Gender Differences in Preferences for Meaning at Work

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Abstract

We provide empirical evidence of the importance of gender differences in preferences for meaning at work. First, we demonstrate that gender differences in preferences for meaning at work derived from social (but not non-social) impact are widespread using a cross-country survey covering individuals in 47 countries. These differences become more pronounced with greater levels of education and economic development. Second, using a conjoint analysis of a cohort of MBA students, we show that preferences for meaning at work derived from social (but not non-social) impact partly explain gender differences in types of courses taken and job industry placement.

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

JEL: J24, J16, D91.

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1. Introduction

Scholars and policymakers alike have sought to understand the factors which influence occupational segregation by gender, particularly given that approximately half of the gender wage gap has been attributed to the sorting of men and women into different jobs (Morchio and Moser, 2019; Blau and Kahn, 2017). Recently, researchers have begun to examine gender differences in preferences for job characteristics, such as flexibility, stability, 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, 2020). 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). Organizational characteristics of meaning and purpose have been shown to influence important human capital outcomes (Gartenberg et al., 2019), yet whether men and women differ in their preferences for meaning at work, and whether these differences in preferences help to partly explain self-selection of men and women into different types of jobs, has been to the best of our knowledge unexplored.

We examine potential gender differences in preferences for two different types of meaning at work (see Cassar and Meier, 2018): *meaning derived from social impact at work* and *meaning derived from non-social impact at work*. Industries, occupations, and employing organizations certainly differ in their perceived impact on the broader community, society, and/or the environment (Dur and Van Lent, 2019), for example, 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. Meaning derived from non-social impact at work has the potential to fulfill individuals' innate psychological needs for feelings of competence and autonomy (Deci and Ryan, 2000).

Gender differences in meaning derived from social impact at work might be expected given prior findings that women seem to be more emphatic (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). And 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). 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 for men and women to self-select into different industries, types of firms, and jobs.

To examine whether there are gender differences in such preferences, and how they compare to gender differences in preferences for other job attributes, 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 while both genders value meaning derived from non-social impact, gender differences in preferences for meaning derived by social impact are large and widespread. We furthermore show that they become more pronounced 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). Given the wide-ranging sample of individuals, this study helps us to establish the generalizability of our findings across countries.

In a next step we 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. 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); Folke and Rickne (2020), helps to address social desirability bias compared to surveys which directly ask individuals how much they value job characteristics such as corporate social responsibility (CSR) (Leveson and Joiner, 2014), yet it has been underused as a methodology to study prospective employee preferences (Montgomery and Ramus, 2011). Specifically, 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 results consistent with those of the cross-national data: while men and women exhibit equivalent preferences for meaning derived from non-social impact, they exhibit starkly different preferences for meaning derived from social impact. We furthermore show that these gender differences in preferences for social impact at work help to explain critical behavioral outcomes: not only students' coursework choices, but also their internship placements and full-time job placements.

We examine whether preferences for meaning at work help to explain why female MBA students are much 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) – the industry with the highest wages (e.g., Bertrand et al., 2010; Barbulescu and Bidwell, 2013). Our results show that preferences for meaning at work indeed explain part of this job placement industry outcome, 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). 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 amongst highly skilled individuals is particularly important.

Our findings contribute to three streams of literature. First, our main contribution is to the discussion about the drivers of the gender wage gap and occupational segregation by gender, which scholars across disciplines 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.[1] Recent studies focus 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).[2] In particular, recent research focuses 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), 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.[3] We not only document that gender differences in preferences for meaning at work exist, but also show that they help to explain differences in industry placement, with implications for the salaries earned by men and women. Based on the results from our MBA sample, preferences for meaning at work explain about 25% of the gender effect of selection into different industries, particularly the finance industry. 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

[1] 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).

[2] 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 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.

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

other factors (certainly, there are many drivers of occupational segregation), it 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. Our findings suggest that firms interested in increasing gender diversity would thus do well to improve the perception of the social impact of their jobs, company, or industry.

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 show that it is important to distinguish between two ways 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.* 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.

We show that gender differences exist only for meaning derived from social impact at work – consistent with research showing gender differences in altruism, compassion, or 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)). 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. Particularly in our cross-country evidence, we show that gender differences are absent in preferences for monetary aspects of a job, are relatively minor for preferences for meaning derived from non-social impact at work, and are highly pronounced for meaning derived from social impact at work.

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 preferences – especially for competitiveness (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 derived from social impact 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. 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 education may help to explain part of the origin in gender differences for certain job attribute preferences.

In what follows we describe the data, analyses, and discuss the results for each of the two data sources and methodologies 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). See Table B.10 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 of the analyses we create a dummy that takes on the value 1 if the individual indicated that a particular job attribute is 'Very important' or 'Important' and 0 otherwise.[4]

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:

$$Job\ Attribute_i = \beta_1 Female_i + \beta_2 Controls_i + c_1 + y_1 + \epsilon_1 \tag{1}$$

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). "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 or not and log of household size. The 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

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

for every country and even inconsistent within country across waves - 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 show 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 not to have a supervisory role (18% vs. 32% for men).

Table 1 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 male and female corporate board directors (Adams and Funk, 2012). We 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.

2.2. Results

We present these results in three 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).

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 previous results for US high school students (Marini et al., 1996).

