Gender Differences in Preferences for Meaning at Work*

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Abstract

Scholars have examined whether preferences for job characteristics help explain why men and women sort into different occupations, but have overlooked preferences for meaning at work. We first document gender differences in preferences for meaning in a large-scale survey covering individuals in 47 countries. We then conduct a choice-based conjoint analysis of a cohort of MBA students at a leading business school to study gender differences in preferences for meaning compared to other job attributes. We show that gender differences in preferences for meaning at work are widespread and partly explain gender differences in behavioral outcomes, including industry of work.

Keywords: Job Preferences, Meaning at Work, Social Mission, Gender Segregation.

JEL: J24, J16, D91.

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1. Introduction

Women continue to earn lower wages than men. Policymakers seeking to eliminate the gender pay gap have often focused on implementing policies intended to increase pay transparency and encourage employers to set salaries to a given position.[1] While it is indeed the case that women earn less than men for the same job, it is important to note that approximately half of the gender wage gap has been attributed not to differences in payment for the same job, but to the sorting of men and women into different jobs (Morchio and Moser, 2019; Blau and Kahn, 2017). To foster gender pay equity, then, policymakers need to better understand what leads men and women to select into different jobs. Towards this understanding, researchers have begun to examine gender differences in preferences for job characteristics, such as flexibility, stability, ability to control one's schedule, and competitiveness, as under-examined factors which help explain why men and women end up in different occupations (Eriksson and Kristensen, 2014; Mas and Pallais, 2017; Wiswall and Zafar, 2017; Buser et al., 2014; Reuben et al., 2017; Flory et al., 2014; Gneezy et al., 2003; Cassar et al., 2016; Reuben et al., 2019; Samek, 2019; Niederle and Vesterlund, 2007; Folke and Rickne, 2022; Bolotnyy and Emanuel, 2022).

We contend that an important job characteristic has been overlooked in this stream of literature to date: meaning at work. Meaning at work refers to an individual's sense of impact as a result of their work; their understanding of the purpose, and what they believe is achieved as a result, of their work (Cassar and Meier, 2018; Wrzesniewski and Dutton, 2001; Brief and Nord, 1990; Rosso et al., 2010). Whether workers believe that their employing firm exhibits high meaning or purpose has been shown to affect organizations' financial performance (Gartenberg et al., 2019), and whether workers agree with company statements of purpose has been shown to affect employee motivation (Burbano, 2021). Yet whether men and women differ in their preferences for meaning at work, and whether these differences in preferences help to explain self-selection of men and women into different types of jobs, has been to the best of our knowledge underexplored.

We examine potential gender differences in preferences for meaning derived from social impact

[1] Insitute for Research on Labor and Employment. State Policy Strategies for Narrowing the Gender Wage Gap. April 10, 2018

at work and meaning derived from non-social impact at work (see Cassar and Meier, 2018). Social impact refers to the impact or effect that an individual's job, employing organization or industry has on the broader community, society, and/or environment. The social orientation of an organization's mission in the case of public and nonprofit organizations, as well as the corporate social responsibility (CSR) of for-profit organizations, have been shown to be valued by employees (Grant, 2008; Burbano, 2016; Henderson and Van den Steen, 2015). A sense of meaning or purpose at work need not be pro-social in nature to generate value for individuals, however (Gartenberg et al., 2019; Rosso et al., 2010). A sense of meaning at work can also be generated from a sense of pride in what one's work, company or industry has accomplished, and from the significance of one's work (Gartenberg et al., 2019) beyond its impact on the community, society, or the environment. Meaning derived from non-social impact has the potential to fulfill individuals' innate psychological needs for feelings of competence and autonomy (Deci and Ryan, 2000). Industries, occupations, and employing organizations certainly differ in their perceived social impact (Dur and Van Lent, 2019), and thus vary in the degree to which they are likely to induce a sense of meaning at work from social impact. Likewise, they also differ in perceptions of work significance and accomplishment (beyond that resulting from perceived impact on the community, or the environment), thus varying in the degree to which they are likely to induce a sense of meaning of work from non-social impact.

We might expect to see gender differences in meaning derived from social impact at work given prior findings that women seem to be more emphathetic (Bertrand, 2011) and value compassion more (for example, Beutel and Marini, 1995) than men. However, the large literature in economics investigating gender differences in prosociality (for a survey, see Croson and Gneezy, 2009) provides more mixed results – that clearly depend on situational factors (e.g. Andreoni and Vesterlund, 2001; Meier, 2007; DellaVigna et al., 2013). Furthermore, there has been little empirical research directly examining whether women place higher value on social impact or meaning from social impact work more broadly (Bode and Singh, 2018; Abraham and Burbano, 2022). It is even less clear whether men or women might place higher value on meaning derived from non-social impact at work. Importantly, if there are indeed gender differences in preferences for either or both of these meaning-at-work attributes, these differences could help to explain the tendency of men and women to self-select into different industries, types of firms, and jobs.

To examine whether there are gender differences in such preferences, how they compare to gender differences in preferences for other job attributes, and whether they influence work industry, we use two different data sources and methods. First, we examine gender differences in job preferences based on a survey of approximately 110,000 individuals in 47 countries, which has previously been used to compare individuals' preferences for different job attributes (Corrigall and Konrad, 2006). We find that gender differences in preferences for meaning derived from social impact are particularly large and widespread, while gender differences in preferences for meaning derived from non-social impact are less pronounced. We show that gender differences in preferences for meaning derived from social impact increase with higher levels of education and economic development (similar to how gender differences for other preferences are more pronounced in richer countries; see Falk and Hermle, 2018). We also show that gender differences in preferences for meaning derived from social impact are correlated with the likelihood of working in the public (versus private) sector. Given the wide-ranging sample of individuals included, this study helps us to establish the generalizability of our findings across countries.

We then focus on a more homogeneous population - a full cohort of an MBA (Master of Business Administration) class at a leading US business school - for which we are able to match preference measures with behavioral outcomes. Given that the gender gap is particularly pronounced, and has not improved, among highly skilled individuals (for overviews, see Blau and Kahn, 2017; Bertrand, 2018), examination of whether differences in preferences help to explain relevant behavioral outcomes among highly skilled individuals such as those completing their MBA is particularly relevant. We use a methodology from marketing, choice-based conjoint analysis, which is commonly used to measure consumer preferences for product attributes (Louviere and Woodworth, 1983). This method, similar to that used by Wiswall and Zafar (2017) and Folke and Rickne (2022), reduces social desirability bias compared to directly asking individuals how much they value job characteristics (Leveson and Joiner, 2014). It has been underused as a methodology to study prospective employee preferences (Montgomery and Ramus, 2011), however. We conducted a hypothetical choice experiment before students started their MBA coursework to measure their preferences for meaning-at-work attributes such as the social responsibility of the employing company (to proxy meaning derived from social impact) and a sense of impact on the job not specified to be social in nature (to proxy meaning derived from non-social impact), as well as other job attributes. We find that men and women exhibit starkly different preferences for meaning derived from social impact, consistent with the cross-national data. We also observe some differences in preferences for meaning derived from non-social impact.

We show that gender differences in preferences for meaning at work help to explain critical behavioral outcomes: not only students' coursework choices and club engagement during the MBA, but also their full-time job placements after the MBA. Notably, these preferences help to explain why female MBA students are less likely to enter the finance industry (in our sample 46% of male MBA students enter the finance industry while only 31% of female students do so). This is particularly important from a gender equity perspective because finance is the industry with the highest wages (e.g., Bertrand et al., 2010; Barbulescu and Bidwell, 2013).

Our findings contribute to three streams of literature. First, we contribute to the discussion about the drivers of the gender wage gap and occupational segregation by gender, which scholars across disciplines – as well as policy-makers – have sought to explain. Factors such as discrimination in screening and hiring (e.g. Goldin and Rouse, 2000; Reuben et al., 2014; Botelho and Abraham, 2017; Fernandez-Mateo and King, 2011), biased evaluations (Rivera and Tilcsik, 2019; Reuben et al., 2014; Brooks et al., 2014; Sheltzer and Smith, 2014; Bohnet et al., 2016), peer bargaining (Pierce et al., 2019), wage penalties for career interruption (e.g. Hotchkiss and Pitts, 2007), and gender of role models at work (Porter and Serra, 2020), which vary across occupations, have been the focus of an extensive body of research.[2] Recent studies have focused on whether part of gender segregation can be attributed to gender differences in attitudes towards (Stoet and Geary, 2018), perceptions of, (Gino et al., 2015) and preferences for, job attributes which in turn affect the job choices made by men and women (Ceci and Williams, 2011; Barbulescu and Bidwell, 2013; Wiswall and Zafar, 2017).[3] In particular, recent research has focused

[2]Recent studies, however, suggest that men and women may be equally likely to be hired into a given job once they apply (Fernandez-Mateo and Fernandez, 2016). In the gig economy, the gender wage gap can be fully explained by difference in experience, driving speed and a preference for where to work (Cook et al., 2018).

[3]Work in social psychology has documented a wide array of gender differences in personality and interpersonal measures (Hyde, 2014) which influence gender differences in beliefs (Bordalo et al., 2019), as well as attitudes such as risk aversion (Sapienza et al., 2009; Charness et al., 2012; Eckel and Grossman, 2008; Charness and

on gender differences in preferences for work characteristics such as competitiveness (Buser et al., 2014; Reuben et al., 2017; Flory et al., 2014; Gneezy et al., 2003; Cassar et al., 2016; Samek, 2019) and flexibility in the workplace (Eriksson and Kristensen, 2014; Mas and Pallais, 2017; Wiswall and Zafar, 2017; Zafar, 2013), which have been demonstrated to help explain gender differences in selection into college majors and jobs, for example.

Our paper adds an important job characteristic to the context of understanding gender differences in preferences for job attributes: the degree to which a job is likely to create a sense of meaning at work for the individual.[4] We not only document that gender differences in preferences for meaning at work exist, but also show that they help to explain important behavioral differences, including industry placement, which in turn has implications for the salaries earned by men and women. Based on the results from our ISSP sample, preferences for meaning at work are correlated with women's increased likelihood of working in the public, rather than the private, sector. Based on our MBA sample, preferences for meaning at work explain about 25% of the gender effect of selection into different industries, particularly the finance industry. Notably, the size of this effect is comparable to that found for competitiveness in extant work (Buser et al., 2014; Reuben et al., 2019). While our effect size indicates that a large part of gender segregation is explained by other factors (certainly, there are many drivers of occupational segregation), it nonetheless sheds light on an important and understudied job attribute which helps to explain why men and women end up in different jobs and industries and, correspondingly, earn different wages.

Second, we add to a growing literature in economics on the importance of meaning of work and non-monetary aspects of a job more broadly (for a review, see Cassar and Meier, 2018). There is increasing recognition that individuals care about a sense of meaning at work (Wrzesniewski and Dutton, 2001; Brief and Nord, 1990; Karlsson et al., 2004; Chater and Loewenstein, 2016; Rosso et al., 2010), which can stem from characteristics attributed to an employee's job design, occupation, employing organization, and/or industry. We distinguish between two ways

Gneezy, 2012) and competitiveness (Niederle and Vesterlund, 2007; Iriberri and Rey-Biel, 2019; Azmat et al., 2016). These differences influence important decision-making outcomes (Eckel and Grossman, 2008), including how men and women assess and weigh job characteristics.

[4] Samek (2019) uses a field experiment that manipulates the competitiveness of different jobs for gender segregation, and also investigates whether a job framed as benefiting a charity or not matters. Results suggest that the gender gap in competitiveness is reduced in a charity frame.

that individuals can derive a sense of meaning at work: meaning derived from social impact at work and meaning derived from non-social impact at work. We show across both our data samples that gender differences exist for preferences for meaning at work; particularly, that derived from social impact (and to a lesser extent, non-social impact) at work. This is consistent with research showing gender differences in altruism, compassion, and inequality aversion (e.g. Bertrand, 2011; Beutel and Marini, 1995; Güth et al., 2007; Ben-Ner et al., 2004; Andreoni and Vesterlund, 2001; Su et al., 2009, for an overview of relevant literature in economics see Croson and Gneezy (2009); for an overview of relevant literature in social psychology, see Hyde (2014)). As both meaning derived from social impact and meaning derived from non-social impact are non-monetary attributes, our findings suggest that prior distinctions between extrinsic and intrinsic job attributes missed an important difference within non-monetary attributes. While existing research shows substantial heterogeneity in how different non-monetary attributes of jobs are evaluated (e.g. Wrzesniewski et al., 2003; Burbano, 2016; Cassar and Meier, 2018; Owens et al., 2014; Bekker and Van Assen, 2008; Adler, 1993), our paper highlights the gendered aspect of these heterogeneous differences.

Third, we make a small contribution to the literature examining the development of differences in preferences. Previous research has tried to understand how preferences for non-monetary aspects of work are shaped (Cotofan et al., 2020) and explain the origin of gender differences in such preferences – especially for competitiveness, for example (e.g. Andersen et al., 2013; Hoffman et al., 2011; Gneezy et al., 2009). While it is outside the scope of this paper to directly explore the origins of gender differences in preferences for meaning at work and we cannot disentangle whether or not the preferences we observe are shaped by expectations about discrimination on the job market, we do show that the gender differences in preferences for meaning derived from social impact are more pronounced in rich countries and educated subgroups (and persist among a highly educated sample of MBAs). These results complement evidence provided by Falk and Hermle (2018) that gender differences in economic preferences increase with economic development, and suggest that trends towards greater development and levels of education may help to explain part of the origin in gender differences in preferences for different job attributes.

For policymakers, our paper suggests that as long as gender differences in preferences for meaning at work persist, gender segregation by industry of work is likely to continue. Related to the literature that investigates policy interventions intended to affect gender segregation (Delfino, 2021; Flory et al., 2021; Guzman et al., 2020; Abraham and Stein, 2020), our results indicate that policies which take into account and seek to re-balance existing gender differences in preferences for meaning at work may thus be one fruitful, yet currently under-recognized, path towards equity. We elaborate on these policy implications in our Discussion.

In what follows we describe the data and methodologies, and discuss the results for each of the two data sources in turn.

2. Cross-Country Differences in Preferences for Meaning at Work

2.1. Data and Methods

To examine potential gender differences in preferences for meaning at work across the globe rather than limited to a single country, we leverage the International Social Survey Program (ISSP). The ISSP surveys around 130,000 individuals across up to 47 countries in up to four waves (1989, 1997, 2005, and 2015). Each country conducts its own surveys, but all agree to a standardized process which includes using probability sampling of a representative sample. Surveys can be conducted face-to-face or self-administered. ISSP has a Methodology Committee which oversees the method used in all countries to ensure comparability. See Table C.1 in the Appendix for number of observations by country and year. We focus on participants who are older than 16 and younger than 65 years old.

We analyze the Work Orientation I - IV modules that have questions about the importance of different attributes of a job. At the core of our analysis is the following question: *For each of the following, please tick one box to show how important you personally think it is in a job. How important is . . . job security?, . . . high income?, . . . good opportunity for advancement?, . . . an interesting job?, . . . a job that allows someone to work independently?, . . . a job that allows someone to decide their times or days of work?, . . . a job that allows someone to help other people?, . . . a job that is useful to society?*

Participants answer on a 5-point scale from 1 "Very important" to 5 "Not important at all". We re-scale the answers so that higher values indicate higher importance. In most analyses we use a dummy that has the value 1 if the individual indicated that a particular job attribute is 'Very important' or 'Important' and 0 otherwise.[5]

In addition to showing raw gender differences in the importance of different attributes, we also control for various variables using OLS regressions of the following form:

$$Job\ Attribute_i = \beta_1 Female_i + \beta_2 Controls_i + c_i + y_i + \epsilon_i \tag{1}$$

in which the dependent variable is whether a specific job attribute is important to individual i. In addition to gender and fixed effects for country (c_i) and year (y_i), we also include two sets of control variables (see Table 1). "Main" control variables include dummies for years of education, age, dummies for marital status, dummies for work status and dummies for household size. "Additional" control variables include whether the individual works in the public or private sector, whether the respondent is a supervisor and log of household size. Information about sector and position is only available for people active in the workforce. Household income is missing for almost half of the respondents. Also, the way this information is elicited is different for every country and even inconsistent within country across waves. It is thus particularly important that but we control for fixed effects for country (c_i) and year (y_i). Standard errors are clustered at the year*country level.

The summary statistics in Table 1 reflect some interesting gender differences. While there are only small differences in years of education, age, household size or marital status, there are substantial differences in work status, occupation/industry and household income. Women are much less likely to be in paid work (57% vs. 74% of men) because they are much more likely to do domestic work (18% vs. 1.5%). If they work, they are more likely to work in the public sector (36% vs. 26%) and less likely to have a supervisory role (18% vs. 32% for men).

Table 1 here

[5] The results are robust to using the full scales (see below).

2.2. Results

We present our results in four steps. First, we look at gender differences in stated preferences for job attributes (excluding and including covariates) in the entire sample of our data, to examine whether such differences are universal in nature and persist across countries. Second, we investigate whether gender differences in job preferences are more or less pronounced in higher income countries. Third, we explore whether the job attribute preferences of men and women differ by educational levels. The latter two analyses help to establish the contingencies under which gender differences in preferences for meaning at work are magnified, as well as shed light on whether such differences are likely to increase or decrease over time (given that, on average, countries are becoming more developed and individuals, more highly educated, over time). Fourth, we analyze how much job attribute attitudes explain the selection by gender into different industries. We focus on selection into "Working in the Public Sector," as it is an industry grouping for which we have data and, furthermore, is one which has previously been characterized as a prosocial industry in which to work (Dur and Zoutenbier, 2014; Perry et al., 2010).

As a baseline, we first compare gender differences in preferences for monetary and non-monetary job attributes, and then focus specifically on non-monetary preferences for meaning at work (Karlsson et al., 2004; Chater and Loewenstein, 2016). Table 2 presents gender differences in stated importance of different job attributes across individuals in 47 countries. Columns (1)-(4) show the raw gender differences. Panel A shows the calculated average importance (from 1 to 5) for monetary attributes (Income, Job Security and Opportunity of Advancement) and for non-monetary attributes (Interesting Job, Independent Work, Flexibility, Helpful to Others, and Useful to Society). Interestingly, these aggregate measures indicate that gender differences exist only for non-monetary attributes, and not for monetary attributes, complementing results previously found for US high school students (Marini et al., 1996). The gender difference in preferences for (aggregate) non-monetary attributes are not very large in size either. However, it is important to note that 'non-monetary attributes' is composed of a number of different job characteristics. We thus next break apart the different non-monetary attributes and examine them separately to observe whether gender differences in preferences for specific non-monetary are more pronounced.

