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Gender Differences in Preferences for Meaning at Work†

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Scholars have examined whether preferences for job characteristics help explain why men and women sort into different occupations but have overlooked preferences for meaning at work. We first document gender differences in preferences for meaning in a large-scale survey covering individuals in 47 countries. We then conduct a choice-based conjoint analysis of a cohort of MBA students at a leading business school to study gender differences in preferences for meaning compared to other job attributes. We show that gender differences in preferences for meaning at work are widespread and partly explain gender differences in behavioral outcomes, including industry of work. (*JEL* D91, I23, J16, J24, J28)

Women continue to earn lower wages than men. Policymakers seeking to eliminate the gender pay gap have often focused on implementing policies intended to increase pay transparency and encourage employers to set salaries for a given position.[1] While it is indeed the case that women earn less than men for the same job, it is important to note that approximately half of the gender wage gap has been attributed not to differences in payment for the same job but to the sorting of men and women into different jobs (Morchio and Moser 2019; Blau and Kahn 2017). To foster gender pay equity, policymakers need to better understand what leads men and women to select into different jobs. Toward this understanding, researchers have begun to examine gender differences in preferences for job characteristics—such as flexibility, stability, ability to control one's schedule, and competitiveness—as underexamined factors that help explain why men and women end up in different occupations (Eriksson and Kristensen 2014; Mas and Pallais 2017; Wiswall and Zafar 2018; Buser, Niederle, and Oosterbeek 2014; Reuben, Wiswall, and Zafar 2017; Flory, Leibbrandt, and List 2015; Gneezy, Niederle, and Rustichini 2003; Cassar, Wordofa, and Zhang 2016; Reuben, Sapienza, and Zingales 2019;

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

Samek 2019; Niederle and Vesterlund 2007; Folke and Rickne 2022; Bolotnyy and Emanuel 2022).

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

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

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

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

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

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

Our findings contribute to three streams of literature. First, we contribute to the discussion about the drivers of the gender wage gap and occupational segregation by gender, which scholars across disciplines—as well as policy-makers—have sought to explain. Factors such as discrimination in screening and hiring (e.g., Goldin and Rouse 2000; Reuben, Sapienza, and Zingales 2014; Botelho and Abraham 2017; Fernandez-Mateo and King 2011), biased evaluations (Rivera and Tilcsik 2019; Reuben, Sapienza, and Zingales 2014; Brooks et al. 2014; Sheltzer and Smith 2014; Bohnet, Geen, and Bazerman 2016), peer bargaining (Pierce, Wang, and Zhang 2020), wage penalties for career interruption (e.g., Hotchkiss and Pitts 2007), and the gender of role models at work (Porter and Serra 2020), which vary across occupations, have been the focus of an extensive body of research.[2] Recent studies have focused on whether part of gender segregation can be attributed to gender differences in attitudes toward (Stoet and Geary 2018), perceptions of, (Gino, Wilmuth, and Brooks 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 2018).[3] In particular, recent research has focused on gender differences in preferences for work characteristics such as competitiveness (Buser, Niederle, and Oosterbeek 2014; Reuben, Wiswall, and Zafar 2017; Flory, Leibbrandt, and List 2015; Gneezy, Niederle, and Rustichini 2003; Cassar, Wordofa, and Zhang 2016; Samek 2019) and flexibility in the workplace (Eriksson and Kristensen 2014; Mas and Pallais 2017; Wiswall and Zafar 2018; Zafar 2013), which have been demonstrated to help explain gender differences in selection into college majors and jobs, for example.

Our paper adds an important job characteristic to the context of understanding gender differences in preferences for job attributes: the degree to which a job is likely to create a sense of meaning at work for the individual.[4] We not only document that gender differences in preferences for meaning at work exist but also show that they help to explain important behavioral differences, including industry placement, which in turn has implications for the salaries earned by men and women. Based on the results from our International Social Survey Program (ISSP) sample, preferences for meaning at work are correlated with women's increased likelihood of working in the public rather than the private sector. Based on our MBA sample, preferences for meaning at

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

[3] Work in social psychology has documented a wide array of gender differences in personality and interpersonal measures (Hyde 2014), which influence gender differences in beliefs (Bordalo et al. 2019), as well as attitudes such as risk aversion (Sapienza, Zingales, and Maestripieri 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, Calsamiglia, and Iriberri 2016). These differences influence important decision-making outcomes (Eckel and Grossman 2008), including how men and women assess and weigh job characteristics.

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

work explain about 25 percent of the gender effect of selection into different industries, particularly the finance industry. Notably, the size of this effect is comparable to that found for competitiveness in extant work (Buser, Niederle, and Oosterbeek 2014; Reuben, Sapienza, and Zingales 2019). While our effect size indicates that a large part of gender segregation is explained by other factors (certainly, there are many drivers of occupational segregation), it nonetheless sheds light on an important and understudied job attribute, which helps to explain why men and women end up in different jobs and industries and, correspondingly, earn different wages.

Second, we add to a growing literature in economics on the importance of meaning at work and the nonmonetary 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, Loewenstein, and McCafferty 2004; Chater and Loewenstein 2016; Rosso, Dekas, and Wrzesniewski 2010), which can stem from characteristics attributed to an employee's job design, occupation, employing organization, and/or industry. We 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 nonsocial impact at work. We show across both our data samples that gender differences exist for preferences for meaning at work—particularly those derived from social impact (and to a lesser extent, nonsocial impact) at work. This is consistent with research showing gender differences in altruism, compassion, and inequality aversion (e.g., Bertrand 2011; Beutel and Marini 1995; Güth, Schmidt, and Sutter 2007; Ben-Ner, Kong, and Putterman 2004; Andreoni and Vesterlund 2001; Su, Rounds, and Armstrong 2009[5]). As both meaning derived from social impact and meaning derived from nonsocial impact are nonmonetary attributes, our findings suggest that prior distinctions between extrinsic and intrinsic job attributes missed an important difference within nonmonetary attributes. While existing research shows substantial heterogeneity in how different nonmonetary attributes of jobs are evaluated (e.g., Wrzesniewski, Dutton, and Debebe 2003; Burbano 2016; Cassar and Meier 2018; Owens, Grossman, and Fackler 2014; Bekker and Van Assen 2008; Adler 1993), our paper highlights the gendered aspect of these heterogeneous differences.

