation content variables, and father's occupation averages (share of men, average age, average hourly income, average hours [scaled down by 100], and share of workers with a college degree). Each regression uses an ordinary least squares (OLS) specification. We employ a missing dummy imputation approach for any control variable that has a missing value where we also add a dummy variable to denote that a missing value is present in the regressions. Robust standard errors are in parentheses where *** p<0.01, ** p<0.05, * p<0.1.

Table 4. The estimated effect of the *Stephen* treatment on the justification for a recommendation of corporate law or civil rights law.

	(1)	(2)	(3)	(4)	(5)
A. Dependent Variable =1 if justification given is extrinsic, 0 otherwise					
<i>Stephen</i> Treatment	0.190*** (0.056)	0.194*** (0.056)	0.194*** (0.056)	0.188*** (0.058)	0.188*** (0.058)
Female	-0.187*** (0.056)	-0.178*** (0.056)	-0.178*** (0.056)	-0.176** (0.057)	-0.183** (0.070)
B. Dependent Variable =1 if justification given is intrinsic, 0 otherwise					
<i>Stephen</i> Treatment	-0.13*** (0.054)	-0.136*** (0.053)	-0.135*** (0.054)	-0.137*** (0.054)	-0.137*** (0.054)
Female	0.201*** (0.054)	0.187*** (0.053)	0.188*** (0.054)	0.190*** (0.055)	0.190*** (0.056)
C. Dependent Variable =1 if justification given is knowledge, 0 otherwise					
<i>Stephen</i> Treatment	0.012 (0.017)	0.010 (0.017)	0.010 (0.017)	0.011 (0.018)	0.013 (0.020)
Female	0.032*** (0.012)	0.028*** (0.010)	0.028*** (0.010)	0.027*** (0.013)	0.029*** (0.012)
<i>Control Variables</i>					
School fixed effects	X	✓	✓	✓	✓
Mother is a homemaker	X	X	✓	✓	✓
Father's job content	X	X	X	✓	✓
Father's occupation averages	X	X	X	X	✓
Observations	307	307	307	307	307

Notes: Dependent variable in each panel is a mutually exclusive binary variable that equals 1 if participants provide a given justification for recommendation of corporate law or civil rights law to their fictitious peer (panel A is extrinsic; panel B is intrinsic; panel C is knowledge). The “other” justification is omitted. See table A.1 for the classification of justifications in this vignette design. *Stephen* treatment is a dummy variable that equals 1 if participants were assigned to *Stephen* and 0 if they were assigned to *Stephanie*. Female equals 1 if the respondent is female. A vector of control variables contains a set of school fixed effects, a dummy variable that is equal to 1 if the child's mother works and 0 otherwise, father's occupation content variables, and father's occupation averages (share of men, average age, average hourly income, average hours [scaled down by 100], and share of workers with a college degree). Each regression uses an OLS specification. We employ a missing dummy imputation approach for any control variable that has a missing value where we also add a dummy variable to denote that a missing value is present in the regressions. Robust standard errors are in parentheses where *** p<0.01, ** p<0.05, * p<0.1.

Table 5. The estimated effect of the *John* treatment on the ratio of women to men in the degree recommended.

	(1)	(2)	(3)	(4)	(5)
A. Dependent Variable: Ratio of females to males enrolled in the degree recommended					
<i>John</i> Treatment	-0.171*	-0.176**	-0.169*	-0.170*	-0.175**
	(0.087)	(0.086)	(0.086)	(0.087)	(0.089)
Female	0.003	0.027	0.025	-0.027	-0.024
	(0.087)	(0.087)	(0.087)	(0.088)	(0.089)
B. Dependent Variable: Whether the degree recommended has a high share of males					
<i>John</i> Treatment	0.077*	0.082**	0.077*	0.076*	0.079*
	(0.042)	(0.041)	(0.041)	(0.041)	(0.042)
Female	-0.017	-0.032	-0.029	-0.030	-0.025
	(0.042)	(0.041)	(0.041)	(0.041)	(0.042)
C. Dependent Variable: Ratio of females to males enrolled in the degree recommended					
<i>John</i> Treatment	-0.175*	-0.175*	-0.172*	-0.176**	-0.171**
	(0.089)	(0.090)	(0.091)	(0.094)	(0.095)
Female	-0.020	0.009	0.019	0.017	0.018
	(0.022)	(0.011)	(0.012)	(0.012)	(0.013)
<i>John</i> * Female	0.040	0.038	0.017	0.054	0.045
	(0.042)	(0.035)	(0.017)	(0.049)	(0.040)
D. Dependent Variable: Whether the degree recommended has a high share of males					
<i>John</i> Treatment	0.077*	0.082**	0.077*	0.081**	0.083**
	(0.042)	(0.041)	(0.041)	(0.040)	(0.041)
Female	-0.015	-0.037	-0.030	-0.039	-0.033
	(0.043)	(0.045)	(0.042)	(0.042)	(0.039)
<i>John</i> * Female	0.021	0.019	0.019	0.018	0.023
	(0.018)	(0.018)	(0.016)	(0.015)	(0.017)
<i>Control Variables</i>					
School fixed effects	X	✓	✓	✓	✓
Mother is a homemaker	X	X	✓	✓	✓
Father's job content	X	X	X	✓	✓
Father's occupation averages	X	X	X	X	✓
Observations	307	307	307	307	307

Notes: Dependent variable of panels A and C is the ratio of females to males enrolled in the degree recommended by the participants. Dependent variable of panels B and D is a binary variable equal to 1 if the degree recommended has a high share of males. *John* treatment is a dummy variable that equals 1 if participants were assigned to *John* and 0 if they were assigned to *Jennifer* in the second vignette design. Female equals 1 if the respondent is female. A vector of control variables contains a set of school fixed effects, a dummy variable that is equal to 1 if the child's mother works and 0 otherwise, father's occupation content variables, and father's occupation averages (share of men, average age, average hourly income, average hours [scaled down by 100], and share of workers with a college degree). Each regression uses an OLS specification. We employ a missing dummy imputation approach for any control variable that has a missing value where we also add a dummy variable to denote that a missing value is present in the regressions. Robust standard errors are in parenthesis where *** p<0.01, ** p<0.05, * p<0.1.

Table 6. The effect of the *John* treatment on STEM majors and job attributes

	(1)	(2)	(3)	(4)	(5)	(6)
A. Dependent Variable: Recommended STEM Major						
<i>John</i> Treatment	0.041* (0.023)	0.038* (0.023)	0.044** (0.022)	0.030 (0.023)		
Female	-0.178*** (0.023)	-0.193*** (0.023)	-0.190*** (0.030)	-0.187*** (0.029)		
<i>John</i> * Female			-0.005 (0.004)	-0.0008 (0.007)		
B. Dependent Variables: Measures of Job Content						
	‘Brains’ Latent Factor		‘Brawn’ Latent Factor		‘People’ Latent Factor	
<i>John</i> Treatment	-0.035 (0.030)	-0.071 (0.049)	0.051 (0.032)	0.020 (0.042)	0.007 (0.020)	0.010 (0.043)
Female	-0.383*** (0.045)	-0.387*** (0.053)	-0.167*** (0.058)	-0.155*** (0.059)	0.333*** (0.041)	0.310*** (0.049)
C. Dependent Variables: Averages of Occupation Characteristics						
	Average Share of Men		Average Income		Average Hours	
<i>John</i> Treatment	0.045** (0.021)	0.019 (0.013)	-0.088 (0.054)	-0.083 (0.047)	0.000 (0.001)	-0.001 (0.002)
Female	-0.158*** (0.012)	-0.129*** (0.014)	-0.168*** (0.058)	-0.156*** (0.070)	-0.022 (0.015)	-0.020 (0.017)
<i>Control Variables</i>						
School fixed effects	✓	✓	✓	✓	✓	✓
Mother is a homemaker	✗	✓	✗	✓	✗	✓
Father’s job content	✗	✓	✗	✓	✗	✓
Father’s occupation averages	✗	✓	✗	✓	✗	✓
Observations	307	307	307	307	307	307

Notes: Dependent variable of panel A is 1 whether the respondent recommended that John/Jennifer studied a STEM major and 0 otherwise. Here, STEM majors are math, engineering, architecture, physics, statistics, computer science, game design, programmer, or science (see also table A.1). The dependent variables of panel B are the measures of job content: brains, brawn, people (in a standardized unit with mean 0 and standard deviation equal to 1). Dependent variables in panel C are the averages of occupation characteristics (share of men, average hourly income, average hours) (see also app. B). John treatment is a dummy variable that equals 1 if participants were assigned to John and 0 if they were assigned to Jennifer in the second vignette design. Female equals 1 if the respondent is female. A vector of control variables contains a set of school fixed effects, a dummy variable that is equal to 1 if the child’s mother works and 0 otherwise, father’s occupation content variables, and father’s occupation averages (share of men, average age, average hourly income, average hours [scaled down by 100], and share of workers with a college degree). Each regression uses an OLS specification. We employ the mean imputation approach for any control variable that has a missing value where we also add a dummy variable to denote that a missing value is present in the regressions. Robust standard errors are in parentheses. Robust standard errors are in parentheses where *** p<0.01, ** p<0.05, * p<0.1.