Table 2 here

We present in Panel B the proportion of females and males indicating that a certain job attribute is 'very important' or 'important.' The magnitude of gender differences in preferences for job attributes varies substantially between attributes. For example, 81.3 percent of women indicate that income is important in a job, and 82.7 percent of men find income important. While the difference is statistically significant at the 99 percent level in an OLS regression, the gender difference is only around 1.4 percentage points. Similarly small gender differences are found for the two other monetary attributes: job security (difference of 1.7 percentage points) and opportunity for advancement (0.7). In terms of non-monetary attributes, gender differences are relatively small with respect to preferences for having an interesting job (difference of 0.8 percentage points) and independent work (0.9), which could be considered proxies for meaning induced from non-social impact at work. The gender difference becomes more sizable for flexibility in terms of working hours: the share of women indicating that flexibility is important is 4.8 percentage points greater than that of men. The gender difference is most pronounced for whether the job is helpful to others or useful to society. In these dimensions of meaning derived from social impact at work, the proportion of women that find the attributes important is 8.2 and 6.1 percentage points higher than that of men. Results in Columns (5) and (6) show that these differences are robust to controlling for an extensive set of variables that include socio-demographic controls and labor market outcomes (Equation (1)). For details on the estimates of all control covariates of these regressions, see Table C.3 in the Appendix. These results are robust to using ordered probit estimations and an analysis using the 5-point scales instead of this dummy variable (see Appendix Table C.4).

Figure 1 and Figure 2 here

Existing work has shown that gender differences for more basic economic preferences increase with economic development (Falk and Hermle, 2018), and that such gender differences in work values exist even within extremely highly educated samples of corporate boards of directors

(Adams and Funk, 2012). We thus investigate whether gender differences in preferences for meaning might also vary by GDP per capita and by education level. Specifically, we estimate equation (1) for each country separately and plot β_1^c, i.e., a country, c, specific gender coefficient against log GDP per capita. To investigate whether gender differences vary by different education levels, we estimate equation (1) with education group dummies and interaction between those dummies and our gender indicator.

Figures 1 and 2 investigate whether the gender differences in preferences for non-monetary attributes are more or less pronounced when individuals reside in richer countries and have higher levels of education. Both figures focus on four attributes: "income" as the primary monetary attribute, as well as "flexibility", "helpful to others" and "useful to society," which emerged as the the non-monetary attributes for which gender differences in preferences were greatest. For an analysis of all attributes, see Figure D.1 and Table C.2 in the Appendix.

Figure 1 indicates that gender differences controlling for socio-demographics are more pronounced in more developed, i.e. richer, countries. Regressing the gender coefficient (which indicates how much more women care about an attribute than men – controlling for many factors, see Figure D.1) on the average log of GDP per capita shows that GDP per capita is significantly associated with gender differences – but mainly for non-monetary attributes (-.017 (s.e.=.006) for Income, .039 (.010) for Flexibility, .055 (.009) for Helpful to Others, and .040 (.008) for Useful to Society (regressions available upon request)). We find very similar results when we use the Gender Equality Index constructed by Falk and Hermle (2018). Gender differences (especially for attributes related to social impact at work) are more pronounced in countries which score higher on the gender equality index (see Figure D.2 in the Appendix).

Figure 2 plots coefficients of interaction terms between gender and different education groups (with 9-12 years of education as the reference group). Full regression results for all attributes are in Table C.2 in the Appendix (controlling for a large set of variables). The figure shows that gender differences in preferences for meaningful jobs become more pronounced with higher levels of education. Especially for the attributes related to social impact at work ('helpful to others' and 'useful for society'), gender differences become significantly larger for groups with more than 12 years of education. These results are important since they suggest that a larger proportion of the population may exhibit gender differences in preferences for meaning induced by social impact at work over time, as the world's population becomes more educated and more developed.

Table 3 here

In Table 3, we explore whether preferences regarding job attributes can help explain part of the gender segregation into different types of industries. In particular, we analyze whether these preferences can partly explain why more women work in the public sector, given that this sector is characterized as more prosocial than the private sector (Dur and Zoutenbier, 2014; Perry et al., 2010). Column 1 shows the results from the summary statistics: 10 percentage points more women work in the public sector than men. Controlling for socio-demographic variables does not explain any part of this gender effect. Adding preferences regarding the importance of different monetary and non-monetary attributes explains about 11 percent of the gender effect. That a job is 'Useful to society' is one of the job attributes most correlated with work in the public sector.

3. Gender Differences in Preferences for Meaning at Work Amongst MBA Students: A Conjoint Analysis

While the aforementioned analyses using the ISSP survey allows us to look at the wide-spread nature of gender differences in job preferences in a representative sample and to look at correlation with economic development using the cross-country feature of the data, the data also poses some limitations. The ISSP uses subjective Likert-scale responses to capture the expressed importance of different job attributes. When comparing responses across men and women, one should keep in mind the possibility that the reference points for men and women could be different (as discussed, for example, Heine et al., 2002, in the context of cross-cultural comparisons). Because these preferences are being elicited after individuals have chosen their workplace, the responses may reflect a desire to avoid cognitive dissonance. The elicitation method furthermore does not force the respondents to consider any trade-offs (i.e. all attributes could potentially be stated as "very important"). Direct elicitation of preferences also makes social desirability bias more likely, particularly for questions related to meaning derived from social impact. Because of gender stereotypes associated with prosociality and communality (Shea and Hawn, 2019; Fiske and Stevens, 1993; Abele, 2003; Abraham and Burbano, 2022), direct elicitation of preferences related to social impact could be particularly problematic given our interest in gender differences. In addition, direct measurement of preferences may not accurately capture the trade-offs among job attributes that individuals face when making job offer decisions. The wide range of individuals included in the ISSP survey, while useful to helping to establish the universality of the difference in job preferences, also poses a challenge due to the difficulty of controlling for personal traits and characteristics, about which we do not have data. To address these issues, we leverage a choice-based conjoint methodology, implemented on a sample of a homogeneous, high-skilled group of individuals. We then track these individuals over time to examine whether differences in preferences predict behavioral outcomes.

3.1. Data and Methods

We implemented a choice-based conjoint survey with the entire entering MBA class of a top US MBA program in September 2017 to infer MBA students' preferences for different job attributes. We administered the survey as a required assignment for the core MBA strategy course, which all entering students take. The survey included questions related to various cases taught as part of the upcoming course, and was conducted before the start of the class.[6] We made it clear that the answers to the survey would not affect grades and that individual answers would be treated confidentially and not be shared, in order to avoid any potential signalling effects (Bursztyn et al., 2017). During the survey, we administered a series of questions to conduct a choice-based conjoint analysis of students' responses to infer their preferences for job attributes.

Choice-based conjoint analyses (CBC) are a series of techniques applied mostly in consumer marketing research to measure individuals' preferences for multi-attributed products (Louviere and Woodworth, 1983). In such analysis, products are decomposed into a combination of levels

[6] For example, students were asked questions about their international experience for a class on global strategy; were asked CSR-related questions for a CSR class; were asked about their beer preferences for a case about a beer company. Their aggregated responses were shown during the corresponding classes to help motivate discussion.

of values for a set of multiple attributes, and respondents' utilities for products are obtained from combining part-worth utilities over these attribute levels. Choice-based conjoint analysis in particular consists of obtaining these utilities by simulating discrete choices over a set of product profiles. Respondents are provided with a set of hypothetical experimentally-generated product profiles and they are asked to choose the one that they prefer the most. By choosing their preferred product amongst numerous sets of products which randomly vary in the level of each attribute shown, participants reveal their relative preferences between product attributes. Researchers can analyze the choice trade-offs made between each attribute to determine participants' implicit valuation of, or preference for, each attribute.

Why is it beneficial to use a choice-based conjoint analysis to elicit preferences rather than a more direct elicitation method? Alternatively framed questions aimed at capturing preferences directly often fail in one of two ways: 1) they do not accurately capture preferences trade-offs in relation to other attributes, and/or 2) they fail to capture the strength of these preferences. For example, direct importance (e.g., Likert scale) questions do not capture trade-offs against other attributes, as respondents are not forced to balance or weigh the importance of social-impact with respect to tradeoffs with other attributes. Ranking questions provide rank-orders of attribute importance but do not capture the magnitude of these differences (which are often not equal). Constant-sum questions may be difficult to interpret and have been shown to provide considerably different measures of attribute importance compared to conjoint discrete choice experiments (Louviere and Islam, 2008) which have been shown to exhibit high external validity in real choices (e.g., Swait and Andrews, 2003; Blamey et al., 2001; Louviere, 2001). Moreover, direct questions may fail to disentangle the correlation among attributes present in the market due to firm-side behavior in the job market and the inferences respondents make about those attributes when asked directly (Wiswall and Zafar, 2017). By contrast, in conjoint experiments the presence of attributes in the product/job profiles is randomly assigned. The choice-based data collection process is furthermore considered to be more realistic and simpler for respondents, resulting in more accurate responses than rating-based or ranking-based conjoint analysis methods (DeSarbo et al., 1995). For these reasons, choice-based conjoint analysis has been shown to be a more reliable way to elicit product attribute preferences than directly asking individuals which attributes they prefer (Akaah and Korgaonkar, 1983) or even, for job attribute preferences, than looking at past job choices (for a great discussion about this, see Wiswall and Zafar, 2017). Given our interest in gender differences in preferences for meaning including meaning induced by social impact, a choice-based-conjoint elicitation of preferences is furthermore likely to reflect less social desirability bias in responses than direct elicitation; something which is particularly important for our study because social desirability related to preferences about social impact are gendered in nature. That is, because of gender stereotypes about communality and prosociality, with such traits being associated with and expected of women but not men (Shea and Hawn, 2019; Fiske and Stevens, 1993; Abele, 2003; Abraham and Burbano, 2022), women are likely to feel greater pressure to respond that they value social impact if asked directly than men. We thus focus on the choice-based conjoint elicitation of preferences in our paper, though we also run our analysis using direct ranking questions for robustness (see Table C.8 in Appendix C.7 for correlations between conjoint-derived preferences and direct ranking questions, and Appendix C.11 for the main analysis using direct ranking questions).

Students were asked ten choice-based conjoint questions, wherein they were asked to choose between three job descriptions and indicate which of the three they would prefer after graduation. The job descriptions varied in five attributes of the job: 1) financial offer, 2) the degree of corporate social responsibility (CSR) of the hiring company (to proxy social impact), 3) the degree of non-social impact of their job, 4) degree of flexibility of work, and 5) degree of prestige of the hiring company. Note that it is common in organizational research to equate companies' social impact with corporate social responsibility (Margolis and Walsh, 2003). The order of the attributes shown, as well as level of each attribute, was randomly generated. Table 4 shows the different levels for each attribute. See Appendix A for exact wording of the conjoint questions. The full list of instructions and questions administered during the survey is available in Appendix B.

Table 4 here

We merged the MBA students' preference parameters inferred from the conjoint study with administrative data from the University. Specifically, we gathered data on admissions, courses taken, engagement with socially-oriented MBA clubs, and full-time job placement.[7] From admissions data, we obtained student gender, whether the student is international (vs. based in the US), their GMAT score (or GRE score, which we standardize into an equivalent GMAT score), their years of work experience and industry prior to the MBA (finance and non-profit), and whether or not they have any loans.

Using course data, we construct the variables *Proportion of Socially Oriented Courses* and *Proportion of Finance Courses*, which are the proportion of socially-oriented elective courses, and of finance-oriented elective courses, respectively, taken by the student during their two-year MBA. Students have complete autonomy of choice in selecting their elective courses.[8] We also obtained data from the university on the industry in which students were employed directly following their MBA. We categorize the students' *Post-MBA Industry*: whether they interned in Consumer Products/Retail, Consulting, Finance, Healthcare, Tech and Media (Advertising, Media, Tech, Entertainment), Nonprofit (Education, Government, Nonprofit) or Other (Other, Agribusiness, Energy, Manufacturing, Transportation, Family Business, or Starting Own Business)[9]. We then focus on whether they were employed in the finance industry, as well as whether they were employed in the nonprofit industry, in our analysis. The finance industry is perceived to lack the trait of social mission and social usefulness (Sapienza and Zingales, 2012; Zingales, 2015), whereas the nonprofit and public industries are the quintessential examples of sectors with high social mission (Dur and Van Lent, 2019). Given that the finance industry pays among the highest wages (e.g., Bertrand et al., 2010; Barbulescu and Bidwell, 2013) and the nonprofit and public sector industry pays amongst the lowest, it is important to examine whether differences in preferences for meaning derived from social impact at work lead to differences in selection into these industries by gender, as these differences could indirectly help to explain the gender wage gap. Indeed, there has been notable inquiry into gender inequities in the finance industry (Niessen-Ruenzi and Ruenzi, 2019).

[7]IRB approval was obtained both to administer the survey and to link the responses to the survey with the administrative data.

[8]To identify whether or not a course was socially oriented, a paid MBA RA (uninformed about the objective of our paper) was asked to classify each of the business school courses as covering topics related to the environment (1 if yes, 0 if not), society (1 if yes, 0 if no), and governance (1 if yes, 0 if no) - the three elements of social impact, or ESG. We then created an aggregated social impact score equal to 1 if the course was identified as covering a topic related to the environment, society, and/or to governance, and 0 otherwise.

[9]Industry was not specified for Family Business or Starting Own Business, so we categorize these as Other

Table 5 here

Table 5 shows summary statistics of the MBA sample's characteristics by gender. Table 5 shows relatively minor differences in background characteristics (Panel A); male and female students differed in whether their prior job was in the finance industry. In their coursework (Panel B), their engagement with socially oriented clubs during the MBA (Panel B) and their job industry post-MBA (Panel C), differences are more pronounced. In particular, female MBA students take on average one finance class less than their male colleagues, and 53% of these female students attend at least one social club event whereas, for male students, only 30% of them attend. Moreover, while 46% of male students go into finance post-MBA, only 31% of female students do so.

3.2. Model specification

Respondent's choices amongst the hypothetical job descriptions allow us to infer their preferences by modeling respondents' choices on each question in the conjoint task, using a multinomial logit model (MNL). In this section, we describe a) how we model respondents' choices, b) how we account for preference heterogeneity, c) what estimation procedure we use, and d) how we ultimately measure how important the different job attributes are for each segment or respondent.

Importantly, we accounted for preference heterogeneity in two ways standard in marketing research (Wedel and Kamakura, 2012): 1) Latent Class MNL Model (LC-MNL) (DeSarbo et al., 1995, 1992), and 2) Hierarchical Bayes MNL Model (HB-MNL) (Lenk et al., 1996). These two approaches are equivalent in how they model choices given preferences, but they differ in how they model respondents' heterogeneity. In the LC-MNL model, we assume that individual-level preferences are drawn from a finite mixture, which allows us to infer preference heterogeneity through a discrete set of segments, such that we can assign each respondent to a "segment" (our segments of "job seeker preferences" are analogous to "consumer preferences" in market research). This approach allows for a relatively intuitive illustration of different preferences by segments, groups, or individuals. To complement this analysis, we estimated an HB-MNL model to infer individual-level preferences, where we assume these preferences are drawn from a continuous distribution (Gaussian in our application). These individual-level preferences allow us to infer gender differences while controlling for other respondent-level covariates. In addition, it allows us to test whether these preferences can partially explain the gender differences in our main variables of interest, i.e., courses taken in the MBA, prosocial club participation, and post-MBA job industry.

3.2.1. Choice model

Respondents make choices between sets of hypothetical job offers described by a combination of attributes at different levels. We index respondents by $i = 1, \ldots, I$; choice-task occasions by $t = 1, \ldots, T$; and job profiles alternatives by $j = 1, \ldots, J$. Consider a set of job attributes indexed by $k = 1, \ldots, K$, each of which captures one dimension of the job offer. Examples of job attributes are a job's salary, the social responsibility of the firm, and the flexibility of the job, among others. Each job attribute k can take levels $l = 1, \ldots, L_k$, where each level represents the specific value of the attribute for a job offer. For example, the job salary could be either \$135K, \$150K, or \$165K.

We modeled Y_{it}, the choice of respondent i on task t, by using a MNL model,

$$P(Y_{it} = j) = \frac{\exp(V_{itj})}{\sum_{n=1}^{J} \exp(V_{itn})}, \tag{2}$$

where V_{itj} represents the deterministic component of utility of job offer j in choice-task t for respondent i. We decomposed the utility into part-worths of attribute levels by,

$$V_{itj} = \sum_{k=1}^{K} \sum_{l=1}^{L_k} X_{itjkl} \beta_{ikl}, \qquad \forall j = 1, \ldots, J, \tag{3}$$

where X_{itjkl} is a dummy variable that equals to 1 if job offer j of choice task t presented to respondent i has level l for attribute k, and 0 otherwise; and β_{ikl} is the part-worth utility of level l of attribute k for respondent i. As in any choice model, only differences of utilities between alternatives can be identified, which implies that we can only identify differences of utilities between attribute levels, as opposed to absolute utilities for these attribute levels. Therefore, we set the first level of each attribute as the baseline level, and we measure part-worths as utilities for deviating from that baseline level by setting $\beta_{ik1} = 0$ for all attributes and all respondents.

3.2.2. Heterogeneity in Preferences

Our model accounts for respondents' heterogeneity in preferences over job attributes. We account for heterogeneity using two alternative approaches: 1) Latent Class MNL Model (LC-MNL), and 2) Hierarchical Bayes MNL Model (HB-MNL). We defined by $\boldsymbol{\beta}_i$ the respondent-specific vector of product utilities, where

$$\boldsymbol{\beta}_i = [\{\beta_{ik2:L_k}\}_{k=1}^{K}]'.$$

We modeled these heterogeneous preferences $\boldsymbol{\beta}_i$ accordingly for LC-MNL and HB-MNL models.