Third, we make a small contribution to the literature examining the development of differences in preferences. Previous research has tried to understand how preferences for nonmonetary aspects of work are shaped (Cotofan et al. 2023) and explain the origin of gender differences in such preferences—especially for competitiveness, for example (e.g., Andersen et al. 2013; Hoffman, Gneezy, and List 2011; Gneezy, Leonard, and List 2009). While it is outside the scope of this paper to directly explore the origins of gender differences in preferences for meaning at work and we cannot disentangle whether or not the preferences we observe are shaped by expectations about discrimination on the job market, we do show that the gender differences in preferences for meaning derived from social impact are more pronounced in rich countries and educated subgroups (and persist among a highly educated sample of MBAs). These results complement evidence provided by

[5] 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).

Falk and Hermle (2018) that gender differences in economic preferences increase with economic development and suggest that trends toward greater development and levels of education may help to explain part of the origin in gender differences in preferences for different job attributes.

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

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

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

A. *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 ISSP. The ISSP surveys around 130,000 individuals across up to 47 countries in up to four waves (1989, 1997, 2005, and 2015).[6] Each country conducts its own surveys, but all agree to a standardized process, which includes using probability sampling of a representative sample. Surveys can be conducted face-to-face or self-administered. ISSP has a Methodology Committee, which oversees the method used in all countries to ensure comparability. See Table C.1 in the online Appendix for the number of observations by country and year. We focus on participants who are older than 16 and younger than 65.

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 five-point scale from 1 "Very important" to 5 "Not important at all." We rescale the answers so that higher values indicate higher importance. In most analyses, we use a dummy that has the value 1 if the individual indicated that a particular job attribute is "Very important" or "Important" and 0 otherwise.[7]

[6] ISSP data accessed Jan 3, 2019 from https://www.gesis.org/en/issp/modules/issp-modules-by-topic/work-orientations.

[7] The results are robust to using the full scales.

Table 1—Summary Statistics (ISSP Study)

Variable	Gender		Diff.
	Male	Female	
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	−0.64
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	−0.46
Work status: In education	6.18	5.91	0.27
Work status: Retired	6.00	6.48	−0.48
Work status: Domestic work	1.50	18.07	−16.57
Work status: Permanently sick or disabled	2.62	2.22	0.4
Work status: Other	1.97	2.10	−0.13
Household size	3.43	3.45	0.02
Observations	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
Observations	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 who have those jobs. Number of observations reflects the variable with the lowest number of observations per panel.

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:

$$\textit{Job Attribute}_i = \beta_1 \textit{Female}_i + \beta_2 \textit{Controls}_i + c_i + y_i + \epsilon_i, \tag{1}$$

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

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

B. *Results*

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

As a baseline, we first compare gender differences in preferences for monetary and nonmonetary job attributes and then focus specifically on nonmonetary preferences for meaning at work (Karlsson, Loewenstein, and McCafferty 2004; Chater and Loewenstein 2016). Table 2 presents gender differences in stated importance of different job attributes across individuals in 47 countries. Columns 1–3 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 nonmonetary attributes (interesting job, independent work, flexibility, helpful to others, and useful to society). Interestingly, these aggregate measures indicate that gender differences exist only for nonmonetary attributes and not for monetary attributes, complementing results previously found for US high school students (Marini et al. 1996). The gender difference in preferences for (aggregate) nonmonetary attributes are not very large in size either. However, it is important to note that nonmonetary attributes are composed of a number of different job characteristics. We thus next break apart the different nonmonetary attributes and examine them separately to observe whether gender differences in preferences for specific nonmonetary attributes are more pronounced.

We present in panel B the proportion of females and males indicating that a certain job attribute is very important or important. The magnitude of gender differences in

Table 2—Gender Differences across Countries (ISSP Study)

	Raw data			Adding controls	
	Women (1)	Men (2)	Diff. (3)	Main (4)	Additional (5)
Panel A. Average importance					
Monetary attributes	4.188	4.188	0.000	−0.006	0.004
			(0.007)	(0.006)	(0.008)
Nonmonetary attributes	4.046	3.966	0.080	0.084	0.087
			(0.007)	(0.006)	(0.008)
Panel B. Proportion finding (various) job attributes important					
Income	0.813	0.827	−0.014	−0.017	−0.015
			(0.005)	(0.004)	(0.006)
Job security	0.946	0.930	0.017	0.0019	0.014
			(0.002)	(0.002)	(0.003)
Opp. for advancement	0.751	0.758	−0.007	−0.015	−0.004
			(0.005)	(0.004)	(0.006)
Interesting job	0.921	0.914	0.008	0.010	0.012
			(0.002)	(0.002)	(0.003)
Independent work	0.761	0.771	−0.009	0.001	0.009
			(0.004)	(0.004)	(0.005)
Flexibility	0.644	0.595	0.048	0.044	0.043
			(0.006)	(0.005)	(0.007)
Helpful to others	0.799	0.717	0.082	0.082	0.074
			(0.006)	(0.006)	(0.008)
Useful to society	0.797	0.735	0.061	0.063	0.056
			(0.005)	(0.005)	(0.007)
Observations				107,006	42,183

Notes: This table shows in panel A the average importance score for monetary attributes (income, security, and advancement) and nonmonetary attributes (interesting, independent, flexibility, helpful, and useful). Panel B shows the proportion of women (column 1) and men (column 2) indicating that they find a job attribute important. Column 3 reports the difference between column 1 and 2 with robust standard errors based on OLS regression with a female dummy plus a constant term. The last two columns show gender coefficients from OLS regressions that control in column 4 for dummies for years of education, age, marital status, work status, household size, and country and year. In column 5, additional controls are included: dummy for public sector, dummy for supervisory role, and log of household income. SEs 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.