Table 7. The estimated effect of the *John* treatment on the justification for a recommendation of an occupation to a fictitious peer.

	(1)	(2)	(3)	(4)	(5)
A. Dependent Variable =1 if justification given is extrinsic, 0 otherwise					
<i>John</i> Treatment	0.084*** (0.032)	0.086*** (0.032)	0.083*** (0.033)	0.081*** (0.035)	0.084*** (0.036)
Female	-0.058*** (0.032)	-0.063*** (0.032)	-0.060** (0.032)	-0.068** (0.035)	-0.065** (0.034)
B. Dependent Variable =1 if justification given is intrinsic, 0 otherwise					
<i>John</i> Treatment	-0.184*** (0.046)	-0.186*** (0.046)	-0.185*** (0.045)	-0.185*** (0.044)	-0.180*** (0.045)
Female	-0.024 (0.046)	-0.017 (0.046)	-0.013 (0.044)	-0.016 (0.040)	-0.021 (0.039)
C. Dependent Variable =1 if justification given is knowledge, 0 otherwise					
<i>John</i> Treatment	0.045 (0.058)	0.048 (0.058)	0.047 (0.059)	0.048 (0.060)	0.041 (0.050)
Female	0.021 (0.058)	0.012 (0.058)	0.001 (0.050)	0.015 (0.059)	0.019 (0.058)
<i>Control Variables</i>					
School fixed effects	X	✓	✓	✓	✓
Mother is a homemaker	X	X	✓	✓	✓
Father's job content	X	X	X	✓	✓
Father's occupation averages	X	X	X	X	✓
Observations	307	307	307	307	307

Notes: Dependent variable in each panel is a mutually exclusive binary variable that equals 1 if participants provide a given justification for recommendation of corporate law or civil rights law to their fictitious peer (panel A is extrinsic; panel B is intrinsic; panel C is knowledge). The “other” justification is omitted. See table A.3 for details for the justification classification. *John* treatment is a dummy variable that equals 1 if participants were assigned to *John* and 0 if they were assigned to *Jennifer* in the second vignette design. Female equals 1 if the respondent is female. A vector of control variables contains a set of school fixed effects, a dummy variable that is equal to 1 if the child’s mother works and 0 otherwise, father’s occupation content variables, and father’s occupation averages (share of men, average age, average hourly income, average hours [scaled down by 100], and share of workers with a college degree). Each regression uses an OLS specification. We employ the mean imputation approach for any control variable that has a missing value where we also add a dummy variable to denote that a missing value is present in the regressions. Robust standard errors are in parentheses. Robust standard errors are in parentheses where *** p<0.01, ** p<0.05, * p<0.1.

Table 8. The estimated effect of Stephen or John treatments, accounting for justifications

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variables:	Corporate Law Recommendation (Stephen Vignette)	Ratio of Females to Males Enrolled (John Vignette)			Degree has high shares of males (John Vignette)	
Stephen Treatment	0.036 (0.029)	0.070** (0.033)
John Treatment	-0.149* (0.087)	-0.185*** (0.088)	0.016 (0.048)	0.018 (0.050)
Female	-0.141*** (0.050)	-0.140*** (0.050)	0.051 (0.091)	0.077 (0.090)	0.140*** (0.049)	0.108** (0.052)
Extrinsic Justification	0.842*** (0.047)	0.955*** (0.059)	-0.346** (0.165)	-0.333* (0.170)	0.283*** (0.077)	0.274*** (0.089)
Intrinsic Justification	-0.025 (0.049)	0.030 (0.041)	0.016 (0.171)	0.040 (0.154)	-0.371*** (0.080)	-0.348*** (0.082)
Knowledge Justification	0.055 (0.100)	0.018 (0.100)	0.214 (0.274)	0.283 (0.246)	-0.0121 (0.163)	-0.092 (0.181)
<i>Control Variables</i>						
School fixed effects	✓	✓	✓	✓	✓	✓
Mother is a homemaker	✗	✓	✗	✓	✗	✓
Father's job content	✗	✓	✗	✓	✗	✓
Father's occupation averages	✗	✓	✗	✓	✗	✓
Observations	307	307	307	307	307	307

Notes: Dependent variable of cols. 1 and 2 is a binary variable equal to 1 if corporate law is recommended and 0 otherwise. Dependent variable of cols. 3 and 4 is the ratio of females to males enrolled in the degree recommended by the participants. Dependent variable of cols. 5 and 6 is a binary variable equal to 1 if the degree recommended has a high share of males. The Stephen treatment is a dummy variable that equals 1 if participants were assigned to Stephen and 0 if they were assigned to Stephanie. The John treatment is a dummy variable that equals 1 if participants were assigned to John and 0 if they were assigned to Jennifer in the second vignette design. Female equals 1 if the respondent is female. Additional covariates include a set of mutually exclusive binary variables that equal 1 if participants provide each given justification for a recommendation of corporate law or civil rights law to their fictitious peer. The “other” justification is omitted. A vector of control variables contains a set of school fixed effects, a dummy variable that is equal to 1 if the child’s mother works and 0 otherwise, father’s occupation content variables, and father’s occupation averages (share of men, average age, average hourly income, average hours [scaled down by 100], and share of workers with a college degree). Each regression uses an OLS specification. We employ the mean imputation approach for any control variable that has a missing value where we also add a dummy variable to denote that a missing value is present in the regressions. Robust standard errors are in parentheses where *** p<0.01, ** p<0.05, * p<0.1.

Supplementary Materials

Appendix A: Materials for the Experiment

A.1. The Stephen/Stephanie Vignette

A.1.1. Instruction for Stephen Williams Vignette

Please read the text below and answer the questions that follow. If you have any questions, please put up your hand.

Stephen Williams

Stephen Williams is finishing his A levels. He has taken 3 subjects and expects he will do very well. He expects to get A and B grades. He has taken Politics, Economics, and English literature. Stephen knows with certainty that law is his passion, however, he does not know what type of lawyer he would like to be. He needs your help to choose between two fields in law: Civil Rights Law and Corporate Law.

If Stephen chooses civil rights law, he will expect to work about 40 hours per week and earn about £60,000 working for the government. He would be the lawyer in civil rights cases, which might involve defending an individual who faces discrimination based on race, age, gender or religion. Stephen would help individuals affected by these issues get justice and compensation for their suffering. Lawyers who take on civil rights cases typically earn less than lawyers who choose careers in business fields, such as corporate law. Civil rights lawyers will have the personal reward of knowing they are helping people who have been wronged.

If Stephen chooses corporate law, he will expect to work about 40 hours per week and earn about £100,000. A primary role of corporate lawyers is to ensure the legality of company transactions. Stephen would be an advisor to a corporation on a range of issues, such as gathering and analysing evidence for legal proceedings, formulating contracts, advising companies on their legal rights and obligations in business transactions, and providing advice on issues related to taxation. With Stephen's help, his company would be more profitable.

Personal Background:

Stephen was born in Hertfordshire, England. His mother is a secondary school teacher. His father is a tax lawyer. Stephen would also like to get married someday and have two children. Stephen is outgoing and well-liked by all his friends.

Questions:

1. Should Stephen choose: (circle your preferred option)
 - a. **Civil Rights Law** or
 - b. **Corporate Law?**
2. Please give a reason for your recommendation to question 1:

A.1.2. Instruction for Stephanie Williams Vignette

Stephanie Williams is finishing her A levels. She has taken 3 subjects and expects she will do very well. She expects to get A and B grades. She has taken Politics, Economics, and English literature. Stephanie knows with certainty that law is her passion, however, she does not know what type of lawyer she would like to be. She needs your help to choose between two fields in law: Civil Rights Law and Corporate Law.