Heterogeneity in LC-MNL model In this approach, we assumed a fixed number of segments S, and we model respondents' preferences as drawn from a finite mixture,

$$\boldsymbol{\beta}_i \sim \sum_{s=1}^{S} \pi_s \cdot \delta_{\mathbf{b}_s}, \tag{4}$$

where π_s represents the size of segment s, and $\mathbf{b}_s$ the set of preferences of segment s. In other words, we assume that a respondent belongs to segment s with probability π_s, and given that a set of respondents belong to segment s, all these respondents have the same preferences $\mathbf{b}_s$.

We computed the likelihood of the model by integrating over this finite mixture for each respondent, which yields the individual-level likelihood

$$p\left(Y_{i,1:T} | \{\pi_s\}_{s=1}^{S}, \{\mathbf{b}_s\}_{s=1}^{S}\right) = \sum_{s=1}^{S} \pi_s \cdot L_{is}, \tag{5}$$

$$L_{is} = \left[\prod_{t=1}^{T}\prod_{j=1}^{J}\left(\frac{\exp(V_{itj|s})}{\sum_{n=1}^{J}\exp(V_{itn|s})}\right)^{\mathbb{1}\{Y_{it}=j\}}\right], \tag{6}$$

where $V_{itj|s}$ is the deterministic component of utility from (3) using preferences $\mathbf{b}_s$.

Heterogeneity in HB-MNL model According to this approach, we modeled respondents' heterogeneity using a multivariate Gaussian distribution,

$$\boldsymbol{\beta}_i \sim \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma}), \tag{7}$$

where $\boldsymbol{\mu}$ is the population mean of utilities, and $\boldsymbol{\Sigma}$ is the population covariance matrix which captures the dispersion of preferences across respondents. According to this model, all respondents have different preferences.

Conditional on each individual-level vector of product utilities $\boldsymbol{\beta}_i$, we obtained the individual-level likelihood by

$$p\left(Y_{i,1:T}|\boldsymbol{\beta}_i\right) = \left[\prod_{t=1}^{T}\prod_{j=1}^{J}\left(\frac{\exp(V_{itj})}{\sum_{n=1}^{J}\exp(V_{itn})}\right)^{\mathbb{1}\{Y_{it}=j\}}\right]. \tag{8}$$

3.2.3. Estimation

We inferred the parameters of both models using Bayesian estimation. We draw samples from the posterior distribution of the parameters using Hamiltonian Monte Carlo (HMC) implemented in Stan (Carpenter et al., 2017). We use zero-centered Gaussian priors with standard deviation of 5 for $\mathbf{b}_s$ and $\boldsymbol{\mu}$; uniform on the simplex priors for $[\pi_s]_{s=1}^{S}$; LKJ correlation priors for the correlation matrix decomposition of $\boldsymbol{\Sigma}$, and uniform priors for the inverse of the hyperbolic tangent of the standard deviations of $\boldsymbol{\Sigma}$ (as suggested in Stan documentation for hierarchical models). In addition, we use 1,000 warm-up iterations and 1,000 iterations to draw from the posterior distribution for the LC-MNL model, and 2,000 warm-up and 2,000 to draw from the posterior, for the HB-MNL model. We assess convergence of these models by observing the traceplots of the parameters.

We estimated the latent class model with different numbers of segments, and chose the model with 3 segments to facilitate the interpretation of these segments (for details on model selection criteria, see Table C.5 in Appendix).

3.2.4. Identification

Variation in salary and other job attributes is exogenous to respondents' preferences, as job profile attributes are randomized both within respondents (on each alternative within a choice set and across choice sets) and across respondents. This experimental variation identifies the parameters in the model.[10]

3.3. Measuring attributes' importance

After estimation, we computed how important each job attribute is for each segment (for the LC-MNL model) or respondent (for the HB-MNL model) as follows. Consider $\widehat{\beta}_{ikl}$, a draw from the posterior distribution of part-worth of level l for attribute k and segment/respondent i. We computed the importance of attribute k for respondent i by using the range per attribute by

$$\text{Importance}_{ik} = \frac{\text{Range}_{ik}}{\sum_l \text{Range}_{il}} \tag{9}$$

$$\text{Range}_{ik} = \max\left(0, \left\{\widehat{\beta}_{ikl}\right\}_{l=2}^{L_k}\right) - \min\left(0, \left\{\widehat{\beta}_{ikl}\right\}_{l=2}^{L_k}\right), \tag{10}$$

where Range_{ik} measures the largest difference in utility that results from a change of level in attribute k, and Importance_{ik} measures the relative importance of attribute k for segment/respondent i.

3.4. Results

We present the results from the conjoint analysis in the MBA sample in three steps. First, we characterize the segments obtained from the LC-MNL model. This allows us to illustrate how male and female MBA students are distributed across different preference segments (just as with consumer product segments, job preference segments are easy to interpret). Second, we present individual-level results from the HB-MNL model which allows us to control for important

[10] Individual-level parameters are identified longitudinally by observing multiple choice questions per respondent and weakly identified cross-sectionally by the mixture distribution (finite mixture or Gaussian). The finite mixture in the LC model provides identification by constraining all parameters within a segment to be constant across respondents. The Gaussian component in the HB model provides weak identification by regularizing individual parameters towards the population mean, and induces unimodality in the prior, but only favors (and does not force) unimodality in the posterior.

individual-level covariates. Third, we analyze whether the preference parameters can help to explain behavioral outcomes such as courses taken and social club engagement during the MBA, as well as industry choices post-MBA.

We start by characterizing the segments obtained from the LC-MNL model. Table 6 shows the posterior mean of the preference parameters $\mathbf{b}_s$ for each segment. The segments are labelled according to the attributes which emerge from the analysis as being the most important to the segment; namely, 1) financial salary motivated, 2) social and non-social impact motivated, and 3) non-social impact motivated.

Table 6 and Figure 3 here

We assigned respondents to the most likely segment; that is, to the segment with the highest membership probability given the individual's set of responses.[11] Figure 3 shows the distribution of individuals across segments, by gender. The figure shows substantial gender differences: while only 20% of male MBA students are motivated by both social and non-social impact, 35% of female students are. On the flip side, 48% of men are primarily motivated by income, while only 32% of women are. The segment of individuals who are motivated by non-social impact at work has about the same proportion of men and women. This suggests that gender differences in preferences for meaning at work are most pronounced for meaning derived from social impact at work as opposed to from non-social impact at work. The segmentation analysis enables intuitive illustration of different varied preferences by segments, or groups of individuals. However, this analysis does not allow one to control for individual-level characteristics.

Given that individual-level characteristics might also be correlated with preferences, we use the individual-level estimates from the HB-MNL model, and explore gender differences controlling for individual-level characteristics (e.g., GMAT scores and other characteristics shown in Panel A of Table 5). We compute the attributes' importance for each respondent based on the model estimates using Eq. (9). To avoid collinearity (attributes' importance sum to 1), we log-transform the attributes' importance and measure them relative to the importance of Financial Offer. Specifically, for each attribute k among Non-Social Impact, Social Impact, Flexibility,

[11]If the likelihood of an individual given a segment is L_{is} from Equation (6), then the probability of segment membership of respondent i to segment s given the set of responses $Y_{i,1:T}$ is $\widetilde{\pi}_{is} = \pi_s L_{is}/(\sum_{s'} \pi_{s'} L_{is'})$.

and Prestige we compute $\log\left(\frac{\text{Importance}_k}{\text{Importance}_{\text{FinancialOffer}}}\right)$.

To highlight the face validity of these metrics, for the case of the social-impact attribute, we show in Table C.8 in Appendix C.7 that this measure is correlated with (but not identical to) the ranking of social impact among the other attributes ($\rho = -0.57$), and the model-free responses from the conjoint questions ($\rho = 0.49$ and $\rho = -0.67$). Finally, we regress these metrics on gender (first column of each DV) plus pre-MBA controls (second column of each DV).

Table 7 here

Table 7 shows results of these regression analyses. We find that the ratios of how important the attributes' Social Impact, Non-Social Impact, and Flexibility are (over how important Financial Offer is) when choosing a job are higher for female respondents than for male respondents. In other words, female respondents assign greater weight to these attributes compared with Financial Offer than do male respondents. Notably, this difference is the highest for Social Impact. Furthermore, from the estimates of the model, we compute how much salary respondents would be willing to sacrifice to improve the social impact of a job offer (details in Appendix E.1). We show the distribution of this quantity by gender in Figure 4. From these distributions, we observe that female respondents exhibit larger salary tradeoffs than male respondents, that is, they are willing to sacrifice more salary for improving the social impact of a job offer. We confirm these insights in Appendix E.2, where we show that gender differences are significant, and that male respondents would make an approximated 25% smaller salary tradeoff to improve the social impact of a job offer compared to their female colleagues, even when controlling for other observables.

Figure 4 here

These results complement the findings of the latent class models: female MBA students value different job attributes than male students, and the gender difference is particularly pronounced for whether the potential employing firm is socially responsible (a proxy for meaning induced by social impact at work). These results are robust to controlling for individual-level characteristics, including the prior industry in which they were employed prior to the MBA (see Table C.6 in the Appendix). These results are also directionally consistent with the gender differences in direct ranking questions and in the model-free conjoint choices shown in Panel D of Table 5.

Table 8 here

Lastly, we analyze whether a preference parameter capturing the importance of social responsibility (meaning derived from social impact at work) relative to income can help to explain the gender differences in important behavioral outcomes.[12] Specifically, we examine the courses taken by MBA students, their engagement in prosocial clubs during their MBA, and the industry in which they work directly after the MBA. For each of these outcomes, the MBA students have complete autonomy of choice. They are completely free to choose their electives, are not required to participate in prosocial clubs, and, of course, choose the jobs to which they apply. We focus our analyses on the finance and nonprofit sectors, but show results for all industries in Table C.12 in the Appendix.[13]

For all six outcomes, Table 8 has columns including and excluding the preference parameter, $\log\left(\frac{\text{Importance}_{\text{SocialImpact}}}{\text{Importance}_{\text{FinancialOffer}}}\right)$, generated from the HB-MNL model. The table shows that there are gender differences in outcome variables, consistent with gender segregation into different industries. Most striking is that the proportion of female students going into the finance industry post-MBA is about 13 percentage points lower than that of male students (Column 1 in 9b). Importantly, we find that adding preference parameters helps to explain part of this outcome. Looking at the increase in adjusted R^2 between OLS models shows that adding the preference parameters increases the explanatory power of the models substantially. The gender difference in courses taken and industry choice decreases by 10-25% across the models (i.e. when controlling for preference parameters). For Post-MBA industry selection into the Finance industry, including the social impact preference parameter decreases the gender effect by 25 %. Our results therefore indicate that differences in preferences for meaning at work may help to partly explain

[12] In Appendix C.8 we also explore how non-social impact can explain the gender differences, and how it compares with social impact.

[13] Including prior industry controls may not truly represent the explanatory power that the estimated preferences may provide to explain post-MBA industry selection as job selection prior to the MBA is most likely also driven by similar preferences. Nevertheless, we include such analyses in Table C.20 in the Appendix. We find results in the same direction, although the explanatory power of preferences is weakened compared to Table 8 for the aforementioned reason.

the types of courses taken, participation in social clubs events and the industry of full-time placement. In terms of assessing the size of the effect, we furthermore observe that preferences for meaning at work explain about the same, or more, than do preferences for competition, which have been highlighted in extant work as important contributors to gender segregation (e.g., Reuben et al., 2019; Buser et al., 2014). In the Appendix, we show in Tables C.9, C.10 and C.11, that social impact explains a larger share of these gender differences than non-social impact for most of the outcomes.

Industry placement is a particularly important outcome because of its implications for both short-term and long-term gender wage differences. Whereas a median MBA student (at the university of our sample) who goes into investment banking receives $200,000 as a starting salary, the equivalent MBA student going into nonprofit, education or government is paid less than $120,000. As a point of comparison, the MBAs going into media, technology, or consumer products are paid in the ballpark of $140,000-150,000. Finance is easily the highest-paying industry for graduating MBA students, with the initial post-MBA differences in salary furthermore paling in comparison to differences in pay between these sectors five or ten years down the line.

Importantly, our results are robust to controlling for measures of risk-taking behavior, competitiveness, aggressiveness and assertiveness, as shown in Tables C.14 and C.15 in the Appendix.[14] These results are also directionally consistent with replacing our conjoint-based preference measure for social impact with either a direct ranking question or summary statistics from the raw conjoint choices (Tables C.16, C.17 and C.18 in the Appendix). We note that the results using these alternative measures are weaker, which is consistent with the fact that conjoint measured preferences are better at capturing the strength of respondents' tradeoffs between attributes. In contrast, ranking position measures do not capture the magnitude of the differences across those positions, which can lead to measurement error and smaller effect sizes.

[14]These variables are constructed from survey responses collected during a Leadership course administered to all students prior to the start of the Strategy course during which the conjoint-based survey was administered. In particular, we use responses to questions from the BEM Sex Role Inventory scale (SRI) (Bem, 1974) (see questions in Appendix C.10). Often used in psychology, this survey consists of a number of questions which are often combined to measure an individuals degree of femininity or masculinity. Note that results are also robust to inclusion of controls for femininity and masculinity based on all questions included in the BEM SRI survey.

4. Discussion

Taken together, our results provide compelling evidence that there are gender differences in preferences for meaning at work. Previous work has shown that about half of the variance in earnings across firms is due to compensating differentials (Sorkin, 2018), and that some of the gender gap across firms can be attributed to taste differences and work conditions (Morchio and Moser, 2019). Our paper complements this research with a stated preferences approach which enables us to measure gender differences in preferences directly – at the individual level. It shows across two samples and methodologies that there are indeed gender differences in preferences for meaning at work. These gender differences in preferences persist across a heterogeneous sample of individuals across 47 countries, and become notably more pronounced amongst individuals of higher education levels and who live in more developed economies. These findings are important because they suggest the universality of gender differences in preferences for meaning, and point to the likely increase in these differences over time, as the population becomes more educated and more economically developed. In this sample, we furthermore find differences in preferences for meaning derived at work to be larger in magnitude than that of other job attribute preferences which have been the focus of attention to date including preferences for flexibility at work (Eriksson and Kristensen, 2014; Mas and Pallais, 2017; Wiswall and Zafar, 2017) and monetary attributes such as variable pay (Dohmen and Falk, 2011), highlighting the importance of incorporating differences in preferences for meaning into this discussion. The correlation in this data between preferences for meaning at work and the likelihood of working in the public sector is furthermore suggestive of a relationship between preferences for meaning at work and occupational segregation by gender.

Amongst a sample of MBA students, we demonstrate that gender differences in preferences for meaning at work, such as that derived from social impact, help to predict the courses pursued during business school, engagement with social impact clubs during business school, as well as the industry of full-time job placement. The latter is a critically important outcome from a gender segregation perspective, as industry of full-time employment not only influences short-term, but also long-term future, wages. Indeed, it has been shown that the gender pay gap increases over the course of careers (Goldin et al., 2017). Our results are furthermore consistent with the general perception that the finance industry lacks social responsibility and social impact relative to other industries (e.g., Johnson et al., 2019; Sapienza and Zingales, 2012; Zingales, 2015).

Our findings have important implications for policymakers seeking to achieve gender pay equity. Understanding gender differences in preferences is critical because, if gender differences in preferences help to explain part of the equity gap, policies directed at affecting gender differences in beliefs (about ability, earnings, etc.) (Zafar, 2013) and in affecting gender differences in access will not be sufficient for achieving gender equity. Our paper suggests the importance of recognizing the role that self-selection of men and women into jobs with different characteristics - in particular meaning induced from social impact - plays in maintaining and exacerbating gender segregation and thus, the gender wage gap. Our findings suggest that, without addressing gender differences in preferences for meaning at work, the prevailing policy recommendations of how to achieve gender pay equity could fall short of their aim. Policy changes or incentives aimed at altering gender stereotypes and increasing men's relative appreciation and preference for meaning at work could be one way to help address the gender imbalance in high-paying vs. low-paying industries and jobs. Likewise, policies which require increased corporate social responsibility or social impact from companies in high-paying industries could be another promising way to increase the representation of women in these occupations and, resulting, narrow the gender wage gap. Though such policies would be somewhat indirect ways to address the gender pay gap, there may in fact be benefits to indirect policies such as these. This is because implementation of policies explicitly directed at minimizing bias or achieving diversity goals can often be met by resistance (Dover et al., 2016; Ip et al., 2019; Leibbrandt et al., 2018; Niederle et al., 2013). Given the increasing political polarization of DEI (diversity, equity and inclusion) issues in recent years, resistance to explicitly equity-oriented policies may increase, potentially making the implementation of indirect policy mechanisms such as these promising avenues for helping to address gender equity.

Our paper points to a number of promising areas for future research. Future work could delve more deeply into characterizing the phenomenon of gender differences in preferences for meaning at work. For example, exploration of cross-country differences and how such differences have evolved over time could be fruitful areas for future research on this topic. Future research could also examine how gender differences in job preferences such as those for meaning at work are shaped (see Cotofan et al., 2020, for a discussion of how experience when young can shape job preferences). Recent work suggests that social mission may be perceived as incongruent with male agentic traits, resulting in penalties for men pursuing social mission (Bode et al., 2017; Abraham and Burbano, 2022), whereas females are rewarded for pursuing social mission (Lee and Huang, 2018), which could influence preferences over time, for example. These preferences could be endogenous to the work situation and society at large, despite the fact that gender differences prevail when we control for job market (e.g. industry or supervisory role) and educational outcomes in our cross-country regressions.

Our results show that for gender-specific job preferences to develop, availability of resources is important, similar to Falk and Hermle (2018). Our results are thus consistent with the notion that greater financial resources relax the relative importance of the gender-neutral goal of subsistence and allow for gender-specific preferences to emerge. Future work could examine whether gender differences for preferences in meaning at work emerge in countries and contexts where individuals' subsistence needs are already addressed.

With respect to the generalizability of our findings from the MBA sample to non-MBAs, it is important to note that MBA students are highly educated and predominantly from more developed economies. Thus, the results from our cross-country study suggest that gender differences in preferences for meaning might be particularly pronounced in this sample. On the other hand, given that gender differences in job preferences have been shown to explain selection into different majors and career types (Buser et al., 2014; Wiswall and Zafar, 2017), the fact that our sample is limited to an MBA career path might indicate that our results are under-, rather than over-estimated. Future work which examines the implications of gender differences in preferences for meaning in the context of other professions and different samples of the population will thus be important complements to our research. Future work which analyzes preferences for meaning at work that are elicited in an incentive-compatible way would also be a nice complement to our choice-based conjoint method. Additionally, our analysis focuses on industry selection into the finance and non-profit sectors. Future research could investigate how gender differences in preferences for meaning influence selection into other industries, as well as into different types of firms within industries.