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

Existing work has shown that gender differences for more basic economic preferences increase with economic development (Falk and Hermle 2018) and that such gender differences in work values exist even within extremely highly educated samples of corporate boards of directors (Adams and Funk 2012). We thus investigate whether gender differences in preferences for meaning might also vary by GDP per capita and by education level. Specifically, we estimate equation (1) for each country separately and plot β_1^c—i.e., a country, c, specific gender coefficient—against log GDP per capita. To investigate whether gender differences vary by different education levels, we estimate equation (1) with education group dummies and interaction between those dummies and our gender indicator.

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

Figure 1 indicates that gender differences controlling for sociodemographics are more pronounced in more developed, that is, richer, countries. Regressing the gender coefficient (which indicates how much more women care about an attribute than men—controlling for many factors; see online Appendix Figure D.1) on the average log of GDP per capita shows that GDP per capita is significantly associated with gender differences—but mainly for nonmonetary attributes (-0.017 (SE $= 0.006$) for income, 0.039 (0.010) for flexibility, 0.055 (0.009) for helpful to others, and 0.040 (0.008) for useful to society (regressions available upon request)). We find very similar results when we use the Gender Equality Index constructed by Falk and Hermle (2018).[8] Gender differences (especially for attributes related to social impact at work) are more pronounced in countries that score higher on the gender equality index (see Figure D.2 in the online Appendix).

Figure 2 plots coefficients of interaction terms between gender and different education groups (with 9–12 years of education as the reference group). Full regression results for all attributes are in Table C.2 in the online Appendix (controlling for

[8]The gender inequality index data used in this paper are from Falk and Hermle (2018). Johannes Hermle provided the data. Researchers interested in access to these data may contact Johannes Hermle. See https://sites.google.com/berkeley.edu/johannes/home.

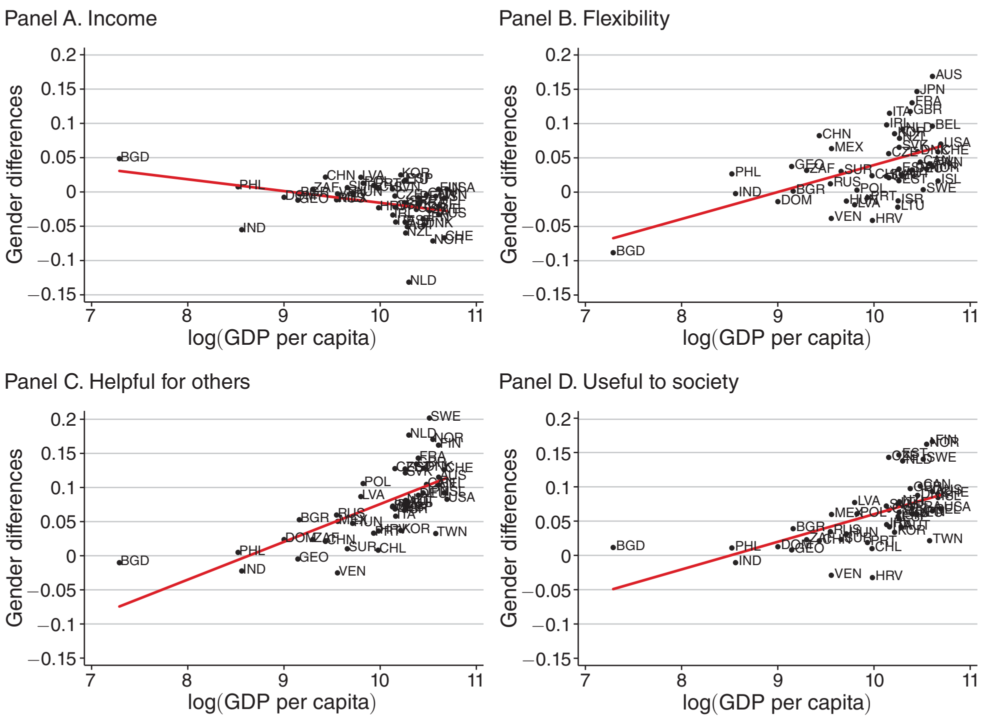

FIGURE 1. FIGURES SHOW ASSOCIATION BETWEEN LOG OF GDP PER CAPITA AND GENDER DIFFERENCES IN STATED IMPORTANCE OF JOB ATTRIBUTES (ISSP STUDY)

Notes: We run regressions for each country, c, of the following form: $JobAttribute_i = \beta_1^c Female_i + \beta_2^c Controls_i + y_i^c + \epsilon_i$. The figure plots the coefficient, β_1^c, which captures the country-level gender differences in the importance of $JobAttribute_i$. 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 (SEs): −0.017 (SE = 0.006) for income, 0.008 (0.004) for security, −0.013 (0.007) for opportunity, 0.004 (0.004) for interesting job, −0.003 (0.006) for independent job, 0.039 (0.010) for flexibility, 0.055 (0.009) for helpful to others, and 0.040 (0.008) for useful to society.

a large set of variables). The figure shows that gender differences in preferences for meaningful jobs become more pronounced with higher levels of education. Especially for the attributes related to social impact at work (helpful to others and useful for society), gender differences become significantly larger for groups with more than 12 years of education. These results are important since they suggest that a larger proportion of the population may exhibit gender differences in preferences for meaning induced by social impact at work over time, as the world's population becomes more educated and more developed.