Table 2 here

Panel B shows the different attributes separately to see which specific attribute drives the aggregate gender difference. The table shows the proportion of females and males indicating that a certain job attribute is 'very important' or 'important' (an analysis using the 5 point scales instead of this dummy is shown in Table B.2 in the Appendix). 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 a Mann-Whitney test (see Column (4)), the gender difference is only around 1.4 percentage points. Similarly small gender differences are found for the other two 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 also minimal for two aspects of meaning derived from non-social impact at work: having an interesting job (difference of 0.8 percentage points) and independent work (0.9). Both genders care equally about having an impactful job that is interesting and that provides autonomy. 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, however, 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 B.1 in the Appendix.

Figure 1 and Figure 2 here

Figures 1 and 2 investigate whether the gender differences 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 only four attributes: "income" as the primary monetary attribute, and "flexibility", "helpful to others" and "useful to society" which emerged as the most important non-monetary attributes. For analysis of all attributes see Figure C.1 and Table B.3 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 C.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 on request)).

Figure 2 plots coefficients of interaction terms between gender and different education groups (9-12 years of education as the reference group). Full regression results for all attributes are in Table B.3 in the Appendix (controlling for a large set of variables). The figure shows that gender differences 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 particularly important since they suggest that gender differences in preferences for meaning induced by social impact at work will only increase over time, as the world's population becomes more educated and more developed.

In sum, these results suggest that gender differences in preferences for meaning induced by social impact at work are widespread and exhibit trends which suggest that they are likely to increase over time.

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 elicitation method does not force the respondents to consider any trade-offs (i.e. all attributes could potentially be stated as "very important"). This could also make social desirability bias more likely. 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 important covariates (despite our best effort given the available data). Furthermore, the data does not allow us to examine whether the differences in preferences translated into any differences in behavioral outcomes of importance. To address each of these issues head-on, we leverage a choice-based conjoint methodology, implemented on a sample of a homogeneous, high-skilled group of individuals, and 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 job attributes. We administered the survey as a required assignment for the core MBA strategy course, which all entering students take. The choice-based survey was therefore conducted before the start of any classes. We made it clear that the answers to the survey would not affect grades and that their individual answers would be treated confidentially and not be shared, in order to avoid any potential signalling effects (Bursztyn et al., 2017). (See Appendix for details on the instructions of the survey.)

During the survey, we administered a series of questions to facilitate choice-based conjoint analyses of their responses. 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 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 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 product attribute to determine participants' implicit valuation of, or preference for, each product attribute. Choice-based conjoint analysis has been shown to be a more reliable way to elicit product attribute preferences than directly asking individuals which product attributes they prefer (Akaah and Korgaonkar, 1983) or even, for job attribute preferences, than looking at job choices (for a great discussion, see Wiswall and Zafar, 2017). The choice-based data collection process is 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).

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 3 shows the different levels for each attribute. See Appendix A for exact wording of the questions.

Table 3 here

We merged the MBA students' preference parameters inferred from the conjoint study with administrative data from the University, in particular admissions data, course data, and internship and full-time job placement data. 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 courses, and of finance-oriented courses, respectively, taken by the student during their two-year MBA. We also obtained data from the university on the industry in which students completed their summer internship, and where they were employed directly following the MBA. We categorize the students' *Internship or 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). We classified the post-MBA employment industry in the same way, also including "Family Business" and "Starting own business" in the Other category, since industry was not specified for those post-MBA jobs.

Table 4 here

Table 4 shows summary statistics of pre-MBA characteristics by gender. Table 4 shows relatively minor differences in background characteristics (Panel A), though male and female students did differ in average GMAT scores and whether their prior job was in the finance industry. In their coursework (Panel B) and especially the industry in which they complete their internship (Panel C) and start a job post-MBA (Panel D), differences are more pronounced. In particular, female MBA students take on average one finance class less than their male colleagues.

And while 46% of male students go into finance post-MBA (58% for internship), only 31% of female students do so (36% for internship).

3.2. Model specification

Respondent's choices amongst the hypothetical job descriptions allows us to infer their preferences by modeling respondents' choices on each question in the conjoint task, using a multinomial logit model. In this section, we describe a) how we model the choices of respondents, 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 Model (LC) (DeSarbo et al., 1995, 1992), and 2) Hierarchical Bayes Model (HB) (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 model we assume 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 relatively intuitive illustration of different preferences by segments, groups, or individuals. To complement this analysis, we estimated an HB 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 covariates available from our respondents.

3.2.1. Choice model

Respondents make choices between sets of hypothetical jobs 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 multinomial logit 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 product 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 Model (LC), and 2) Hierarchical Bayes Model (HB). 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 and HB models.

While both approaches allow respondents to present different preferences, the two modeling approaches are aimed at achieving different goals: The LC model allows us to interpret respondents' heterogeneity through segments, helping us to derive insights on how preferences over job attributes are different for both gender. Specifically, how the segments proportions are different for male and female groups of respondents. The HB model allows us to infer respondent-specific preferences, which are necessary to be able to capture gender differences in preferences while controlling for other individual-level covariates.

Heterogeneity in LC 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

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

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

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

Heterogeneity in HB 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

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

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 model, and 2,000 warm-up and 2,000 to draw from the posterior, for the HB 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 B.4 in Appendix).