If Stephanie chooses civil rights law, she will expect to work about 40 hours per week and earn about £60,000 working for the government. She would be the lawyer in civil rights cases, which might involve defending an individual who faces discrimination based on race, age, gender or religion. Stephanie would help individuals affected by these issues get justice and compensation for their suffering. Lawyers who take on civil rights cases typically earn less than lawyers who choose careers in business fields, such as corporate law. Civil rights lawyers will have the personal reward of knowing they are helping people who have been wronged.

If Stephanie chooses corporate law, she will expect to work about 40 hours per week and earn about £100,000. A primary role of corporate lawyers is to ensure the legality of company transactions. Stephanie would be an advisor to a corporation on a range of issues, such as gathering and analysing evidence for legal proceedings, formulating contracts, advising companies on their legal rights and obligations in business transactions, and providing advice on issues related to taxation. With Stephanie's help, her company would be more profitable.

Personal Background:

Stephanie was born in Hertfordshire, England. Her mother is a secondary school teacher. Her father is a tax lawyer. Stephanie would also like to get married someday and have two children. Stephanie is outgoing and well-liked by all her friends.

Questions:

1. Should Stephanie choose: (circle your preferred option)
 - a. **Civil Rights Law** or
 - b. **Corporate Law?**
2. Please give a reason for your recommendation to question 1:

A.2. The John/Jennifer Vignette

A.2.1. Instruction for John Collins Vignette

Please read the case study below and answer the questions that follow. If you have any, questions please put up your hand

John Collins is a colleague of Stephanie Williams at school. He is taking Economics, Maths, Physics and French for his A levels. He is a straight A student. His mother died when he was very young. His father is a very successful builder. John has many friends. He enjoys reading, listening to music and playing computer games. He does not know what to do in university and needs your help.

- 1. Please name a university degree that you think John should consider?**

- 2. Please say why you recommended that degree to John?**

A.2.2. Instruction for Jennifer Collins Vignette

Please read the case study below and answer the questions that follow. If you have any questions, please put up your hand

Jennifer Collins is a colleague of Stephen Williams at school. She is taking Economics, Maths, Physics and French for her A levels. She is a straight A student. Her mother died when she was very young. Her father is a very successful builder. Jennifer has many friends. She enjoys reading, listening to music and playing computer games. She does not know what to do in university and needs your help.

- 1. Please name a university degree that you think Jennifer should consider?**

- 2. Please say why you recommended that degree to Jennifer?**

A.3. Justification classification for the Stephen/Stephanie vignette

Table A.1. Ten sample responses given in each classification (intrinsic, extrinsic, knowledge, others) in the Stephen/Stephanie vignette

<p>Panel A: The ‘intrinsic’ justification category in the Stephen/Stephanie vignette.</p> <ol style="list-style-type: none">1. “Although she gets less pay, she gets to <i>help people’s rights</i>”2. “Because she is outgoing and liked and it sounds like it will be more fun for her, although she will receive less money. But she will know that she is <i>helping people</i> who have been wronged”3. “More <i>morally rewarding</i>”4. “Despite the clear less amount of money she will earn, working with people in her community will <i>develop her personally as opposed to the richer</i>, but less socially interactive life as a corporate lawyer”5. “She <i>obviously likes maths</i> which suits these - if she did engineering she could use sexist affirmative action schemes to get ahead easily of her male counterparts; she could use these to her advantage.”6. “Civil Rights law because it is more suitable for her personality and although she is earning less <i>she will enjoy her job more</i> and know that she is <i>helping out people</i>.”7. “Because it is more interesting and <i>personally rewarding</i>.”8. “Although the pay is less, you’re able to work with and <i>help people</i> rather than a company, and you get the satisfaction/reward of <i>helping these people</i>”9. “Stephanie is outgoing and may feel the need to <i>help people</i>. This would set a good example for her children.”10. “He would be happier as he is <i>helping people</i> and would be a good example to his kids. 60000 pounds is a good salary and he would be able to support a family with this amount.”
<p>Panel B: The ‘intrinsic’ justification category in the Stephen/Stephanie vignette.</p> <ol style="list-style-type: none">1. “100000 is more than 60000.”2. “40000 <i>more</i> per year.”3. “A lot more <i>money</i> to support his future family.”4. “He wants kids. Kids cost money to raise. Better to be more <i>financially sound</i>.”5. “Someone will do civil rights law anyway, may as well <i>earn more money</i> and let someone else do civil rights law.”6. “She will get more <i>money</i>.”7. “More <i>money</i> to make a more secure family for the future.”8. “Because he will earn a lot more <i>money</i> for the same hours as a civil rights lawyer.”9. “<i>Money!</i>”10. “More <i>money</i> for Stephanie.”
<p>Panel C: The ‘knowledge’ justification category in the Stephen/Stephanie vignette.</p> <ol style="list-style-type: none">1. “Corporate law suits him more as it <i>involves economics</i> which is something he has studied.”2. “It aligns best with <i>his A-levels</i>.”3. “It matches with what she <i>knows</i>.”

4. “Because he *studies* politics and economics, corporate law involves more about companies' transactions and taxation.”
5. “Stephen's father was working as a tax lawyer so may have inherited *the skills* needed from him.”
6. “The subjects he is studying are more related to corporate law, his qualifications could help him get a job in corporate law and his *knowledge* could assist him with his work.”
7. “He has taken *economics* so will be good with company profits. Politics will also help with issues like tax evasion”
8. “She took *economics* so should know a little about corporations.”
9. “This is what her *subjects* relate to.”
10. “She would be better at this job.”

Panel D: The ‘other’ justification category in the Stephen/Stephanie vignette.

1. “I don't know.”

Notes: The table lists 10 reasons (as a sample) of justifications (in the Stephan/Stephanie vignette) that are classified as ‘intrinsic’, ‘extrinsic’, ‘knowledge’ and ‘others’, with the keywords for each classification highlighted in italic.

A.4. The list of college majors as indicated in the John/Jennifer vignette

Table A.2. Top 20 college majors (in ranking) as named by respondents in the John/Jennifer vignette

		(1) Frequency (%)	(2) STEM
1.	Math	38	Yes
2.	Economics	34	
3.	Physics/Astrophysics	33	Yes
4.	Computer Science	31	Yes
5.	Accounting/Accountant	25	
6.	Engineering	23	Yes
7.	French	20	
8.	Business	18	
9.	Statistics	16	Yes
10.	Translator/Languages	14	
11.	International Studies	11	
12.	Game Design	10	Yes
13.	Media Studies	5	
14.	Architecture	5	Yes
15.	Psychology	4	
16.	Finance	3	
17.	Teaching	2	
18.	Government/Politics	2	
19.	Law	2	
20.	Electronics	2	Yes
Number of Respondents = 307			

Notes: The table lists the top 20 college majors as named by the respondents, from the highest frequency (Math) to the 20th (Electronics). Column 1 shows the frequency of each major and column 2 indicates whether the major is a STEM major.

A.5. Justification classification for the John/Jennifer vignette

Table A.3. Responses in the John/Jennifer vignette

<p>Panel A. The ‘intrinsic’ justification category in the John/Jennifer vignette.</p> <ol style="list-style-type: none">1. “He <i>enjoys</i> it,”2. “She <i>enjoys</i> this stuff.”3. “Because she <i>enjoys</i> this subject.”4. “She might <i>like</i> it.”5. “She obviously <i>likes</i> maths which suits these.”6. “She <i>likes</i> reading.”7. “She <i>likes</i> computer games.”8. “She clearly <i>likes</i> and is good at maths.”9. “Because that is what his <i>interests</i> are.”10. “He <i>likes</i> playing computer games so would be interest and he took maths and physics.”
<p>Panel B. The ‘extrinsic’ justification category in the John/Jennifer vignette.</p> <ol style="list-style-type: none">1. “You can earn lots of <i>money</i>.”2. “Because you can get so much <i>money</i>.”3. “High <i>paying</i>.”4. “She could go abroad and <i>get paid</i> more.”5. “A language is useful for the future as it is looking globalist and she needs engineering to <i>earn money</i> as there is a demand for that.”6. “This can be very beneficial to her and her family even though her dad is successful at his job, but jobs in business areas have <i>high pay</i> and MBA can be a good gateway to work in a famous business.”7. “Lots of <i>money</i>, even if they don’t like it.”8. “He can go into a <i>well-paid</i> job.”9. “Good <i>money</i>.”10. “It allows him to become a <i>high-status</i> decision maker.”
<p>Panel C. The ‘knowledge’ justification category in the John/Jennifer vignette.</p> <ol style="list-style-type: none">1. “His <i>A-levels</i> link to my choice.”2. “It involves <i>economics and physics</i>.”3. “She is good at <i>maths and economics</i>.”4. “He is <i>good at</i> it.”5. “She is <i>good at</i> it.”6. “I would recommend this as she took this for <i>A-levels</i>.”7. “Because he takes those subjects at <i>A-levels</i>.”8. “She’s <i>good at</i> those subjects.”9. “<i>A-levels</i> she is taking would suit this.”10. “She does economics and has good supporting <i>A-levels</i>. French will help her with the international side.”
<p>Panel D. Responses given in the ‘other’ justification category.</p> <ol style="list-style-type: none">1. “I’m not gonna make it to university. Maybe this guy can.”