In Table 3, we explore whether preferences regarding job attributes can help explain part of the gender segregation into different types of industries. In particular, we analyze whether these preferences can partly explain why more women work in the public sector given that this sector is characterized as more prosocial than the private sector (Dur and Zoutenbier 2014; Perry, Hondeghem, and Wise 2010). Column 1 shows the results from the summary statistics: more women work in the

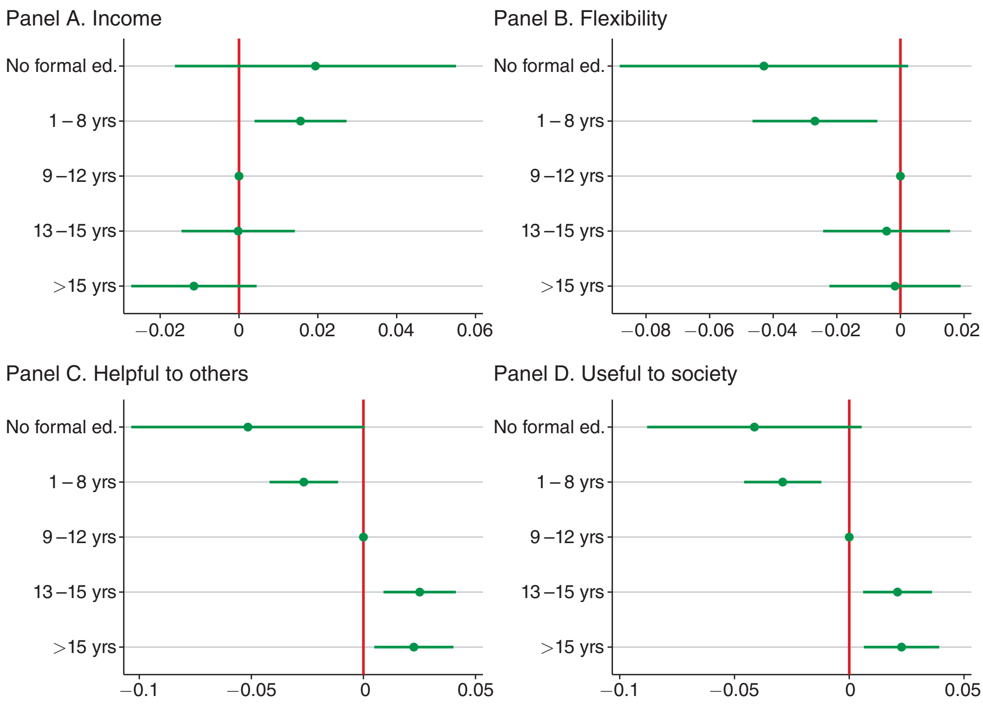

Figure 2. Figures Plot Interaction Effects between Gender and Education Groups (ISSP Study)

Notes: We estimate a regression of the following form: $JobAttribute_i = \beta_1 Female_i + \beta_3 EducationGroup_1 + \beta_4 Education \times Female_i + \beta_5 Controls_i + c_i + y_i + \epsilon_i$. Figure plots β_4 with 9–12 years of education × 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, and country and year dummies. Regression results for all categories available in Table C.2 in the online Appendix.

public sector than men by 10 percentage points. Controlling for sociodemographic variables does not explain any part of this gender effect. Adding preferences regarding the importance of different monetary and nonmonetary attributes explains about 11 percent of the gender effect. That a job is useful to society is one of the job attributes most correlated with work in the public sector.

II. Gender Differences in Preferences for Meaning at Work among MBA Students: A Conjoint Analysis

While the aforementioned analyses using the ISSP survey allow us to look at the widespread 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 pose some limitations. The ISSP uses subjective Likert-scale responses to capture the expressed importance of different job attributes. When comparing responses across men and women, one should keep in mind the possibility that the reference points for men and women could be different (as discussed, for example, in Heine et al. 2002 in the context of cross-cultural comparisons). Because

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

	Public sector (1)	Public sector (2)	Public sector (3)
Gender: Female	0.107	0.108	0.096
	(0.011)	(0.010)	(0.009)
Income			−0.012
			(0.003)
Job security			0.031
			(0.004)
Opportunity for advancement			−0.011
			(0.003)
Interesting job			−0.004
			(0.003)
Independent work			−0.026
			(0.003)
Flexibility			−0.014
			(0.002)
Helpful to others			0.021
			(0.004)
Useful to society			0.046
			(0.004)
Constant	Yes	Yes	Yes
Main controls	No	Yes	Yes
Mean public sector (for male)	0.257	0.257	0.257
Adjusted R^2	0.013	0.151	0.166
Observations	83,495	83,495	83,495

Notes: Coefficients of OLS regressions and SEs in parentheses. Working in the public sector (=1) as the dependent variable. Main control variables are age, dummies for marital status, dummies for work status, dummies for household size, and country and year dummies.

these preferences are being elicited after individuals have chosen their workplace, the responses may reflect a desire to avoid cognitive dissonance. The elicitation method furthermore does not force the respondents to consider any trade-offs (i.e., all attributes could potentially be stated as “very important”). Direct elicitation of preferences also makes social desirability bias more likely, particularly for questions related to meaning derived from social impact. Because of gender stereotypes associated with prosociality and communality (Shea and Hawn 2019; Fiske and Stevens 1993; Abele 2003; Abraham and Burbano 2022), direct elicitation of preferences related to social impact could be particularly problematic given our interest in gender differences. In addition, direct measurement of preferences may not accurately capture the trade-offs among job attributes that individuals face when making job offer decisions. The wide range of individuals included in the ISSP survey, while useful in helping to establish the universality of the difference in job preferences, also poses a challenge due to the difficulty of controlling for personal traits and characteristics about which we do not have data. To address these issues, we leverage a choice-based conjoint methodology, implemented on a sample of a homogeneous, high-skilled group of individuals. We then track these individuals over time to examine whether differences in preferences predict behavioral outcomes.

