The Gender Pay Gap Beyond Human Capital

Heterogeneity in Noncognitive Skills and in Labor Market Tastes

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ABSTRACT

Focused on human capital, economists typically explain about half of the gender earnings gap. For a national sample of MBAs, we account for 82 percent of the gap by incorporating noncognitive skills (for example, confidence and assertiveness) and preferences regarding family, career, and jobs. Those two sources of gender heterogeneity account for a quarter of the "explained" pay gap, with half due to human capital variables and the other quarter due to hours worked and current job characteristics. Female MBAs appear to pay a penalty for "good citizen" behavior (choosing jobs that contribute to society) and characteristics (higher ethical standards).

I. Introduction

Although the gender earnings gap has narrowed sharply since World War II, women continue to earn 20 percent less than men.[1] Aware of gender pay disparity, Americans, according to a 2004 survey, attribute it (1) largely and equally to women's priority for family over careers and to employers' discrimination against

1. For gender wage gap literature surveys, see Altonji and Blank (1999) and Polachek (2006).

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women in hiring and promotion practices, then to (2) differences in noncognitive skills, namely assertive negotiating, and finally, and least importantly, to (3) the possession of education and skills needed for high paying jobs (Hill and Silva 2005, p. 3). After decades of publications investigating male-female earnings differences, economists have formed a consensus that human capital variables—like education, work experience and skills—explain more and discrimination explains less of the gender income gap than the public thinks.[2]

Despite the public's common sense understanding that career success is influenced by noncognitive skills, such as confidence, motivation, and assertiveness, and by work/life preferences, economists cannot offer a consensus judgment regarding the wage gap effect of either. The human capital model of Becker (1964) predicted earnings differences to arise from differences in the broad array of individual abilities and in educational investments. Due to the ease of using cognitive test scores and the difficulty of empirically operationalizing personality traits and noncognitive characteristics, to date empirical analyses have used cognitive test scores to proxy for "individual ability."[3] Social scientists, able to typically account for only half of the gender pay gap with human capital models based on nationally representative data sets, have long hypothesized that gender heterogeneity may characterize noncognitive skills[4] and a variety of work/life preferences, both of which cause wage differences.[5] Now a burgeoning literature, especially by those conducting lab and field experiments, reports gender heterogeneity of preferences and noncognitive skills (Croson and Gneezy 2009; Booth 2009). Economists and others, though, are just beginning to test the labor market outcomes of such gendered work-life choices and personality traits.[6]

Using an especially rich national data set, the twin goals of this paper are (1) to identify noncognitive and preference sources of otherwise unobserved gender heterogeneity and then (2) to estimate whether such heterogeneity accounts for more of the male-female earnings gaps than can be explained by an extensive set of human capital variables. We view our analysis, then, as part of a broad agenda to enrich

2. Although the unexplained component of the gender wage gap is often attributed to discrimination, it also may result from a misspecification of the relationships or from unobserved gender heterogeneity (Polachek and Kim 1994; Altonji and Blank 1999). Regarding discriminatory behavior, see, for example, Neumark et al. (1996) and Goldin and Rouse (2000). Although we do not test for discrimination, Montgomery and Powell (2003), using the first three waves of our data set, found that obtaining an MBA sharply diminishes the gender wage gap, comparing wages of MBAs and non-MBAs.

3. Regarding the challenges of systematically analyzing the labor market outcomes of noncognitive skills, see Borghans et al. (2008) and ter Weel (2008).

4. Psychologists prefer the term character or personality traits (see Thiel and Thomsen 2009).

5. For example, Blau and Kahn (1997), using the Panel Study of Income Dynamics (PSID) for full-time workers with incomes and labor market experience, found an unadjusted male-female wage ratio of 72.4 percent in 1988. Controlling for human capital variables, occupation, industry, and unionism explains half of the gap. Polachek and Kim (1994), also using the PSID, estimate that half of the male-female earnings differences results from unobserved gender heterogeneity.

6. See, for example, Bowles et al.'s (2001) review of the early explanations of wage differences due to personality and the 2008 *Journal of Human Resources* symposium issue entitled "The Noncognitive Determinants of Labor Market Outcomes and Behavioral Outcomes." In response to criticisms of narrowly measuring ability, as of July 2009. the GRE includes a formal measure that attempts to capture noncognitive skills (the "Personal Potential Index").

the human capital model as envisioned by Becker (1964) by more fully understanding the variation of individual abilities, especially of noncognitive skills and of work/life preferences, and how such heterogeneity influences labor market outcomes.

Economists have taken three approaches to better understand the gender pay gap. First, the growing lab and field experiment findings about gender differences in, for example, confidence, career-orientation, and assertiveness, are consistent with gender earnings gaps, with the under-representation of women in the upper tier of leadership in professions and corporations, and with the anecdotal evidence of professional women "opting out" of careers;[7] to date, though, little empirical analysis has investigated those potential relationships (Thiel and Thomsen 2009). The notable exceptions focus on the personality traits of the Big Five (see Braakmann 2009; Mueller and Plug 2006) and measures of locus of control and self-esteem (Fortin 2008; Urzua 2008). We test the role of various confidence measures and 15 noncognitive skills (deemed especially important for business professionals) in explaining the MBA male-female pay gap.

Secondly, scholars have focused upon gender differences in labor market tastes such as the priority of family, career, wealth, and job characteristics. According to Long (1995) and Fortin (2008), the priority of work and money contributes to the pay gap. Chevalier (2007) finds that women with a preference for childbearing earn less even before they have children due to their choice of college major and because they engage less intensively in job searching (also see Goldin and Polachek 1987). Our data contain a variety of individuals' priorities regarding family and career, as well as the reported importance of nonpecuniary job attributes, recorded about eight years prior to the earnings data we assess.

Finally, because nation-wide data sets, like the Panel Study of Income Dynamics (PSID), lack information regarding, for example, college quality, college major, and detailed work histories, researchers have sought smaller, specialized, and homogeneous data sets with greater educational and labor market detail; examples from individual institutions of higher education include studies based on surveys of undergraduates from Harvard College (Goldin and Katz 2008), lawyers from the University of Michigan (Wood, Corcoran, and Courant 1993), and MBAs from the University of Chicago (Bertrand et al. 2009) and the London School of Business (Graddy and Pistaferri 2000). Children, according to Bertrand et al. (2009), mainly contribute to female MBAs' reduced earnings via fewer hours worked and increased career interruptions.[8] Furthermore, from the Harvard and Beyond data set, female MBAs have greater difficulty balancing careers and children than do medical doctors, lawyers, or Ph.D.s (Goldin and Katz 2008; Herr and Wolfram 2009). In addition to

7. A recent survey by Catalyst, for example, found that "26 percent of women at the cusp of the most senior level of management don't want the promotion" (Belkin 2003). For anecdotal evidence of high powered professional women "opting out" of careers, see Belkin's (2003) widely read article in *The New York Times Magazine*. In contrast, Stone (2007) argues that mostly professional women want to but cannot manage to raise children and function in demanding careers (see also Leonhardt 2010). However, Antecol (2010) find that professional women largely return to work within two years of childbirth.

8. A recent New York Times article entitled "A Labor Market Punishing to Mothers" (Leonhardt 2010), which cites Bertrand et al. (2009), makes a similar argument about professional women generally, noting that the three recent female Supreme Court nominees do not have children.

children, though, Bertrand et al. (2009) also attribute the gender wage gap to differences in MBA training and hours worked. Because these data sets come from individual elite institutions, it is not clear how their results generalize either to typical MBAs or to other average highly educated professionals.

The existence of a unique and especially rich data set, the GMAT Registrant Survey, allows us to estimate the role of preferences and noncognitive skills in explaining the gender earnings gap. A stratified random sample of all registrants for the Graduate Management Admission Test (GMAT), the GMAT Registrant Survey, contains longitudinal data in four waves from 1990 to 1998. After registering to take the GMAT but prior to enrolling in an MBA program (Wave I), respondents provided information regarding career and family priorities, 15 noncognitive skills, expected future managerial responsibility, individuals' job preferences regarding the importance of nonmonetary job characteristics, and information used to create five confidence measures. The data set also provides detailed information about both undergraduate and MBA educational experiences, work histories, earnings, family background, marriage, children, and more. Drawn from a national sample of aspiring MBAs, this data set includes the wide range of MBA program qualities and types available in the United States (Arcidiacono et al. 2007), rather than merely graduates of the most elite programs (for example, Bertrand et al. 2009; Graddy and Pistaferri 2000).[9]

Among our sample of MBAs, females employed full-time earn 15.5 percent less per year than do males, a smaller gap than is found in economy-wide data sets (for instance, Blau and Kahn 1997). When we add basic human capital variables (for example, family background, work experience, ability measures, undergraduate and MBA educational experiences), the unexplained gap falls to 9.5 percent, and then further to 6.5 percent with the addition of hours worked and current employment characteristics. Finally, the addition of work/life preferences and noncognitive variables to the human capital model yields a marginally significant earnings gap of 4.3 percent.

The results from Oaxaca-Blinder and Gelbach decompositions (Gelbach 2009) clarify how differently men's and women's experiences, expectations, preferences, and noncognitive skills influence career outcomes and how much these novel variables help account for the gap. The final decomposition analysis, based on all of our variables, accounts for up to 82 percent of the raw gender pay gap (versus 49–69 percent with just the human capital variables). Of the explained gap, about a quarter is accounted for by gender heterogeneity in labor market tastes and noncognitive skills—remarkably, about the same proportion explained by both hours worked and current job characteristics; human capital variables explain the remaining half. To put our results in context, Fortin (2008), the study most similar to ours, explains up to 25 percent of the raw gender pay gap, of which her set of noncognitive skills accounts for 5–6 percent.[10]

9. Since a majority of the overall increase in wage inequality from 1973 to 2003 resulted from wage differences across levels of educational attainment (Lemieux 2006), our sample allows us to focus on differences between men and women with the same graduate degree (MBAs).

10. Fortin (2008), investigating the role of self-esteem, locus of control, priority on money and work, and the importance of family, finds the priority on money and work to most influence the gender pay gap.

"Good citizen" characteristics and behaviors of female MBAs, namely their high ethical standards and choice of jobs that contribute to society, account for some of the earnings gap. Thus, the MBA women in our sample apparently desire to work differently than do male MBAs, and consequently earn less.

II. Data

The data used in our analysis comes from the GMAT Registrant Survey, a longitudinal survey of individuals who registered for the Graduate Management Admission Test (GMAT), an admission requirement for the vast majority of MBA programs in the United States. The survey, sponsored by the Graduate Management Admission Council (GMAC), was mailed to the same individuals in four waves, between 1990 and 1998, whether or not they actually took the GMAT.[11] The Wave I survey occurred from April 1990 to May 1991, shortly after test registration, but prior to MBA enrollment. Of the 7,006 registrants initially sent a survey, 5,885 responded to the first survey, 4,327 to the third survey, and 3,771 to the fourth in 1998.[12]

The GMAT Registrant Survey includes information about the following eight categories: (1) demographics and family status, (2) previous higher education (college major, area of study,[13] GPA, school quality, and whether they possessed a post-baccalaureate degree other than an MBA), (3) an employment history including prior earnings, industry, and work experience, (4) a set of self-assessed noncognitive skills deemed important for success in business, (5) preferences regarding work/life priorities and nonpecuniary job characteristics, (6) career expectations, (7) MBA concentration, program quality, pace (full- or part-time), and type (whether an executive program), and (8) current employment, earnings, and information about nonmonetary assessments of their job.