2. “Better job security.”
3. “Relevant in today's society.”
4. “More self-happiness.”
5. “Feels like it would suit.”
6. “Because it leaves a lot of options open.”
7. “It is a very broad subject, allowing her to delay her choice in what she wants to do.”
8. “A degree is a language that opens up your job opportunities.”
9. “Gives her a wide variety of career paths to follow.”
10. “Opens doors to many jobs and is very useful.”
11. “Versatile.”
12. “It can open a lot of new doors for her.”
13. “It may open up more doors in the future.”
14. “This will be able to open up more opportunities for Jennifer with jobs.”
15. “So she can do her father's finances.”
16. “The widest range of jobs can be applied with economics.”

Notes: The table lists 10 reasons (as a sample) of justifications (in the John/Jennifer vignette) that are classified as ‘intrinsic’, ‘extrinsic’, ‘knowledge’ and ‘others’, with the keywords for each classification highlighted in *italic*. Also, the remaining 15 replies with ‘other’ responses are either ‘I don’t know’ (8 replies) or blank (7 replies).

A.6. Robustness check for the classification

Table A.4. Robustness to Classifying Intrinsic, Extrinsic and Knowledge Justifications in the Stephen/Stephanie and John/Jennifer Experiments:

**Panel A. Final Lexicon to Extract Intrinsic Motivation
(Original lexicon is in bold)**

1. **Caring**
2. **Children**
3. Community
4. Compassion
5. Discrimination
6. **Empathy**
7. **Enjoy**
8. Family
9. **Fun**
10. Good for society
11. **Happy**
12. Like it
13. **Likes**
14. **Loves**
15. **Help**
16. **Interesting**
17. Job Satisfaction
18. Married
19. Moral
20. Passion
21. People
22. Personality
23. Personal reward
24. Personal satisfaction
25. Significant difference
26. **Wellbeing**
27. **Work life balance**

Responses classified as intrinsic motivation in the Stephen/Stephanie experiment by human coders that were not assigned by the algorithm:

- a. “Defending suffering individuals”
- b. “Because Stephanie is taking economics and politics and this is more suitable as she will have more understanding.”

Responses classified as intrinsic motivation in the John/Jennifer experiment that were not assigned by the algorithm:

- c. “She probably likes the subject and is capable”
- d. “Because she has to do what is right for her and not listen to what others say what she has to do.”
- e. “Jennifer should do what she wants to do why does my opinion matter?”

<p>f. “It will mean he can be creative.”</p>
--

Panel B. Final Lexicon to Extract Extrinsic Motivation.

- 1. Money**
- 2. Paid more
- 3. 40000 more
- 4. Pays more
- 5. Better pay**
- 6. High wage
- 7. Income**
- 8. Earns more
- 9. Better wage
- 10. High pay
- 11. Higher pay
- 12. Salary**

Responses classified as extrinsic motivation in the Stephen/Stephanie experiment by human coders that were not assigned by the algorithm:

- g. Earn considerably more
- h. Pay is better

Responses classified as extrinsic motivation in the John/Jennifer experiment by human coders that were not assigned by the algorithm:

- i. “He can get more jobs with maths”
- j. “Opens doors to many jobs and is very useful”
- k. “This will be able to open up more opportunities for Jennifer with jobs.”

Panel C. Final Lexicon to Extract Extrinsic Motivation.

- 1. Ability**
- 2. A levels**
- 3. A-levels**
- 4. Clever
- 5. Economics**
- 6. Economic background
- 7. Good at it
- 8. Good at those subjects
- 9. Knows about it
- 10. Math**
- 11. Physics**
- 12. Politics**
- 13. Skills**
- 14. Straight A student
- 15. Subjects
- 16. Talent

Responses classified as knowledge motivation in the Stephen/Stephanie experiment by human coders that were not assigned by the algorithm:

None.

Responses classified as knowledge motivation in the John/Jennifer experiment by human coders that were not assigned by the algorithm:

- a. “Because he sounds smart”
- b. “Because he does it”
- c. “She did it at A level”
- d. “Has straight As”
- e. “He’s smart”

Notes: The table lists the lexicon used to extract the intrinsic, extrinsic and knowledge motivations in the Stephen/Stephanie and John/Jennifer experiment. In bold is the original lexicon devised by one of the authors. The remaining words were identified during a co-occurrence analysis. We also document the exact responses given that were coded as intrinsic, extrinsic or knowledge by human coders, that were not picked up by our lexicon. We note, that the estimates are robust with precision to re-classifying these responses in the ‘other’ classification category. However, we believe it is intuitive in all instances that the human coders made an appropriate assignment, so therefore stick to their classifications for our main analysis.

Appendix B. Exploring Heterogeneous Treatment Effects

Table B.1. The estimated effect of the *Stephen* treatment on the justification for a recommendation of corporate law or civil rights law including an interaction between the *Stephen* treatment and a female respondent

	(1)	(2)	(3)	(4)	(5)
A. Dependent Variable =1 if justification given is extrinsic, 0 otherwise					
<i>Stephen</i> Treatment	0.181*** (0.075)	0.186*** (0.077)	0.186** (0.077)	0.185*** (0.090)	0.189*** (0.088)
Female	-0.232*** (0.083)	-0.221*** (0.083)	-0.222*** (0.084)	-0.240*** (0.087)	-0.234*** (0.091)
<i>Stephen</i> *Female	0.082 (0.054)	0.078 (0.112)	0.079 (0.112)	0.079 (0.120)	0.084 (0.122)
B. Dependent Variable =1 if justification given is intrinsic, 0 otherwise					
<i>Stephen</i> Treatment	-0.124 (0.075)	-0.133* (0.074)	-0.134* (0.074)	-0.144** (0.074)	-0.145** (0.075)
Female	0.229*** (0.080)	0.213*** (0.079)	0.212*** (0.079)	0.240*** (0.084)	0.241*** (0.091)
<i>Stephen</i> *Female	-0.053 (0.107)	-0.047 (0.107)	-0.045 (0.107)	-0.059 (0.102)	-0.070 (0.110)
C. Dependent Variable =1 if justification given is knowledge, 0 otherwise					
<i>Stephen</i>	0.010 (0.023)	0.000 (0.025)	0.001 (0.025)	0.000 (0.019)	0.000 (0.021)
Female	0.029** (0.015)	0.025*** (0.011)	0.024*** (0.010)	0.025* (0.015)	0.024* (0.014)
<i>Stephen</i> *Female	0.000 (0.001)	0.000 (0.004)	0.000 (0.003)	0.000 (0.004)	0.000 (0.005)
<i>Control Variables</i>					
School fixed effects	✗	✓	✓	✓	✓
Mother is a homemaker	✗	✗	✓	✓	✓
Father's job content	✗	✗	✗	✓	✓
Father's occupation averages	✗	✗	✗	✗	✗
Observations	307	307	307	307	307

Notes: Robust standard errors are in parentheses where *** p<0.01, ** p<0.05, * p<0.1. The dependent variable in each panel is a mutually exclusive binary variable that equals 1 if participants provide a given justification for a recommendation of corporate law or civil rights law to their fictitious peer (Panel A is extrinsic; Panel B is intrinsic; Panel C is knowledge). The 'other' justification is omitted. See Appendix Table A.1 for details for the justification classification. The *Stephen* treatment is a dummy variable which equals 1 if participants were assigned to *Stephen* and zero if they were assigned to *Stephanie*. Female equals to 1 if the respondent is female. A vector of control variables contains a set of school fixed effects, a dummy variable that is equal to 1 if the child's mother works and zero otherwise, father's occupation content variables, and father's occupation averages (share of men, average age, average hourly income, average hours (scaled down by 100), and share of workers with a college degree). Each regression uses an OLS specification. We employ a missing dummy imputation approach for any control variable that has a missing value where we also add a dummy variable to denote that a missing value is present in the regressions.