A. *Data and Methods*

We implemented a choice-based conjoint survey with the entire entering MBA class of a top US MBA program in September 2017 to infer MBA students' preferences for different job attributes. We administered the survey as a required assignment for the core MBA strategy course, which all entering students take. The survey included questions related to various cases taught as part of the upcoming course and was conducted before the start of the class.[9] We made it clear that the answers to the survey would not affect grades and that individual answers would be treated confidentially and not be shared in order to avoid any potential signaling effects (Bursztyn, Fujiwara, and Pallais 2017). During the survey, we administered a series of questions to conduct a CBC analysis of students' responses to infer their preferences for job attributes.

CBCs are a series of techniques applied mostly in consumer marketing research to measure individuals' preferences for multiattributed products (Louviere and Woodworth 1983). In such analyses, 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. CBC in particular consists of obtaining these utilities by simulating discrete choices over a set of product profiles. Respondents are provided with a set of hypothetical experimentally generated product profiles, and they are asked to choose the one that they prefer the most. By choosing their preferred product among numerous sets of products, which randomly vary in the level of each attribute shown, participants reveal their relative preferences among product attributes. Researchers can analyze the choice trade-offs made between each attribute to determine participants' implicit valuation of, or preference for, each attribute.

Why is it beneficial to use a CBC to elicit preferences rather than a more direct elicitation method? Alternatively framed questions aimed at capturing preferences directly often fail in one of two ways: (i) they do not accurately capture preferences trade-offs in relation to other attributes, and/or (ii) they fail to capture the strength of these preferences. For example, direct importance (e.g., Likert scale) questions do not capture trade-offs against other attributes, as respondents are not forced to balance or weigh the importance of social impact with respect to trade-offs with other attributes. Ranking questions provide rank orders of attribute importance but do not capture the magnitude of these differences (which are often not equal). Constant-sum questions may be difficult to interpret and have been shown to provide considerably different measures of attribute importance compared to conjoint discrete choice experiments (Louviere and Islam 2008), which have been shown to exhibit high external validity in real choices (e.g., Swait and Andrews 2003; Blamey, Louviere, and Bennett 2001; Louviere 2001). Moreover, direct questions may fail to disentangle the correlation among attributes present in the market due to firm-side behavior in the job market and the inferences

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

respondents make about those attributes when asked directly (Wiswall and Zafar 2018). By contrast, in conjoint experiments the presence of attributes in the product/job profiles is randomly assigned. The choice-based data collection process is furthermore considered to be more realistic and simpler for respondents, resulting in more accurate responses than rating-based or ranking-based conjoint analysis methods (DeSarbo, Ramaswamy, and Cohen 1995). For these reasons, CBC has been shown to be a more reliable way to elicit product attribute preferences than directly asking individuals which attributes they prefer (Akaah and Korgaonkar 1983) or even—for job attribute preferences—than looking at past job choices (for a great discussion about this, see Wiswall and Zafar 2018). Given our interest in gender differences in preferences for meaning including meaning induced by social impact, a choice-based-conjoint elicitation of preferences is furthermore likely to reflect less social desirability bias in responses than direct elicitation—something that is particularly important for our study because social desirability related to preferences about social impact are gendered in nature. That is, because of gender stereotypes about communality and prosociality, with such traits being associated with and expected of women but not men (Shea and Hawn 2019; Fiske and Stevens 1993; Abele 2003; Abraham and Burbano 2022), women are likely to feel greater pressure to respond that they value social impact if asked directly than men. We thus focus on the choice-based conjoint elicitation of preferences in our paper, though we also run our analysis using direct ranking questions for robustness (see Table C.8 in online Appendix C.7 for correlations between conjoint-derived preferences and direct ranking questions and online Appendix C.11 for the main analysis using direct ranking questions).

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

We merged the MBA students' preference parameters inferred from the conjoint study with administrative data from the university. Specifically, we gathered data on admissions, courses taken, engagement with socially oriented MBA clubs, and full-time job placement.[10] From admissions data, we obtained student gender, whether the student is international (versus based in the United States), their GMAT score (or GRE score, which we standardize into an equivalent GMAT score), their

[10]International Review Board (IRB) approval was obtained both to administer the survey and to link the responses to the survey with the administrative data. IRB Protocol AAAQ5257, Columbia University.

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

	Attributes				
Level	Financial offer	Social impact	Nonsocial 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)	–	–

Note: We set the following levels as baseline: $135,000 for financial offer, *Best CSR record* for social impact, *High* (*strongly feel*) for nonsocial impact, *Has* for flexibility, and *Top 20* for prestige.

years of work experience and industry prior to the MBA (finance and nonprofit), and whether or not they have any loans.

Using course data, we construct the variables *proportion of socially oriented courses* and *proportion of finance courses*, which are the proportion of socially oriented elective courses and of finance-oriented elective courses, respectively, taken by the student during their two-year MBA. Students have complete autonomy of choice in selecting their elective courses.[11] We also obtained data from the university on the industry in which students were employed directly following their MBA. We categorize the students' *post-MBA industry*: whether they interned in consumer products/retail, consulting, finance, healthcare, tech and media (advertising, media, tech, entertainment), nonprofit (education, government, nonprofit), or other (other, agribusiness, energy, manufacturing, transportation, family business, or starting own business).[12] We then focus on whether they were employed in the finance industry and whether they were employed in the nonprofit industry in our analysis. The finance industry is perceived to lack the trait of social mission and social usefulness (Sapienza and Zingales 2012; Zingales 2015), whereas the nonprofit and public industries are the quintessential examples of sectors with high social mission (Dur and Van Lent 2019). Given that the finance industry pays among the highest wages (e.g., Bertrand, Goldin, and Katz 2010; Barbulescu and Bidwell 2013) and the nonprofit and public sector industry pay among the lowest, it is important to examine whether differences in preferences for meaning derived from social impact at work lead to differences in selection into these industries by gender, as these differences could indirectly help to explain the gender wage gap. Indeed, there has been notable inquiry into gender inequities in the finance industry (Niessen-Ruenzi and Ruenzi 2019).