Of the 3,771 respondents to the fourth and final survey, we limit our analysis to those who: (1) obtained an MBA in the sample period (approximately 43 percent of respondents); (2) worked full-time (35 hours per week or more) at the time of the fourth survey and reported the associated earnings information (82 percent of the remaining individuals); (3) took the GMAT and had nonmissing values for the multitude of control variables included in the analysis (70 percent of remaining individuals). Our final sample includes 933 individuals, of whom 586 are males and 347 females.

11. These data were collected by the Battelle Memorial Institute (Seattle, Washington State) for the Graduate Management Admission Council (GMAC). The same data set has been used by Montgomery (2002), Montgomery and Powell (2003), Arcidiacono, et al. (2007), and Grove and Hussey (2011).

12. Though attrition more heavily affected those who never entered into an MBA program than those who did, those who left the sample look similar to those who remain in a number of different observable characteristics, including gender, race, test scores, and labor market outcomes. An appendix characterizing the attrition in more detail is available on request.

13. Rather than individual majors, we only know which of the following five broad areas students studied: business, engineering, the humanities, science, and social science.

For descriptive statistics of our sample, see Table 1 in which we report separate means and standard deviations by gender and *p*-values for tests of the equality of means between males and females. The dependent variable is the logarithm of total annual earnings on the job, for currently employed individuals at the time of the fourth survey (note we also conduct our analyses for hourly wage and hours worked; see the Robustness section). The average male in our sample earned $67,116, which is $9,483 more per year (in 1997 dollars) than the average female, for a raw wage gap of about 15.5 percent. To account for some variation in the timing of survey responses, we used the Consumer Price Index to adjust all earnings to January 1997 dollars.

A. Human Capital Control Variables

In order to explain the gender gap in earnings, we begin by considering demographic variables, namely age, race, and both the mother's and father's years of schooling attainment. Our sample of MBAs contains slightly younger females and more black women than black men. Family circumstances differ substantially, with men much more likely to be married and twice as likely to be married with children.

Total work experience and current job tenure were constructed from responses to questions in the initial survey regarding the total number of years the respondent worked full-time for pay since the age of 21 and then with subsequent surveys' questions about starting and stopping dates (to the nearest month) of jobs. Women have fewer years of total work experience and job tenure at the time of the Wave I survey. Brown and Corcoran (1997) attribute as much as a third of the gender wage gap in their sample to work experience (also see Joy 2003 and Daymont and Andrisani 1984).

To account for differences in undergraduate educational background, we include cumulative grade point average (out of 4.00), college major, and measures of the selectivity of the college attended (from Barron's *Profiles of American Colleges*). Females earned higher undergraduate grades than males, a typical finding in the higher education literature.[14] Using Barron's selectivity categories,[15] men attended somewhat more "moderately selective" undergraduate institutions but no statistically significant differences existed in graduating from "highly selective" schools. Although our data includes information regarding students' general areas of study, rather than specific majors, according to Weinberger (1998) narrowly or more broadly measuring college major causes no notable differences in estimated gender wage gaps. We include dummy variables for whether the individual received a degree in the social sciences, humanities, sciences, or engineering, with business as the omitted category. Twice as many males majored in engineering as undergraduates, whereas females were more likely to have majored in business and the humanities.

14. This reflects fewer science and math courses taken by women (Montmarquette et al. 2002).
15. We collapsed the various undergraduate admission selectivity categories as designated in Barron's into the following three categories: highly selective (19 percent of our sample), moderately selective (26 percent), and the omitted category representing the least selective schools and those not included in the Barron's guide (55 percent).

Table 1
Descriptive Statistics of Sample, by Gender

	(1) Male		(2) Female			
Variable	Mean	Standard Deviation	Mean	Standard Deviation	Difference: 1–2	*p*-value for Male = Female
Annual salary ($)	67,116	27,813	57,633	23,467	9,483	0.00
Demographic/background						
Age	34.84	6.00	34.07	5.82	0.77	0.06
Asian	0.13	0.34	0.12	0.32	0.01	0.61
Black	0.07	0.25	0.18	0.38	−0.11	0.00
Hispanic	0.15	0.36	0.17	0.38	−0.02	0.36
Mother's education (years)	14.49	3.55	14.03	3.80	0.45	0.07
Father's education	13.63	3.15	13.62	3.25	0.02	0.94
Employment experience						
Work experience(years)	10.75	6.70	9.98	6.03	0.78	0.08
	4.35	4.61	3.61	3.41	0.74	0.01
Family variables						
Married	0.72	0.45	0.59	0.49	0.13	0.00
Kids (1 = yes)	0.48	0.50	0.26	0.44	0.22	0.00
Married*kids	0.47	0.50	0.22	0.41	0.25	0.00
Undergraduate variables						
Highly selective	0.22	0.41	0.21	0.41	0.01	0.70
Moderately selective	0.31	0.46	0.25	0.44	0.06	0.06
Business major	0.46	0.50	0.56	0.50	–0.1	0.00
Social science major	0.18	0.38	0.16	0.36	0.02	0.39

(continued)

Table 1 *(continued)*

Variable	(1) Male Mean	(1) Male Standard Deviation	(2) Female Mean	(2) Female Standard Deviation	Difference: 1–2	p-value for Male = Female
Humanities major	0.06	0.25	0.11	0.31	−0.04	0.02
Engineering major	0.19	0.40	0.07	0.26	0.12	0.00
Science major	0.10	0.30	0.10	0.30	0.00	0.96
Cumulative GPA	3.02	0.41	3.15	0.40	−0.13	0.00
Ability measures						
Quantitative GMAT	32.39	8.00	28.31	7.51	4.08	0.00
Verbal GMAT	30.70	7.12	29.88	7.35	0.82	0.09
MBA variables						
Cumulative GPA	3.33	0.88	3.28	0.91	0.05	0.40
Top 10	0.06	0.24	0.05	0.22	0.01	0.37
Top 11–25	0.08	0.28	0.08	0.27	0.00	0.88
Part-time program	0.50	0.50	0.52	0.50	−0.02	0.60
Executive program	0.07	0.26	0.04	0.20	0.03	0.07
Finance concentration	0.23	0.42	0.13	0.34	0.10	0.00
Marketing concentration	0.10	0.30	0.14	0.35	−0.05	0.04
Accounting concentration	0.05	0.22	0.06	0.24	−0.01	0.37
MIS concentration	0.06	0.23	0.05	0.22	0.01	0.56
International concentration	0.06	0.24	0.04	0.19	0.02	0.11
Other concentration	0.19	0.39	0.28	0.45	−0.1	0.00
Noncognitive Skills						
Initiative	3.54	0.54	3.61	0.53	−0.07	0.05
High ethical standards	3.66	0.54	3.76	0.45	−0.10	0.00
Communication skills	3.36	0.59	3.45	0.58	−0.10	0.02
Work with diversity	3.57	0.59	3.66	0.55	−0.09	0.03

Shrewdness	2.77	0.74	2.59	0.74	0.18	0.00
Ability to organize	3.49	0.59	3.59	0.56	−0.10	0.01
Physical attractiveness	3.03	0.59	3.11	0.60	−0.08	0.05
Assertiveness	3.16	0.64	3.20	0.60	−0.05	0.27
Ability to capitalize on change	3.18	0.64	3.13	0.62	0.05	0.23
Ability to delegate tasks	3.25	0.67	3.22	0.69	0.03	0.51
Adapt theory to practical situations	3.19	0.68	3.08	0.68	0.11	0.02
Understanding business in other cultures	2.54	0.83	2.58	0.87	−0.04	0.46
Good intuition	3.27	0.64	3.33	0.66	−0.06	0.19
Ability to motivate others	3.25	0.67	3.33	0.60	−0.08	0.07
Being a team player	3.60	0.56	3.64	0.55	−0.04	0.28
Confidence: ability						
Quantitative expectations	3.85	0.81	3.43	0.78	0.42	0.00
Verbal expectations	3.48	0.73	3.55	0.67	−0.07	0.17
Work/life preferences						
Family important	0.89	0.31	0.90	0.31	0.00	0.86
Career important	0.51	0.50	0.47	0.50	0.04	0.22
Wealth important	0.20	0.40	0.14	0.35	0.06	0.03
Relatives/friends important	0.49	0.50	0.66	0.48	−0.17	0.00
Confidence: admissions	25.22	6.57	25.57	6.79	−0.35	0.44
Confidence: connections						
Knowing the right people: admissions	3.79	2.41	3.74	2.48	0.05	0.76
Knowing the right people: managerial success	2.55	0.77	2.53	0.71	0.02	0.69
Managerial goals						
High managerial responsibility	0.70	0.46	0.69	0.46	0.00	0.88
Medium managerial responsibility	0.23	0.42	0.27	0.44	−0.04	0.20

(continued)

Table 1 *(continued)*

Variable	(1) Male Mean	(1) Male Standard Deviation	(2) Female Mean	(2) Female Standard Deviation	Difference: 1–2	p-value for Male = Female
Job preferences						
Nonmonetary job attributes	33.75	3.45	34.62	3.37	−0.87	0.00
Contributes to society	0.11	0.31	0.19	0.39	−0.08	0.00
Current job: hours and characteristics						
Hours per week	50.26	8.54	48.94	8.82	1.32	0.02
Self-employed	0.05	0.21	0.02	0.13	0.03	0.02
Large firm	0.36	0.48	0.39	0.49	−0.03	0.34
Medium-sized firm	0.50	0.50	0.48	0.50	0.03	0.41
Small firm	0.13	0.34	0.13	0.34	0.00	0.88
Nonprofit	0.04	0.20	0.10	0.29	−0.05	0.00
Government	0.12	0.32	0.14	0.35	−0.03	0.24
Agricultural, forestries, & fisheries	0.01	0.08	0.00	0.00	0.01	0.12
Manufacturing	0.28	0.45	0.21	0.41	0.07	0.02
Service industries	0.29	0.45	0.35	0.48	−0.07	0.04
Finance, insurance, & real estate	0.17	0.38	0.15	0.36	0.02	0.48
Public administration	0.09	0.29	0.11	0.32	−0.02	0.28
Percent female in occupation	0.41	0.13	0.44	0.15	−0.04	0.00
Observations	586		347			

Notes: Sample includes respondents to both the first and fourth waves of the GMAT Registrant Survey who obtained an MBA, were employed in a full-time job ($> = 35$ hours/week) at the time of the fourth survey, and had nonmissing values for all variables (except for MBA GPA, for which a missing value dummy variable was included in all regressions). Most variables were obtained from Wave I of the survey, except for current employment variables, job tenure, work/life preferences variables, the 'contributes to society' variable (which were obtained from Wave IV), and work experience (which was determined from all four survey waves).

An advantage of our data is that the survey information was merged with GMAT registration and testing records; thus, we have actual quantitative and verbal GMAT scores, not self-reported standardized test scores, as is typical of higher education studies.[16] Males received much higher scores on the quantitative GMAT than did females (14 percent higher) and slightly higher verbal scores (3 percent higher).

Regarding the MBA experience, we include cumulative grade point average (out of 4.00) and indicators of program quality and program schedule, namely whether part-time, full-time, or an Executive program. Unlike with undergraduate grades, MBA's grade point averages did not statistically differ by sex (Table 1). For program quality, we include variables indicating whether the program attended was ranked in either the Top 10 or Top 11–25, according to *U.S. News and World Report* 1992 rankings. No gender divide existed for MBA attainment from top programs. Note that only about 5 percent of our sample attended Top 10 and about 8 percent Top 11–25 programs; thus, our sample is of the average MBA graduates in the U.S., whereas other prominent MBA gender gap studies have been of graduates of elite programs, such as the University of Chicago (Bertrand et al. 2009) and the London School of Business (Graddy and Pistaferri 2000).