3.3. Measuring attributes' importance

After estimation, we computed how important each job attribute is for each segment (for the LC model) or respondent (for the HB 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 model. This allows us to intuitively illustrate how male and female MBA students are distributed across the different preference segments. Second, we present individual-level results from the HB model which allows us to control for important individual-level covariates. Third, we analyze whether the preference parameters can explain behavioral outcomes such as courses taken and industry choices.

We start by characterizing the segments obtained from the LC model. Table 5 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) finance motivated, 2) social and non-social impact motivated , and 3) non-social impact motivated.

Table 5 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.[5] 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 model, and explore gender differences controlling for individual-level characteristics (e.g., GMAT scores and other characteristics shown in Panel A of Table 4). To avoid colinearity (attribute importances sum to 1), we log-transform these attribute importances and measure them relative to the importance of Financial Offer. Specifically, 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).

Table 6 here

Table 6 shows results of these regression analyses. We find that the ratios of how important the attributes Non-Social Impact, 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. 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

[5] 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 $\widetilde{\pi}_{is} = \pi_s L_{is}/(\sum_{s'} \pi_{s'} L_{is'})$.

for whether the potential employing firm is socially responsible (meaning induced by social impact at work). These results are robust to controlling for individual-level characteristics, in particular, to the industry the respondents worked before joining the MBA program. (We also corroborate in Table B.5 in the Appendix that these insights hold when controlling for whether respondents held a prior job in finance or non-profit.)

Table 7 here

Finally, we analyze whether a preference parameter capturing the importance of social responsibility (meaning derived from social impact at work) relative to income can explain important behavioral outcomes: the courses taken by MBA students, the industry in which they intern for the summer, and the industry in which they work directly after the MBA. 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 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). We thus focus our analyses on the finance and nonprofit sectors, but show results for all industries in Tables B.8 and B.9 in the Appendix.[6]

For all six outcomes, Table 7 has columns including and excluding the preference parameter, $\log\left(\frac{\text{Importance}_{\text{SocialImpact}}}{\text{Importance}_{\text{FinancialOffer}}}\right)$, generated from the HB model (Table B.7 in the Appendix includes the whole set of preference parameters for all the different attributes relative to importance of financial offer). The table shows that there are gender differences in outcome variables, consistent with gender segregation into different industries. Most striking is that the proportion

[6]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 B.6 in the Appendix. We find results in the same direction, although the explanatory power of preferences is weaken compared to Table 7 for the aforementioned reason.

of female students going into the finance industry post-MBA is about 11 percentage points lower than that of male students (Column 9). Importantly, we find that adding preference parameters explains 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, including the social impact preference parameter decreases the gender effect by 25 %. Our results therefore indicate that differences in preferences for meaning at work help to partly explain both the types of courses taken and the industry of summer internship and 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).

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.

4. Discussion

Taken together, our results provide compelling evidence that there are gender differences in preferences for meaning at work, with important variation in types of 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 gender differences are particularly pronounced with regard to preferences for meaning derived from social impact 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 induced by social impact at work, and point to the likely increase in these differences over time, as the population becomes more educated and more economically developed over time. In this sample we furthermore find differences in preferences for meaning derived from social impact 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.

Amongst a homogeneous sample of highly educated MBA students, gender differences in preferences for one type of meaning at work, that derived from social impact, help to predict the nature of the courses pursued during business school, as well as the industry of the summer internship and full-time job placement. These are critically important outcomes from a gender segregation perspective, as industry of full-time employment not only influences short-term, but long-term future, wages. Indeed, it has been shown that the gender pay gap increases over the course of careers (Goldin et al., 2017). These estimates are furthermore likely to be under-, rather than over-, estimated, given that this sample is limited to a career subset of MBA students and 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). Future work can examine gender differences in preferences in other professions and in different samples of the population. Given that MBA students make up an important segment of workers for the business world, our findings are highly relevant for the many businesses that recruit and employ MBAs.

How gender differences in job preferences such as those for meaning at work are shaped falls outside of the scope of this paper, and would be an interesting topic for exploration in future research (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, 2019), 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 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. We therefore can expect gender differences for preferences in meaning at work to emerge in countries and contexts where individuals' subsistence needs are already addressed.

As long as gender differences in preferences for meaning at work persist, gender segregation by industry of work is likely to continue, at least to some degree. For policymakers, NGOs, and individuals seeking to decrease gender segregation by industry of work, our results suggest that policy or cultural changes that serve to increase men's relative appreciation and preference for meaning derived from social impact would help to address the gender imbalance in high-paying industries. In the meantime, given that these differences in gender preferences currently exist, the addition of social impact attributes such as corporate social responsibility to companies in high-paying industries could be one promising way to increase the representation of women in these occupations and, resulting, narrow the gender wage gap. Given that there can be resistance against workplace policies explicitly directed at achieving diversity goals (Dover et al., 2016; Ip et al., 2019; Leibbrandt et al., 2018; Niederle et al., 2013), our findings suggest a promising means toward increasing gender equality through implementation of company-level policies which are not directed at gender bias per se, and as such are likely to be met with less resistance. Namely, inducing a sense of social impact at work through policies such as the implementation of corporate social responsibility programs.