Table B.2. The estimated effect of the *John* treatment on the ratio of women to men in the degree recommended.

	(1)	(2)	(3)	(4)	(5)
A. Dependent Variable: Log of ratio of females to males enrolled in the degree recommended					
<i>John</i> Treatment	-0.212** (0.097)	-0.210** (0.096)	-0.206** (0.096)	-0.192** (0.091)	-0.195** (0.092)
Female	0.050 (0.098)	0.052 (0.097)	0.052 (0.097)	0.052 (0.098)	0.054 (0.098)
B. Dependent Variable: Log of ratio of females to males enrolled in the degree recommended					
<i>John</i> Treatment	-0.214** (0.099)	-0.216** (0.100)	-0.172* (0.091)	-0.176** (0.094)	-0.171** (0.095)
Female	0.047 (0.102)	0.048 (0.099)	0.049 (0.100)	0.049 (0.099)	0.049 (0.099)
<i>John</i> * Female	0.008 (0.010)	0.008 (0.011)	0.007 (0.011)	0.007 (0.011)	0.008 (0.010)
<i>Control Variables</i>					
School fixed effects	X	✓	✓	✓	✓
Mother is a homemaker	X	X	✓	✓	✓
Father's job content	X	X	X	✓	✓
Father's occupation averages	X	X	X	X	✓
Observations	307	307	307	307	307

Notes: Robust standard errors are in parenthesis where *** p<0.01, ** p<0.05, * p<0.1. The dependent variable of panels A and B is the log ratio of females to males enrolled in the degree recommended by the participants. 'John' treatment is a dummy variable which equals 1 if participants were assigned to 'John' and zero if they were assigned to 'Jennifer' in the second vignette design. Female equals to 1 if the respondent is female. A vector of control variables contains a set of school fixed effects, a dummy variable that is equal to 1 if the child's mother works and zero otherwise, father's occupation content variables, and father's occupation averages (share of men, average age, average hourly income, average hours (scaled down by 100), and share of workers with a college degree). Each regression uses an OLS specification. We employ a missing dummy imputation approach for any control variable that has a missing value where we also add a dummy variable to denote that a missing value is present in the regressions.

Table B.3. The estimated effect of the *John* treatment on the justification for a recommendation of an occupation to a fictitious peer adding the interaction of *John* treatment and female respondent

	(1)	(2)	(3)	(4)	(5)
A. Dependent Variable =1 if justification given is extrinsic, 0 otherwise					
<i>John</i> Treatment	0.098*** (0.043)	0.082** (0.043)	0.081** (0.043)	0.079* (0.041)	0.078* (0.040)
Female	0.042 (0.068)	0.034 (0.068)	0.037 (0.080)	0.033 (0.071)	0.036 (0.070)
<i>John</i> * Female	-0.033 (0.092)	-0.030 (0.091)	-0.039 (0.092)	-0.050 (0.055)	-0.047 (0.057)
B. Dependent Variable =1 if justification given is intrinsic, 0 otherwise					
<i>John</i> Treatment	-0.178** (0.078)	-0.172*** (0.064)	-0.171*** (0.063)	-0.191*** (0.070)	-0.195*** (0.070)
Female	-0.015 (0.085)	-0.033 (0.068)	-0.037 (0.068)	-0.017 (0.070)	-0.015 (0.075)
<i>John</i> * Female	0.034 (0.112)	0.030 (0.092)	0.039 (0.092)	0.035 (0.098)	0.034 (0.094)
C. Dependent Variable =1 if justification given is knowledge, 0 otherwise					
<i>John</i> Treatment	0.041 (0.055)	0.046 (0.056)	0.048 (0.050)	0.045 (0.060)	0.054 (0.065)
Female	0.015 (0.059)	0.011 (0.052)	0.011 (0.048)	0.025 (0.040)	0.017 (0.045)
<i>John</i> * Female	0.008 (0.005)	0.010 (0.008)	0.009 (0.008)	0.003 (0.002)	0.005 (0.004)
<i>Control Variables</i>					
School fixed effects	✗	✓	✓	✓	✓
Mother is a homemaker	✗	✗	✓	✓	✓
Father's job content	✗	✗	✗	✓	✓
Father's occupation averages	✗	✗	✗	✗	✗
Observations	307	307	307	307	307

Notes: Robust standard errors are in parentheses where *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are in brackets. The dependent variable in each panel is a mutually exclusive binary variable that equals 1 if participants provide a given justification for the recommendation to their fictitious peer (Panel A is extrinsic; Panel B is intrinsic; Panel C is knowledge). The ‘other’ justification is omitted. See Appendix Table A.3 for details for the justification classification. The *John* treatment is a dummy variable which equals 1 if participants were assigned to *John* and zero if they were assigned to *Jennifer* in the second vignette design. Female equals to 1 if the respondent is female. A vector of control variables contains a set of school fixed effects, a dummy variable that is equal to 1 if the child’s mother works and zero otherwise, father’s occupation content variables, and father’s occupation averages (share of men, average age, average hourly income, average hours (scaled down by 100), and share of workers with a college degree). Each regression uses an OLS specification. We employ a missing dummy imputation approach for any control variable that has a missing value where we also add a dummy variable to denote that a missing value is present in the regressions.

Table B.4. The estimated effect of the *Stephen* treatment on the justification for a recommendation of an occupation to a fictitious peer adding interaction between parent's occupation attributes

	(1)	(2)	(3)	(4)
Dependent Variable =1 if the respondent recommended corporate law and 0 otherwise				
<i>Stephen</i> Treatment	0.121*	0.126*	0.159**	0.165**
	(0.073)	(0.073)	(0.077)	0.078
Female	-0.137**	-0.138**	-0.138**	-0.135**
	(0.068)	(0.069)	(0.070)	(0.068)
<i>Stephen</i> * Mum-at-home dummy	0.059			0.072
	(0.176)			(0.178)
<i>Stephen</i> * Dad's job 'brains' content		0.010		0.008
		(0.046)		(0.045)
<i>Stephen</i> * Dad's job 'brawn' content		-0.031		-0.032
		(0.055)		(0.056)
<i>Stephen</i> * Dad's job 'people' content		-0.002		-0.003
		(0.062)		(0.062)
<i>Stephen</i> * Dad's job 'average age'			0.996	1.163
			(1.754)	(2.084)
<i>Stephen</i> * Dad's job average income			-0.013	-0.013
			(0.023)	(0.026)
<i>Stephen</i> * Dad's job average hours (/100)			-0.276**	-0.347***
			(0.102)	(0.126)
<i>Stephen</i> * Dad's job average education			0.168	0.326
			(0.375)	(0.399)
<i>Control Variables</i>				
School fixed effects	✓	✓	✓	✓
Mother is a homemaker	✓	✓	✓	✓
Father's job content	✓	✓	✓	✓
Father's occupation averages	✓	✓	✓	✓
Observations	216	216	216	216

Notes: Robust standard errors are in brackets where *** p<0.01, ** p<0.05, * p<0.1. The dependent variable in each panel is a mutually exclusive binary variable that equals 1 if participants provide a recommendation of corporate law or civil rights law to their fictitious peer. The *Stephen* treatment is a dummy variable which equals 1 if participants were assigned to *Stephen* and zero if they were assigned to *Stephanie*. Female equals to 1 if the respondent is female. A vector of control variables contains a set of school fixed effects, a dummy variable that is equal to 1 if the child's mother works and zero otherwise, father's occupation content variables, and father's occupation averages (share of men, average age, average hourly income, average hours (scaled down by 100), and share of workers with a college degree). Each regression uses an OLS specification with non-missing balanced sample.

Table B.5. The estimated effect of the *Stephen* treatment on an extrinsic justification being given for a recommendation of an occupation to a fictitious peer adding interaction between parent's occupation attributes.