Consistent with greater work experience, men were more likely to attend Executive MBA programs than women (Table 1). Grove and Hussey (2011) found, as in the context of undergraduate studies, that particular areas of emphasis in graduate business studies affect post-MBA earnings as much as can overall program quality. Thus, we include variables indicating whether the individual focused their studies in particular areas of concentration (finance, marketing, accounting, management information systems (MIS), international business, or others[17]). Females were more likely to concentrate in marketing, while males were about twice as likely to concentrate in finance, which Grove and Hussey (2011) find results in higher earnings.

In several specifications we control for differences in current employment characteristics. Since our dependent variable is annual earnings, we include hours worked per week (although recall that our sample is already limited to those working 35 hours or more per week). Females in our sample report working about one hour less per week than men, a statistically significant difference (see Table 1). Since an earnings premium for employees of larger firms has consistently been found in the literature (see Oi and Idson 1999 for a review), we include variables indicating employment at a large firm (defined as having 25,000 or more employees worldwide), a medium firm (between 100 and 25,000 employees), or a small firm (less than 100 employees). No gender differences exist in employment by firm size (Table 1).

Using two-digit industry codes, we include indicator variables for five broad industry areas, as well as indicator variables for self-employment and whether em-

16. While we refer to GMAT scores as ability measures, according to the Graduate Management Admission Council the GMAT "is a standardized test designed to measure verbal, mathematical, and analytical writing skills that have been developed over a long period of time through education and work."
17. The "other" category includes the following reported concentration areas: human resources, health care administration, entrepreneurial management, industrial management, production/operations management, public administration, real estate, statistics or operations research, transportation, and economics. Due to small numbers of individuals reporting concentrations in these areas, we collapsed them into one variable.

ployed by the government or a nonprofit organization. Men were significantly more likely to be self-employed and to work in manufacturing, whereas women were more likely to work at a nonprofit organization or in the service industry (see Table 1). Three-digit occupational codes and a Bureau of Labor Statistics variable representing the estimated percentage of females within the occupation reveal that women, in this sample, worked in occupations with a high percentage of females (Table 1). Although Boraas and Rodgers (2003) find that occupational segregation constitutes the largest component of the gender wage gap, MacPherson and Hirsch (1995) attribute it to less than 7 percent of the male-female wage gap.

B. Gender Heterogeneity of Nontraditional Variables

Beyond the human capital and employment variables, the GMAT Registrant Survey allows us to construct and include several variables related to individuals' noncognitive skills, confidence, expectations, and preferences. Although economists have only recently begun to pinpoint these factors as potentially relevant in helping to explain the gender earnings gap, individual differences due to personality have long been a core research agenda among personality psychologists (see, for example, Roberts, Kuncel, Shiner, Caspi and Goldberg 2007).

The first survey wave asked individuals to rate the extent to which they have fifteen different noncognitive skills (what psychologist prefer to label as character or personality traits; see Thiel and Thomsen 2009), deemed relevant for success as a manager or business professional. We include variables for responses ranging from one ("not at all" having the characteristic or skill) to four ("very much" having the characteristic or skill) for each of the following: initiative; high ethical standards; communication abilities; ability to work with people from diverse backgrounds; shrewdness; ability to organize; physical attractiveness; assertiveness; ability to capitalize on change; ability to delegate tasks; ability to adapt theory to practical situations; understanding business in other cultures; good intuition; ability to motivate others; and being a team player. Montgomery and Powell (2003) combined all of these responses into a single variable, which they refer to as a "confidence index." In order to relate our results to the scholarship focused on gender heterogeneity in noncognitive skills, we enter each trait separately to isolate its individual effect. Of the 15 self-reported traits, eight exhibit statistically significant (at the 5 percent level) gender differences. Specifically, females rated themselves as possessing greater initiative, higher ethical standards, better communication abilities, better organizational abilities, and a stronger ability to work with people from diverse backgrounds. Males, on the other hand, reported greater shrewdness and ability to adapt theory to practical situations. At the 10 percent level of significance, women self-reported greater physical attractiveness and ability to motivate others.

We create five confidence measures which may help to explain earnings and the gender earnings gap, since individuals may either sort into jobs or be rewarded on the job due to their perceived, rather than actual, abilities. First, we include variables intended to represent one's confidence in their quantitative and verbal abilities. Immediately after registering to take the GMAT but before taking the exam, respondents were asked, in the first survey wave, how well they expected to do on the quantitative and verbal sections of the GMAT. Responses ranged from one ("excellent") to five ("poor"), which we reversed so that a higher number means greater confidence. Because actual GMAT scores are controlled for in all of the specifications where we include these expectations, we interpret these expectations of verbal and quantitative performance as indicating confidence in one's own abilities. Men reported significantly more confidence in their quantitative abilities but not more in their verbal abilities than did women. Actual GMAT scores reveal that, on average, men received much higher quantitative and marginally higher verbal GMAT scores (Table 1).

In addition, we include an admission confidence measure. The initial survey, on a scale from one ("very") to four ("not at all"), asked how difficult particular steps in the admission process would be, such as obtaining letters of recommendation, preparing for the GMAT, or making the right impression on the application form.[18] We reverse the order of these responses and, using equal weight for each response, combine them into a single index, which we call "admission confidence." No differences exist in men's and women's confidence of succeeding in admission-related tasks (Table 1).

Finally, because personal connections may importantly affect job success, we include two related measures of confidence in one's connections. First, we extract one component of the admission confidence index—"knowing the right people"—and include it on its own. Second, we include a variable from the noncognitive skill self-assessment section of the initial survey of "knowing the right people," ranging from one ("not at all") to four ("very much"). Here, women and men report similar levels of confidence in both types of connections (Table 1).

Different family and career priorities may sort women and men into higher or lower paying jobs. The fourth survey asked individuals to evaluate, on a scale from one to four, the importance of various aspects of their lives. In particular, we include separate variables indicating whether the surveyees reported as "very important" (the highest category) each of the following: family and children, career and work, friends and acquaintances, and wealth. The importance of family and career do not statistically differ but more males considered wealth and females considered friends and acquaintances as very important aspects of life (Table 1).

We also include variables reflecting future job expectations, intended to pick up potential differences between males and females in their managerial aspirations. In the initial survey wave (approximately seven to eight years prior to the earnings observations included in our analysis), individuals were asked about their expected employment situation five years in the future. We include variables indicating whether the individual reported expecting to be a nonmanager (the omitted category), an entry-level manager, or a mid- to upper-level manager. Two-thirds of both men and women report expecting "high managerial responsibility" and a quarter of both expected "medium managerial responsibility."

The initial survey also asks individuals to indicate the importance of several work environment characteristics for the position they expect to have five years later. We

18. The following is a complete listing of the included admission steps: prior work experience; undergraduate grades; letters of recommendation; Preparing for the GMAT; doing well on the GMAT; knowing the right people; visiting graduate schools; making the right impression on the application form; paying application fees.

combine these responses (each on a scale from one to four) into an index intended to capture individual preferences over nonmonetary job characteristics.[19] Females reported significantly higher importance of the nonmonetary job attributes of their expected future job. Finally, we allow for possible gender differences in preferences over the social stewardship of their work. In deciding to take their current job, 19 percent of females reported (in Wave IV surveys) their job contributing to society was "very important," while only 11 percent of males reported the same thing—a statistically significant difference.[20]

III. Empirical Methodology

We begin by specifying the following model of earnings determination:

$$\text{(1)}\quad \mathrm{Ln}(S_i) = \gamma_f Female_i + X_i^b \beta_b + X_i^e \beta_e + \varepsilon_i$$

where S_i is reported annual log earnings and ε_i is an individual error term. Our primary parameter of interest is γ_f, the coefficient on the Female indicator variable. X_i^b contains a vector of the basic human capital control variables, as described in the previous section. This analysis assumes that the social processes under examination operate the same way for men and women. We initially run regressions containing only these covariates, and do so by adding each variable or subset of variables sequentially. We then include X_i^e, which contains our expanded set of controls, also described in the previous section. Once again, particular variables or classes of variables are added in sequential regressions in order to investigate the effect of their inclusion on the estimate of γ_f.

Although some information regarding the contribution of each set of variables can be gleaned from sequential addition of these variables to the model, the observed effect of each set of variables is influenced by the order in which they are added, a point that is emphasized by Gelbach (2009). To address this concern, we also carry out two types of decompositions to more concretely explore the role of particular variables in explaining the gender earnings gap. In the first method, in the style of Oaxaca (1973) and Blinder (1973), earnings for each gender (g) are estimated by:

$$\text{(2)}\quad \mathrm{Ln}(S_{ig}) = X_{ig}\beta_g + \varepsilon_{ig}$$

where X_{ig} contains, alternatively, either our basic set of human capital variables, our expanded set of variables, or both. The male and female models can be subtracted

19. The following characteristics are included in this index, giving equal weight to responses for each: the work is interesting; the people I work with are friendly; the chances for promotion are good; the job security is good; my responsibilities are clearly defined; I am free from the conflicting demands that others make of me; the hours are good; promotions are handled fairly; my employer is concerned with everyone getting ahead; I have enough time to get the job done.

20. This variable ranges from one ("Not at all important/Not applicable") to four ("Very important"). For variables where answers range from one to four (or five respectively), we tried using dummies in various combinations (for example, grouping responses of one—not at all having the attribute—and two vs. three and four) but our results did not meaningfully change.

from each other to decompose the mean gender salary gap into the mean difference in observed characteristics and the difference in returns to these characteristics:

$$(3) \quad \overline{\mathrm{Ln}(S_M)} - \overline{\mathrm{Ln}(S_F)} = \overline{(X_M - X_F)}\beta_F + \overline{X_M}(\beta_M - \beta_F)$$

where the first term on the right-hand side represents the explained part of the gender salary gap—the group differences in observed characteristics, and the second term allows for gender differences in returns to characteristics. Equation 3 is written from the perspective of females, describing their predicted outcome if they had males' characteristics and returns to those characteristics. Of course, it also could be written from the perspective of males. Depending on the choice of reference group—and therefore the point of view—results will vary. As an alternative, it may be useful to employ a weighting scheme in assigning a reference group, rather than placing full weight on one gender versus the other. The discrimination literature offers several such alternatives.[21] For the Oaxaca-Blinder decomposition analyses, we use three such weighting schemes. We report decompositions where all of the weight is placed alternatively on either male or female coefficients.[22] In our preferred specification, following the approach advocated by Neumark (1988) and Chevalier (2007), we use the coefficients from a pooled regression over both males and females. In this case, the salary gap can be decomposed as follows:

$$(4) \quad \overline{\mathrm{Ln}(S_M)} - \overline{\mathrm{Ln}(S_F)} = \overline{(X_M - X_F)}\beta^* + \overline{X_M}(\beta_M - \beta_F) + (\beta^* - \beta_F)\overline{X_F}$$

where β^* is the vector of pooled coefficient estimates. In each case, we focus on the "explained" portion of the gap, the first term in Equations 3 and 4.