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6. Tables and Figures

Table 1: Summary statistics of ISSP Data

	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 Data)

	(1)	(2)	(3)	(4)	(5)	(6)
	Raw Data				Adding Controls	
	Women	Men	Diff.	Prob> $\|z\|$	Main	Additional
Panel A: Average Importance						
Monetary Attributes	4.188	4.188	0.000	0.899	-0.006	0.004
					(0.006)	(0.008)
Non-Monetary Attributes	4.046	3.966	0.080	0.000	0.084	0.087
					(0.006)	(0.008)
Panel B: Proportion Finding Attribute [Different Job Characteristics] Important						
Income	0.813	0.827	-0.014	0.000	-0.017	-0.015
					(0.004)	(0.006)
Job security	0.946	0.930	0.017	0.000	.0019	0.014
					(0.002)	(0.003)
Opp. for advancement	0.751	0.758	-0.007	0.001	-0.015	-0.004
					(0.004)	(0.006)
Interesting job	0.921	0.914	-0.008	0.000	0.010	0.012
					(0.002)	(0.003)
Independent work	0.761	0.771	-0.009	0.000	0.001	0.009
					(0.004)	(0.005)
Flexibility	0.644	0.595	0.048	0.000	0.044	0.043
					(0.005)	(0.007)
Helpful to others	0.799	0.717	0.082	0.000	0.082	0.074
					(0.006)	(0.008)
Useful to society	0.797	0.735	0.061	0.000	0.063	0.056
					(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). For Panel A, Column (4) reports t-test results. 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, and column (4) reports results of Mann-Whitney tests. The last two columns show gender coefficients from OLS regressions that control for in Column (5) for dummies for years of education, age, dummies for marital status, dummies for work status, dummies for household size, country and year dummies. In Column (6) 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.

Table 3: Conjoint Design: Attributes and Levels (MBA Sample)

	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 4: Summary Statistics of MBA Study

Variable	Gender: Male	Gender: Female	Diff.	$P(\|T\| > \|t\|)$
Panel A: Background				
Have loans? (=1)	0.546	0.507	0.039	0.379
GMAT (total)	729.276	709.491	19.785	0.000
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
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
N	291	217		
Panel C: Internship Industry				
Finance	0.578	0.355	0.223	0.000
Consulting	0.146	0.172	-0.026	0.433
CPG-Retail	0.060	0.103	-0.043	0.092
Healthcare	0.026	0.059	-0.033	0.087
Nonprofit	0.004	0.025	-0.021	0.071
Other	0.015	0.020	-0.005	0.697
Tech and Media	0.172	0.266	-0.094	0.015
N	268	283		
Panel D: 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		

Notes: Table shows proportions for dummy variables and means for continuous variables. Based on data from university administration.

Table 5: Posterior Statistics of Attribute Preferences $\mathbf{b}_s$ per Segment (MBA Sample)

		Segment 1				**Segment 2**				**Segment 3**			
		Finance Motivated				**Social & Non-Social Impact Motivated**				**Non-Social Impact Motivated**			
Segment size		42%				26%				32%			
Attribute	Level	Mean	(se)	2.5%	97.5%	Mean	(se)	2.5%	97.5%	Mean	(se)	2.5%	97.5%
Job	(Intercept)	6.051	0.350	3.292	11.800	6.012	0.682	4.555	13.420	10.433	0.090	7.371	15.459
Financial Offer	$135,000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	$150,000	2.115	0.006	1.845	2.387	0.895	0.022	0.500	1.276	1.804	0.010	1.422	2.285
	$165,000	2.976	0.007	2.661	3.321	1.038	0.033	0.584	1.492	2.675	0.014	2.145	3.328
Social Impact	Best CSR Record	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Average CSR Record	-0.355	0.005	-0.556	-0.127	-0.522	0.006	-0.810	-0.271	-0.030	0.005	-0.354	0.300
	Worst CSR Record	-0.637	0.007	-0.918	-0.336	-2.569	0.013	-3.199	-2.055	-0.795	0.008	-1.178	-0.416
Non-Social Impact	High (strongly feel)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Mid (moderately feel)	-0.345	0.004	-0.562	-0.110	-0.829	0.006	-1.138	-0.541	-1.994	0.010	-2.461	-1.595
	Low (do not feel)	-1.634	0.007	-1.959	-1.309	-2.686	0.010	-3.262	-2.167	-6.841	0.034	-8.574	-5.506
Flexibility	Has	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Does not have	-1.150	0.011	-1.395	-0.910	-1.262	0.019	-1.614	-0.902	-0.948	0.006	-1.295	-0.606
Prestige	Top 20	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Not top 20	-1.703	0.006	-1.977	-1.442	-1.050	0.005	-1.373	-0.725	-1.370	0.006	-1.720	-1.023

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 6: Gender Differences in Job Preferences (MBA Sample)

	Dependent variable:							
	Non-Social Impact		Social Impact		Flexibility		Prestige	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gender: Female	0.184***	0.184***	0.243***	0.220***	0.210***	0.177***	0.001	0.005
	(0.062)	(0.064)	(0.058)	(0.060)	(0.049)	(0.050)	(0.047)	(0.048)
International		−0.106		−0.022		0.005		−0.011
		(0.065)		(0.061)		(0.051)		(0.049)
GMAT (total)		−0.010		−0.056*		−0.062**		0.007
		(0.032)		(0.030)		(0.025)		(0.024)
Work exp.		−0.020		0.001		−0.010		−0.044*
		(0.031)		(0.029)		(0.025)		(0.024)
Have loans?		0.075		0.060		−0.061		0.096**
		(0.063)		(0.060)		(0.050)		(0.048)
Constant	0.206***	0.230***	−0.603***	−0.612***	−0.783***	−0.739***	−0.512***	−0.558***
	(0.040)	(0.062)	(0.038)	(0.058)	(0.032)	(0.049)	(0.031)	(0.047)
Observations	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.