	(1)	(2)	(3)	(4)
Dependent Variable =1 if the respondent gave extrinsic justification				
<i>Stephen</i> Treatment	0.192*** (0.072)	0.187** (0.072)	0.164** (0.087)	0.177*** (0.077)
Female	-0.167*** (0.067)	-0.165** (0.068)	-0.181*** (0.065)	-0.160** (0.069)
<i>Stephen</i> *Mum-at-home dummy	-0.097 (0.214)			0.100 (0.176)
<i>Stephen</i> *Dad's job 'brains' content		0.022 (0.045)		0.020 (0.045)
<i>Stephen</i> *Dad's job 'brawn' content		-0.035 (0.068)		-0.004 (0.055)
<i>Stephen</i> *Dad's job 'people' content		-0.008 (0.084)		-0.040 (0.062)
<i>Stephen</i> *Dad's job 'average age			0.444 (1.743)	0.634 (2.065)
<i>Stephen</i> *Dad's job average income			0.001 (0.023)	-0.004 (0.026)
<i>Stephen</i> *Dad's job average hours (/100)			-2.795*** (1.303)	-2.267* (1.211)
<i>Stephen</i> *Dad's job average education			0.042 (0.374)	0.171 (0.396)
<i>Control Variables</i>				
School fixed effects	✓	✓	✓	✓
Mother is a homemaker	✓	✓	✓	✓
Father's job content	✓	✓	✓	✓
Father's occupation averages	✓	✓	✓	✓
Observations	216	216	216	216

Notes: Robust standard errors are in brackets where *** p<0.01, ** p<0.05, * p<0.1. The dependent variable in each panel equals 1 if participants provide an extrinsic justification for their recommendation of corporate law or civil rights law to their fictitious peer and zero otherwise. The *Stephen* treatment is a dummy variable which equals 1 if participants were assigned to *Stephen* and zero if they were assigned to *Stephanie*. Female equals to 1 if the respondent is female. A vector of control variables contains a set of school fixed effects, a dummy variable that is equal to 1 if the child's mother works and zero otherwise, father's occupation content variables, and father's occupation averages (share of men, average age, average hourly income, average hours (scaled down by 100), and share of workers with a college degree). Each regression uses an OLS specification with non-missing balanced sample.

Table B.6. The estimated effect of the *Stephen* treatment on intrinsic justification being given for recommendation of an occupation to a fictitious peer adding interaction between parent's occupation attributes.

	(1)	(2)	(3)	(4)
Dependent Variable =1 if respondent gave intrinsic justification				
<i>Stephen</i> Treatment	-0.173*** (0.068)	-0.144** (0.068)	-0.246*** (0.096)	-0.199*** (0.072)
Female	0.199*** (0.064)	0.207*** (0.065)	0.219 (0.062)	0.195*** (0.065)
<i>Stephen</i> * Mum-at-home dummy	-0.191 (0.163)			-0.204 (0.167)
<i>Stephen</i> * Dad's job 'brains' content		-0.012 (0.065)		-0.032 (0.089)
<i>Stephen</i> * Dad's job 'brawn' content		-0.052 (0.064)		-0.074 (0.078)
<i>Stephen</i> * Dad's job 'people' content		-0.056 (0.080)		-0.051 (0.085)
<i>Stephen</i> * Dad's job 'average age'			0.131 (1.668)	0.745 (1.953)
<i>Stephen</i> * Dad's job average income			0.015 (0.022)	0.018 (0.024)
<i>Stephen</i> * Dad's job average hours (/100)			0.033 (0.247)	0.072 (0.524)
<i>Stephen</i> * Dad's job average education			-0.076 (0.358)	-0.085 (0.374)
<i>Control Variables</i>				
School fixed effects	✓	✓	✓	✓
Mother is a homemaker	✓	✓	✓	✓
Father's job content	✓	✓	✓	✓
Father's occupation averages	✓	✓	✓	✓
Observations	216	216	216	216

Notes: Robust standard errors are in parentheses where *** p<0.01, ** p<0.05, * p<0.1. The dependent variable equals 1 if participants provide an intrinsic justification for recommendation of corporate law or civil rights law to their fictitious peer and zero otherwise. The *Stephen* treatment is a dummy variable which equals 1 if participants were assigned to *Stephen* and zero if they were assigned to *Stephanie*. Female equals to 1 if the respondent is female. A vector of control variables contains a set of school fixed effects, a dummy variable that is equal to 1 if the child's mother works and zero otherwise, father's occupation content variables, and father's occupation averages (share of men, average age, average hourly income, average hours (scaled down by 100), and share of workers with a college degree). Each regression uses an OLS specification with non-missing balanced sample.

Table B.7. Estimated effect of the ‘John’ treatment on recommendation of a degree pathway to a fictitious peer adding interaction between parent’s occupation attributes.

	(1)	(2)	(3)	(4)
Dependent variable is the ratio of females to males enrolled in the degree recommended				
<i>John</i> Treatment	-0.167*	-0.150*	-0.242***	-0.294***
	(0.092)	(0.090)	(0.094)	(0.100)
Female	-0.082	-0.085	-0.072	0.081
	(0.088)	(0.087)	(0.086)	(0.088)
<i>John</i> *Mum-at-home dummy	0.066			0.133
	(0.302)			(0.304)
<i>John</i> *Dad’s job ‘brains’ content		-0.046		0.265**
		(0.057)		(0.113)
<i>John</i> *Dad’s job ‘brawn’ content		0.065		0.031
		(0.070)		(0.105)
‘ <i>John</i> *Dad’s job ‘people’ content		-0.093		-0.206*
		(0.071)		(0.118)
<i>John</i> *Dad’s job ‘average age			1.278	2.589
			(1.763)	(2.095)
<i>John</i> *Dad’s job average income			-0.021	-0.022
			(0.029)	(0.031)
<i>John</i> *Dad’s job average hours (/100)			-1.739***	-2.601***
			(0.731)	(0.815)
<i>John</i> *Dad’s job average education			0.163	0.034
			(0.466)	(0.482)
<i>Control Variables</i>				
School fixed effects	✓	✓	✓	✓
Mother is a homemaker	✓	✓	✓	✓
Father’s job content	✓	✓	✓	✓
Father’s occupation averages	✓	✓	✓	✓
Observations	216	216	216	216

Notes: Robust standard errors are in parentheses where *** p<0.01, ** p<0.05, * p<0.1. The dependent variable of Panel A is the ratio of females to males enrolled in the degree recommended by the participants. The *John* treatment is a dummy variable which equals 1 if participants were assigned to *John* and zero if they were assigned to *Jennifer* in the second vignette design. Female equals to 1 if the respondent is female. A vector of control variables contains a set of school fixed effects, a dummy variable that is equal to 1 if the child’s mother works and zero otherwise, father’s occupation content variables, and father’s occupation averages (share of men, average age, average hourly income, average hours (scaled down by 100), and share of workers with a college degree). Each regression uses an OLS specification with non-missing balanced sample.

Table B.8. The estimated effect of the *John* treatment on a recommendation of career pathway to a fictitious peer adding interaction between parent's occupation attributes.

	(1)	(2)	(3)	(4)
Dependent variable is whether the degree recommended has a high share of males				
<i>John</i> Treatment	0.079*	0.073*	0.156***	0.137***
	(0.042)	(0.042)	(0.053)	(0.063)
Female	-0.087	-0.087	-0.088	-0.086
	(0.058)	(0.059)	(0.057)	(0.059)
<i>John</i> * Mum-at-home dummy	-0.182			-0.139
	(0.186)			(0.186)
<i>John</i> *Dad's job 'brains' content		0.011		0.002
		(0.059)		(0.038)
<i>John</i> *Dad's job 'brawn' content		-0.025		0.070
		(0.059)		(0.046)
<i>John</i> *Dad's job 'people' content		0.102		0.020
		(0.072)		(0.049)
' <i>John</i> *Dad's job 'average age			1.854	2.286*
			(1.161)	(1.357)
<i>John</i> *Dad's job average income			0.015	0.012
			(0.020)	(0.022)
<i>John</i> *Dad's job average hours (/100)			0.027***	0.025*
			(0.010)	(0.013)
' <i>John</i> ' Treatment *Dad's job average education			-0.456	-0.669**
			(0.327)	(0.337)
<i>Control Variables</i>				
School fixed effects	✓	✓	✓	✓
Mother is a homemaker	✓	✓	✓	✓
Father's job content	✓	✓	✓	✓
Father's occupation averages	✓	✓	✓	✓
Observations	216	216	216	216

Notes: Robust standard errors are in parentheses where *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is a binary variable that equals 1 if the degree recommended has a high share of males. The *John* treatment is a dummy variable which equals 1 if participants were assigned to *John* and zero if they were assigned to *Jennifer* in the second vignette design. Female equals to 1 if the respondent is female. A vector of control variables contains a set of school fixed effects, a dummy variable that is equal to 1 if the child's mother works and zero otherwise, father's occupation content variables, and father's occupation averages (share of men, average age, average hourly income, average hours (scaled down by 100), and share of workers with a college degree). Each regression uses an OLS specification with non-missing balanced sample.