Apart from the Oaxaca-Blinder decompositions, we also employ an approach advocated by Gelbach (2009). Unlike the Oaxaca-Blinder approach, this decomposition is grounded in the formula for sample omitted variables bias. Gelbach's approach provides a method to decompose cross-specification differences in pooled OLS estimates of the female coefficient (along the lines of our multitude of specifications from Tables 2 and 5), but does so in a path-independent manner.[23] We view this approach as an additional robustness check against the results obtained from the traditional Oaxaca-Blinder decomposition using pooled coefficients. Like in the explained portion of the Oaxaca-Blinder decompositions, whether gender heterogeneity in a variable (or set of variables) increases or decreases the gap depends on whether,

21. Reimers (1983), for example, suggested the use of the average coefficients over both groups: $\beta^* = 0.5\beta_m + 0.5\beta_f$. Similarly, Cotton (1988) proposed the use of coefficients weighted by sample group sizes: $\beta^* = n_m/(n_m + n_f)\beta_m + n_f/(n_m + n_f)\beta_f$.
22. In addition to robustness, an advantage of reporting both of these decompositions is that, unlike the initial pooled regressions including both genders, they provide some insight into the different magnitudes of returns to certain characteristics across genders.
23. In particular, Gelbach notes that if X_i contains K variables, the contribution of the k-th variable to the gap $\overline{\mathrm{Ln}(S_M)} - \overline{Ln(S_F)}$ is given by $\hat{\beta}_k^*$ multiplied by $\hat{\alpha}_k$, where $\hat{\alpha}_k$ are the estimates of the coefficients on the *female* variable from K auxiliary regressions of each of the k covariates on *female*. See Gelbach (2009) for more details. In addition, the Stata code for the Gelbach decomposition can be found on the author's website: http://gelbach.eller.arizona.edu/papers/b1x2/. We thank an anonymous referee for suggesting this procedure.

Table 2
Pooled OLS Estimates of Gender Salary Gap: Human Capital Variables

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female	−0.155**	−0.137**	−0.138**	−0.129**	−0.109**	−0.134**	−0.114**
	(0.026)	(0.026)	(0.026)	(0.027)	(0.026)	(0.026)	(0.027)
Demographic							
Age		0.104**	0.045	0.042	0.055*	0.057*	0.058*
		(0.019)	(0.032)	(0.032)	(0.032)	(0.031)	(0.031)
Asian		0.060	0.076**	0.079**	0.032	0.025	0.031
		(0.038)	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)
Black		0.003	0.011	0.016	0.003	0.038	0.084**
		(0.042)	(0.041	(0.042)	(0.041)	(0.041)	(0.042)
Hispanic		0.039	0.046	0.051	0.040	0.046	0.066*
		(0.036)	(0.035)	(0.035)	(0.035)	(0.034)	(0.034)
Mother's education		0.008*	0.009**	0.009**	0.006	0.005	0.004
		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Father's education		0.011**	0.011**	0.011**	0.009*	0.009*	0.007
		(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Employment experience							
Experience			0.038**	0.037**	0.032**	0.033**	0.030**
			(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Tenure			−0.004	−0.004	−0.005	−0.007	−0.005
			(0.007)	(0.007)	(0.007)	(0.007)	(0.007)

Family variables							
Married				0.007	0.008	−0.000	0.005
				(0.032)	(0.031)	(0.030)	(0.030)
Kids				−0.087	−0.074	−0.081	−0.068
				(0.087)	(0.086)	(0.084)	(0.084)
Married*kids				0.114	0.113	0.120	0.111
				(0.092)	(0.090)	(0.089	(0.088)
Undergraduate variables							
Highly selective					0.194**	0.201**	0.160**
					(0.033)	(0.033)	(0.034)
Selective					0.073**	0.076**	0.060**
					(0.029)	(0.028)	(0.028)
Engineering major					0.080**	0.098**	0.068*
					(0.037)	(0.037)	(0.038)
Grade point average						0.172**	0.135**
						(0.030)	(0.031)
Ability measures							
Quantitative GMAT							0.005**
							(0.002)
Verbal GMAT							0.004
							(0.002)
R-Square	0.04	0.09	0.12	0.12	0.17	0.20	0.21

(continued)

Table 2 *(continued)*

Variable	(8)	(9)	(10)	(11)
Female	−0.092**	−0.095**	−0.069**	−0.065**
	(0.026)	(0.026)	(0.025)	(0.024)
MBA variables				
Executive program	0.127**	0.126**	0.124**	0.107**
	(0.053)	(0.052)	(0.049)	(0.049)
Top 10	0.396**	0.385**	0.280**	0.295**
	(0.053)	(0.053)	(0.050)	(0.049)
Top 11–25	0.170**	0.189**	0.118**	0.140**
	(0.044)	(0.044)	(0.041)	(0.041)
Finance concentration	0.121**	0.119**	0.104**	0.071**
	(0.035)	(0.034)	(0.032)	(0.032)
Cumulative GPA		0.100**	0.041	0.039
		(0.046)	(0.043)	(0.042)
Current job: hours and characteristics				
Hours per week			0.015**	0.014**
			(0.001)	(0.001)

Large firm				0.087**
				(0.036)
Medium firm				0.070**
				(0.034)
Nonprofit				−0.142**
				(0.047)
Government				−0.190**
				(0.048)
Finance, insurance, & real estate				0.094**
				(0.037)
Percent female in occupation				−0.252**
				(0.083)
R-Square	0.29	0.30	0.39	0.43

Notes: Dependent variable is log of annual salary of current, full-time ($>$ 35 hours/week) jobs of MBA graduates reported in Wave IV (933 observations in each regression). Models 2–11 include age^2; 3–11 include experience^2 and tenure^2; 5–11 control for social science, humanities, and science majors; 8–11 include the variables of 7, dummies for part-time program, and various concentrations: Marketing, Accounting, MIS, International, and Other; 11 includes whether the individual is self-employed and dummies for the following industries: agriculture, forestries, . . . fisheries, manufacturing, service, and public administration. Statistical significance of the coefficient at the 5 and 10 percent levels are indicated by ** and *.

conditional on other covariates, the variable positively or negatively affects wages, and whether the mean of the variable is higher for males or females.

IV. Empirical Results

A. Standard Human Capital Model Variables

1. Pooled OLS Estimates

The estimates from a series of pooled OLS regression models are shown in Table 2. Moving from left to right in the table coincides with the inclusion of additional control variables, which are generally added in groups by variable classification. The primary coefficient of interest is that on the Female variable, which, due to the log specification of the dependent variable, represents the unexplained percentage gap in salary between male and female MBA graduates in the data set.

As shown in Column 1, in terms of raw differentials, females earn approximately 15.5 percent less than males in the sample. Not surprisingly, this gender gap is smaller than nationwide estimates since ours is of a more homogeneous group: MBAs. The inclusion of demographic variables slightly decreases the gap to below 14 percent (the specification in Column 2). Despite significantly lower average female job tenure (at the 1 percent level) and marginally lower work experience (at the 10 percent level), the inclusion of the employment experience variables, both years of work experience and tenure in the current job, does not alter the wage gap, even though total work experience is highly related to earnings in all specifications (Column 3). Because of the nonlinearity in returns to both experience and tenure, the combined returns to these variables flatten out somewhat by their sample means (about 10.5 and 4 years, respectively), resulting in relatively little effect on the earnings gap due to the modest differences in experience between men and women. Furthermore, these variables are highly correlated with age, and the coefficient on age decreased substantially in this specification. Excluding age from the regressions results in the work experience variables decreasing the gender earnings gap by 1.3 percentage points. As exemplified here, the fact that the order in which variables are added influences their perceived effect provides motivation for the decompositions performed in the next section. Under the decompositions, the work experience variables generally explain positive and significant portions of the gap. Still, the relatively small effect of work experience observed here contrasts with the findings of, for example, Brown and Corcoran (1997), who report that differences in work experience account for as much as about one-third of the 24 percent wage gap for women with some college education.[24]

Although more males are married and have children than females in the sample, including these control variables, as well as an interaction term of married with children, decreases the gender salary gap by 6.5 percent, from 13.8 to 12.9 percent;

24. This difference is due to the fact that men in our sample only had about 7 percent more work experience than did women, whereas in their sample of college graduates the difference exceeded 35 percent (Brown and Corcoran 1997, Table 1, p. 436).

surprisingly though, none of those variables significantly influences salaries. This outcome is in stark contrast to the labor market literature and to Bertrand et al. (2009) and Wood et al. (1993), who find a strong mother penalty for University of Chicago MBAs and University of Michigan lawyers, respectively. Although the inclusion of human capital variables in subsequent specifications does not change these relationships, married-with-children becomes strongly significant with the introduction of hours worked (Column 10) and then with the addition of employer characteristics (Column 11). The only child penalty we find is for unmarried women (but not unmarried men; from results not displayed here). Note that the average age in our sample was 34 for women and 35 for men, by which point female University of Chicago MBAs had already experienced a child penalty, according to Bertrand et al. (2009).

The model specifications presented in Columns 5 through 9 correspond to the addition of several human capital and ability variables. Columns 5 and 6 show an interesting effect of undergraduate variables—the gap decreases by two percentage points when controlling for college major choice and selectivity of undergraduate institution attended. The results concur with previous findings in the literature that choice of major is one reason for raw gender gaps; here, the effect is smaller than in previous studies (McDonald and Thornton 2007; Joy 2003; Daymont and Andrisani 1984), perhaps because the average individual in the sample is 12 years beyond college graduation. Although having attended a highly selective or moderately selective college strongly influences earnings, again despite being years after graduation, only those from the highly selective undergraduate institutions continue to have that effect in all specifications (not shown in Table 2).[25]

Despite the passage of time, undergraduate grades prove to strongly predict earnings, to the extent that increasing one's GPA by one letter grade increases their earnings by 17.2 percent (Column 6). Taking the respondent's undergraduate GPA into account sharply increases the unexplained salary gap back up to over 13 percent, since females in our sample report higher grades than their male counterparts.

Adding GMAT scores to the regression (Column 7) decreases the gender salary gap to 11.4 percent. These quantitative score results are similar to the relationship reported by Paglin and Rufolo (1990) between quantitative GRE scores and wages. Interestingly, the addition of MBA experience variables (Column 8) causes quantitative GMAT scores to lose significance and verbal GMAT scores to gain significance (not reported in Table 2), suggesting that perhaps part of the reason for GMAT scores' high returns is through their ability to get students into a better quality MBA program or for students to select particular areas of concentration. Though not shown, it is worth noting that while quantitative GMAT scores' significance continued to decrease with the addition of employment characteristics (in Columns 10 and 11), verbal GMAT scores' significance increased, suggesting that quantitative abilities may serve to sort individuals into particular types of jobs, while verbal abilities appear to independently affect earnings.

25. In the specification reported in column 11 of Table 2, the coefficient for highly selective undergraduate institutions was 0.06** and 0.032 for schools of moderate selectivity.

The addition of MBA variables (Column 8) dramatically reduces the wage gap by two percentage points. The effect of the graduate program variables parallels that of the undergraduate variables: Aspects of the program such as overall quality (we included Top 10 and Top 11–25) and the choice of particular study concentrations decrease the gap to about 9 percent. Both MBA program selectivity measures are strongly significant in all specifications. Only those who concentrated in finance earned more than others (similar to the result found by Grove and Hussey 2011).