Table 7: Course and Industry Selection of MBA Sample

	Courses				*Industry*							
	Finance		Social		Finance (Summer)		Nonprofit (Summer)		Finance (Post-MBA)		Nonprofit (Post-MBA)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Female=1	-0.044***	-0.041***	0.022***	0.019***	-0.208***	-0.183***	0.020*	0.015	-0.133***	-0.099**	0.013	0.009
	(0.009)	(0.009)	(0.006)	(0.006)	(0.047)	(0.047)	(0.011)	(0.011)	(0.048)	(0.048)	(0.010)	(0.010)
$\frac{\text{Importance}_{\text{SocialImpact}}}{\text{Importance}_{\text{FinancialOffer}}}$		-0.015**		0.015***		-0.110***		0.021***		-0.148***		0.019***
		(0.007)		(0.004)		(0.035)		(0.008)		(0.036)		(0.007)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.208***	0.199***	0.153***	0.162***	0.586***	0.519***	0.001	0.014	0.454***	0.367***	0.000	0.011
	(0.009)	(0.010)	(0.006)	(0.006)	(0.047)	(0.051)	(0.011)	(0.012)	(0.048)	(0.051)	(0.009)	(0.010)
Adjusted R^2	0.0847	0.0916	0.0329	0.0539	0.0480	0.0660	0.0049	0.0175	0.0246	0.0601	0.0047	0.0179
F-value	10.071	9.237	4.336	5.650	5.717	6.512	1.458	2.392	3.183	5.618	1.412	2.316
N	491	491	491	491	469	469	469	469	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 7 in the Appendix. Significance levels: *** p<.01, ** p<.05, * p<.1.

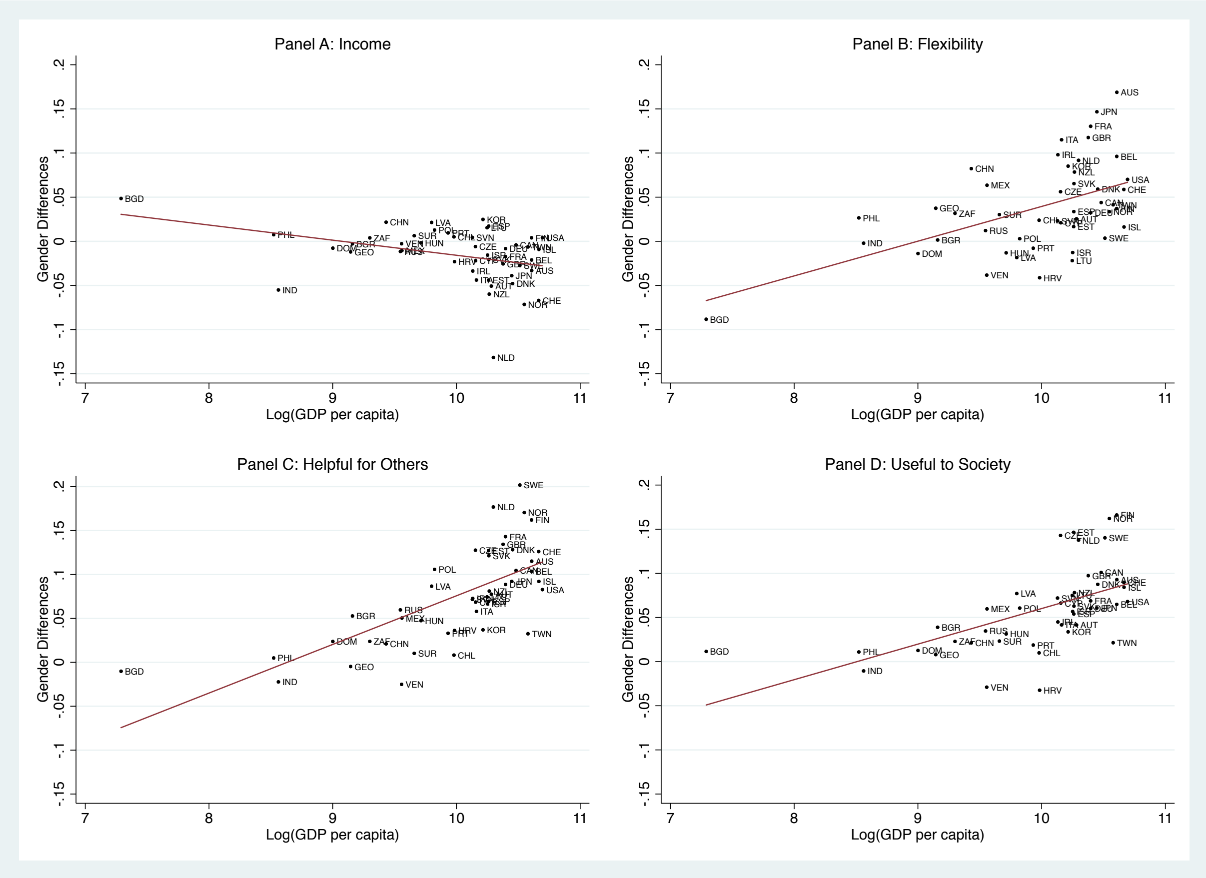

Figure 1: Figures show association between log of GDP per capita and gender differences in stated importance of job attributes. We run regressions for each country, c, of the following form: $Job\ Attribute_i = \beta_1^c Female_i + \beta_2^c Controls_i + y_1^c + \epsilon_1$. The figure plots the coefficient, 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.