Table 5 shows summary statistics of the MBA sample's characteristics by gender. Table 5 shows relatively minor differences in background characteristics (panel A): male and female students differed in whether their prior job was in the finance industry. In their coursework (panel B), their engagement with socially oriented clubs during the MBA (panel B) and their job industry post-MBA (panel C), differences

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

[12] Industry was not specified for family business or starting own business, so we categorize these as other.

Table 5—Summary Statistics, Gender Differences (MBA Study)

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

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

are more pronounced. In particular, female MBA students take on average one finance class less than their male colleagues, and 53 percent of these female students attend at least one social club event, whereas, of male students, only 30 percent attend. Moreover, while 46 percent of male students go into finance post-MBA, only 31 percent of female students do so.

B. *Model Specification*

Respondents' choices among the hypothetical job descriptions allow us to infer their preferences by modeling respondents' choices on each question in the conjoint task using a multinomial logit model (MNL). In this section, we describe (i) how we model respondents' choices, (ii) how we account for preference heterogeneity, (iii) what estimation procedure we use, and (iv) 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): (i) Latent Class MNL Model (LC-MNL) (DeSarbo, Ramaswamy, and Cohen 1995; DeSarbo et al. 1992) and (ii) Hierarchical Bayes MNL Model (HB-MNL) (Lenk et al. 1996). These two approaches are equivalent in how they model choices given preferences, but they differ in how they model respondents' heterogeneity. In the LC-MNL model, we assume that individual-level preferences are drawn from a finite mixture, which allows us to infer preference heterogeneity through a discrete set of segments, such that we can assign each respondent to a segment (our segments of job seeker preferences are analogous to consumer preferences in market research). This approach allows for a relatively intuitive illustration of different preferences by segments, groups, or individuals. To complement this analysis, we estimated an HB-MNL model to infer individual-level preferences, where we assume these preferences are drawn from a continuous distribution (Gaussian in our application). These individual-level preferences allow us to infer gender differences while controlling for other respondent-level covariates. In addition, it allows us to test whether these preferences can partially explain the gender differences in our main variables of interest, that is, courses taken in the MBA, prosocial club participation, and the post-MBA job industry.

Choice Model.—Respondents make choices between sets of hypothetical job offers described by a combination of attributes at different levels. We index respondents by $i = 1, \ldots, I$; choice-task occasions by $t = 1, \ldots, T$; and job profiles alternatives by $j = 1, \ldots, J$. Consider a set of job attributes indexed by $k = 1, \ldots, K$, each of which captures one dimension of the job offer. Examples of job attributes are a job's salary, the social responsibility of the firm, and the flexibility of the job, among others. Each job attribute k can take levels $l = 1, \ldots, L_k$, where each level represents the specific value of the attribute for a job offer. For example, the job salary could be either \$135,000, \$150,000, or \$165,000.

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

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

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

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

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.

Heterogeneity in Preferences.—Our model accounts for respondents' heterogeneity in preferences over job attributes. We account for heterogeneity using two alternative approaches: (i) LC-MNL and (ii) HB-MNL. We defined $\boldsymbol{\beta}_i$ as the respondent-specific vector of preferences, where

$$\boldsymbol{\beta}_i = \left[\left(\beta_{ik2:L_k}\right)_{k=1}^{K}\right]^{\mathrm{T}}.$$

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

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

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

where π_s represents the relative 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

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

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

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

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

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

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

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

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

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

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

Identification.—Variation in salary and other job attributes is exogenous to respondents' preferences, as job profile attributes are randomized both within respondents (on each alternative within a choice set and across choice sets) and across respondents. This experimental variation identifies the parameters in the model.[13]

C. *Measuring Attributes' Importance*

After estimation, we computed how important each job attribute is for each segment (for the LC-MNL model) or respondent (for the HB-MNL model) as follows.

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

TABLE 6—POSTERIOR STATISTICS OF ATTRIBUTE PREFERENCES $\mathbf{b}_s$ PER SEGMENT (MBA STUDY)

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

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

Consider $\hat{\beta}_{ikl}$, 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

$$Importance_{ik} = \frac{Range_{ik}}{\sum_l Range_{il}} \tag{9}$$

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

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.

D. *Results*

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

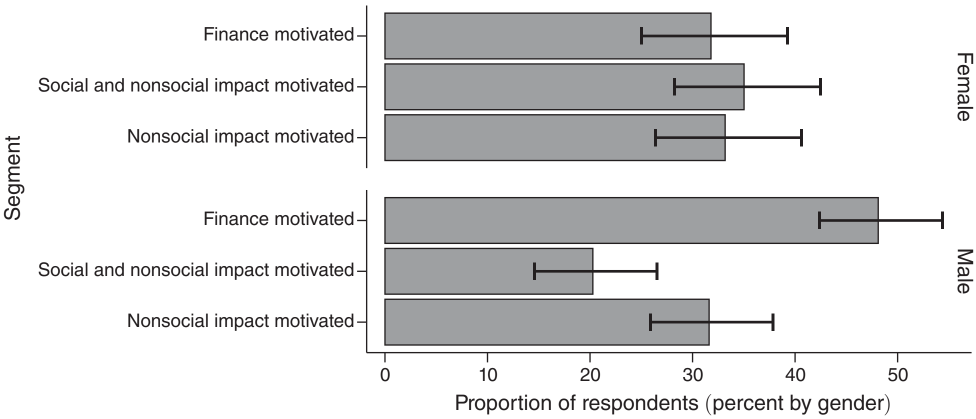

Figure 3. Gender Proportion by Segment (MBA Study)

Notes: 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 SE bars are shown.

behavioral outcomes such as courses taken and social club engagement during the MBA, as well as industry choices post-MBA.