As with undergraduate grades, adding MBA GPA (Column 9) slightly increases the size of the unexplained gap (even though those grades did not significantly differ by sex); unlike with undergraduate grades, though, MBA GPA loses significance when work characteristics are included. Respondents' work hours strongly influence wages (Column 10), reducing the unexplained gap by more than 25 percent or 2.6 percentage points; adding hours worked causes MBA grades to lose significance, but the married with children coefficient to gain significance (neither shown in Table 2). Finally, the inclusion of various characteristics of the individual's firm in Wave IV, namely company size, types and industries (Column 11), narrows the gender wage gap slightly to 6.5 percent. Those employed in big and medium sized firms and in the finance industry earn more compared to nonprofit or government employees who make significantly less. Although our results confirm the literature regarding the role of firm size on wages (Oi and Idson 1999), unlike Graham et al. (2000), firm size explains little of the gender salary gap because in our sample women and men with MBAs do not work in different sized firms (see Table 1). Lastly, women disproportionately work in occupations with a high percentage of women which strongly and negatively affects earnings (akin to MacPherson and Hirsch's 1995 finding of a small but important role in accounting for gender wage gaps, rather than the largest component of it as reported by Boraas and Rodgers 2003).

In sum, these detailed demographic, family, and human capital measures explain 58 percent of the raw gender wage gap $[(15.5-6.5)/15.5]$. However, because the order in which we add control variables affects these results, we now turn to the decomposition analysis to examine the simultaneous contribution of each set of our basic variables in explaining the male-female earnings gap.

2. Decomposition Analyses for Standard Human Capital Model Variables

As described in Section III, to determine the contribution of each category of variables in explaining the raw wage differentials, we conduct several decompositions. Initially, we perform Oaxaca-Blinder decompositions using coefficients from pooled (male and female) regressions; then, we compare these results to similar decompositions using coefficients from either male-only or female-only regressions, as well as Gelbach decompositions (2009). Table 3 illustrates the contribution of each individual category in explaining the wage gap, based on the coefficients from a pooled model. Columns 1–11 display, for each category individually, (1) the amount of explained contribution and (2) the percent of the contribution to the overall raw salary gap. Column 12 contains all categories together except the hours worked and job characteristics variables, which explain 59 percent of the gap. Finally, in Column

Table 3
Oaxaca-Blinder Decompositions of Gender Log Salary Gap: Explained Contributions of Human Capital Variables

Included Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Demographic/background	0.02**											0.00	0.00
	15.2%											5.4%	0.7%
Employment experience		0.01										0.02**	0.02**
		5.7%										12.9%	10.3%
Family variables			0.03**									0.02**	0.02**
			20.1%									12.4%	15.3%
Undergrad variables				0.03**								0.02**	0.01**
				16.2%								9.9%	8.0%
Undergrad GPA					−0.01**							−0.01*	−0.01*
					−9.1%							−5.4%	−4.8%
Quantitative GMAT						0.05**						0.01*	0.01
						30.7%						9.2%	4.2%
Verbal GMAT							0.01					0.00	0.00
							6.0%					1.5%	2.2%
MBA variables								0.02*				0.02**	0.01*
								13.4%				11.7%	8.0%
MBA GPA									0.005			0.00	0.00
									3.0%			1.3%	0.5%
Current job: hours										0.03**			0.02**
										16.3%			12.2%
Current Job: characteristics											0.03**		0.02**
											22.2%		12.2%

Notes: Reported are explained contribution and percent contribution (percentage of the raw gap explained). Each class of variables corresponds to variables from Table 1. Each specification includes 933 observations. ** and * indicates coefficient is statistically significantly different from zero at the 5 and 10 percent level.

13, all categories together explain 69 percent of the male-female earnings gap. So, for example, quantitative GMAT scores by themselves can explain 30.7 percent of the salary gap (Column 6) but only a marginally significant 9 percent with all variables except work hours (Column 12), and then lose significance with the addition of current job characteristics (Column 13). Several classes of variables individually explain modest but significant portions of the gap; quantitative GMAT scores explain almost a third of it, even more than the job variables can on their own. Altogether in Column 13, the most important classes of variables determining male-female wage differences are family variables (15.3 percent), hours worked and current job characteristics (each 12.2 percent), employment experience (10.3 percent), and undergraduate and MBA variables (each 8.0 percent).

We now investigate the robustness of these results by carrying out alternative decompositions, including a Gelbach decomposition and Oaxaca-Blinder decompositions using either male or female coefficients. Table 4 displays the results, as well as those from the previous decomposition for comparison. Conducting separate analyses by gender also allows us to determine whether men's and women's outcomes are influenced differently by their demographic and family backgrounds, educational and work experience, and current work environment.[26] Whereas five categories of variables are strongly significant in the pooled coefficient decompositions, only three are when using male coefficients and two with female coefficients; only one variable, hours worked per week, mattered for both men and women and employment experience was only significant in the pooled results. While hours matter for both men and women in explaining earnings, other significant effects on the wage gap are gendered: When we use the male coefficients, family circumstances and undergraduate experiences account for 16 and 9 percent of the gap, respectively; when we use the female coefficients, job characteristics account for 21 percent of the gap.

Furthermore, our results suggest that the effect of college quality on earnings is larger for males than for females, as the estimated explained contribution of these variables is significantly larger when male's coefficients are used than when female's coefficients are used. Alternatively, the positive return to quantitative GMAT scores appears to be driven solely by females and not males.[27] Finally, the results from the Gelbach decomposition are found to be very similar to the Oaxaca-Blinder decomposition using coefficients from the pooled model. The same sets of variables tend to be statistically significant predictors of the earnings gap, though the percentage of the gap explained by the Gelbach decomposition is generally slightly lower for each set of variables, and the overall gap explained is also lower (57.8 percent for the Gelbach decomposition as opposed to 68.9 percent for the pooled Oaxaca-Blinder decomposition).

In summary, then, while the effects of several variables are fairly robust to the specification of decomposition used, other variables affect the earnings gap in strikingly different ways for men and women drawn from a relatively homogeneous pool:

26. Full regression results separated by gender are available on request.

27. Recall that males have higher GMAT scores than females (Table 1). A larger percentage of the earnings gap is explained by quantitative GMAT scores when female coefficients are used in the decomposition as opposed to male coefficients (due to females' estimated high return to quantitative GMAT, compared to no return for males).

Table 4
Multiple Decompositions of Gender Log Salary Gap: Explained Contributions of Human Capital Variables

	Oaxaca-Blinder		Oaxaca-Blinder		Oaxaca-Blinder		Gelbach	
	Using pooled coefficients		Using male coefficients		Using female coefficients		Decomposition	
Variable (group)	contribution	% of gap	contribution	% of gap	contribution	% of gap	contribution	% of gap
Demographics/background	0.001	0.7%	−0.004	−2.6%	0.007	4.6%	−0.001	0.8%
Employment experience	0.016**	10.3%	0.012	7.8%	0.010	6.6%	0.015*	9.9%
Family variables	0.024**	15.3%	0.025**	15.8%	0.005	3.0%	0.020**	12.7%
Undergraduate variables	0.012**	8.0%	0.014**	8.8%	0.003	1.7%	0.012**	7.5%
Undergraduate GPA	−0.007*	−4.8%	−0.009	−5.9%	−0.011	−7.2%	−0.009**	−6.0%
Quantitative GMAT	0.006	4.2%	−0.008	−4.9%	0.019	12.3%	0.002	1.3%
Verbal GMAT	0.003	2.2%	0.006	3.8%	0.000	0.2%	0.004	2.4%
MBA variables	0.012*	8.0%	0.012	7.5%	0.007	4.7%	0.010	6.7%
MBA GPA	0.001	0.5%	0.001	0.6%	−0.001	−0.4%	0.001	0.5%
Current job hours	0.019**	12.2%	0.022**	14.0%	0.015**	9.7%	0.019**	12.0%
Current job characteristics	0.019**	12.2%	0.006	3.9%	0.032**	20.7%	0.018**	11.5%
Total	0.107**	68.9%	0.076**	48.8%	0.086**	55.5	0.090**	57.8%

Notes: For each variable or set of variables, reported are the net explained contribution of the raw salary gap and the percentage of the gap explained due to gender differences in values of each category of variables. Gelbach decomposition follows Gelbach (2009). Each specification includes all of the variables from Table 1, and includes 933 observations. ** and * indicate explained contribution is statistically significantly different from zero at the 5 and 10 percent level.

MBA recipients. Overall, the decompositions using slope coefficients estimated from both males and females resulted in a higher percentage of the raw gap explained (in particular the pooled Oaxaca-Blinder approach, explaining 69 percent of the gap), and the specification using male coefficients performed the worst (explaining only 49 percent of the gap).

B. Results for Human Capital Model, Noncognitive Skills, and Labor Market Tastes

1. Pooled OLS Estimates

Beyond the standard set of demographic and human capital variables discussed above, we now wish to investigate the role of noncognitive factors and preferences on incomes, as long speculated by social scientists. We specifically evaluate gender heterogeneity among proxies for some noncognitive skills, various measures of confidence, and work and life preferences. In Table 5, the initial OLS gender wage gap estimate of 9.5 percent (Column 1) corresponds to the specification of Column 9 in Table 2, including all human capital variables but not hours and job characteristics. In Columns 2–8 of Table 5, we sequentially add the following: self-assessed noncognitive skills (Column 2), confidence in quantitative and verbal abilities (Column 3), work and life preferences (Column 4), confidence of admission to MBA program (Column 5), confidence to "have the right connections" (Column 6), managerial expectations (Column 7), and nonmonetary job preferences (Column 8). All told, adding these variables to our full human capital model, in Specification 9, reduces the unexplained gap to just 4.3 percent.

The inclusion of all 15 noncognitive skills only slightly decreases the wage gap. Three of those traits are statistically significant: initiative and assertiveness positively influence earnings, whereas high ethical standards do so negatively. While for each of the three coefficients the magnitude and significance diminishes as more control variables are added, assertiveness loses significance in the final specification whereas ability to adapt theory to practice gains significance. Individually, while initiative, assertiveness, and high ethical standards significantly affect wages, their effects cancel each other out (the two former positively and the latter negatively); thus, we find no evidence of an important net role for these particular proxies for noncognitive skills in explaining wage inequality by sex (neither in the OLS results from Table 5, nor in either set of the decomposition results reported in Tables 6 and 7).[28]

Next, we consider the influence of five confidence measures on the gender earnings gap. The first indicates respondents' expectations about their quantitative and verbal scores on the GMAT exam, namely whether they expected to perform in a range from well above average to well below average. Including those expectations marginally narrows the gap but the confidence measures themselves are not significant (Table 5, Column 3). Also, respondents indicated how confident they were that they would be admitted to an MBA program. Although that variable positively and significantly influences wages when introduced in Column 5, it loses significance

28. Initiative serves to slightly increase the unexplained salary gap, since women report slightly more of that characteristic, whereas women's self-reported higher ethical standards decreased the unexplained gap.