Table B.9. The estimated effect of the *John* treatment on the justification for their recommendation of an occupation to a fictitious peer adding interaction between parent's occupation attributes.

	(1)	(2)	(3)	(4)
Dependent Variable is 1 if justification given is extrinsic, 0 otherwise				
<i>John</i> Treatment	0.044 (0.042)	0.053 (0.042)	0.064 (0.042)	0.071 (0.048)
Female	-0.068** (0.037)	-0.068** (0.037)	-0.065* (0.038)	-0.074** (0.039)
<i>John</i> * Mum-at-home dummy	-0.078 (0.215)			-0.074 (0.217)
<i>John</i> *Dad's job 'brains' content		0.019 (0.035)		0.015 (0.045)
<i>John</i> *Dad's job 'brawn' content		-0.020 (0.033)		0.007 (0.054)
<i>John</i> *Dad's job 'people' content		-0.042 (0.042)		-0.088 (0.088)
<i>John</i> *Dad's job 'average age			2.097 (1.328)	2.965* (1.586)
<i>John</i> *Dad's job average income			0.002 (0.023)	-0.009 (0.026)
<i>John</i> *Dad's job average hours (/100)			-1.154 (1.281)	-2.064* (1.081)
<i>John</i> *Dad's job average education			0.020 (0.373)	0.131 (0.394)
<i>Control Variables</i>				
School fixed effects	✓	✓	✓	✓
Mother is a homemaker	✓	✓	✓	✓
Father's job content	✓	✓	✓	✓
Father's occupation averages	✓	✓	✓	✓
Observations	216	216	216	216

Notes: Robust standard errors are in parentheses where *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is a binary variable that equals 1 if the justification given for the response implied an extrinsic motivation and zero otherwise. The *John* treatment is a dummy variable which equals 1 if participants were assigned to *John* and zero if they were assigned to *Jennifer* in the second vignette design. Female equals to 1 if the respondent is female. A vector of control variables contains a set of school fixed effects, a dummy variable that is equal to 1 if the child's mother works and zero otherwise, father's occupation content variables, and father's occupation averages (share of men, average age, average hourly income, average hours (scaled down by 100), and share of workers with a college degree). Each regression uses an OLS specification with non-missing balanced sample.

Table B.10. The estimated effect of the *John* treatment on the justification for their recommendation of an occupation to a fictitious peer adding interaction between parent's occupation attributes

	(1)	(2)	(3)	(4)
Dependent Variable is 1 if justification given is intrinsic, 0 otherwise				
<i>John</i> Treatment	-0.175*** (0.067)	-0.140** (0.067)	-0.294*** (0.085)	-0.207 *** (0.071)
Female	0.020 (0.035)	0.021 (0.036)	0.022 (0.026)	0.028 (0.029)
<i>John</i> *Mum-at-home dummy	0.268 (0.202)			0.258 (0.206)
<i>John</i> *Dad's job 'brains' content		0.001 (0.042)		-0.075 (0.088)
<i>John</i> *Dad's job 'brawn' content		-0.008 (0.051)		-0.042 (0.077)
<i>John</i> *Dad's job 'people' content		0.042 (0.054)		-0.005 (0.083)
<i>John</i> *Dad's job 'average age			-0.064 (1.268)	-0.562 (1.499)
<i>John</i> *Dad's job average income			0.013 (0.022)	0.023 (0.024)
<i>John</i> *Dad's job average hours (/100)			0.147 (1.224)	0.743 (1.495)
<i>John</i> *Dad's job average education			-0.042 (0.357)	-0.139 (0.373)
<i>Control Variables</i>				
School fixed effects	✓	✓	✓	✓
Mother is a homemaker	✓	✓	✓	✓
Father's job content	✓	✓	✓	✓
Father's occupation averages	✓	✓	✓	✓
Observations	216	216	216	216

Notes: Robust standard errors are in parentheses where *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is a binary variable that equals 1 if the justification given for the response implied an intrinsic motivation and zero otherwise. The *John* treatment is a dummy variable which equals 1 if participants were assigned to *John* and zero if they were assigned to *Jennifer* in the second vignette design. Female equals to 1 if the respondent is female. A vector of control variables contains a set of school fixed effects, a dummy variable that is equal to 1 if the child's mother works and zero otherwise, father's occupation content variables, and father's occupation averages (share of men, average age, average hourly income, average hours (scaled down by 100), and share of workers with a college degree). Each regression uses an OLS specification with non-missing balanced sample.

Appendix C. Balanced Samples Across All Regressions

Table C.1. The estimated effect of the *Stephen* treatment (Vignette 1) on the probability of recommending corporate law to a fictitious peer based on the balanced sample for each regression

	(1)	(2)	(3)	(4)	(5)
Baseline Model					
‘Stephen’ Treatment	0.133** (0.067)	0.119* (0.067)	0.109 (0.068)	0.104 (0.069)	0.110 (0.069)
Female	-0.138** (0.067)	-0.132*** (0.067)	-0.133*** (0.068)	-0.136*** (0.068)	-0.121*** (0.070)
Adding Interaction Between ‘Stephen’ Treatment and Female Dummy					
‘Stephen’ Treatment	0.129* (0.078)	0.130* (0.078)	0.105 (0.092)	0.102 (0.093)	0.102 (0.093)
Female	-0.197** (0.084)	-0.196** (0.084)	-0.135 (0.100)	-0.145 (0.101)	-0.145 (0.101)
‘Stephen’ Treatment * Female	0.004 (0.112)	0.001 (0.113)	0.005 (0.136)	0.014 (0.138)	0.0135 (0.138)
<i>Control Variables</i>					
School fixed effects	X	✓	✓	✓	✓
Mother is a homemaker	X	X	✓	✓	✓
Father’s job content	X	X	X	✓	✓
Father’s occupation averages	X	X	X	X	✓
Observations	216	216	216	216	216

Notes: Robust standard errors are in parentheses where *** p<0.01, ** p<0.05, * p<0.1. The sample in this regression is restricted so that the regressions have a balanced sample across all specifications. The dependent variable is a binary variable that equals 1 if the students choose corporate law for their fictitious peer and 0 if they choose civil rights law. ‘Stephen’ treatment is a dummy variable which equals 1 if participants were assigned to ‘Stephen’ and zero if they were assigned to ‘Stephanie’. Female equals to 1 if the respondent is female. A vector of control variables contains a set of school fixed effects, a dummy variable that is equal to 1 if the child’s mother works and zero otherwise, the father’s occupation content variables, and father’s occupation averages (share of men, average age, average hourly income, average hours (scaled down by 100), and share of workers with a college degree). Each regression uses an OLS specification.

Table C.2. The estimated effect of the *Stephen* treatment on the justification for a recommendation of corporate law or civil rights law based on a balanced sample across all regressions

	(1)	(2)	(3)	(4)	(5)
A. Dependent Variable =1 if justification given is extrinsic, 0 otherwise					
‘Stephen’ Treatment	0.173*** (0.067)	0.183*** (0.067)	0.176*** (0.067)	0.177*** (0.068)	0.189*** (0.068)
Female	-0.172*** (0.067)	-0.163*** (0.069)	-0.167** (0.067)	-0.171** (0.068)	-0.163** (0.070)
B. Dependent Variable =1 if justification given is intrinsic, 0 otherwise					
‘Stephen’ Treatment	-0.132** (0.063)	-0.148** (0.063)	-0.144*** (0.064)	-0.139*** (0.064)	-0.149*** (0.064)
Female	0.219*** (0.063)	0.204 (0.063)	0.207*** (0.063)	0.208*** (0.064)	0.178*** (0.066)
C. Dependent Variable =1 if justification given is knowledge, 0 otherwise					
‘Stephen’ Treatment	-0.000 (0.001)	-0.000 (0.002)	-0.003 (0.020)	-0.003 (0.020)	-0.003 (0.020)
Female	0.022 (0.029)	0.023 (0.029)	0.026 (0.030)	0.027 (0.030)	0.022 (0.030)
<i>Control Variables</i>					
School fixed effects	✗	✓	✓	✓	✓
Mother is a homemaker	✗	✗	✓	✓	✓
Father’s job content	✗	✗	✗	✓	✓
Father’s occupation averages	✗	✗	✗	✗	✓
Observations	216	216	216	216	216

Notes: Robust standard errors are in parentheses where *** p<0.01, ** p<0.05, * p<0.1. The sample in this regression is restricted so that the regressions have a balanced sample across all specifications. The dependent variable in each panel is a mutually exclusive binary variable that equals 1 if participants provide a given justification for recommendation of corporate law or civil rights law to their fictitious peer (panel A is extrinsic; panel B is intrinsic; panel C is knowledge). The ‘other’ justification is omitted. See Appendix Table A.1 for details for the justification classification. Female equals to 1 if the respondent is female. A vector of control variables contains a set of school fixed effects, a dummy variable that is equal to 1 if the child’s mother works and zero otherwise, the father’s occupation content variables, and father’s occupation averages (share of men, average age, average hourly income, average hours (scaled down by 100), and share of workers with a college degree). Each regression uses an OLS specification.