Overall, this paper establishes that men and women differ in their preferences for meaning at work, and that gender differences in preferences for this job attribute have implications for behavioral outcomes including sorting into different types of occupations. It contributes to our understanding of the contributors to occupational segregation by gender, to our understanding of gender differences in preferences for job attributes more broadly, and to the importance of meaning of work and non-monetary job attributes more broadly.

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6. Tables and Figures

Table 1: Summary statistics (ISSP Study)

	Gender		
Variable	Male	Female	Diff.
Panel A: Main Control Variables			
Age	40.83	40.79	0.04
Year of Education	12.08	11.98	0.10
Marital status: Married	57.66	57.24	0.42
Marital status: Widowed	1.34	5.06	-3.72
Marital status: Divorced	5.50	8.15	-2.65
Marital status: Separated	1.59	2.23	-.64
Marital status: Single	33.90	27.32	6.58
Work status: In paid work	73.95	56.97	16.98
Work status: Unemployed	7.79	8.25	-.46
Work status: In education	6.18	5.91	0.27
Work status: Retired	6.00	6.48	-.48
Work status: Domestic work	1.50	18.07	-16.57
Work status: Permanently sick or disabled	2.62	2.22	.4
Work status: Other	1.97	2.10	-.13
Household size	3.43	3.45	0.02
N	52,583	60,833	
Panel B: Additional Controls			
Log Household Income	9.08	8.95	-0.13
Works in public sector	25.82	36.31	10.48
Supervises other people	31.65	18.18	-13.47
N	28,140	31,999	

Notes: Table shows summary statistics for ISSP data. It shows average value for age, education, household size, and household income. For marital status and work status, it shows the distribution across the different categories in percentages. For public sector and supervisor, it shows percentage of men and women having those jobs. Number of observations reflects the variable with the lowest number of observations per panel.

Table 2: Gender Differences Across Countries (ISSP Study)

	(1)	(2)	(3)	(4)	(5)
	Raw Data			Adding Controls	
	Women	Men	Diff.	Main	Additional
Panel A: Average Importance					
Monetary Attributes	4.188	4.188	0.000	-0.006	0.004
			(0.007)	(0.006)	(0.008)
Non-Monetary Attributes	4.046	3.966	0.080***	0.084***	0.087***
			(0.007)	(0.006)	(0.008)
Panel B: Proportion Finding [Various] Job Attributes Important					
Income	0.813	0.827	-0.014***	-0.017***	-0.015***
			(0.005)	(0.004)	(0.006)
Job security	0.946	0.930	0.017***	.0019***	0.014***
			(0.002)	(0.002)	(0.003)
Opp. for advancement	0.751	0.758	-0.007	-0.015***	-0.004
			(0.005)	(0.004)	(0.006)
Interesting job	0.921	0.914	0.008***	0.010***	0.012***
			(0.002)	(0.002)	(0.003)
Independent work	0.761	0.771	-0.009**	0.001	0.009
			(0.004)	(0.004)	(0.005)
Flexibility	0.644	0.595	0.048***	0.044***	0.043***
			(0.006)	(0.005)	(0.007)
Helpful to others	0.799	0.717	0.082***	0.082***	0.074***
			(0.006)	(0.006)	(0.008)
Useful to society	0.797	0.735	0.061***	0.063***	0.056***
			(0.005)	(0.005)	(0.007)
N				107,006	42,183

Notes: This table shows in Panel A the average importance score for monetary attributes (Income, Security, and Advancement) and non-monetary attributes (Interesting, Independent, Flexibility, Helpful, and Useful). Panel B shows the proportion of women (column (1)) and men (column (2)) indicating that they find a job attribute important. Column (3) reports the difference between column 1 and 2 with significance level based on OLS regression with a female dummy plus a constant term. The last two columns show gender coefficients from OLS regressions that control in Column (4) for dummies for years of education, age, marital status, work status, household size, country and year. In Column (5) additional controls are included: dummy for public sector, dummy for supervisory role, and log of household income. S.e. are clustered at the year*country level. Number of observations differs by job attributes and depends on availability of control variables. The last row shows the minimum number of observations. Significance levels: *** p<.01, ** p<.05, * p<.1.

Table 3: Working in the Public Sector (ISSP Study)

	Public Sector (1)	Public Sector (2)	Public Sector (3)
Gender: Female	0.107***	0.108***	0.096***
	(0.011)	(0.010)	(0.009)
Income			-0.012***
			(0.003)
Job security			0.031***
			(0.004)
Opp. for advancement			-0.011***
			(0.003)
Interesting job			-0.004
			(0.003)
Independent work			-0.026***
			(0.003)
Flexibility			-0.014***
			(0.002)
Helpful to others			0.021***
			(0.004)
Useful to society			0.046***
			(0.004)
Constant	Yes	Yes	Yes
Main Controls	No	Yes	Yes
Mean Public Sector (for Male)	0.257	0.257	0.257
Adjusted R^2	0.013	0.151	0.166
N	83,495	83,495	83,495

Notes: Coefficients of OLS regressions and standard errors in parentheses. Dependent variable: "Working in the Public Sector (=1)" as the dependent variable. Main control variables are age, dummies for marital status, dummies for work status, dummies for household size, country and year dummies. Significance levels: *** p<.01, ** p<.05, * p<.1.

Table 4: Conjoint Design: Attributes and Levels (MBA Study)

	Attributes				
Level	Financial Offer	Social Impact	Non-Social Impact	Flexibility	Prestige
1	$135,000	Best CSR Record	High (strongly feel)	Has	Top 20
2	$150,000	Average CSR Record	Mid (moderately feel)	Does not have	Not top 20
3	$165,000	Worst CSR Record	Low (do not feel)	–	–

Notes: We set the following levels as baseline: *$135,000* for Financial Offer, *Best CSR Record* for Social Impact, *High (strongly feel)* for Non-Social Impact, *Has* for Flexibility, and *Top 20* for Prestige.

Table 5: Summary Statistics, gender differences (MBA Study)

Variable	Gender: Male	Gender: Female	Diff.	$P(\|T\| > \|t\|)$
Panel A: Background				
International (=1)	0.584	0.627	-0.043	0.332
Work experience (in months)	61.282	59.364	1.918	0.252
Prior job in finance	0.433	0.318	0.115	0.008
Prior job in nonprofit	0.045	0.055	-0.011	0.590
Donation frequency (Likert 1-5)	2.959	3.189	-0.230	0.011
Volunteering frequency (Likert 1-5)	2.876	3.281	-0.405	0.000
N	291	217		
Panel B: MBA				
Coursework				
Proportion Social courses	0.154	0.176	-0.022	0.000
Proportion Finance courses	0.209	0.158	0.051	0.000
Social club events				
Participation in a social club event? (=1)	0.302	0.525	-0.223	0.000
N	291	217		
Panel C: Post-MBA Industry				
Finance	0.460	0.312	0.148	0.002
Consulting	0.256	0.296	-0.040	0.362
CPG-Retail	0.044	0.091	-0.047	0.057
Healthcare	0.016	0.048	-0.032	0.068
Nonprofit	0.004	0.016	-0.012	0.230
Other	0.092	0.048	0.044	0.072
Tech and Media	0.128	0.188	-0.060	0.093
N	250	186		
Panel D: Survey				
Conjoint questions				
Highest social impact chosen	0.362	0.390	-0.028	0.043
Lowest social impact chosen	0.275	0.239	0.035	0.020
Direct elicitation questions				
Social impact ranking position	4.447	4.152	0.295	0.001
Social impact rank Top 2	0.038	0.101	-0.064	0.004
N	291	217		

Notes: Table shows proportions for dummy variables and means for continuous variables. Based on data from university administration and questions from the survey described in Appendix B.

Table 6: Posterior Statistics of Attribute Preferences $\mathbf{b}_s$ per Segment (MBA Study)

		Segment 1 Finance Motivated		**Segment 2 Social & Non-Social Impact Motivated**		**Segment 3 Non-Social Impact Motivated**	
Segment size		42%		26%		32%	
Attribute	Level	Mean	(se)	Mean	(se)	Mean	(se)
Job	(Intercept)	6.051	0.35	6.012	0.682	10.433	0.09
Financial Offer	$135,000	0	0	0	0	0	0
	$150,000	2.115	0.006	0.895	0.022	1.804	0.01
	$165,000	2.976	0.007	1.038	0.033	2.675	0.014
Social Impact	Best CSR Record	0	0	0	0	0	0
	Average CSR Record	-0.355	0.005	-0.522	0.006	-0.03	0.005
	Worst CSR Record	-0.637	0.007	-2.569	0.013	-0.795	0.008
Non-Social Impact	High (strongly feel)	0	0	0	0	0	0
	Mid (moderately feel)	-0.345	0.004	-0.829	0.006	-1.994	0.01
	Low (do not feel)	-1.634	0.007	-2.686	0.01	-6.841	0.034
Flexibility	Has	0	0	0	0	0	0
	Does not have	-1.15	0.011	-1.262	0.019	-0.948	0.006
Prestige	Top 20	0	0	0	0	0	0
	Not top 20	-1.703	0.006	-1.05	0.005	-1.37	0.006

Notes: For each segment we show the posterior mean, posterior standard errors of the mean, and the two bounds of the 95% central posterior interval (2.5% and 97.5%). All baseline levels are in the first row of each attribute. Utilities measure deviations from the baseline level.

Table 7: Gender Differences in Job Preferences (MBA Study)

	Attribute importance (relative to Financial Offer):							
	Social Impact		Non-Social Impact		Flexibility		Prestige	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gender: Female	0.242***	0.203***	0.180***	0.166**	0.211***	0.180***	0.002	0.003
	(0.058)	(0.061)	(0.062)	(0.064)	(0.049)	(0.051)	(0.047)	(0.049)
International		-0.026		-0.106		-0.002		-0.008
		(0.061)		(0.065)		(0.051)		(0.049)
GMAT (total)		-0.051*		-0.003		-0.064**		0.008
		(0.030)		(0.032)		(0.025)		(0.024)
Work exp.		-0.005		-0.027		-0.012		-0.043*
		(0.029)		(0.031)		(0.025)		(0.024)
Have loans?		0.069		0.081		-0.051		0.090*
		(0.060)		(0.064)		(0.050)		(0.049)
Donation		0.065**		0.041		0.051*		-0.025
		(0.032)		(0.034)		(0.026)		(0.026)
Volunteer		0.007		0.021		-0.035		0.021
		(0.029)		(0.030)		(0.024)		(0.023)
Constant	-0.601***	-0.826***	0.209***	0.048	-0.784***	-0.791***	-0.513***	-0.542***
	(0.038)	(0.111)	(0.040)	(0.118)	(0.032)	(0.093)	(0.031)	(0.090)
Observations	505	505	505	505	505	505	505	505

Notes: Table shows results of regressions of the following form. For each attribute k among Non-Social Impact, Social Impact, Flexibility, and Prestige; we regress the log importance of attribute k with respect to the importance of the attribute Financial Offer, $\log\left(\frac{\text{Importance}_k}{\text{Importance}_{\text{FinancialOffer}}}\right)$, on gender (first column of each DV) plus pre-MBA controls (second column of each DV). Significance levels: *** p<.01, ** p<.05, * p<.1.

Table 8: Course, Social Club events and Industry Selection (MBA Study)

(a) Course and Social Club events (MBA Study)

	Courses				*Social engagement*	
	Finance (MBA)		Social (MBA)		Club events attendance (MBA)	
	(1)	(2)	(3)	(4)	(5)	(6)
Gender: Female	-0.044***	-0.041***	0.022***	0.019***	0.201***	0.174***
	(0.009)	(0.009)	(0.006)	(0.006)	(0.044)	(0.044)
$\frac{\text{Importance}_{\text{SocialImpact}}}{\text{Importance}_{\text{FinancialOffer}}}$		-0.015**		0.015***		0.122***
		(0.007)		(0.004)		(0.032)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.208***	0.199***	0.153***	0.162***	0.233***	0.308***
	(0.009)	(0.010)	(0.006)	(0.006)	(0.043)	(0.046)
Adjusted R^2	0.085	0.092	0.033	0.054	0.063	0.087
F-value	10.071	9.237	4.336	5.650	7.779	9.020
N	491	491	491	491	506	506

Notes: This table reports coefficients and standard errors in parentheses of OLS regressions. Control variables are International, GMAT, Work experience, and whether the student has loans. For all coefficients see Table C.7 in the Appendix. Significance levels: *** p<.01, ** p<.05, * p<.1.

(b) Industry Selection (MBA Study)

	Industry			
	Finance (Post-MBA)		Nonprofit (Post-MBA)	
	(1)	(2)	(3)	(4)
Gender: Female	-0.133***	-0.099**	0.013	0.009
	(0.048)	(0.048)	(0.010)	(0.010)
$\frac{\text{Importance}_{\text{SocialImpact}}}{\text{Importance}_{\text{FinancialOffer}}}$		-0.148***		0.019***
		(0.036)		(0.007)
Control Variables	Yes	Yes	Yes	Yes
Constant	0.454***	0.367***	0.000	0.011
	(0.048)	(0.051)	(0.009)	(0.010)
Adjusted R^2	0.025	0.060	0.005	0.018
F-value	3.183	5.618	1.412	2.316
N	434	434	434	434

Notes: This table reports coefficients and standard errors in parentheses of OLS regressions. Control variables are International, GMAT, Work experience, and whether the student has loans. For all coefficients see Table C.7 in the Appendix. Significance levels: *** p<.01, ** p<.05, * p<.1.

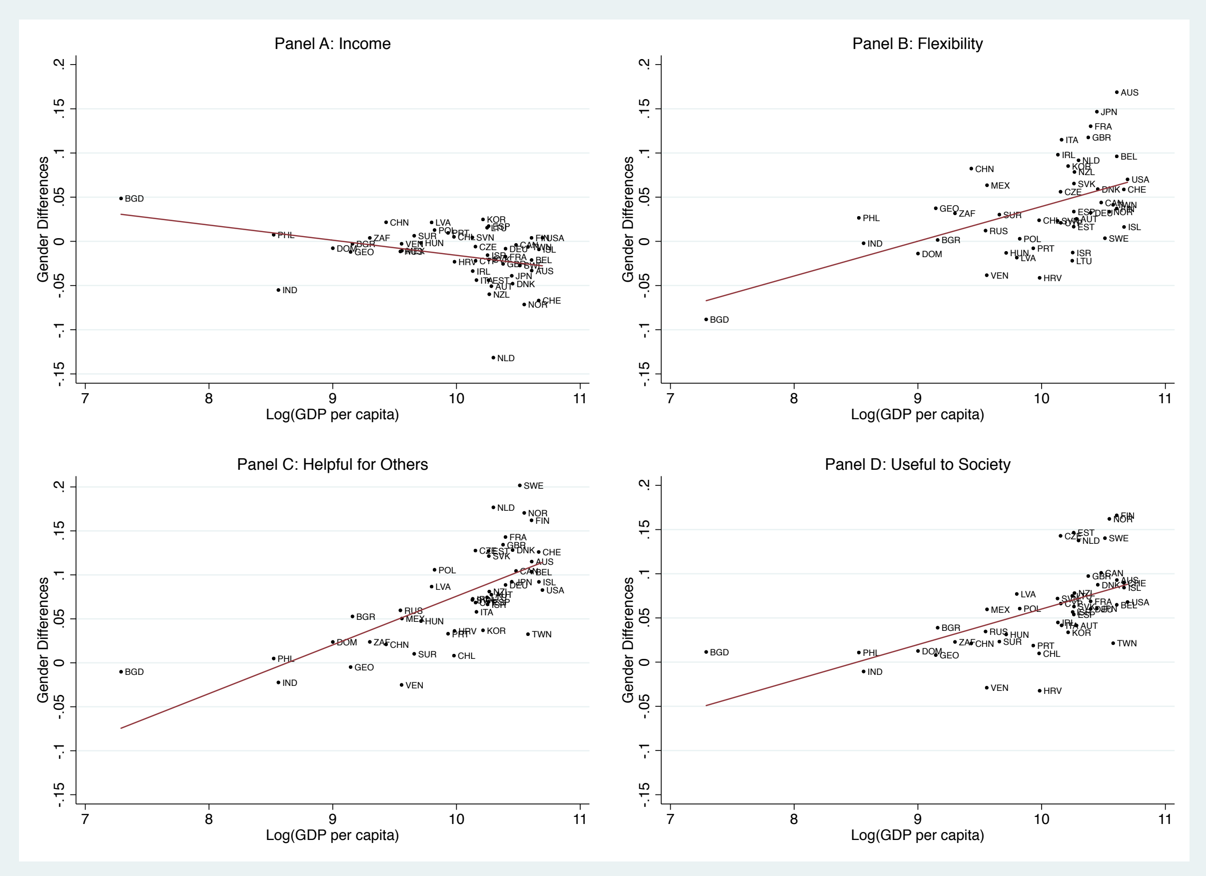


Figure 1: Figures show association between log of GDP per capita and gender differences in stated importance of job attributes (ISSP Study). We run regressions for each country, c, of the following form: $Job\ Attribute_i = \beta_1^c Female_i + \beta_2^c Controls_i + y_i^c + \epsilon_i$. The figure plots the coefficient, β_1^c, which captures the country-level gender differences in the importance of $Job\ Attribute_i$. The regression includes the main control variables: dummies for years of education, age, dummies for marital status, dummies for work status, dummies for household size, and year dummies. Regressing the gender coefficient on average log GDP per capita in an OLS regression yields the following coefficients (standard errors): -.017 (s.e.=.006) for Income, .008 (.004) for Security, -.013 (.007) for Opportunity, .004 (.004) for Interesting Job, -.003 (.006) for Independent Job, .039 (.010) for Flexibility, .055 (.009) for Helpful to Others, and .040 (.008) for Useful to Society.