Table 5
Pooled OLS Estimates of Gender Salary Gap: Addition of Noncognitive Skills and Labor Market Tastes

Variable	(1)	(2)	(3)	(4)	(5)
Female	−0.095**	−0.093**	−0.089**	−0.079**	−0.078**
	(0.026)	(0.027)	(0.027)	(0.027)	(0.027)
Noncognitive skills					
Initiative		0.056**	0.055**	0.048**	0.048**
		(0.023)	(0.023)	(0.023)	(0.023)
High ethical standards		−0.076**	−0.076**	−0.069**	−0.071**
		(0.023)	(0.023)	(0.023)	(0.023)
Communication skills		0.023	0.023	0.026	0.027
		(0.022)	(0.022)	(0.022)	(0.022)
Work with diversity		0.010	0.011	0.013	0.016
		(0.022)	(0.022)	(0.022)	(0.022)
Shrewdness		−0.006	−0.006	−0.012	−0.015
		(0.017)	(0.017)	(0.017)	(0.017)
Physical attractiveness		0.032	0.031	0.030	0.028
		(0.020)	(0.020)	(0.020)	(0.020)
Assertiveness		0.050**	0.050**	0.050**	0.050**
		(0.021)	(0.021)	(0.021)	(0.021)
Adapt theory to practice		0.029	0.028	0.030	0.034*
		(0.019)	(0.019)	(0.019)	(0.019)
Being a team player		0.027	0.025	0.027	0.028
		(0.022)	(0.022)	(0.022)	(0.022)

(continued)

Table 5 *(continued)*

Variable	(1)	(2)	(3)	(4)	(5)
Confidence: Ability					
Quantitative expectations			0.021	0.017	0.021
			(0.018)	(0.018)	(0.018)
Verbal expectations			−0.006	−0.001	0.002
			(0.018)	(0.018)	(0.018)
Work/Life Preferences					
Family important				0.019	0.019
				(0.039)	(0.039)
Career important				0.071**	0.072**
				(0.023)	(0.023)
Wealth important				0.070**	0.066**
				(0.030)	(0.030)
Relatives/friends important				−0.011	−0.010
				(0.023)	(0.023)
Confidence: Admissions					0.004**
					(0.002)
R-Square	0.30	0.34	0.34	0.35	0.36

(continued)

Table 5 *(continued)*

Variable	(6)	(7)	(8)	(9)
Female	−0.072**	−0.070**	−0.059**	−0.043*
	(0.027)	(0.027)	(0.026)	(0.025)
Confidence: Connections				
Knowing the right people: managerial success	0.016	0.016	0.014	0.021
	(0.014)	(0.014)	(0.014)	(0.013)
Managerial Goals				
High managerial responsibility		0.077	0.070	0.052
		(0.047)	(0.047)	(0.044)
Job preferences				
Nonmonetary job attributes			−0.011**	−0.009**
			(0.003)	(0.003)
Contributes to society			−0.118**	−0.087**
			(0.032)	(0.032)
Current job: Hours and characteristics				
Hours per week				0.012**
				(0.001)
Large firm				0.080**
				(0.035)

(continued)

Table 5 *(continued)*

Variable	(6)	(7)	(8)	(9)
Nonprofit				−0.129**
				(0.047)
Government				−0.172**
				(0.049)
Finance, insurance, & real estate				0.096**
				(0.037)
Percent female in occupation				−0.202**
				(0.082)
R-Squared	0.36	0.37	0.39	0.47

Notes: Dependent variable is log of annual salary of current, full-time (> = 35 hours/week) jobs of MBA graduates reported in Wave IV (933 observations in each regression). Models 2–9 include ability to organize, to motivate others, to capitalize on change, to delegate tasks, understanding business in other cultures, and good intuition; 5–9 include all variables from Model 4; 6–9 control for knowing the right people for admissions; 7–9 include medium managerial responsibility; 9 controls for self-employed, medium firm size, agriculture, forestries & fisheries, manufacturing, service industry, and public administration. Statistical significance of the coefficient at the 5 and 10 percent levels are indicated by ** and *.

Table 6
Oaxaca-Blinder Decompositions of Gender Log Salary Gap: Explained Contributions of Full Model

Included Variables	(1)–(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
Noncognitive skills	0.002	−0.006	0.000							−0.002	0.000
	1.1%	−3.7%	0.2%							−1.2%	0.0%
Confidence: Abilities	0.036**	0.031**		0.019**						0.006	0.006
	23.5%	20.2%		11.9%						4.1%	3.8%
Work/life preferences	0.013**	0.010*			0.010*					0.009*	0.003
	8.3%	6.4%			6.6%					6.1%	1.9%
Confidence: Admissions	0.000	0.000				0.000				0.001	0.000
	0.3%	0.3%				0.3%				0.6%	0.2%
Confidence: Connections	0.001	0.001					0.003			0.003	0.004
	0.4%	0.9%					1.8%			1.8%	2.3%
Managerial goals	0.003	0.003						0.001		0.001	0.001
	1.7%	2.1%						0.5%		0.8%	0.5%
Job preferences	0.022**	0.023**							0.015**	0.019**	0.016**
	13.9%	14.9%							9.9%	12.4%	10.0%
Basic human capital			0.089**	0.072**	0.083**	0.083**	0.086**	0.087**	0.074**	0.077**	0.066**
variables			57.4%	46.5%	53.5%	53.6%	55.6%	55.8%	47.7%	49.6%	42.5%
Current job characteristics											0.032**
& hours											20.5%
Total percentage explained		41.1%	57.7%	58.4%	60.1%	53.8%	57.4%	56.3%	57.6%	74.2%	81.6%

Notes: Reported are the explained contribution (using coefficients from a pooled model) and the percent contribution (percentage of the raw gap explained). Each class of variables includes variables from Table 1. Basic Human Capital Variables refers to all variables included in Table 2 other than Current Job variables. Coefficients in columns labeled 1–7 are from separate regression decompositions including only each class of variables separately. Each specification includes 933 observations. ** and * indicates coefficient is statistically significantly different from zero at the 5 and 10 percent level.

Table 7
Multiple Decompositions of Gender Log Salary Gap: Explained Contributions of Full Model

Variable (group)	Oaxaca-Blinder Using pooled coefficients		Oaxaca-Blinder Using male coefficients		Oaxaca-Blinder Using female coefficients		Gelbach Decomposition	
	contribution	% of gap	contribution	% of gap	contribution	% of gap	contribution	% of gap
Demographic/background	0.001	0.8%	−0.008	−5.0%	0.012	7.8%	0.000	−0.1%
Employment experience	0.017**	11.1%	0.014*	8.8%	0.011	6.9%	0.017*	10.8%
Family variables	0.019**	12.3%	0.020**	12.8%	−0.001	−0.7%	0.016**	10.6%
Undergraduate variables	0.014**	9.3%	0.014**	9.1%	0.008	5.0%	0.014**	9.0%
Undergraduate GPA	−0.009**	−5.6%	−0.010**	−6.6	−0.008	−5.3%	−0.010**	−6.3%
Quantitative GMAT	0.008	5.1%	−0.004	−2.4%	0.026	16.8%	0.006	3.8%
Verbal GMAT	0.004	2.4%	0.005	3.1%	0.002	1.4%	0.004	2.5%
MBA variables	0.010	6.7%	0.010	6.5%	0.008	5.1%	0.009	6.0%
MBA GPA	0.001	0.5%	0.001	0.4%	0.00	0.1%	0.001	0.5%
Current job hours	0.016**	10.4%	0.019**	12.1%	0.014**	9.1%	0.016**	10.3%
Current job characteristics	0.015**	10.0%	0.006	3.7%	0.026**	17.0%	0.015**	9.7%
Noncognitive skills	0.000	0.0%	0.000	−0.2%	−0.007	−4.7%	−0.002	−1.4%
Confidence: ability	0.006	3.8%	0.005	3.1%	−0.002	−1.0%	0.005	3.0%
Work/life preferences	0.003	1.9%	0.006	3.7%	−0.006	−3.9%	0.002	1.3%
Confidence: admissions	0.000	0.2%	0.001	0.3%	0.001	0.6%	0.000	0.1%
Confidence: connections	0.004	2.3%	0.003	2.2%	0.002	1.6%	0.003	2.2%
Managerial goals	0.001	0.5%	0.000	0.1%	0.001	0.5%	0.001	0.5%
Job preferences	0.016**	10.0%	0.013**	8.2%	0.020**	12.7%	0.015**	9.7%
Total	0.126	81.6%	0.093	0.60%	0.107	6.90%	0.111	72.2%

Notes: For each variable or set of variables, reported are the net explained contribution of the raw salary gap and the percentage of the gap explained due to gender differences in values of each category of variables. Gelbach decomposition follows Gelbach (2009). Each specification includes all of the variables from Table 1 and includes 933 observations. ** and * indicate explained contribution is statistically significantly different from zero at the 5 and 10 percent level.

thereafter (not shown here). Finally, we probe two confidence indicators associated with having the right connections. "Knowing the right people" as a criterion for getting into an MBA program is positive but not significant. On the other hand, the extent to which individuals think they "know the right people" as a criterion for being a successful manager strongly influences wages in all specifications. The addition of these two connection measures decreases the gap by about 8 percent, from 7.8 percent to 7.2 percent (Columns 5 and 6).

The final set of nontraditional labor market variables that might help explain the observed male-female salary gap relate to labor market tastes regarding family, careers, and jobs. Including work and life preferences decreases the wage gap by a full percentage point, from 8.9 to 7.9 percent (Column 4). Career importance remains significant in all specifications, but the priority of wealth loses significance in the final specification (not shown in Table 5). Job aspirations, in terms of expected managerial status (whether respondents reported expecting to be an entry-level manager or a mid-to-upper-level manager relative to a nonmanager) are not significant, yet slightly lower the gap when included (Column 7).

We include two job preference categories: (1) an index of nonmonetary job attributes (for instance, friendly people, job security, chances for promotions, hours are good, clear responsibilities) collected from the Wave I surveys and (2) the importance of making a positive contribution to society when choosing their current job. Both are strongly significant and negative in all specifications (Column 8), suggesting that these characteristics serve as compensating differentials. They also appear to importantly account for the gender earnings gap, decreasing the unexplained portion by 1.1 percentage points, which corresponds to almost 16 percent of the remaining gap.

Collectively, additional variables representing preferences, confidence, and self-assessed noncognitive skills, when added to the initial set of background and human capital variables, serve to substantially decrease the gender gap, from 9.5 percent down to 5.9 percent. In comparison, the addition of these less traditional variables is shown to be more effective than was the inclusion of several actual job characteristics, which resulted in an unexplained difference of 6.5 percent (Table 2). In our final model specification (Column 9) in Table 5, in which we add hours worked and other current job characteristics (as in Table 2), the unexplained gender wage gap narrows to a marginally significant 4.3 percent; that represents merely 28 percent of the raw differential found in our sample, so this model explains over 70 percent of the gap.

Of the novel gender heterogeneity variables, seven individually influence wages in the final specification: three noncognitive skills (initiative, assertiveness, and high ethical standards), the importance of career, knowing the right people as a key to managerial success, and preferences for (1) jobs with nonmonetary attributes and (2) work that contributes to society. The earnings-gap-reducing role of "knowing the right people" for MBAs is especially interesting since it has been shown to disadvantage female business leaders (Bartlett and Miller 1985).

2. Decomposition Analyses

Next we use decomposition analysis to isolate the overall effects of particular classes of less traditional variables, namely various proxies for or measures of confidence, expectations, and preferences, as we did with the more basic human capital model in Tables 3 and 4. Table 6 depicts the sequential addition of these variables using pooled regression coefficients. We begin including each class of variables separately in the first column, labeled 1–7 to signal that each of these results corresponds to carrying out separate regressions with only that set of variables. The second column, labeled 8, includes decomposition results for a model containing all of the novel variables without our full set of human capital variables. Then, the next seven Columns 9–15 include our full set of human capital variables (excluding current employment characteristics), adding in separately each class of nontraditional variables.