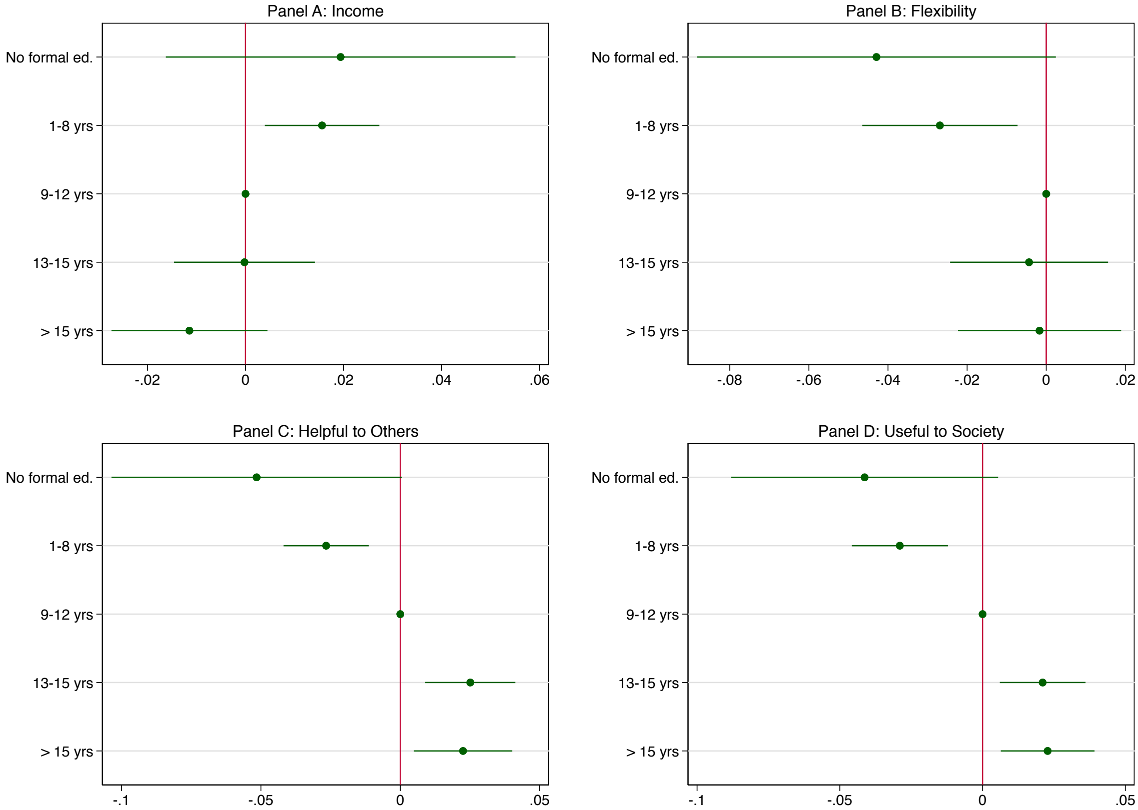

Figure 2: Figures plot interaction effects between gender and education groups. We estimate a regression of the following form: $Job\ Attribute_i = \beta_1 Female_i + \beta_3 EducationGroup_1 + \beta_4 Education \times Female_i + \beta_5 Controls_i + c_1 + y_1 + \epsilon_1$. Figure plots β_4 with 9-12 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 B.3 in the Appendix.

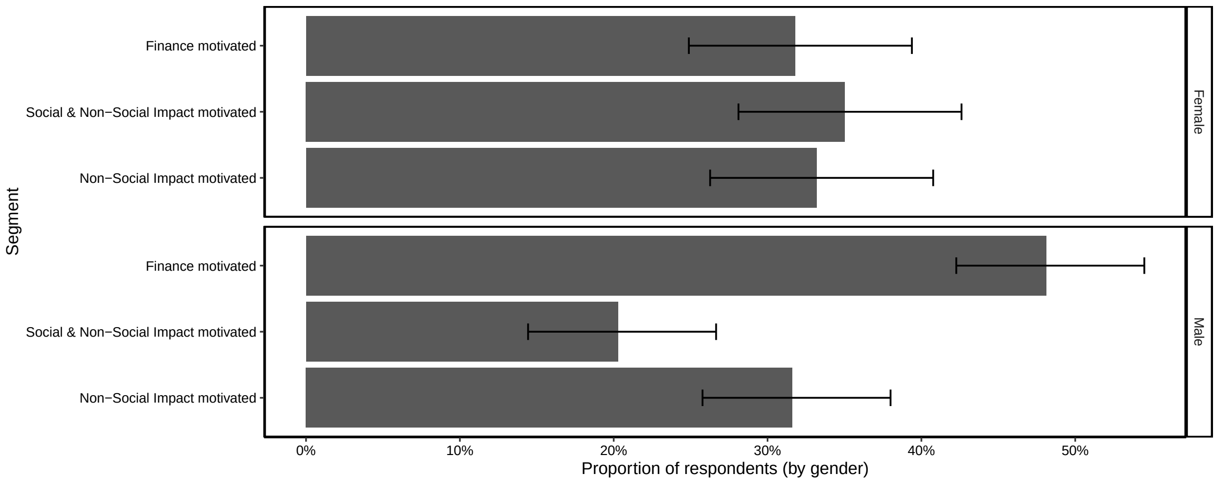

Figure 3: This plots the proportion of respondents belonging to each segment of the latent class choice model for female and male respondents. Each respondent was assigned to the segment with the highest posterior membership probability. Mean and standard error bars are shown.