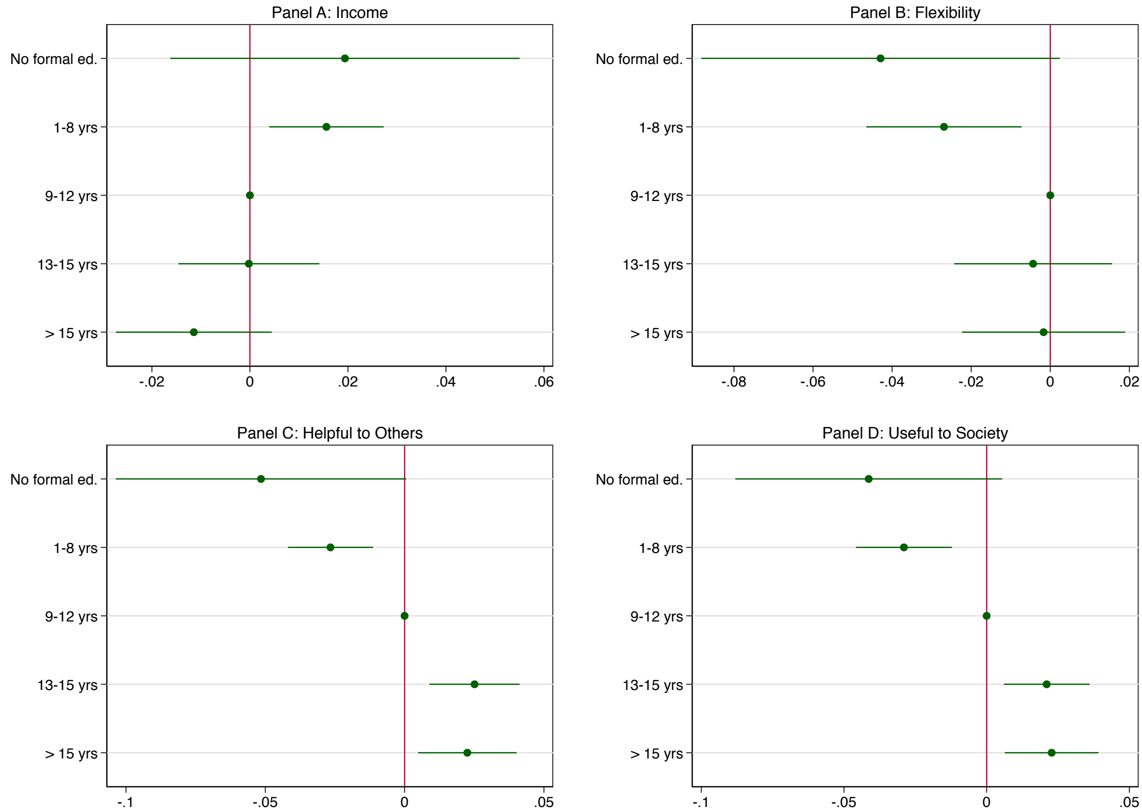


Figure 2: Figures plot interaction effects between gender and education groups (ISSP Study). We estimate a regression of the following form: $Job\ Attribute_i = \beta_1 Female_i + \beta_3 EducationGroup_1 + \beta_4 Education \times Female_i + \beta_5 Controls_i + c_i + y_i + \epsilon_i$. Figure plots β_4 with 9-12 years of education $\times$ Female as reference group. The regressions include the main control variables: dummies for years of education, age, dummies for marital status, dummies for work status, dummies for household size, country and year dummies. Regression results for all categories available in Table C.2 in the Appendix.

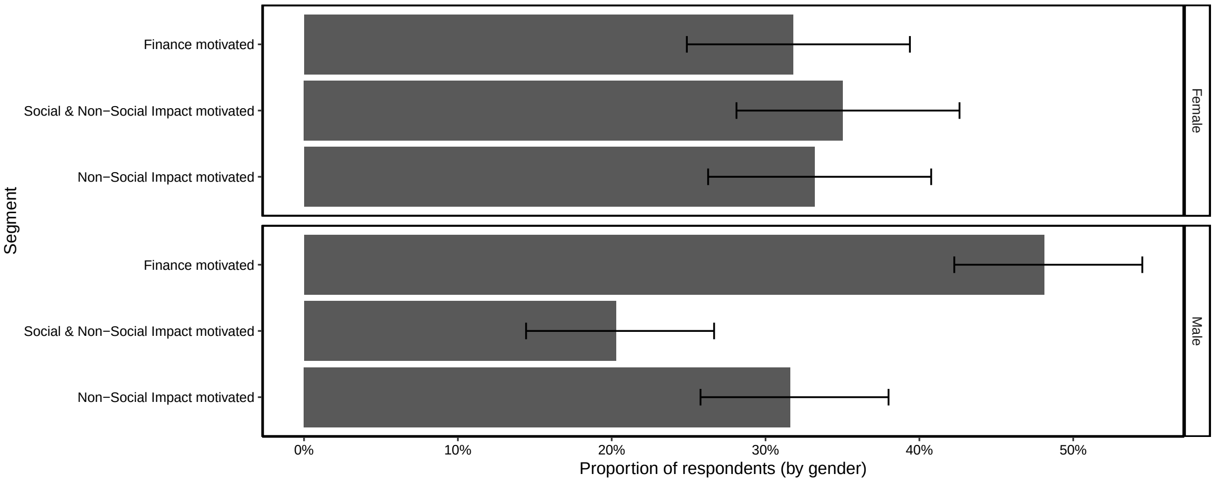
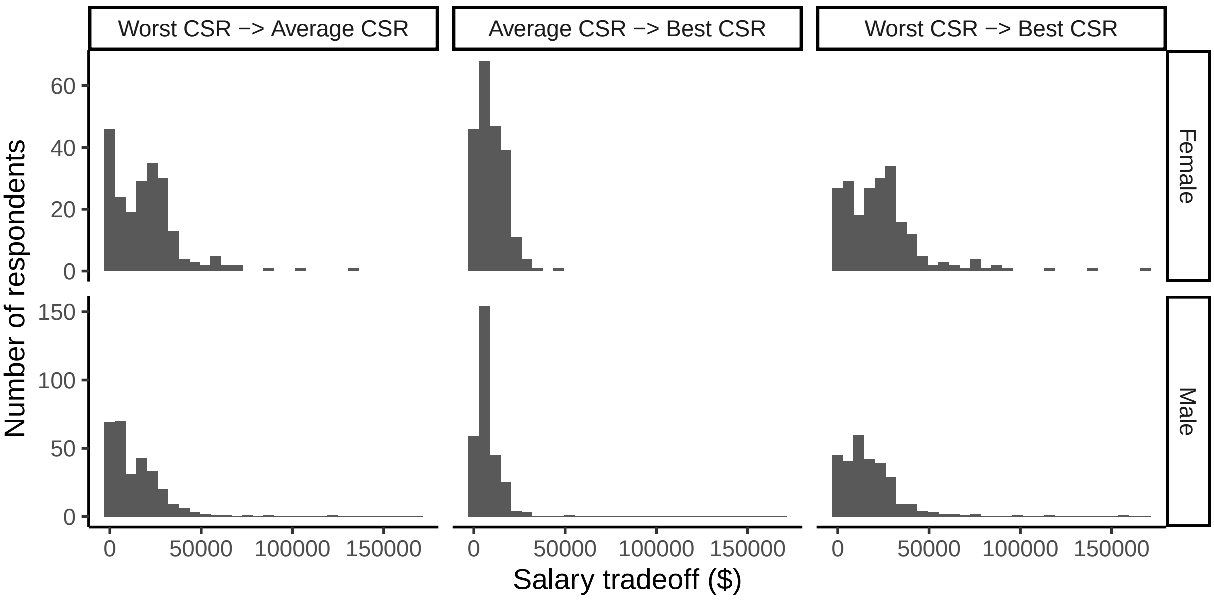


Figure 3: Gender proportion by segment (MBA Study). This plots the proportion of respondents belonging to each segment of the latent class choice model for female and male respondents. Each respondent was assigned to the segment with the highest posterior membership probability. Mean and standard error bars are shown.

Figure 4: Distribution of salary tradeoffs by gender



Online Appendix for "Gender Differences in Preferences for Meaning at Work"

A. Instructions of Conjoint Analysis survey

The instructions for the choice-based conjoint part of the survey were as follows (survey instructions and other questions asked during the survey are reported in Appendix B).

[Introduction]. "We would like to get a sense of what is important to you in your future job. In what follows you will be shown three job options at a time. Please imagine that these are the only job options you have when graduating. You then have to select which one of the three you would most prefer.

We will show you 10 sets of 3 jobs each.

Any characteristics of the job not explicitly described in each option, you can assume are the same across all of the job options you are shown. **Please read the job characteristics carefully.**"

[Attribute and Level Text]. Description of attributes and levels:

1. Financial Offer: "Financial offer (including salary, bonus, stock options, and all other monetary benefits)"
    - $135,000
    - $150,000
    - $165,000
2. Social Impact: "Corporate Social Responsibility (CSR) rating in 2016 according to neutral rating agency"
    - Amongst the 10 companies with the best CSR records.
    - Average CSR record.
    - Amongst the 10 companies with the worst CSR records.
3. Non-Social Impact: "When working in this job, how much you feel that your day-to-day work has direct impact on your customers, your clients, and/or your company"
    - You strongly feel that your day-to-day work has impact.
    - You moderately feel that your day-to-day work has impact.
    - You do not feel that your day-to-day work has impact.
4. Flexibility: "Availability of flexibility to work remotely or at non-traditional work times"
    - The company has flexible work policies.
    - The company does not have flexible work policies.
5. Prestige: "How prestigious it is to work for this organization"

- One of the top 20 most prestigious firms to work for.
- Not one of the top 20 most prestigious firms to work for.

B. Survey Instructions and Questions

[Instructions]. We would like to ask you a few questions about yourself in preparation for name of course. There are no right or wrong answers to these questions; we would simply like to gather some information about your experiences and future aspirations to inform and tailor our upcoming strategy class.

While it is important that everybody answers the survey, your answers to these questions will not affect your grade in this class, so please answer honestly. Your answers will be treated confidentially and will not be shared. Any reference to answers to this survey will be in aggregate and will never reference individuals.

This survey should take 15 minutes.

[Initial Questions].

- What is your cluster?
- Do you have experience working in an internal strategy role at a company?
- Do you have experience working as a strategy consultant?
- For how many years have you worked as a strategy consultant?
- Would you like to work in a strategy-related position upon graduation (as a consultant or in an internal strategy role)?
- How important do you think that strategy will be in your future career?
- How comfortable do you think you will feel speaking during class discussions?
- How strong do you feel your quantitative ability/knowledge is currently?
- What industry did you work in prior to joining [name of university]?
- What industry would you like to work in after [name of university]?
- Have you worked in a geographic location that is not where you are from?
- Would you like to work in a geographic location that is not where you are from in the future?
- How many countries have you lived in for more than 6 months?
- How are you financing the approximate [amount] cost of your MBA? Select all that apply.
- How many years, if any, do you expect it will take you to pay off your MBA debt?

[Conjoint Job Preference Questions - see Appendix A].

[Ranking Job Preference Questions]. Please rank these attributes in order of importance to you when you consider the job you would like to go into after your MBA. Rank the attributes by dragging items from the left column to the right column.

- Financial offer - including salary, bonus, stock options, and all other monetary benefits
- Corporate Social Responsibility (CSR) rating in 2016 according to neutral rating agency
- When working in this job, how much you feel that your day-to-day work has direct impact on your customers, your clients, and/or your company
- How prestigious it is to work for this organization

[**Questions about responses to CSR records and claims**] A job option could be with a company that has a relatively [randomly assigned: good/bad] CSR record, and [randomly assigned: heavily publicizes a positive CSR image in all its communications / is discreet about a positive CSR image and does not include it in all its communications.] Please rate your sense of the degree of social responsibility of such a job option.

[**Questions about inputs to CSR perceptions**] Please rate how attractive a company with a good CSR record would be to work for, when they do the following: The firm heavily publicizes its CSR initiatives and uses it in all its communications with consumers, investors and the public. / The firm is discreet about its CSR initiatives and does not use it in communications with consumers, investors and the public. / The firm closely tracks and measures whether its CSR initiatives have a positive effect on the bottom line, i.e. whether they increase profits. / The firm does not track or measure whether its CSR initiatives have any positive effect on the bottom line, i.e. whether they increase profits. / The firm explicitly aligns its CSR initiatives with its business strategy. / The firm does not explicitly align its CSR initiatives with its business strategy. / The CEO believes there is a strong business case for CSR. / The CEO does not believe there is a strong business case for CSR. / The CEO drives the companys CSR causes and initiatives. /The companys employees drive the companys CSR causes and initiatives.

[**Questions about what constitutes CSR**] Below is a list of ways that the company you work for in the future could vary in terms of its social responsibility/social irresponsibility. Please rank these in order of importance to you:

- Governance - political accountability, transparency, business ethics, corruption
- Community - community impact, charitable giving, community engagement / Diversity - workforce diversity, work-life benefits
- Employee relations - union relations, employee health and safety, retirement benefits, professional development
- Environment - emissions, supply chain management, climate change footprint, supply chain environmental footprint
- Product - product quality and safety, anticompetitive practices, customer relations

[**Agreement with Milton Friedman Quote**] How much do you agree/disagree with the statement: "There is one and only one social responsibility of business to increase its profits."

[**Additional Questions**]

- How often did you volunteer with a charity/nonprofit organization in the past year?
- How often did you donate to a charity/nonprofit organization in the past year?

Almost done! Three more extremely important questions, critical to our first case discussion! :)

- I consider myself a: Beer drinker / Wine drinker / Other alcohol drinker/ All of the above/ None of the above
- What's your favorite beer?
- What type of beer do you normally buy?

[**Ending Message**] Thank you for completing this survey! If you haven't already, don't forget to read the [name of] case and [name of reading assignment] before class! We look forward to seeing you in class very soon!

C. Additional Tables

C.1. Table C.1: Number of Observations Per Country and Year in ISSP

- Table C.1 show number of observations by country and year in ISSP.

Table C.1: Number of Observations Per Country and Year

	1989	1997	2005	2015	Total
Australia	0	0	1,530	817	2,347
Austria	1,554	0	0	837	2,391
Belgium	0	0	1,099	1,737	2,836
Chile	0	0	0	1,091	1,091
China	0	0	0	1,439	1,439
Taiwan	0	0	1,868	1,699	3,567
Croatia	0	0	0	860	860
Czech Republic	0	808	1,024	1,108	2,940
Denmark	0	871	1,432	0	2,303
Estonia	0	0	0	871	871
Finland	0	0	0	945	945
France	0	894	1,380	931	3,205
Georgia	0	0	0	1,150	1,150
Germany	1,183	1,442	1,318	1,301	5,244
Hungary	843	1,214	784	821	3,662
Iceland	0	0	0	936	936
India	0	0	0	1,225	1,225
Israel	962	1,424	2,065	975	5,426
Japan	0	986	651	1,096	2,733
Latvia	0	0	913	854	1,767
Lithuania	0	0	0	877	877
Mexico	0	0	1,330	1,082	2,412
New Zealand	0	964	1,062	628	2,654
Norway	1,612	1,933	1,200	1,279	6,024
Phillipines	0	1,115	1,095	1,062	3,272
Poland	0	957	0	1,530	2,487
Russia	0	1,460	1,351	1,374	4,185
Slovakia	0	0	0	901	901
Slovenia	0	868	829	769	2,466
South Africa	0	0	2,609	2,566	5,175
Spain	0	1,000	974	1,432	3,406
Suriname	0	0	0	962	962
Sweden	0	1,086	1,157	868	3,111
Switzerland	0	2,283	854	977	4,114
UK	1,036	825	666	1,264	3,791
USA	1,171	990	1,289	1,181	4,631
Venezuela	0	0	0	954	954
Bangladesh	0	1,813	0	0	1,813
Cyprus	0	922	875	0	1,797
Italy	939	853	0	0	1,792
DR	0	0	1,810	0	1,810
South Korea	0	0	1,368	0	1,368
Portugal	0	1,328	1,387	0	2,715
Canada	0	852	690	0	1,542
Bulgaria	0	806	840	0	1,646
Netherlands	1,433	1,850	759	0	4,042
Ireland	824	0	807	0	1,631
Total	11,557	29,544	37,016	40,399	118,516

Notes: This table shows the number of observations with non-missing observations for the question about importance of income for job per country and year of survey wave.

C.2. Table C.2: Gender Differences and Education

- Table C.2 show results of OLS regressions of the following form:

$$Job\,Attribute_i = \beta_1 Female_i + \beta_3 EducationGroup_1 + \beta_4 Education \times Female_i + \beta_5 Controls_i + c_i + y_i + \epsilon_i. \tag{C.11}$$

  The regressions include the "Main" control variables (odd-numbered columns) includes dummies for years of education, age, dummies for marital status, dummies for work status and dummies for household size. "Additional" control variables (even-numbered columns) include whether the individual works in the public or private sector, whether the respondent is a supervisor or not, and log of household size.