Although at least some variables in four of the nontraditional categories were significant in earnings regressions (Table 5), only two groups as a whole significantly explain differences in men's and women's salaries when human capital variables are included (Table 6, Column 16): work/life preferences and job preferences. Note that, for example, ability confidence (not significant in OLS results reported in Table 5) loses significance with the inclusion of the human capital variables (in Column 16), suggesting that self-evaluation of one's managerial noncognitive skills is embodied in other human capital variables. Job Preferences (prioritizing nonmonetary job attributes and employment that contributes to society) are strongly significant in all decomposition specifications shown in Table 6, explaining 10 percent of the gender wage gap when all variables are included (Column 17). Work/life preferences, though, matter only until job characteristics are included (Column 17). Thus, work/life preferences, in particular the importance respondents attributed to career and wealth, seem to predict actual selection into jobs.

Finally, in Table 7, like in Table 4, we display the Oaxaca-Blinder and Gelbach decompositions with all variables included. As just discussed, of the new classes of noncognitive variables only job preferences significantly explain the wage gap (in all four specifications), although such preferences matter much more when using the female coefficients (accounting for 13 percent of the gap) than with the male coefficients (8 percent). Beyond that, even more notable than from the human capital model analysis in Table 5, is the starkness of the sources of gender differences: only hours worked and job preferences are commonly important in the decompositions using either male or female coefficients; job characteristics only significantly explain the gap with female coefficients and account for 17 percent of it.[29] Four other categories explain the gap using male coefficients—family circumstances (13 percent), undergraduate variables and grades (9 and -7 percent, respectively), and prior employment experience (9 percent). Note that employment experience and undergraduate GPA only gained significance in Table 7 with the presence of the nontraditional classes of variables (see, by contrast, Table 4). Finally, we should note that adding

29. That is, hours worked are positively related to earnings and nonmonetary job preferences are negatively related to earnings in both female-only and male-only regressions. Since males report more hours worked and females report greater preferences toward nonmonetary job attributes, both explain a portion of the gap when either male or female coefficients are used in the Oaxaca-Blinder decompositions. Interestingly, actual job characteristics are more important to female earnings than they are to male earnings, so male-female differences in these variables result in a larger portion of the earnings gap explained when female coefficients are used in the decomposition than when male coefficients are used.

these nontraditional variables increased the total explained percentage of the gender wage gap by 11–13 percentage points.[30]

In sum, then, the addition of noncognitive skills and labor market tastes accounts for about a quarter of our explained gender earnings gap[31]; quite remarkably, this approximately equals that accounted for by hours worked and current job characteristics. The results in Table 7 also serve to indicate the way that experiences, noncognitive skills, and priorities distinctly shape men's and women's outcomes—even among a group of relatively homogeneous individuals, MBAs. Women's socially desirable choices of jobs that contribute to society and personality traits, namely high ethical standards, significantly reduce their earnings.

V. Robustness Checks

In this section we discuss some additional specifications carried out to check the robustness of our results. First, throughout our previous analysis we have used annual salary as the dependent variable. Although this specification of earnings has been used in other studies of highly educated professionals (see Altonji and Blank 1999), the number of hours an individual works may be endogenously determined. To the degree that females often work fewer hours than males, this may be of particular concern in the context of explaining the gender earnings gap. However, the gap in hours worked is relatively small among our sample of MBAs. Nonetheless, to investigate the effect of our choice of dependent variable, we repeated our analysis from Tables 2, 5, and 7 using hourly wage instead of annual earnings. These results are given in Appendix Tables A1 through A3. It can be seen that, throughout our sequential OLS specifications, the coefficients on the female variable are a little smaller than the coefficients obtained from the corresponding annual salary regressions in Tables 2 and 5. This is not surprising, since including hours explicitly in Table 2 caused the gap to decrease, and using hourly wage effectively controls for hours in all specifications. Thus, the influence of variables in our OLS regressions changes very little whether our dependent variable is annual salary or hours worked. Decomposition results also indicate that the choice of hourly wage or annual salary is generally not a pivotal one, since the contribution to the explained gap of each set of variables is generally very similar with either dependent variable.[32]

In addition to annual salary and hourly wages, we also use hours worked as our dependent variable, despite the relatively small hours gap of 1.32 hours per week

30. The difference between the total explained percentage of the gender wage gap from Tables 4 and 7 is 11.2 percentage points with the male coefficients (60.0–48.8), 13.5 with the female coefficients (69.0–55.5), 12.7 (81.6–68.9) using pooled coefficients, and 14.4 (72.2–57.8) with the Gelbach decompositions.

31. Adding the percentage of the gap explained by the last seven categories in Table 7 equals 18.7 percent which is 23 percent of the total explained gap of 81.6 percent.

32. One interesting difference is that the amount of the gender gap explained by the Oaxaca-Blinder decomposition using female coefficients increases substantially when hourly wage is used as the dependent variable, while the percentage explained when male coefficients are used decreases under the hourly wage specification. Most notably, quantitative GMAT scores account for a full 24 percent of the explained wage gap under the female coefficient specification.

(results available upon request). Oaxaca-Blinder decompositions using pooled coefficients of the gender gap in either hours or log hours result in a total explained contribution of 41 to 42 percent of the gap. With either hours or log hours under the full model, the categories of variables found to be statistically significant at the 5 percent level were job characteristics, work/life preferences and family variables, whereas noncognitive skills and undergraduate GPA were significant at the 10 percent level.

Second, although our sample is already fairly selective, including only recent MBAs working more than 35 hours per week, it may be possible that outliers with particularly high or low earnings affect our results. To test this, we dropped from the sample individuals with the top and bottom 2 percent of earnings for both males and females and repeated our analysis. The results were not meaningfully different (results available from authors upon request).

Finally, the amount of the gender gap explained by particular variables may vary across salary ranges. We use quantile regression to conduct this analysis. Specifically, we performed quantile (least absolute value) regressions at the 25th, 50th (median), and 75th percentile of earnings. Interestingly, both the raw gap and the remaining unexplained gap are affected by location within the earnings distribution. In particular, the largest raw gap, 18.7 percent, exists for "low earners," those at the 25th percentile, compared with 15.5 and 13.5 percent, for the 50th and the 75th percentiles. After including our full set of covariates, the unexplained gap shrinks to 6.1 percent at the 25th percentile, 4.3 percent at the 50th percentile, and only 1.3 percent at the 75th percentile. Thus, the covariates do a better job of explaining earnings differences at the upper part of the distribution (about 96 percent of the raw gap). That said, however, the impact of respective groups of variables is quite similar across percentiles.[33]

VI. Discussion

Three stark conclusions emerge from this study of how the gender earnings gap is affected by the inclusion of previously omitted variables, namely a broad array of noncognitive skills and indicators of work/life preferences, using the GMAT Registrant Survey, a data set especially rich in traditional human capital variables. First, statistically significant gender heterogeneity exists (at the 5 percent level) among 7 of 15 self-reported noncognitive skills, one confidence measure, and among five labor market taste variables.[34] Secondly, decomposition analysis reveals gender heterogeneity of factors significantly associated with the wage gap—with

33. Notable exceptions are GMAT scores and MBA variables, which have a significant (decreasing) effect on the gap at the 75th percentile and very little effect at the 25th percentile.

34. Among noncognitive skills, women self-reported more initiative, ethical behavior, communication skills, better ability to organize, motivate others, and work with diversity. Men reported greater shrewdness and ability to adapt theory to practice. Among the labor market taste variables, women put more importance on relatives/friends, nonmonetary job characteristics, and a job that contributes to society, whereas men placed more value on wealth. In addition, men exhibited greater confidence in doing well on the quantitative part of the GMAT.

male coefficients used in Oaxaca-Blinder decompositions, the traditional human capital variables of employment experience, family variables, and undergraduate experiences[35] matter (but not with female coefficients), whereas current job characteristics matter when female coefficients are used (but not with male coefficients).[36] Finally, beyond a rich set of human capital variables, the noncognitive skills and work/life preference variables in our specification account for a quarter of the "explained" gender wage gap, from 69 to 82 percent. Our results, along with the other work connecting personality traits and preferences to earnings and with the growing gender heterogeneity literature, attempt to more fully measure "individual abilities," as envisioned in the original human capital model by Becker (1964).

MBA women appear to incur penalties for "good citizen" behavior, according to our findings and those of three other noncognitive skills-wage gap studies. While we observe gender heterogeneity regarding numerous stereotyped variables, namely assertiveness, shrewdness, physical attractiveness, initiative, and the importance of wealth and friends, our decomposition results indicate that two novel variables with good citizen characteristics are associated with the male-female earnings gap: women's higher ethical standards and their priority for jobs that contribute to society.[37] Other noncognitive skills-wage gap studies provide evidence that might similarly be construed as penalties for "good citizen" behavior: wider gender wage gaps result from greater importance put on people and family (Fortin 2008)[38] and higher female levels of agreeableness (Mueller and Plug 2006; Braakmann 2009). Unlike Fortin's (2008) conclusion that men's greater priority of work and money helps account for the wage gap, the MBA men and women in our sample place similar importance on career; although men in our sample place more importance on wealth, that difference is not associated with the wage gap.

Human capital models typically explain gender wage gaps as the consequence of females' lower human capital investment and reduced labor market attachment (Polachek 2006). Although differences in MBA experiences do not help explain the earnings gap, the gap is importantly accounted for by males' college experiences and by their greater job tenure and work experience.[39] Reduced labor market attachment, most importantly due to the presence of children, influences male-female wage gaps among Harvard undergraduates (Goldin and Katz 2008), University of Michigan lawyers (Noonan, Corcoran and Courant 2005), and University of Chicago MBAs (Bertrand et al. 2009). In stark contrast with these three studies, married MBA women in our sample (who work at least 35 hours a week) suffer no wage

35. Notably, men's undergraduate experiences (institution quality, grades, and major among others), though not their MBA education, explain about 10 percent of the gender earnings gap, despite matriculating a decade earlier on average.
36. This is akin to Semykina and Linz's (2007) findings that showed Russian women's, but not men's, personalities strongly affected their earnings.
37. Job attributes and a smaller self-reported ability to adapt theory to practice by females are also significantly related to the gap.
38. While we also find that women put significantly more importance on "family and friends" (see Table 1), those priorities are not significantly associated with the gender wage gap in our decomposition analysis.
39. Females' lower tenure and experience explains 1.7 percentage points of the gap in our decompositions analysis, which is substantial and at least marginally significant (see Table 7).

penalties relative to MBA women without children. In addition, MBA fathers earn more than unmarried males.[40]

Why do our results differ? Since large gender disparities had already emerged by the third year after graduation for the University of Chicago MBAs (Bertrand et al. 2009), the effect of the presence of children is not accounted for by our analysis ending 3–4 years after obtaining the degree. We speculate that for MBA women with degrees from typical non-elite MBA programs, having such education increased their intra-household earnings beyond the usual imbalance which often led women to bear greater household responsibilities. So, despite the extraordinarily high mean female earnings of University of Chicago MBAs, those with less labor market attachment may have had husbands with even higher earnings. In addition, the Bertrand et al. (2009) analysis includes part-time workers (which were between two and five times more likely to be female, depending on the number of years since graduation), whereas our analysis focuses on full-time (35+ hours per week) workers.

As scholars investigating educational and labor market outcomes[41] continue to seek to remedy the call for missing data and unobserved heterogeneity with noncognitive variables, they face challenges. First, no consensus exists about what constitutes noncognitive skills or how to measure them (see Borghans et al. 2008). Next, compared with the stability of cognitive ability (as of late adolescence), various noncognitive skills appear to evolve into middle age. Thus, for example, it will be of great interest to determine the efficacy of the GRE's newly adopted noncognitive skills assessment ("personal potential index"), which the ETS thinks will make the test more relevant to business schools in predicting graduate school outcomes (De Vise 2009).