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

A. Instructions of Conjoint Analysis survey

The instructions for the choice-based conjoint survey were as follows.

Before the beginning of the survey: "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."

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. Additional Tables

B.1. Table B.1: Gender Differences in Preferences (ISSP Data)

- Table B.1 shows results of OLS regressions of the following form:

$$Job\ Attribute_i = \beta_1 Female_i + \beta_2 Controls_i + c_1 + y_1 + \epsilon_1 \tag{B.11}$$

  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 B.2 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 B.1: 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										
Female=1	-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										
Female=1	-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 B.2: Gender Differences Across Countries (ISSP Data)

	(1)	(2)	(3)	(4)	(5)	(6)
	Raw Data				Adding Controls	
	Women	Men	Diff.	Prob> $\|z\|$	Main	Additional
Income	4.082	4.118	-0.036	0.000	-0.045	-0.041
					(0.007)	(0.011)
Job security	4.524	4.473	0.052	0.000	0.064	0.060
					(0.009)	(0.011)
Opp. for advancement	3.951	3.969	-0.019	0.000	-0.038	-0.007
					(0.009)	(0.013)
Interesting job	4.392	4.366	-0.025	0.000	0.032	0.038
					(0.005)	(0.008)
Independent work	3.983	4.013	-0.029	0.000	-0.009	0.021
					(0.009)	(0.011)
Flexibility	3.715	3.611	0.104	0.000	0.092	0.100
					(0.012)	(0.016)
Helpful to others	4.058	3.888	0.170	0.000	0.171	0.161
					(0.012)	(0.015)
Useful to society	4.052	3.924	0.128	0.000	0.133	0.121
					(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, and column (4) reports results of t-test results. The last two columns show gender coefficients from OLS regressions (standard errors in parenthesis) that control for in Column (5) for dummies for years of education, age, dummies for marital status, dummies for work status, dummies for household size, country and year dummies. In Column (6) 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.

B.2. Table B.3: Gender Differences and Education

- Table B.3 show results of OLS regressions of the following form:

$$Job\ Attribute_i = \beta_1 Female_i + \beta_3 EducationGroup_1 + \beta_4 Education \times Female_i + \beta_5 Controls_i + c_1 + y_1 + \epsilon_1. \tag{B.12}$$

  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 B.3: Gender Differences and Education (Including Additional Control Variables)

	(1) Income	(2) Income	(3) Security	(4) Security	(5) Opp.	(6) Opp.	(7) Interesting	(8) Interesting	(9) Indep.	(10 Indep.	(11) Flex.	(12 Flex.	(13) Helpful	(14) Helpful	(15) Useful	(16) Useful
Female=1	-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.

B.3. Table B.4: Selection of Number of Segments of LC Model (MBA Sample)

- Table B.4 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 model.

Table B.4: Selection of Number of Segments of LC 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.

B.4. Table B.5: Gender Differences in Job Preferences (MBA Sample) with Prior Employment Industry Controls

Table B.5: Gender Differences in Job Preferences (MBA Sample)

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

B.5. Table B.6: Course and Industry Selection of MBA Sample with Prior Employment Industry Controls

- Table B.6 show results of OLS regressions on type of a) courses taken, b) on dummies for whether student did an internship in either the i) finance or not and ii) nonprofit industry or not, and c) post-MBA employment industry i) finance and ii) nonprofit.
- The table includes the social impact preference parameters and dummy controls for prior employment in finance and nonprofit industries.

Table B.6: Course and Industry Selection of MBA Sample

	Courses				*Industry*							
	Finance		Social		Finance (Summer)		Nonprofit (Summer)		Finance (Post-MBA)		Nonprofit (Post-MBA)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Gender: Female	-0.038***	-0.036***	0.021***	0.018***	-0.187***	-0.168***	0.019*	0.015	-0.111**	-0.082*	0.012	0.008
	(0.009)	(0.009)	(0.006)	(0.006)	(0.046)	(0.046)	(0.011)	(0.011)	(0.047)	(0.047)	(0.010)	(0.010)
$\frac{\text{Importance}_{\text{SocialImpact}}}{\text{Importance}_{\text{FinancialOffer}}}$		-0.011		0.014***		-0.087**		0.018**		-0.132***		0.018**
		(0.007)		(0.004)		(0.034)		(0.008)		(0.035)		(0.007)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.180***	0.175***	0.154***	0.162***	0.461***	0.414***	0.007	0.016	0.335***	0.264***	0.009	0.018
	(0.010)	(0.010)	(0.006)	(0.007)	(0.051)	(0.054)	(0.012)	(0.013)	(0.051)	(0.054)	(0.010)	(0.011)
Adjusted $R2^2$	0.164	0.167	0.055	0.071	0.114	0.125	0.026	0.034	0.092	0.120	0.005	0.018
F-value	13.053	11.935	4.554	5.183	8.550	8.408	2.534	2.848	6.493	7.559	1.292	1.868
Observations	491	491	491	491	469	469	469	469	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. For all coefficients see Table 7 in the Appendix. Significance levels: *** p<.01, ** p<.05, * p<.1.