Table C.2: Gender Differences and Education (Including Additional Control Variables)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10	(11)	(12	(13)	(14)	(15)	(16)
	Income	Income	Security	Security	Opp.	Opp.	Interesting	Interesting	Indep.	Indep.	Flex.	Flex.	Helpful	Helpful	Useful	Useful
Gender: Female	-0.017***	0.010	0.013***	0.034***	-0.008*	0.001	0.009***	0.010	-0.003	0.011	0.051***	0.022	0.077***	0.096***	0.059***	0.079***
	(0.005)	(0.025)	(0.003)	(0.012)	(0.005)	(0.019)	(0.003)	(0.009)	(0.005)	(0.014)	(0.008)	(0.035)	(0.007)	(0.028)	(0.006)	(0.027)
No formal × Female	0.019	-0.026	-0.015	-0.009	0.023	0.072**	-0.015	0.013	-0.013	-0.065**	-0.043*	-0.104***	-0.052*	-0.055	-0.041*	-0.035
	(0.018)	(0.048)	(0.010)	(0.015)	(0.020)	(0.028)	(0.021)	(0.035)	(0.021)	(0.030)	(0.023)	(0.033)	(0.026)	(0.033)	(0.024)	(0.033)
(1-8 yrs) × Female	0.016***	0.010	-0.002	-0.009	0.000	0.002	-0.000	-0.002	-0.007	-0.006	-0.027***	-0.036**	-0.027***	-0.032***	-0.029***	-0.043***
	(0.006)	(0.010)	(0.004)	(0.006)	(0.007)	(0.012)	(0.005)	(0.009)	(0.007)	(0.012)	(0.010)	(0.017)	(0.008)	(0.012)	(0.008)	(0.013)
(9-12 yrs) × Female								Excluded								
(13-15 yrs) × Female	-0.000	0.011	0.009**	0.006	-0.014**	-0.017	0.007	0.011	0.004	-0.004	-0.004	-0.012	0.025***	0.031**	0.021***	0.020*
	(0.007)	(0.010)	(0.004)	(0.005)	(0.007)	(0.013)	(0.004)	(0.007)	(0.007)	(0.010)	(0.010)	(0.015)	(0.008)	(0.013)	(0.008)	(0.011)
(more than 15 yrs) × Female	-0.011	-0.004	0.019***	0.015*	-0.017**	-0.001	0.000	-0.003	0.020***	0.026**	-0.002	-0.004	0.023**	0.024*	0.023***	0.016
	(0.008)	(0.011)	(0.005)	(0.008)	(0.007)	(0.012)	(0.004)	(0.007)	(0.007)	(0.011)	(0.010)	(0.016)	(0.009)	(0.014)	(0.008)	(0.012)
No formal education	0.026	0.078	0.003	0.009	-0.039**	-0.035*	-0.068***	-0.050**	-0.030	0.003	0.047**	0.072**	-0.006	0.008	-0.014	0.005
	(0.027)	(0.052)	(0.009)	(0.009)	(0.016)	(0.019)	(0.016)	(0.019)	(0.023)	(0.024)	(0.018)	(0.029)	(0.021)	(0.034)	(0.024)	(0.033)
1-8 yrs in school	0.010	0.020*	0.004	0.006	-0.012*	-0.005	-0.035***	-0.034***	-0.023***	-0.021*	0.012	0.014	0.015**	0.017**	0.016**	0.028***
	(0.006)	(0.012)	(0.004)	(0.004)	(0.007)	(0.008)	(0.005)	(0.006)	(0.007)	(0.011)	(0.008)	(0.012)	(0.007)	(0.008)	(0.008)	(0.009)
9-12 yrs in school								Excluded								
13-15 yrs in school	-0.015***	-0.013*	-0.014***	-0.012**	0.030***	0.024**	0.020***	0.020***	0.020***	0.024***	0.018**	0.030**	-0.001	-0.009	0.005	0.009
	(0.005)	(0.007)	(0.004)	(0.006)	(0.007)	(0.009)	(0.004)	(0.006)	(0.006)	(0.008)	(0.008)	(0.011)	(0.006)	(0.010)	(0.006)	(0.010)
more than 15 yrs in school	-0.005	-0.010	-0.039***	-0.040***	0.041***	0.019	0.044***	0.041***	0.028***	0.029**	0.038***	0.054***	-0.005	-0.007	0.033***	0.042***
	(0.007)	(0.011)	(0.005)	(0.008)	(0.010)	(0.014)	(0.005)	(0.007)	(0.008)	(0.012)	(0.009)	(0.014)	(0.007)	(0.012)	(0.007)	(0.011)
Constant	0.808***	0.748***	0.928***	0.901***	0.948***	0.786***	0.962***	0.920***	0.734***	0.726***	0.525***	0.588***	0.634***	0.561***	0.619***	0.534***
	(0.015)	(0.028)	(0.009)	(0.020)	(0.029)	(0.033)	(0.010)	(0.017)	(0.023)	(0.029)	(0.028)	(0.059)	(0.032)	(0.031)	(0.030)	(0.031)
Main Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Additional Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.085	0.098	0.028	0.035	0.136	0.152	0.055	0.066	0.074	0.094	0.041	0.052	0.055	0.073	0.059	0.086
N	108,905	42,888	108,793	42,906	108,187	42,676	108,651	42,790	108,192,	42,666	107,633	42,454	108,148	42,627	108,185	42,642

Notes: Coefficients of OLS regressions and standard errors in parentheses. Main Control Variables are age, dummies for marital status, dummies for work status, dummies for household size, country and year dummies. Additional control variables are log of household income, dummy for whether working in the public sector and dummy for whether supervisory role. s.e. are clustered at the year*country level. Significance levels: *** p<.01, ** p<.05, * p<.1.

C.3. Table C.3: Gender Differences in Preferences (ISSP Data)

- Table C.3 shows results of OLS regressions of the following form:

$$Job\ Attribute_i = \beta_1 Female_i + \beta_2 Controls_i + c_i + y_i + \epsilon_i \tag{C.12}$$

  in which the dependent variable is whether a specific job attribute is important to individual, i. In addition to gender, fixed effects for country (c_i) and year (y_i), we include two sets of control variables (see Table 1 for summary statistics). "Main" control variables (Panel A) includes dummies for years of education, age, dummies for marital status, dummies for work status and dummies for household size. "Additional" control variables (Panel B) include whether the individual works in the public or private sector, whether the responder is a supervisor or not and log of household size.

- Table C.4 shows results using the 5-point scale from 1 'not important at all' to 5 'very important' as the dependent variable instead of the dummy variable.

Table C.3: Gender Differences in Preferences (ISSP Sample)

	(1) Income	(2) Security	(3) Opportunity	(4) Interesting	(5) Independent	(6) Helpful	(7) Useful	(8) Flexible	(9) Monetary	(10) Non-Monetary
Panel A: With Main Controls										
Gender: Female	-0.017***	0.019***	-0.015***	0.010***	0.001	0.082***	0.063***	0.044***	-0.006	0.084***
	(0.004)	(0.002)	(0.004)	(0.002)	(0.004)	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)
Constant	0.868***	0.898***	0.935***	0.870***	0.698***	0.512***	0.520***	0.513***	4.243***	3.729***
	(0.038)	(0.013)	(0.036)	(0.020)	(0.038)	(0.038)	(0.036)	(0.034)	(0.048)	(0.056)
Main Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Additional Controls	No	No	No	No	No	No	No	No	No	No
R^2	0.085	0.029	0.137	0.057	0.077	0.055	0.060	0.042	0.153	0.080
N	110,721	110,598	109,973	110,466	109,984	109,946	109,976	109,428	109,117	107,006
Panel B: Including Additional Controls										
Gender: Female	-0.015***	0.014***	-0.004	0.012***	0.009	0.074***	0.056***	0.043***	0.004	0.087***
	(0.006)	(0.003)	(0.006)	(0.003)	(0.005)	(0.008)	(0.007)	(0.007)	(0.008)	(0.008)
Constant	0.835***	0.897***	0.795***	0.859***	0.701***	0.484***	0.494***	0.559***	3.842***	3.617***
	(0.058)	(0.020)	(0.038)	(0.024)	(0.040)	(0.046)	(0.033)	(0.061)	(0.061)	(0.051)
Main Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Additional Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.099	0.036	0.154	0.068	0.098	0.073	0.087	0.053	0.194	0.115
N	43,486	43,500	43,266	43,387	43,258	43,221	43,235	43,047	43,018	42183,

Notes: Coefficients of OLS regressions and standard errors in parentheses. Main control variables are age, dummies for marital status, dummies for work status, dummies for household size, country and year dummies. Additional control variables are log of household income, whether participant works in the public sector and whether participant has supervisory role at work. s.e. are clustered at the year*country level. Significance levels: *** p<.01, ** p<.05, * p<.1.

Table C.4: Gender Differences Across Countries (ISSP Data)

	(1)	(2)	(3)	(4)	(5)
	Raw Data			Adding Controls	
	Women	Men	Diff.	Main	Additional
Income	4.082	4.118	-0.036***	-0.045***	-0.041***
			(0.011)	(0.007)	(0.011)
Job security	4.524	4.473	0.052***	0.064***	0.060***
			(0.008)	(0.009)	(0.011)
Opp. for advancement	3.951	3.969	-0.019*	-0.038***	-0.007
			(0.011)	(0.009)	(0.013)
Interesting job	4.392	4.366	-0.025***	0.032***	0.038***
			(0.007)	(0.005)	(0.008)
Independent work	3.983	4.013	-0.029***	-0.009	0.021*
			(0.010)	(0.009)	(0.011)
Flexibility	3.715	3.611	0.104***	0.092***	0.100***
			(0.014)	(0.012)	(0.016)
Helpful to others	4.058	3.888	0.170***	0.171***	0.161***
			(0.012)	(0.012)	(0.015)
Useful to society	4.052	3.924	0.128***	0.133***	0.121***
			(0.011)	(0.010)	(0.013)
N				107,006	42,183

Notes: Table shows the average importance score for women (column (1)) and men (column (2)) for different job attribute. Column (3) reports the difference between column 1 and 2. Significance levels from OLS regressions with a female dummy and a constant term. The last two columns show gender coefficients from OLS regressions (standard errors in parenthesis) that control in Column (4) for dummies for years of education, age, marital status, work status, household size, country and year. In Column (5) additional controls are included: dummy for public sector, dummy for supervisory role, and log of household income. S.e. are clustered at the year*country level. Number of observations differs by job attributes and depends on availability of control variables. The last row shows the minimum number of observations. Significance levels: *** p<.01, ** p<.05, * p<.1.

C.4. Table C.5: Selection of Number of Segments of LC-MNL Model (MBA Sample)

- Table C.5 shows in-sample fit criteria (WAIC and LMD), and out-of-sample likelihood (Val. log likelihood) and prediction (Hit rate). These metrics suggest there is a significant increase in fit and prediction moving from 2 segments to 3 segments, but this improvement levels when moving from 3 to 4 segments, particularly in prediction, where hitrate increases in only 0.36% points. Therefore, in order to use a more parsimonious solution, we choose the 3-segment LC-MNL model.

Table C.5: Selection of Number of Segments of LC-MNL Model (MBA Sample)

Number of segments	Log-likelihood	WAIC	LMD	Val. log-likelihood	Hit rate
1	-3286.09	6591.63	-3290.77	-768.72	69.39%
2	-3146.86	6333.04	-3156.63	-707.33	75.02%
3	**-3071.87**	**6214.79**	**-3089.98**	**-680.48**	**77.34%**
4	-3012.49	6096.94	-3029.73	-647.79	77.70%

Notes: We bold the chosen model as it achieves a good balance between interpretability and prediction (hit rate). We show the log-likelihood, the Watanabe-Akaike information criterion (WAIC), the log-marginal density (LMD), the log-likelihood in a set of validation questions not used in the training sample, and the hit rate of respondents choices on the validation questions.

C.5. Table C.6: Gender Differences in Job Preferences (MBA Sample) with Prior Employment Industry Controls

We show in Table C.6 that even when controlling for the industry of the job to the MBA program, the gender differences in these preferences still exist.

Table C.6: Gender Differences in Job Preferences (MBA Sample)

	Dependent variable:											
	Social Impact			Non-Social Impact			Flexibility			Prestige		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Gender: Female	0.243***	0.220***	0.189***	0.184***	0.184***	0.170***	0.210***	0.177***	0.149***	0.001	0.005	-0.016
	(0.058)	(0.060)	(0.061)	(0.062)	(0.064)	(0.065)	(0.049)	(0.050)	(0.051)	(0.047)	(0.048)	(0.049)
International		-0.022	-0.025		-0.106	-0.095		0.005	0.006		-0.011	-0.005
		(0.061)	(0.062)		(0.065)	(0.066)		(0.051)	(0.052)		(0.049)	(0.050)
GMAT (total)		-0.056*	-0.044		-0.010	-0.003		-0.062**	-0.056**		0.007	0.012
		(0.030)	(0.030)		(0.032)	(0.032)		(0.025)	(0.025)		(0.024)	(0.024)
Work exp.		0.001	-0.004		-0.020	-0.020		-0.010	-0.008		-0.044*	-0.043*
		(0.029)	(0.030)		(0.031)	(0.032)		(0.025)	(0.025)		(0.024)	(0.024)
Have loans?		0.060	0.055		0.075	0.070		-0.061	-0.062		0.096**	0.083*
		(0.060)	(0.060)		(0.063)	(0.064)		(0.050)	(0.050)		(0.048)	(0.049)
Constant	-0.603***	-0.612***	-0.290**	0.206***	0.230***	0.442***	-0.783***	-0.739***	-0.551***	-0.512***	-0.558***	-0.400***
	(0.038)	(0.058)	(0.131)	(0.040)	(0.062)	(0.140)	(0.032)	(0.049)	(0.110)	(0.031)	(0.047)	(0.107)
Prior job controls			Yes			Yes			Yes			Yes
Observations	506	506	506	506	506	506	506	506	506	506	506	506

Notes: Table shows results of regressions of the following form. For each attribute k among Non-Social Impact, Social Impact, Flexibility, and Prestige; we regress the log importance of attribute k with respect to the importance of the attribute Financial Offer, $\log\left(\frac{\text{Importance}_k}{\text{Importance}_{\text{FinancialOffer}}}\right)$, on gender (first column of each DV) plus pre-MBA controls (second column of each DV). Significance levels: *** p<.01, ** p<.05, * p<.1.

C.6. Table C.7: All parameters for Course, Social Club events and Industry Selection of MBA Sample

Table C.7: Course, Social Club events and Industry Selection - All parameters (MBA Study)

	Courses				*Social engagement*		*Industry*			
	Finance (MBA)		Social (MBA)		Club events attendance (MBA)		Finance (Post-MBA)		Nonprofit (Post-MBA)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Gender: Female	-0.044***	-0.041***	0.022***	0.019***	0.201***	0.174***	-0.133***	-0.099**	0.013	0.009
	(0.009)	(0.009)	(0.006)	(0.006)	(0.044)	(0.044)	(0.048)	(0.048)	(0.010)	(0.010)
$\frac{\text{Importance}_{\text{SocialImpact}}}{\text{Importance}_{\text{FinancialOffer}}}$		-0.015**		0.015***		0.122***		-0.148***		0.019***
		(0.007)		(0.004)		(0.032)		(0.036)		(0.007)
International	-0.005	-0.006	-0.006	-0.006	0.067	0.070	0.068	0.063	0.018*	0.019*
	(0.009)	(0.009)	(0.006)	(0.006)	(0.045)	(0.044)	(0.050)	(0.049)	(0.010)	(0.010)
GMAT (total)	0.016***	0.016***	-0.002	-0.002	-0.045**	-0.038*	0.036	0.026	0.004	0.005
	(0.005)	(0.005)	(0.003)	(0.003)	(0.022)	(0.022)	(0.024)	(0.024)	(0.005)	(0.005)
Work Experience	-0.003	-0.003	0.002	0.002	-0.010	-0.010	0.024	0.021	0.001	0.002
	(0.004)	(0.004)	(0.003)	(0.003)	(0.022)	(0.021)	(0.025)	(0.024)	(0.005)	(0.005)
Any Loan? (=1)	0.004	0.004	0.013**	0.012**	0.069	0.061	-0.073	-0.067	-0.015	-0.015
	(0.009)	(0.009)	(0.006)	(0.006)	(0.044)	(0.043)	(0.048)	(0.047)	(0.010)	(0.009)
Constant	0.208***	0.199***	0.153***	0.162***	0.233***	0.308***	0.454***	0.367***	0.000	0.011
	(0.009)	(0.010)	(0.006)	(0.006)	(0.043)	(0.046)	(0.048)	(0.051)	(0.009)	(0.010)
Adjusted R^2	0.085	0.092	0.033	0.054	0.063	0.087	0.025	0.060	0.005	0.018
F-value	10.071	9.237	4.336	5.650	7.779	9.020	3.183	5.618	1.412	2.316
N	491	491	491	491	506	506	434	434	434	434

Notes: This table reports coefficients and standard errors in parentheses of OLS regressions. Control variables are International, GMAT, Work experience, and whether the student has loans. . Significance levels: *** p<.01, ** p<.05, * p<.1.

C.7. Table C.8: Correlations Between Social Impact Preferences and Model-free measures (MBA Study)

Table C.8: Correlations between Social impact preferences and model-free measures (MBA Study)

Correlations between Social impact preferences and model-free measures				
	$\frac{\text{Importance}_{\text{SocialImpact}}}{\text{Importance}_{\text{FinancialOffer}}}$	Highest SI.	Lowest SI.	SI rank.
$\frac{\text{Importance}_{\text{SocialImpact}}}{\text{Importance}_{\text{FinancialOffer}}}$	1.0000			
Highest SI chosen	0.4887	1.0000	.	.
Lowest SI chosen	-0.6661	-0.6151	1.0000 .	.
SI ranking position	-0.5746	-0.4818	0.4462	1.0000

Notes: Pearson pairwise correlations. SI stands for Social Impact. Highest/Lowest SI chosen is the proportion of job offers with highest/lowest level of CSR that is chosen in the survey. SI ranking position is the order in which the respondent place social impact among all 5 attributes (a lower value means more important).

C.8. Tables C.9, C.10 and C.11: Course, Social Club events and Industry Selection of MBA Sample with social and non-social impact preferences

- Table C.9 show results of OLS regressions on type of courses taken.
- Table C.10 show results of OLS regressions on dummies for whether student participated in social clubs events or not.
- Table C.11 show results of OLS regressions on dummies for post-MBA employment industry i) finance and ii) nonprofit.
- These table compare the gender differences captured by social impact, non-social impact, and both impact measures simultaneously.

Table C.9: Course Selection of MBA Sample (social and non-social impact variables)

	Courses							
	Finance				Social			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8))
Gender: Female	-0.044***	-0.041***	-0.041***	-0.040***	0.022***	0.019***	0.020***	0.018***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.006)	(0.006)	(0.006)	(0.006)
$\frac{\text{Importance}_{\text{SocialImpact}}}{\text{Importance}_{\text{FinancialOffer}}}$		-0.015**		-0.005		0.015***		0.012**
		(0.007)		(0.009)		(0.004)		(0.006)
$\frac{\text{Importance}_{\text{NonSocialImpact}}}{\text{Importance}_{\text{FinancialOffer}}}$			-0.017***	-0.014*			0.012***	0.005
			(0.006)	(0.008)			(0.004)	(0.005)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.208***	0.199***	0.212***	0.208***	0.153***	0.162***	0.150***	0.159***
	(0.009)	(0.010)	(0.009)	(0.011)	(0.006)	(0.006)	(0.006)	(0.007)
Adjusted R^2	0.085	0.092	0.096	0.095	0.033	0.054	0.047	0.054
F-value	10.071	9.237	9.697	8.359	4.336	5.650	5.028	4.965
N	491	491	491	491	491	491	491	491

Notes: This table reports coefficients and standard errors in parentheses of OLS regressions. Control variables are International, GMAT, Work experience, and whether the student has loans. . Significance levels: *** p<.01, ** p<.05, * p<.1.