Particular limitations of our analysis include the fact that the last survey occurred less than four years, on average, after completing the MBA program, when women's average age was 34 and men's 35. Differences in lifetime returns by gender may vary substantially over a longer time frame, especially with the presence of children. We should reiterate that we report estimated relationships between our novel variables (various confidence measures, a variety of work/life preferences, managerial expectations, and fifteen noncognitive skills, such as physical attractiveness, assertiveness, and initiative) and the gender pay gap, not causal links. Regarding the quality and reliability of our data, while we use actual rather than self-reported GMAT scores, several other variables are self-reported. Our data appropriately contain self-reported expectations and preferences (especially when they were reported prior to the observed earnings outcome). However, regarding the 15 noncognitive managerial skills and attributes, it would be desirable to have both self-reported data, since self-perception matters, and external assessments.

40. In all decompositions, except the one where female coefficients are used, family variables significantly explain a nontrivial amount of the gap.

41. Regarding educational outcomes, see, for example, Carneiro and Heckman (2003) and for labor market outcomes, see, for example, Murnane, Willett, Braatz and Duhaldeborde (2001), Heckman, Stixrud and Urzua (2006), and Groves (2005).

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Appendix

Table A1
Pooled OLS Estimates of Gender Wage Gap: Human Capital Variables

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female	−0.128**	−0.111**	−0.110**	−0.093**	−0.073**	−0.091**	−0.077**
	(0.023)	(0.024)	(0.023)	(0.024)	(0.024)	(0.024)	(0.024)
Demographic/background							
Age		0.086**	0.038	0.031	0.044	0.046	0.045
		(0.018)	(0.029)	(0.029)	(0.029)	(0.028)	(0.028)
Asian		0.029	0.044	0.048	0.004	−0.001	0.011
		(0.035)	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)
Black		−0.007	0.002	0.008	−0.004	0.021	0.062
		(0.038)	(0.037)	(0.037)	(0.037)	(0.037)	(0.038)
Hispanic		0.023	0.030	0.037	0.025	0.030	0.048
		(0.032)	(0.032)	(0.032)	(0.031)	(0.031)	(0.031)
Mother's education		0.006*	0.007*	0.007*	0.005	0.004	0.004
		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Father's education		0.005	0.005	0.006	0.004	0.004	0.002
		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Employment experience							
Experience			0.032**	0.030**	0.025**	0.026**	0.023**
			(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Tenure			−0.003	−0.004	−0.005	−0.006	−0.004
			(0.006)	(0.006)	(0.006)	(0.006)	(0.006)

Family variables							
Married				−0.001	−0.002	−0.007	−0.003
				(0.028)	(0.028)	(0.028)	(0.027)
Children				−0.121	−0.109	−0.114	−0.100
				(0.078)	(0.077)	(0.076)	(0.076)
Married*children				0.183**	0.180**	0.185**	0.173**
				(0.083)	(0.081)	(0.080)	(0.080)
Undergraduate variables							
Highly selective					0.162**	0.167**	0.131**
					(0.030)	(0.030)	(0.031)
Selective					0.057**	0.059**	0.044*
					(0.026)	(0.026)	(0.026)
Engineering major				0.089**	0.102**	0.081**	
					(0.034)	(0.033)	(0.034)
Grade point average					0.122**	0.087**	
						(0.027)	(0.028)
Ability measures							
Quantitative GMAT						0.003	
							(0.002)
Verbal GMAT							0.005**
							(0.002)
R-Square	0.03	0.08	0.11	0.12	0.16	0.18	0.20

(continued)

Table A1 *(continued)*

Variable	(8)	(9)	(10)
Female	−0.060**	−0.061**	−0.056**
	(0.024)	(0.024)	(0.024)
MBA Variables			
Executive program	0.126**	0.126**	0.111**
	(0.049)	(0.049)	(0.049)
Top 10	0.258**	0.250**	0.261**
	(0.049)	(0.049)	(0.049)
Top 11–25	0.092**	0.098**	0.116**
	(0.040)	(0.041)	(0.040)
Finance concentration	0.101**	0.100**	0.066**
	(0.032)	(0.032)	(0.032)
MIS concentration	0.101**	0.101**	0.083*
	(0.049)	(0.049)	(0.048)
Cumulative GPA		0.023	0.018
		(0.042)	(0.042)

Current job: hours and characteristics			
Large firm			0.077**
			(0.036)
Medium firm			0.060*
			(0.034)
Nonprofit			−0.117**
			(0.046)
Government			−0.167**
			(0.048)
Finance, insurance & real estate			0.107**
			(0.037)
Percent female in occupation			−0.227**
			(0.083)
R-Square	0.25	0.25	0.29

Notes: Dependent variable is log of hourly wage of current, full-time (> = 35 hours/week) jobs reported in Wave IV. Each regression includes 933 observations. Models 2–10 include age^2; 3–10 include experience^2 and tenure^2; 5–10 control for social science, humanities, and science major; 8–10 include the variables from 7, whether the program was part-time and the following concentrations: marketing, accounting, international, and other; 10 includes whether the individual is self-employed and dummies for the following industries: agriculture, forestries, & fisheries, manufacturing, service, and public administration. Statistical significance of the coefficient at the 5 and 10 percent level is indicated by ** and *.

Table A2
Pooled OLS Estimates of Gender Wage Gap: Addition of Noncognitive Skills and Labor Market Tastes

Variable	(1)	(2)	(3)	(4)
Female	−0.061**	−0.057**	−0.053**	−0.051**
	(0.024)	(0.025)	(0.025)	(0.025)
Noncognitive skills				
Initiative		0.045**	0.044**	0.044**
		(0.021)	(0.022)	(0.022)
High ethical standards		−0.067**	−0.067**	−0.066**
		(0.021)	(0.021)	(0.022)
Communication skills		0.014	0.014	0.015
		(0.021)	(0.021)	(0.021)
Work with diversity		0.006	0.007	0.008
		(0.020)	(0.020)	(0.020)
Shrewdness		−0.004	−0.004	−0.006
		(0.016)	(0.016)	(0.016)
Physical attractiveness		0.023	0.022	0.022
		(0.019)	(0.019)	(0.019)
Assertiveness		0.027	0.028	0.027
		(0.020)	(0.020)	(0.020)
Adapt theory to practice		0.029	0.027	0.028
		(0.018)	(0.018)	(0.018)
Ability to motivate		0.014	0.014	0.013
		(0.019)	(0.019)	(0.019)
Being a team player		0.019	0.017	0.016
		(0.021)	(0.021)	(0.021)
Confidence: ability				
Quantitative expectations			0.019	0.018
			(0.017)	(0.017)
Verbal expectations			−0.002	−0.001
			(0.017)	(0.017)
Work/life preferences				
Family important				0.032
				(0.037)
Career important				0.006
				(0.022)
Wealth important				0.028
				(0.029)
Relatives/friends important				−0.001
				(0.022)
R-Square	0.25	0.27	0.27	0.27

(continued)

Table A2 *(continued)*

Variable	(5)	(6)	(7)	(8)	(9)
Female	−0.051**	−0.044*	−0.043*	−0.032	−0.033
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
Confidence: admissions	−0.002	−0.001	−0.001	−0.001	−0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Confidence: connections					
Knowing the right people—		0.029*	0.028*	0.034**	0.034**
managerial success		(0.016)	(0.016)	(0.016)	(0.015)
Managerial goals					
High managerial responsibility			0.054	0.049	0.038
			(0.045)	(0.044)	(0.044)
Job preferences					
Nonmonetary job attributes				−0.008**	−0.009**
				(0.003)	(0.003)
Contributes to society				−0.143**	−0.106**
				(0.031)	(0.032)
Current job: hours and characteristics					
Large firm					0.068*
					(0.036)
Nonprofit					−0.094**
					(0.047)
Government					−0.144**
					(0.049)
Finance, insurance, & real estate					0.112**
					(0.037)
Public administration					0.110*
					(0.057)
Percent female in occupation					−0.178**
					(0.082)
R-Squared	0.28	0.28	0.29	0.31	0.34

Notes: Dependent variable is log of hourly wage of current, full-time (> =35 hours/week) jobs reported in Wave IV (933 observations). Models 2–9 include ability to organize, to capitalize on change, to delegate tasks, understanding business in other cultures, and good intuition; 5–9 include all variables from Model 4; 6–9 include whether one had confidence in knowing the right people for admissions; 7–9 controls for medium managerial responsibility; 9 includes whether the individual was self-employed, employed at a medium sized firm and the following industries: agriculture, forestries & fisheries, manufacturing, service, and public administration. Statistical significance of the coefficient at the 5 and 10 percent level is indicated by ** and *.

Table A3
Multiple Decompositions of Gender Log Wage Gap: Explained Contributions of Full Model

	Oaxaca-Blinder Using pooled coefficients		Oaxaca-Blinder Using male coefficients		Oaxaca-Blinder Using female coefficients		Gelbach Decomposition	
Variable (group)	contribution	% of gap	contribution	% of gap	contribution	% of gap	contribution	% of gap
Demographic/background	0.001	0.6%	−0.007	−5.6%	0.010	8.2%	0.000	−2.3%
Employment experience	0.016**	12.7%	0.013	9.9%	0.015	11.7%	0.016*	12.4%
Family variables	0.022**	17.3%	0.021**	16.3%	0.009	7.1%	0.020**	15.9%
Undergraduate variables	0.015**	11.4%	0.015**	11.4%	0.010	7.5%	0.014**	11.1%
Undergraduate GPA	−0.008**	6.4%	−0.010**	−7.9%	−0.005	−4.0%	−0.009**	−7.0%
Quantitative GMAT	0.006	4.6%	−0.007	−5.7%	0.030*	23.7%	0.004	3.3%
Verbal GMAT	0.004	0.3%	0.005	4.0%	0.002	−1.5%	0.004	3.1%
MBA Variables	0.010	7.5%	0.009	7.1%	0.009	−7.0%	0.009	6.8%
MBA GPA	0.000	0.1%	0.002	1.8%	−0.000	−0.1%	0.000	0.1%
Current job characteristics	0.011*	8.7%	0.003	2.0%	0.023**	17.7%	0.011*	8.4%
Noncognitive skills	0.002	1.2%	0.001	0.4%	−0.004	−2.8%	0.000	0.0%
Confidence: ability	0.006	4.8%	0.006	5.1%	−0.006	−5.0%	0.005	4.1%
Work/life preferences	0.001	0.5%	0.005	3.7%	−0.011	−8.3%	0.000	0.0%
Confidence: admissions	0.000	0.0%	0.000	0.3%	0.001	0.7%	0.000	0.0%
Confidence: connections	0.004	2.9%	0.004	2.8%	0.003	2.2%	0.004	2.8%
Managerial goals	0.001	0.4%	0.000	0.0%	0.001	0.7%	0.001	0.4%
Job preferences	0.016**	12.8%	0.014**	10.9%	0.019**	14.7%	0.016**	12.6%
Total	0.106	82.5%	0.070	54.9%	0.105**	82.4%	0.094	73.8%

Notes: For each variable or set of variables, reported are the net explained contribution of the raw wage gap and the percentage of the gap explained due to gender differences in values of each category of variables. Gelbach decomposition follows Gelbach (2009). Each specification includes all of the variables from Table 1, and includes 933 observations. ** and * indicate explained contribution is statistically significantly different from zero at the 5 and 10 percent level.