We start by characterizing the segments obtained from the LC-MNL model. Table 6 shows the posterior mean of the preference parameters $\mathbf{b}_s$ for each segment. The segments are labeled according to the attributes that emerge from the analysis as being the most important to the segment, namely, (i) financial salary motivated, (ii) social and nonsocial impact motivated, and (iii) nonsocial impact motivated.

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.[14] Figure 3 shows the distribution of individuals across segments by gender. The figure shows substantial gender differences: while only 20 percent of male MBA students are motivated by both social and nonsocial impact, 35 percent of female students are. On the flip side, 48 percent of men are primarily motivated by income, while only 32 percent of women are. The segment of individuals who are motivated by nonsocial 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 nonsocial impact at work. The segmentation analysis enables intuitive illustration of different varied preferences by segments or groups of individuals. However, this analysis does not allow one to control for individual-level characteristics.

Given that individual-level characteristics might also be correlated with preferences, we use the individual-level estimates from the HB-MNL model and explore gender differences controlling for individual-level characteristics (e.g., GMAT

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

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

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

Notes: Table shows results of regressions of the following form. For each attribute k among nonsocial impact, social impact, flexibility, and prestige, we regress the log importance of attribute k with respect to the importance of the attribute financial offer, $\log\left(\frac{Importance_k}{Importance_{FinancialOffer}}\right)$, on gender (first column of each dependent variable) plus pre-MBA controls (second column of each dependent variable).

scores and other characteristics shown in panel A of Table 5). We compute the attributes' importance for each respondent based on the model estimates using equation (9). To avoid collinearity (attributes' importance sum to 1), we log-transform the attributes' importance and measure them relative to the importance of financial offer. Specifically, for each attribute k among nonsocial impact, social impact, flexibility, and prestige, we compute $\log\left(\frac{Importance_k}{Importance_{FinancialOffer}}\right)$.

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

Table 7 shows results of these regression analyses. We find that the ratios of how important the attributes' social impact, nonsocial 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 to financial offer than do male respondents. Notably, this difference is the highest for social impact. Furthermore, from the estimates of the model, we compute how much salary respondents would be willing to

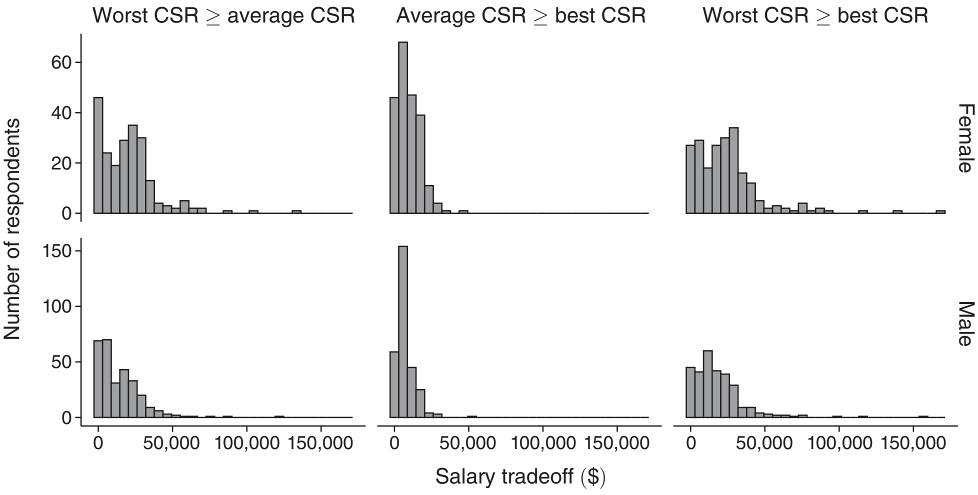

Figure 4. Distribution of Salary Tradeoffs by Gender

sacrifice to improve the social impact of a job offer (details in online Appendix E.1). We show the distribution of this quantity by gender in Figure 4. From these distributions, we observe that female respondents exhibit larger salary trade-offs than male respondents, that is, they are willing to sacrifice more salary for improving the social impact of a job offer. We confirm these insights in online Appendix E.2, where we show that gender differences are significant and that male respondents would make an approximated 25 percent smaller salary trade-off to improve the social impact of a job offer compared to their female colleagues, even when controlling for other observables.

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

Lastly, we analyze whether a preference parameter capturing the importance of social responsibility (meaning derived from social impact at work) relative to income can help to explain the gender differences in important behavioral outcomes.[15] Specifically, we examine the courses taken by MBA students, their engagement in prosocial clubs during their MBA, and the industry in which they work directly after the MBA. For each of these outcomes, the MBA students have complete autonomy

[15] In online Appendix C.8, we also explore how nonsocial impact can explain the gender differences and how it compares with social impact.

Table 8—Course, Social Club Events, and Industry Selection (MBA Study)

	Courses				Social engagement	
	Finance (MBA)		Social (MBA)		Club events attendance (MBA)	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Course and social club events (MBA study)						
Gender: Female	−0.044	−0.041	0.022	0.019	0.201	0.174
	(0.009)	(0.009)	(0.006)	(0.006)	(0.044)	(0.044)
$\frac{Importance_{SocialImpact}}{Importance_{FinancialOffer}}$		−0.015		0.015		0.122
		(0.007)		(0.004)		(0.032)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.208	0.199	0.153	0.162	0.233	0.308
	(0.009)	(0.010)	(0.006)	(0.006)	(0.043)	(0.046)
Adjusted R^2	0.085	0.092	0.033	0.054	0.063	0.087
F-value	10.071	9.237	4.336	5.650	7.779	9.020
Observations	491	491	491	491	506	506

	Industry			
	Finance (post-MBA)		Nonprofit (post-MBA)	
	(1)	(2)	(3)	(4)
Panel B. Industry selection (MBA study)				
Gender: Female	−0.133	−0.099	0.013	0.009
	(0.048)	(0.048)	(0.010)	(0.010)
$\frac{Importance_{SocialImpact}}{Importance_{FinancialOffer}}$		−0.148		0.019
		(0.036)		(0.007)
Control variables	Yes	Yes	Yes	Yes
Constant	0.454	0.367	0.000	0.011
	(0.048)	(0.051)	(0.009)	(0.010)
Adjusted R^2	0.025	0.060	0.005	0.018
F-value	3.183	5.618	1.412	2.316
Observations	434	434	434	434