Table C.10: Social Club events MBA Sample (social and non-social impact variables)

	Social engagement			
	Club events attendance			
	(1)	(2)	(3)	(4)
Gender: Female	0.201***	0.174***	0.186***	0.173***
	(0.044)	(0.044)	(0.044)	(0.044)
$\frac{\text{Importance}_{\text{SocialImpact}}}{\text{Importance}_{\text{FinancialOffer}}}$		0.122***		0.116***
		(0.032)		(0.042)
$\frac{\text{Importance}_{\text{NonSocialImpact}}}{\text{Importance}_{\text{FinancialOffer}}}$			0.077**	0.009
			(0.031)	(0.039)
Control Variables	Yes	Yes	Yes	Yes
Constant	0.233***	0.308***	0.215***	0.302***
	(0.043)	(0.046)	(0.043)	(0.053)
Adjusted R^2	0.063	0.087	0.073	0.085
F-value	7.779	9.020	7.609	7.725
N	506	506	506	506

Notes: This table reports coefficients and standard errors in parentheses of OLS regressions. SI stands for Social Impact. Control variables are International, GMAT, Work experience, and whether the student has loans. . Significance levels: *** p<.01, ** p<.05, * p<.1.

Table C.11: Industry Selection of MBA Sample (social and non-social impact variables)

	Industry							
	Finance (Post-MBA)				Nonprofit (Post-MBA)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gender: Female	-0.133***	-0.099**	-0.106**	-0.095**	0.013	0.009	0.010	0.008
	(0.048)	(0.048)	(0.048)	(0.048)	(0.010)	(0.010)	(0.010)	(0.010)
$\frac{\text{Importance}_{\text{SocialImpact}}}{\text{Importance}_{\text{FinancialOffer}}}$		-0.148***		-0.105**		0.019***		0.015
		(0.036)		(0.046)		(0.007)		(0.009)
$\frac{\text{Importance}_{\text{NonSocialImpact}}}{\text{Importance}_{\text{FinancialOffer}}}$			-0.130***	-0.066			0.015**	0.006
			(0.035)	(0.044)			(0.007)	(0.009)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.454***	0.367***	0.488***	0.410***	0.000	0.011	-0.004	0.007
	(0.048)	(0.051)	(0.048)	(0.059)	(0.009)	(0.010)	(0.010)	(0.012)
Adjusted R^2	0.025	0.060	0.054	0.063	0.005	0.018	0.013	0.017
F-value	3.183	5.618	5.098	5.149	1.412	2.316	1.970	2.049
N	434	434	434	434	434	434	434	434

Notes: This table reports coefficients and standard errors in parentheses of OLS regressions. SI stands for Social Impact. Control variables are International, GMAT, Work experience, and whether the student has loans. . Significance levels: *** p<.01, ** p<.05, * p<.1.

C.9. Table C.12: Choice of Different Industries of MBA Sample for Post-MBA job

- Table C.12 shows results of multinominal regression in which "Finance" is the reference level for Post-MBA Employment Industry.

Table C.12: Post-MBA Employment Industry and Preferences (MBA Sample)

	Dependent variable:					
	CPG-Retail	Consulting	Healthcare	Nonprofit	Other	Tech and Media
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: No Controls						
Gender: Female	1.120***	0.533**	1.495**	1.783	-0.254	0.774***
	(0.419)	(0.244)	(0.622)	(1.166)	(0.425)	(0.293)
Constant	-2.347***	-0.586***	-3.359***	-4.745***	-1.609***	-1.279***
	(0.316)	(0.156)	(0.509)	(1.004)	(0.228)	(0.200)
Panel B: Including Background Controls						
Gender: Female	0.958**	0.456*	1.526**	1.895	-0.346	0.798***
	(0.434)	(0.254)	(0.707)	(1.210)	(0.436)	(0.304)
Background Controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-1.794***	-0.592**	-4.014***	-18.416	-1.288***	-1.542***
	(0.409)	(0.248)	(0.842)	(856.990)	(0.354)	(0.322)
Panel C: Including Background Controls and Preferences						
Gender: Female	0.793*	0.364	1.489**	0.366	-0.526	0.631**
	(0.442)	(0.262)	(0.722)	(1.439)	(0.447)	(0.313)
Background Controls	Yes	Yes	Yes	Yes	Yes	Yes
Preference Parameters	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-1.330**	0.142	-4.072***	-19.337	-1.112*	-0.839*
	(0.646)	(0.379)	(1.150)	(579.892)	(0.605)	(0.468)

Notes: Table shows result from a multinominal regressions in which "Finance" is the reference level. Significance levels: *** p<.01, ** p<.05, * p<.1.

C.10. BEM Sex Role Inventory questions and Tables C.14 and C.15: Course, Social Club events and Industry Selection of MBA Sample with additional controls

- Table C.13 shows the questions used to construct the BEM Sex Role Inventory scores
- Tables C.14 and C.15 show results of OLS regressions on type of a) courses taken, b) on dummies for whether student participated in social clubs events or not, and c) post-MBA employment industry i) finance and ii) nonprofit.
- Table C.14 includes the social impact preference parameters and control measures for Risk-aversion, Competitiveness, Aggressiveness, Assertion scores.
- Table C.15 adds the SRI Masculinity and Femininity scores to the controls in Table C.14.

BEM Sex Role Inventory questions We construct the BEM Sex Role Inventory scores in Tables C.14 and C.15 using the following set of questions.

Table C.13: BEM Sex Role Inventory questions

[Instructions]. Rate how well each adjective describes you:

	Almost never true (1)	(2)	(3)	Neutral (4)	(5)	(6)	Almost always true (7)
Assertive	○	○	○	○	○	○	○
Dominant	○	○	○	○	○	○	○
Stands up under pressure	○	○	○	○	○	○	○
Aggressive	○	○	○	○	○	○	○
Competitive	○	○	○	○	○	○	○
Independent	○	○	○	○	○	○	○
Unexcitable	○	○	○	○	○	○	○
Defends beliefs	○	○	○	○	○	○	○
Willing to take risks	○	○	○	○	○	○	○
Confident	○	○	○	○	○	○	○
Warm	○	○	○	○	○	○	○
Kind	○	○	○	○	○	○	○
Sensitive	○	○	○	○	○	○	○
Supportive	○	○	○	○	○	○	○
Nurturing	○	○	○	○	○	○	○
Gentle	○	○	○	○	○	○	○
Compassionate	○	○	○	○	○	○	○

We averaged responses to the following BEM questions to construct our SRI Masculinity and Femininity variables: (a) Masculinity: Assertiveness, Dominant, Stands Pressure, Aggressiveness, Competitiveness, Independent, Defends Beliefs, Confident), and (b) Femininity: Warm, Sensitive, Nurturing, Gentle, Compassionate, Supportive.

Table C.14: Course, Social Club events and Industry Selection of MBA Sample with additional survey controls

	Courses					*Social engagement*			*Industry*			
	Finance (MBA)		Social (MBA)			Club events attendance (MBA)			Finance (Post-MBA)		Nonprofit (Post-MBA)	
	(1)	(2)	(3)	(4)		(5)	(6)		(7)	(8)	(9)	(10)
Gender: Female	-0.051***	-0.044***	0.018***	0.013*		0.157***	0.150***		-0.147***	-0.124**	0.014	0.019
	(0.011)	(0.011)	(0.007)	(0.007)		(0.053)	(0.056)		(0.055)	(0.058)	(0.011)	(0.012)
$\frac{\text{Importance}_{\text{SocialImpact}}}{\text{Importance}_{\text{FinancialOffer}}}$	-0.009	-0.008	0.017***	0.018***		0.128***	0.141***		-0.155***	-0.156***	0.029***	0.029***
	(0.008)	(0.008)	(0.005)	(0.005)		(0.040)	(0.041)		(0.043)	(0.043)	(0.009)	(0.009)
Risk-taking		0.007*		-0.007**			-0.017			0.025		0.003
		(0.004)		(0.003)			(0.021)			(0.021)		(0.004)
Competitiveness		-0.001		-0.003			-0.014			-0.028		0.010*
		(0.005)		(0.003)			(0.024)			(0.025)		(0.005)
Aggressiveness		0.004		0.004			0.040**			0.019		-0.002
		(0.004)		(0.002)			(0.019)			(0.020)		(0.004)
Assertiveness		-0.003		-0.002			-0.024			-0.037		-0.002
		(0.004)		(0.003)			(0.022)			(0.023)		(0.005)
Control Variables	Yes	Yes	Yes	Yes		Yes	Yes		Yes	Yes	Yes	Yes
Constant	0.209***	0.176***	0.160***	0.207***		0.355***	0.490***		0.371***	0.495***	0.010	-0.040
	(0.012)	(0.034)	(0.007)	(0.022)		(0.057)	(0.168)		(0.059)	(0.178)	(0.012)	(0.037)
Adjusted R^2	0.095	0.097	0.072		0.085	0.078		0.081	0.076	0.080	0.037	0.038
F-value	7.194	4.765	5.551	4.263		6.069	4.194		5.225	3.684	2.962	2.210
N	353	353	353	353		361	361		310	310	310	310

Notes: This table reports coefficients and standard errors in parentheses of OLS regressions. Control variables are International, GMAT, Work experience, and whether the student has loans. . Significance levels: *** p<.01, ** p<.05, * p<.1.

Table C.15: Course, Social Club events and Industry Selection of MBA Sample with all BEM SRI controls

	Courses				*Social engagement*		*Industry*			
	Finance (MBA)		Social (MBA)		Club events attendance (MBA)		Finance (Post-MBA)		Nonprofit (Post-MBA)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Gender: Female	-0.051***	-0.043***	0.018***	0.013*	0.156***	0.153***	-0.145***	-0.118**	0.014	0.019
	(0.011)	(0.012)	(0.007)	(0.007)	(0.053)	(0.057)	(0.055)	(0.059)	(0.011)	(0.012)
$\frac{\text{Importance}_{\text{SocialImpact}}}{\text{Importance}_{\text{FinancialOffer}}}$	-0.008	-0.008	0.018***	0.018***	0.126***	0.140***	-0.153***	-0.156***	0.029***	0.030***
	(0.008)	(0.008)	(0.005)	(0.005)	(0.040)	(0.041)	(0.043)	(0.043)	(0.009)	(0.009)
Risk-taking		0.006		-0.007**		-0.015		0.019		0.004
		(0.004)		(0.003)		(0.021)		(0.022)		(0.005)
Competitiveness		-0.004		-0.004		-0.010		-0.046		0.014**
		(0.006)		(0.004)		(0.029)		(0.031)		(0.007)
Aggressiveness		0.000		0.002		0.043*		-0.005		0.001
		(0.005)		(0.003)		(0.023)		(0.024)		(0.005)
Assertiveness		-0.008		-0.003		-0.017		-0.062**		0.002
		(0.006)		(0.004)		(0.030)		(0.031)		(0.006)
SRI Masculine		0.017		0.007		-0.026		0.106		-0.016
		(0.015)		(0.010)		(0.076)		(0.079)		(0.016)
SRI Femenine		-0.002		-0.001		-0.017		-0.029		0.003
		(0.006)		(0.004)		(0.029)		(0.030)		(0.006)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.209***	0.158***	0.159***	0.198***	0.356***	0.646**	0.368***	0.460*	0.010	-0.034
	(0.012)	(0.052)	(0.008)	(0.034)	(0.057)	(0.257)	(0.059)	(0.269)	(0.012)	(0.056)
Adjusted R^2	0.090	0.090	0.074	0.081	0.074	0.074	0.072	0.076	0.037	0.036
F-value	6.781	3.880	5.686	3.583	5.747	3.397	4.993	3.117	2.971	1.958
N	351	351	351	351	359	359	308	308	308	308

Notes: This table reports coefficients and standard errors in parentheses of OLS regressions. Control variables are International, GMAT, Work experience, and whether the student has loans. . Significance levels: *** p<.01, ** p<.05, * p<.1.

C.11. Tables C.16, C.17 and C.18: Course, Social club events participation and Industry Selection of MBA Sample with alternatives measures for social impact preferences

- Table C.16 show results of OLS regressions on type of courses taken.
- Table C.17 show results of OLS regressions on dummies for whether student participated in social clubs events or not.
- Table C.18 show results of OLS regressions on dummies for post-MBA employment industry i) finance and ii) nonprofit.
- These table compare the gender differences captured with our measure for social impact captured by the model estimates with a direct ranking question or model-free summary statistics of the conjoint questions. Specifically we compare our preference measure against: a) the ranking position of social impact from the direct elicitation question in the survey, b) whether social impact is ranked among the top 2 attributes, c) the proportion of alternatives chosen in the conjoint choice questions that have the highest level of social impact, and d) the proportion of alternatives chosen in the conjoint choice questions that have the lowest level of social impact.

Table C.16: Course Selection of MBA Sample (with alternative model-free social impact variables)

	Courses											
	Finance						Social					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Gender: Female	-0.044***	-0.041***	-0.044***	-0.043***	-0.044***	-0.044***	0.022***	0.019***	0.017***	0.020***	0.020***	0.020***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
$\frac{\text{Importance}_{\text{SocialImpact}}}{\text{Importance}_{\text{FinancialOffer}}}$		-0.015**						0.015***				
		(0.007)						(0.004)				
SI ranking position			0.002						-0.016***			
			(0.005)						(0.003)			
SI rank Top 2				-0.009						0.029**		
				(0.018)						(0.012)		
Highest SI chosen					0.001						0.069***	
					(0.029)						(0.019)	
Lowest SI chosen						0.018						-0.054***
						(0.026)						(0.017)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.208***	0.199***	0.201***	0.208***	0.208***	0.203***	0.153***	0.162***	0.222***	0.152***	0.128***	0.169***
	(0.009)	(0.010)	(0.023)	(0.009)	(0.014)	(0.012)	(0.006)	(0.006)	(0.014)	(0.006)	(0.009)	(0.008)
Adjusted R^2	0.085	0.092	0.083	0.083	0.083	0.084	0.033	0.054	0.083	0.044	0.057	0.051
F-value	10.071	9.237	8.396	8.427	8.375	8.463	4.336	5.650	8.405	4.740	5.932	5.364
N	491.000	491.000	491.000	491.000	491.000	491.000	491.000	491.000	491.000	491.000	491.000	491.000

Notes: This table reports coefficients and standard errors in parentheses of OLS regressions. SI stands for Social Impact. Control variables are International, GMAT, Work experience, and whether the student has loans. . Significance levels: *** p<.01, ** p<.05, * p<.1.

Table C.17: Social Club events MBA Sample (with alternative model-free social impact variables)

	Social engagement					
	Club events attendance					
	(1)	(2)	(3)	(4)	(5)	(6)
Gender: Female	0.201***	0.174***	0.182***	0.191***	0.193***	0.195***
	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)
$\frac{\text{Importance}_{\text{SocialImpact}}}{\text{Importance}_{\text{FinancialOffer}}}$		0.122***				
		(0.032)				
SI ranking position			-0.063***			
			(0.023)			
SI rank Top 2				0.140		
				(0.086)		
Highest SI chosen				0.287**		
					(0.140)	
Lowest SI chosen						-0.212*
						(0.127)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.233***	0.308***	0.514***	0.230***	0.130**	0.296***
	(0.043)	(0.046)	(0.109)	(0.043)	(0.066)	(0.057)
Adjusted R^2	0.063	0.087	0.076	0.066	0.069	0.066
F-value	7.779	9.020	7.879	6.943	7.219	6.970
N	506.000	506.000	506.000	506.000	506.000	506.000

Notes: This table reports coefficients and standard errors in parentheses of OLS regressions. SI stands for Social Impact. Control variables are International, GMAT, Work experience, and whether the student has loans. . Significance levels: *** p<.01, ** p<.05, * p<.1.

Table C.18: Industry Selection of MBA Sample (with alternative model-free social impact variables)

	Industry											
	Finance (Post-MBA)						Nonprofit (Post-MBA)					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Gender: Female	-0.133***	-0.099**	-0.121**	-0.120**	-0.130***	-0.121**	0.013	0.009	0.009	0.014	0.010	0.012
	(0.048)	(0.048)	(0.049)	(0.049)	(0.049)	(0.048)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
$\frac{\text{Importance}_{\text{SocialImpact}}}{\text{Importance}_{\text{FinancialOffer}}}$		-0.148***						0.019***				
		(0.036)						(0.007)				
SI ranking position			0.041						-0.015***			
			(0.026)						(0.005)			
SI rank Top 2				-0.170*						-0.013		
				(0.101)						(0.020)		
Highest SI chosen					-0.099						0.085***	
					(0.154)						(0.030)	
Lowest SI chosen						0.408***						-0.029
						(0.142)						(0.028)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.454***	0.367***	0.272**	0.456***	0.489***	0.337***	0.000	0.011	0.065***	0.001	-0.031**	0.009
	(0.048)	(0.051)	(0.126)	(0.047)	(0.073)	(0.062)	(0.009)	(0.010)	(0.025)	(0.009)	(0.014)	(0.012)
Adjusted R^2	0.025	0.060	0.028	0.029	0.023	0.041	0.005	0.018	0.021	0.003	0.021	0.005
F-value	3.183	5.618	3.061	3.138	2.717	4.080	1.412	2.316	2.527	1.250	2.528	1.353
N	434.000	434.000	434.000	434.000	434.000	434.000	434.000	434.000	434.000	434.000	434.000	434.000

Notes: This table reports coefficients and standard errors in parentheses of OLS regressions. SI stands for Social Impact. Control variables are International, GMAT, Work experience, and whether the student has loans. . Significance levels: *** p<.01, ** p<.05, * p<.1.

C.12. Table C.19: Industry Selection for all industries (MBA Study)

- Table C.19 show results of OLS regressions on dummies for post-MBA employment industry i) finance, ii) nonprofit, iii) healthcare and nonprofit, iv) consulting, and v) media and tech.