B.6. Table B.7: Course and Industry Selection of MBA Sample

- Table B.7 show results of OLS regressions on type of a) courses taken, b) on dummies for whether student did an internship in either the i) finance or not and ii) nonprofit industry or not, and c) post-MBA employment industry i) finance and ii) nonprofit.
- The table includes the whole set preference parameters for all job attributes. For each attribute k among Non-Social Impact, Social Impact, Flexibility, and Prestige; we show the log importance of attribute k with respect to the importance of the attribute Financial Offer, $\log\left(\frac{\text{Importance}_k}{\text{Importance}_{\text{FinancialOffer}}}\right)$,

Table B.7: Course and Industry Selection of MBA Sample

	Courses				*Industry*							
	Finance		Social		Finance (Summer)		Nonprofit (Summer)		Finance (Post-MBA)		Nonprofit (Post-MBA)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Female=1	-0.044***	-0.039***	0.022***	0.020***	-0.208***	-0.176***	0.020*	0.016	-0.133***	-0.096**	0.013	0.009
	(0.009)	(0.009)	(0.006)	(0.006)	(0.047)	(0.048)	(0.011)	(0.011)	(0.048)	(0.048)	(0.010)	(0.010)
Non-Social Impact		-0.008		0.003		-0.054		0.006		-0.042		0.009
		(0.008)		(0.005)		(0.043)		(0.010)		(0.046)		(0.009)
Social Impact		0.011		0.013**		-0.025		0.023**		-0.054		0.023**
		(0.010)		(0.006)		(0.051)		(0.012)		(0.051)		(0.010)
Flexibility		-0.031***		-0.008		-0.078		-0.016		-0.099*		-0.018*
		(0.010)		(0.006)		(0.051)		(0.012)		(0.052)		(0.011)
Prestige		-0.016*		0.011*		-0.034		0.005		-0.066		-0.004
		(0.009)		(0.006)		(0.049)		(0.011)		(0.049)		(0.010)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.208***	0.185***	0.153***	0.160***	0.586***	0.506***	0.018	0.028	0.454***	0.323***	0.006	-0.001
	(0.009)	(0.013)	(0.006)	(0.008)	(0.047)	(0.067)	(0.021)	(0.030)	(0.048)	(0.070)	(0.018)	(0.027)
Adjusted R^2	0.0847	0.1155	0.0329	0.0592	0.0480	0.0707	0.0049	0.0161	0.0246	0.0698	0.0047	0.0193
F-value	10.071	8.108	4.336	4.426	5.717	4.956	2.870	2.197	3.183	4.612	1.846	1.423
N	491	491	491	491	469	469	469	469	434	434	434	434

Notes: Coefficients of OLS regressions and standard errors in parentheses. Significance levels: *** p<.01, ** p<.05, * p<.1.

B.7. Table B.8 and B.9: Choice of Different Industries of MBA Sample for Internship and Post-MBA

- Table B.8 shows results of multinominal regression in which "Finance" is the reference level for Summer Internship.
- Table B.9 shows results of multinominal regression in which "Finance" is the reference level for Post-MBA Employment Industry.

Table B.8: Summer Internship 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	1.039***	0.659**	1.306***	2.376**	0.767	0.927***
	(0.361)	(0.273)	(0.497)	(1.105)	(0.721)	(0.246)
Constant	-2.271***	-1.380***	-3.098***	-5.043***	-3.657***	-1.215***
	(0.263)	(0.179)	(0.386)	(1.003)	(0.506)	(0.168)
Panel B: Including Background Controls						
Gender: Female	0.968***	0.709**	1.338**	2.266**	0.479	0.813***
	(0.374)	(0.285)	(0.541)	(1.121)	(0.755)	(0.255)
Background Controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-2.002***	-1.710***	-3.710***	-5.796***	-3.460***	-1.164***
	(0.367)	(0.300)	(0.644)	(1.440)	(0.745)	(0.257)
Panel C: Including Background Controls and Preferences						
Gender: Female	0.986***	0.612**	1.146**	1.700	0.743	0.660**
	(0.381)	(0.292)	(0.558)	(1.178)	(0.783)	(0.265)
Background Controls	Yes	Yes	Yes	Yes	Yes	Yes
Preference Parameters	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-1.898***	-1.386***	-3.665***	-5.741***	-3.966***	-0.890**
	(0.542)	(0.420)	(0.893)	(1.790)	(1.186)	(0.379)

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

Table B.9: 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.

B.8. Table B.10: Number of Observations Per Country and Year in ISSP

- Table B.10 show number of observations by country and year in ISSP.

Table B.10: 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. Additional Figures

C.1. Figure C.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: $Job\ Attribute_i = \beta_1^c Female_i + \beta_2^c Controls_i + y_1^c + \epsilon_1$. 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 C.1: Gender Differences and GDP