Notes: This table reports coefficients and SEs in parentheses of OLS regressions. Control variables are international, GMAT, work experience, and whether the student has loans. For all coefficients, see Table C.7 in the online Appendix.

of choice. They are completely free to choose their electives, are not required to participate in prosocial clubs, and, of course, choose the jobs to which they apply. We focus our analyses on the finance and nonprofit sectors but show results for all industries in Table C.12 in the online Appendix.[16]

For all six outcomes, Table 8 has columns including and excluding the preference parameter, $\log\left(\frac{Importance_{SocialImpact}}{Importance_{FinancialOffer}}\right)$, generated from the HB-MNL model. The table shows that there are gender differences in outcome variables consistent with gender

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

segregation into different industries. Most striking is that the proportion of female students going into the finance industry post-MBA is about 13 percentage points lower than that of male students (column 1 in 10). Importantly, we find that adding preference parameters helps to explain part of this outcome. Looking at the increase in adjusted R^2 between OLS models shows that adding the preference parameters increases the explanatory power of the models substantially. The gender difference in courses taken and industry choice decreases by 10–25 percent across the models (i.e., when controlling for preference parameters). For post-MBA industry selection into the finance industry, including the social impact preference parameter decreases the gender effect by 25 percent. Our results therefore indicate that differences in preferences for meaning at work may help to partly explain the types of courses taken, participation in social clubs events, and the industry of full-time placement. In terms of assessing the size of the effect, we furthermore observe that preferences for meaning at work explain about the same, or more, than do preferences for competition, which have been highlighted in extant work as important contributors to gender segregation (e.g., Reuben, Sapienza, and Zingales 2019; Buser, Niederle, and Oosterbeek 2014). In the online Appendix, we show in Tables C.9, C.10, and C.11 that social impact explains a larger share of these gender differences than nonsocial impact for most of the outcomes.

Industry placement is a particularly important outcome because of its implications for both short-term and long-term gender wage differences. Whereas a median MBA student (at the university of our sample) who goes into investment banking receives $200,000 as a starting salary, the equivalent MBA student going into nonprofit, education, or government is paid less than $120,000. As a point of comparison, 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 further paling in comparison to differences in pay between these sectors five or ten years down the line.

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

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

III. Discussion

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

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

Our findings have important implications for policymakers seeking to achieve gender pay equity. Understanding gender differences in preferences is critical because, if gender differences in preferences help to explain part of the equity gap, policies directed at affecting gender differences in beliefs (about ability, earnings, etc.) (Zafar 2013) and access will not be sufficient for achieving gender equity. Our paper suggests the importance of recognizing the role that self-selection of men and women into jobs with different characteristics—in particular meaning induced from social impact—plays in maintaining and exacerbating gender segregation and, thus, the gender wage gap. Our findings suggest that, without addressing gender differences in preferences for meaning at work, the prevailing policy recommendations of how to achieve gender pay equity could fall short of their aim. Policy changes or incentives aimed at altering gender stereotypes and increasing men's relative appreciation and preference for meaning at work could be one way to help address the gender imbalance in high-paying versus low-paying industries and jobs. Likewise, policies that require increased CSR or social impact from companies in high-paying industries could be another promising way to increase the representation of women in these occupations and, resultingly, narrow the gender wage gap. Though such policies would be somewhat indirect ways to address the gender pay gap, there may in fact be benefits to indirect policies such as these. This is because implementation of policies explicitly directed at minimizing bias or achieving diversity goals can often be met by resistance (Dover, Major, and Kaiser 2016; Ip, Leibbrandt, and Vecci 2019; Leibbrandt, Wang, and Foo 2018; Niederle, Segal, and Vesterlund 2012). Given the increasing political polarization of DEI (diversity, equity, and inclusion) issues in recent years, resistance to explicitly equity-oriented policies may increase, potentially making the implementation of indirect policy mechanisms such as these promising avenues for helping to address gender equity.

Our paper points to a number of promising areas for future research. Future work could delve more deeply into characterizing the phenomenon of gender differences in preferences for meaning at work. For example, exploration of cross-country differences and how such differences have evolved over time could be fruitful areas for future research on this topic. Future research could also examine how gender differences in job preferences such as those for meaning at work are shaped (see Cotofan et al. 2023 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, Rogan, and Singh 2022; Abraham and Burbano 2022), whereas females are rewarded for pursuing social mission (Lee and Huang 2018), which could influence preferences over time, for example. These preferences could be endogenous to the work situation and society at large, despite the fact that gender differences prevail when we control for job market (e.g., industry or supervisory role) and educational outcomes in our cross-country regressions.

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

With respect to the generalizability of our findings from the MBA sample to non-MBAs, it is important to note that MBA students are highly educated and predominantly from more developed economies. Thus, the results from our cross-country study suggest that gender differences in preferences for meaning might be particularly pronounced in this sample. On the other hand, given that gender differences in job preferences have been shown to explain selection into different majors and career types (Buser, Niederle, and Oosterbeek 2014; Wiswall and Zafar 2018), the fact that our sample is limited to an MBA career path might indicate that our results are under-, rather than overestimated. Future work which examines the implications of gender differences in preferences for meaning in the context of other professions and different samples of the population will thus be important complements to our research. Future work that analyzes preferences for meaning at work that are elicited in an incentive-compatible way would also be a nice complement to our choice-based conjoint method. Additionally, our analysis focuses on industry selection into the finance and nonprofit sectors. Future research could investigate how gender differences in preferences for meaning influence selection into other industries, as well as into different types of firms within industries.

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

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