Table C.19: Industry Selection for all industries (MBA Study)

	Industry									
	Finance (Post-MBA)		Nonprofit (Post-MBA)		Healthcare & Nonprofit (Post-MBA)		Consulting (Post-MBA)		Media & Tech (Post-MBA)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Gender: Female	-0.133***	-0.099**	0.013	0.009	0.041**	0.038**	0.030	0.020	0.070*	0.061*
	(0.048)	(0.048)	(0.010)	(0.010)	(0.018)	(0.018)	(0.045)	(0.045)	(0.036)	(0.037)
$\frac{\text{Importance}_{\text{SocialImpact}}}{\text{Importance}_{\text{FinancialOffer}}}$		-0.148***		0.019***		0.013		0.045		0.043
		(0.036)		(0.007)		(0.014)		(0.034)		(0.027)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.454***	0.367***	0.000	0.011	0.006	0.014	0.251***	0.277***	0.088**	0.112***
	(0.048)	(0.051)	(0.009)	(0.010)	(0.018)	(0.020)	(0.044)	(0.048)	(0.035)	(0.039)
Adjusted R^2	0.025	0.060	0.005	0.018	0.010	0.009	0.002	0.004	0.004	0.008
F-value	3.183	5.618	1.412	2.316	1.846	1.684	1.156	1.262	1.386	1.571
N	434	434	434	434	434	434	434	434	434	434

Notes: This table reports coefficients and standard errors in parentheses of OLS regressions. SI stands for Social Impact. Control variables are International, GMAT, Work experience, and whether the student has loans. . Significance levels: *** p<.01, ** p<.05, * p<.1.

C.13. Table C.20: Course, Social Club events and Industry Selection of MBA Sample with Prior Employment Industry Controls

- Table C.20 show results of OLS regressions on type of a) courses taken, b) on dummies for whether student attended any MBA social club event or not, and c) whether post-MBA employment industry is i) finance or not, and ii) nonprofit or not.
- The table includes the social impact preference parameters and dummy controls for prior employment in finance and nonprofit industries.
- We caution about interpreting the estimates of this table as preferences in general (and for social impact in particular) are very likely to have impacted the choice of industry for the prior job to begin with. That means, controlling for prior job industry could partially capture the variation in preferences for meaning at work that may explain the gender differences in the outcomes.

Table C.20: Course, Social Club events and Industry Selection with Prior Employment Industry Controls (MBA Study)

	Courses				*Social engagement*		*Industry*			
	Finance (MBA)		Social (MBA)		Club events attendance (MBA)		Finance (Post-MBA)		Nonprofit (Post-MBA)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Gender: Female	-0.038***	-0.036***	0.021***	0.018***	0.193***	0.169***	-0.110**	-0.081*	0.012	0.008
	(0.009)	(0.009)	(0.006)	(0.006)	(0.044)	(0.044)	(0.047)	(0.047)	(0.010)	(0.010)
$\frac{\text{Importance}_{\text{SocialImpact}}}{\text{Importance}_{\text{FinancialOffer}}}$		-0.011		0.014***		0.114***		-0.133***		0.018**
		(0.007)		(0.004)		(0.033)		(0.035)		(0.007)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.179***	0.174***	0.154***	0.162***	0.268***	0.331***	0.328***	0.257***	0.008	0.017
	(0.009)	(0.010)	(0.006)	(0.007)	(0.047)	(0.050)	(0.051)	(0.053)	(0.010)	(0.011)
Adjusted $R2^2$	0.165	0.168	0.057	0.073	0.070	0.090	0.092	0.120	0.007	0.019
F-value	14.880	13.391	5.215	5.842	6.417	7.279	7.271	8.376	1.410	2.040
Observations	491	491	491	491	506	506	434	434	434	434

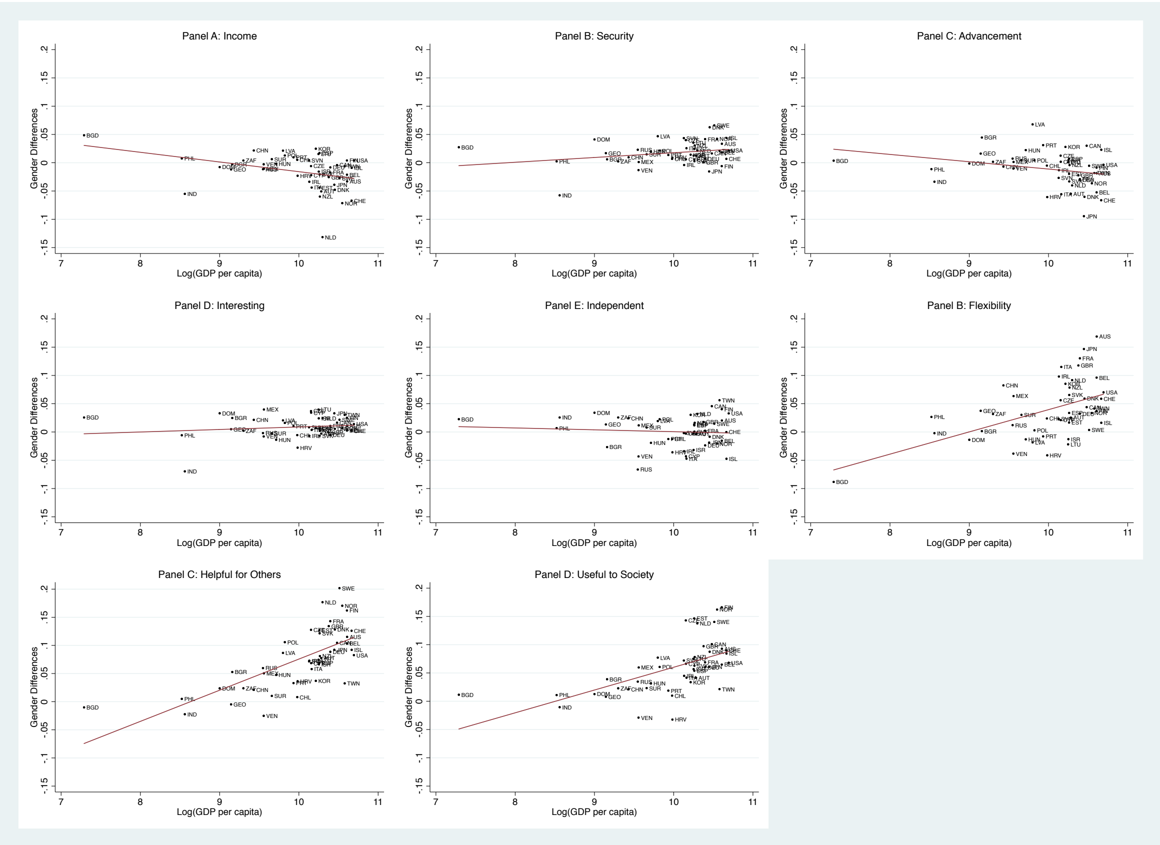
Notes: This table reports coefficients and standard errors in parentheses of OLS regressions. Control variables are International, GMAT, Work experience, Prior Industry, and whether the student has loans. . Significance levels: *** p<.01, ** p<.05, * p<.1.

D. Additional Figures

D.1. Figure D.1: Gender Differences and GDP

- Figures show the association between log of GDP per capita and gender differences in stated importance of job attributes. We run regressions for each country, c, of the following form: $Job\ Attribute_i = \beta_1^c Female_i + \beta_2^c Controls_i + y_i^c + \epsilon_i$. The figure plots the coefficient, β_1^c, which captures the country-level gender differences in the importance of $Job\ Attribute_i$. The regressions include the main control variables: dummies for years of education, age, dummies for marital status, dummies for work status, dummies for household size, and year dummies.
- Regressing the gender coefficient on average log GDP per capita in an OLS regression yields the following coefficients (standard errors): -.017 (s.e.=.006) for Income, .008 (.004) for Security, -.013 (.007) for Opportunity, .004 (.004) for Interesting Job, -.003 (.006) for Independent Job, .039 (.010) for Flexibility, .055 (.009) for Helpful to Others, and .040 (.008) for Useful to Society.

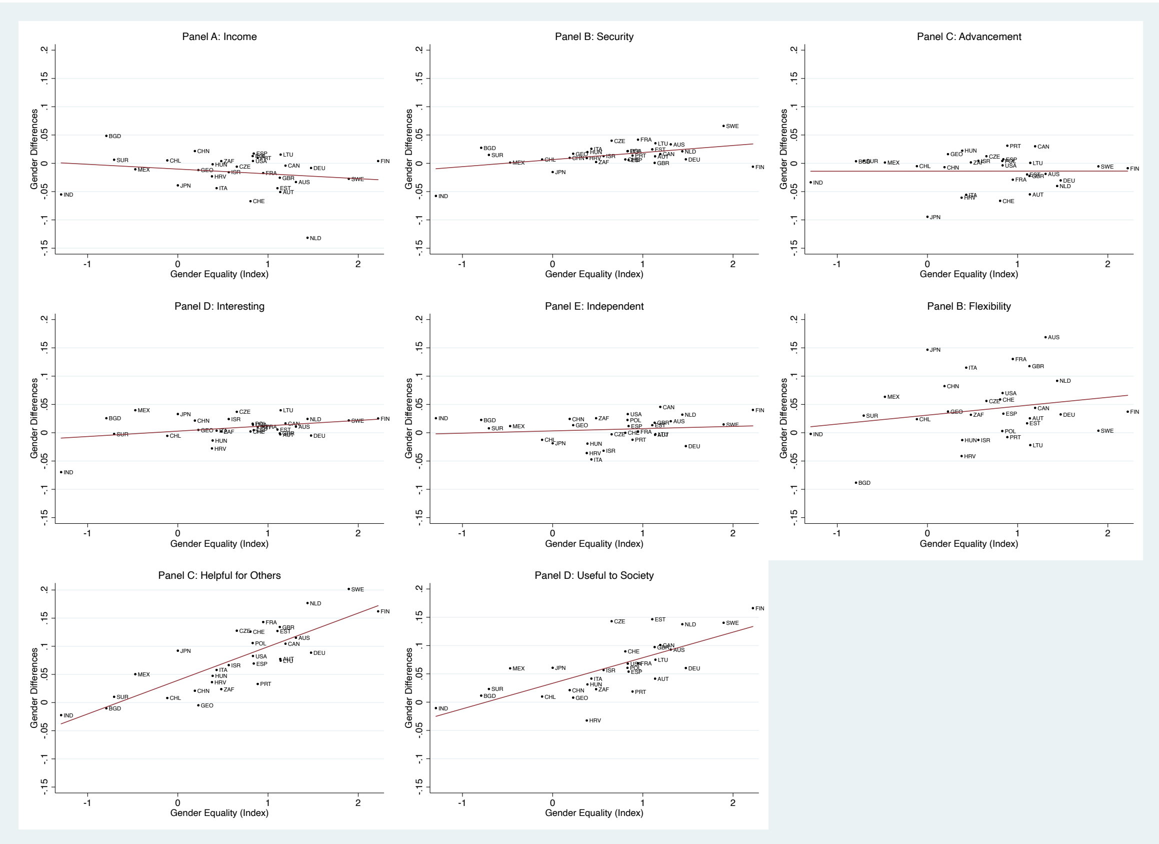
Figure D.1: Gender Differences and GDP



D.2. Figure D.2: Gender Differences and Gender Equality Index

- Figures show the association between Gender Equality Index by Falk and Hermle (2018) and gender differences in stated importance of job attributes. We run regressions for each country, c, of the following form: $Job\ Attribute_i = \beta_1^c Female_i + \beta_2^c Controls_i + y_i^c + \epsilon_i$. The figure plots the coefficient, β_1^c, which captures the country-level gender differences in the importance of $Job\ Attribute_i$. The regressions include the main control variables: dummies for years of education, age, dummies for marital status, dummies for work status, dummies for household size, and year dummies.
- We thank Johannes Hermle for providing us with the index. Given the overlap of the countries in ISSP and the Gender Equality Index, we end up with 30 countries in this analysis.
- Regressing the gender coefficient on the Gender Equality Index in an OLS regression yields the following coefficients (standard errors): -0.008 (s.e.=0.008) for Income, 0.012 (0.004) for Security, 0.000 (0.007) for Opportunity, 0.009 (0.005) for Interesting Job, 0.004 (0.006) for Independent Job, 0.016 (0.013) for Flexibility, 0.060 (0.008) for Helpful to Others, and 0.045 (0.008) for Useful to Society.

Figure D.2: Gender Differences and Gender Equality



E. Salary - social impact tradeoffs

We compute back-of-envelope calculations to analyze if there are gender differences on how much salary respondents would be willing to sacrifice for improving the social impact component of a potential job offer. That is, how much is the maximum respondents could sacrifice to obtain a job offer with better social impact, such that it yields the same utility as a higher paying-, lower social impact job offer.

E.1. Computing tradeoffs from preferences

First, we assume a starting benchmark salary S. Second, using the preferences from the model, we compute for each individual i, how much their utility increases by switching from level ℓ to ℓ' for any given attribute k,

$$\Delta u_i(k, \ell \to \ell') = \beta_{ik\ell'} - \beta_{ik\ell}. \tag{E.13}$$

Third, we implicitly define the salary sacrifice x, by

$$\Delta u_i \left(\text{Salary}, S \to S - x\right) = -\Delta u_i(k, \ell \to \ell'), \tag{E.14}$$

where x is the reduction in salary that makes an alternative job offer with salary $S - x$ and social impact ℓ' equally attractive than the initial job offer with salary S and social impact ℓ.

From the model, we can compute the utility for salaries within the range of the levels in the conjoint study by interpolating the salary component of the utility using a piecewise linear function of salary given by

$$f_i\left(s\right) = \begin{cases} \beta_{i,SO,\$135k} + \frac{\beta_{i,SO,\$150k} - \beta_{i,SO,\$135k}}{150{,}000 - 135{,}000} \cdot (s - 135,000) & \text{if} s \leq \$150,000 \\ \beta_{i,SO,\$150k} + \frac{\beta_{i,SO,\$165k} - \beta_{i,SO,\$150k}}{165{,}000 - 150{,}000} \cdot (s - 150,000) & \text{if} s \geq \$150,000 \end{cases}, \tag{E.15}$$

where $\beta_{i,SO,\$135k}$, $\beta_{i,SO,\$150k}$, $\beta_{i,SO,\$165k}$ are the associated preferences for the corresponding salary offers of \$135k, \$150k, and \$165k, respectively.

Finally, we can compute x by solving

$$\begin{aligned} f_i\left(S - x\right) - f_i\left(S\right) &= -\Delta u_i(k, \ell \to \ell') \\ f_i\left(S - x\right) &= f_i\left(S\right) - \Delta u_i(k, \ell \to \ell') \\ \implies S - x &= f_i^{-1}\left[f_i\left(S\right) - \Delta u_i(k, \ell \to \ell')\right] \end{aligned} \tag{E.16}$$

Assuming a benchmark salary of $S = \$165k$,[15] we can write x as

$$\begin{aligned} x = &\min\left\{\lambda_1 \cdot \Delta u_i(k, \ell \to \ell'),\ \$165k - \$150k\right\} \\ &+ \max\left\{\lambda_2 \cdot \Delta u_i(k, \ell \to \ell') - \frac{\lambda_2}{\lambda_1} \cdot \left(\$165k - \$150k\right),\ 0\right\}, \end{aligned} \tag{E.17}$$

where $\lambda_1 = \frac{\$165k - \$150k}{\beta_{i,SO,\$165k} - \beta_{i,SO,\$150k}}$ and $\lambda_2 = \frac{\$150k - \$135k}{\beta_{i,SO,\$150k} - \beta_{i,SO,\$135k}}$.

[15] We assume the highest benchmark salary such that the majority of the resulting salaries fall within the salary levels in the study.

E.2. Salary - social impact tradeoffs results

We compute the salary tradeoffs from Equation (E.17) for each individual using the posterior mean estimates of our model. We compute the maximum salary respondents would sacrifice to switch the social impact of their potential job from: (1) Worst CSR to Average CSR, (2) Average CSR to Best CSR, and (3) Worst CSR to Best CSR.

We show distribution of salary sacrifices by gender in Figure 4 in the paper, and the gender differences on their means in Table E.21.

Table E.21: Gender differences in salary tradeoffs (MBA Study)

	Gender			
Variable	Male	Female	Diff.	$P(\|T\| > \|t\|)$
Salary - Social impact tradeoffs				
Worst CSR → Average CSR ($)	14115.66	19611.61	-5495.95	0.000
Average CSR → Best CSR ($)	7069.35	9388.16	-2318.82	0.000
Worst CSR → Best CSR ($)	18264.69	24654.86	-6390.17	0.001
N	291	217		

Notes: Table shows means for continuous variables. All coefficients are measured in US dollars ($). Based on data from university administration and the individual level posterior preferences estimated from the conjoint study. All salary sacrifice figures assume starting salary of $165.000. Utility changes in salary increases are lower bounded at zero to ensure monotonic utility on salary offers.

Consistent with the estimates of our model shown in Table 6, respondents are more willing to sacrifice salary in order to avoid the lowest level of social impact. More importantly, these tradeoffs are larger for female respondents than their male colleagues. The gender difference represents around 25% of the overall salary tradeoff for female respondents, across the three different scenarios. These gender differences are robust to controlling for other observables (Table E.22).

Table E.22: Gender differences in salary tradeoffs with additional controls (MBA Study)

	Salary sacrifice for change in Social impact		
	Worst CSR → Average CSR ($) (1)	Average CSR → Best CSR ($) (2)	Worst CSR → Best CSR ($) (3)
Gender: Female	5146.172***	2260.173***	5954.242***
	(1546.348)	(636.475)	(1896.088)
International	1969.183	652.221	2887.124
	(1569.635)	(646.060)	(1924.642)
GMAT (total)	-259.764	14.006	-206.462
	(774.925)	(318.958)	(950.191)
Work Experience	236.107	284.336	188.241
	(758.926)	(312.373)	(930.574)
Any Loan? (=1)	734.757	184.150	567.646
	(1538.016)	(633.045)	(1885.871)
Constant	12625.315***	6579.437***	16314.481***
	(1497.931)	(616.546)	(1836.720)
Adjusted R^2	0.020	0.021	0.018
F-value	3.055	3.148	2.835
N	506	506	506

Notes: This table reports coefficients and standard errors in parentheses of OLS regressions. All coefficients are measured in US dollars ($). Control variables are International, GMAT, Work experience, and whether the student has loans. Significance levels: *** p<.01, ** p<.05, * p<.1.

Based on data from university administration and the individual level posterior preferences estimated from the conjoint study.

All salary sacrifice figures assume starting salary of $165.000. Utility changes in salary increases are lower bounded at zero to ensure monotonic utility on salary offers.