Table C.3. The estimated effect of the *John* treatment on the ratio of women to men in the degree recommended with the samples balanced across all regressions

	(1)	(2)	(3)	(4)	(5)
A. Dependent Variable: Ratio of females to males enrolled in the degree recommended					
<i>John</i> Treatment	-0.174** (0.086)	-0.181** (0.086)	-0.186** (0.087)	-0.181** (0.087)	-0.195** (0.089)
Female	-0.092 (0.057)	-0.078 (0.087)	-0.073 (0.088)	-0.079 (0.088)	-0.093 (0.093)
B. Dependent Variable: Whether the degree recommended has a high share of males					
<i>John</i> Treatment	0.080* (0.043)	0.081** (0.042)	0.083* (0.050)	0.086* (0.050)	0.085* (0.050)
Female	-0.017 (0.042)	-0.032 (0.041)	0.001 (0.049)	-0.004 (0.049)	0.010 (0.052)
C. Dependent Variable: Ratio of females to males enrolled in the degree recommended					
<i>John</i> Treatment	-0.155* (0.087)	-0.169* (0.090)	-0.231** (0.115)	-0.245** (0.114)	-0.237** (0.117)
Female	-0.017 (0.013)	0.006 (0.031)	-0.010 (0.012)	0.014 (0.013)	-0.026 (0.016)
<i>John</i> * Female	0.035 (0.082)	0.038 (0.175)	-0.120 (0.176)	-0.167 (0.176)	-0.113 (0.182)
D. Dependent Variable: Whether the degree recommended has a high share of males					
<i>John</i> Treatment	0.077* (0.042)	0.082** (0.041)	0.083* (0.050)	0.086* (0.050)	0.085* (0.050)
Female	-0.015 (0.043)	-0.037 (0.045)	0.001 (0.049)	-0.004 (0.049)	0.010 (0.052)
<i>John</i> * Female	0.014 (0.015)	0.017 (0.016)	0.020 (0.014)	0.019 (0.015)	0.024 (0.014)
<i>Control Variables</i>					
School fixed effects	X	✓	✓	✓	✓
Mother is a homemaker	X	X	✓	✓	✓
Father's job content	X	X	X	✓	✓
Father's occupation averages	X	X	X	X	✓
N	216	216	216	216	216

Notes: Robust standard errors are in parentheses where *** p<0.01, ** p<0.05, * p<0.1. The sample in this regression is restricted so that the regressions have a balanced sample across all specifications. The dependent variable of panels A and C is the ratio of females to males enrolled in the degree recommended by the participants. The dependent variable of panels B and C a binary variable equals 1 if the degree recommended has a high share of males. 'John' treatment is a dummy variable which equals 1 if participants were assigned to 'John' and zero if they were assigned to 'Jennifer' in the second vignette design. Female equals to 1 if the respondent is female. A vector of control variables contains a set of school fixed effects, a dummy variable that is equal to 1 if the child's mother works and zero otherwise, the father's occupation content variables, and father's occupation averages (share of men, average age, average hourly income, average hours (scaled down by 100), and share of workers with a college degree). Each regression uses an OLS specification.

Table C.4. The estimated effect of the *John* treatment on the justification for a recommendation of an occupation to a fictitious peer with balanced samples across all regressions

	(1)	(2)	(3)	(4)	(5)
A. Dependent Variable =1 if justification given is extrinsic, 0 otherwise					
<i>John</i> Treatment	0.078** (0.034)	0.089*** (0.035)	0.052 (0.036)	0.055 (0.036)	0.056 (0.036)
Female	-0.032 (0.054)	-0.023 (0.054)	-0.086*** (0.035)	-0.089*** (0.036)	-0.100*** (0.037)
B. Dependent Variable =1 if justification given is intrinsic, 0 otherwise					
<i>John</i> Treatment	-0.178*** (0.055)	-0.189*** (0.055)	-0.190*** (0.055)	-0.181*** (0.054)	-0.187*** (0.055)
Female	0.012 (0.054)	0.023 (0.055)	0.023 (0.054)	0.025 (0.054)	0.030 (0.057)
C. Dependent Variable =1 if justification given is knowledge, 0 otherwise					
<i>John</i> Treatment	0.040 (0.061)	0.040 (0.064)	0.043 (0.069)	0.034 (0.069)	0.024 (0.069)
Female	0.019 (0.055)	0.015 (0.057)	0.029 (0.069)	0.027 (0.069)	0.009 (0.072)
<i>Control Variables</i>					
School fixed effects	✗	✓	✓	✓	✓
Mother is a homemaker	✗	✗	✓	✓	✓
Father's job content	✗	✗	✗	✓	✓
Father's occupation averages	✗	✗	✗	✗	✓
N	216	216	216	216	216

Notes: Robust standard errors are in parentheses where *** p<0.01, ** p<0.05, * p<0.1. The sample in this regression is restricted so that the regressions have a balanced sample across all specifications. The dependent variable in each panel is a mutually exclusive binary variable that equals 1 if participants provide a given justification for recommendation of corporate law or civil rights law to their fictitious peer (panel A is extrinsic; panel B is intrinsic; panel C is knowledge). The 'other' justification is omitted. See Appendix Table A.3 for details for the justification classification. 'John' treatment is a dummy variable which equals 1 if participants were assigned to 'John' and zero if they were assigned to 'Jennifer' in the second vignette design. Female equals to 1 if the respondent is female. Female equals to 1 if the respondent is female. A vector of control variables contains a set of school fixed effects, a dummy variable that is equal to 1 if the child's mother works and zero otherwise, the father's occupation content variables, and father's occupation averages (share of men, average age, average hourly income, average hours (scaled down by 100), and share of workers with a college degree). Each regression uses an OLS specification.

Appendix D. Construction of additional occupation measures from the US's ONET and the UK's QLFS

Characteristics of father's occupation: Our occupation averages that relate to the father's occupation are calculated based on 2017-2019 Quarterly Labour Force Survey data (QLFS). The QLFS is the main survey of individual economic activity in Britain and provides the official measure of the national unemployment rate. The 2017-2019 data utilises SOC10 four-digit codes and, first, we assign a SOC10 four-digit code to the occupation as reported by the respondent of our survey. We then calculate occupation averages of age of workers, weekly hours, log of an hourly wage, the share of college-graduate workers as well as the share of male workers in each occupation. In the tables, these are referred to as *father's occupation averages*.

Job content of father's occupation: Our analysis also utilises three variables which capture what a job is about. These variables are created following the approach described by Lordan and Pischke (2022). Specifically, we retrieve from ONET version 5 items relating to the activities and context of an individual's work. These items on activities and context are linked to US Standard Occupation Codes (SOC) 2000. These 79 items report the level at which an occupation has a particular characteristic from 1 to 7. We match the US SOC00 codes in the ONET data directly to the British SOC10 using an amended crosswalk, to the SOC00 crosswalk provided by Lordan and Pischke (2022). We then match the ONET items to the QLFS using the British SOC10 codes. Three latent factors 'people,' 'brains,' and 'brawn' (PBB) are calculated using this data. We match these three factors for each occupation to the father's SOC10 occupation codes. In the tables, these are referred to as *father's job content*. Note that for father's average hours worked, we scale down the actual hours by 100.

Mother's employment: We create a dummy variable that is equal to 1 if the child's mother is employed at the time of the survey and 0 otherwise.