

Dynamics of the Gender Gap for Young Professionals in the Financial and Corporate Sectors

by

Marianne Bertrand (University of Chicago Booth School of Business, NBER, CEPR and IZA)

Claudia Goldin (Harvard University and NBER)

Lawrence F. Katz (Harvard University and NBER)

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Abstract

This paper assesses the relative importance of various explanations for the gender gap in career outcomes for highly-educated workers in the U.S. corporate and financial sectors. The careers of MBAs, who graduated between 1990 and 2006 from a top U.S. business school, are studied to understand how career dynamics differ by gender. Although male and female MBAs have nearly identical labor incomes at the outset of their careers, their earnings soon diverge, with the male annual earnings advantage reaching almost 60 log points at ten to 16 years after MBA completion. We identify three proximate factors that explain the vast majority of the large and rising gender gap in earnings: differences in training prior to MBA graduation; differences in career interruptions; and differences in weekly hours. The presence of children is the main contributor to the lesser job experience, greater career discontinuity and shorter work hours for female MBAs. Disparities in the productive characteristics of male and female MBAs are small, but the pecuniary penalties from shorter hours and any job discontinuity are enormous for MBAs.

I. Introduction

Positions in the business and financial sectors have commanded exceptionally high earnings in recent years and attracted extraordinary talent.¹ Professionals in these sectors often have a master's in business administration (MBA) and the degree has grown in popularity among graduates of the best universities and colleges. Among individuals with a BA from a selective institution, those earning an MBA within ten years of graduation increased from 4.3 percent for those finishing college in the early 1970s to 7.1 percent in the early 1990s.² During the same period, the share of MBAs among the graduates of selective undergraduate institutions earned by females increased by more than a factor of three.³ The fraction female among *all* MBAs increased from 1970 to 2006 by a factor of ten, rising from 4 percent to 43 percent.⁴

Despite the narrowing of the gender gap in business education, there is a growing sense that women are not getting ahead fast enough in the corporate and financial world. Bertrand and Hallock (2001) document the under-representation of women among the five highest paid executives in Execucomp's (S&P 1500) firms from 1992 to 1997. Only about 2.5 percent of the executives in their sample are women, and the under-representation is especially severe at the highest levels of the corporate ladder. The number of female CEOs among Execucomp firms

¹ Among men who received their BAs from Harvard University around 1970, 5 percent had positions in the financial sector 15 years later in 1985. But among those who graduated around 1990, fully 15 percent worked in the financial sector in 2005. Considering both the corporate and financial sectors the change was from 22.1 percent to 38.5 percent across the two graduating cohorts. The increase for women was from 11.7 percent to 22.5 percent. The premium to working in the financial sector among Harvard graduates was a whopping 195 percent and the premium in the corporate sector (executive and management jobs) was 25 percent relative to the average of other occupations in 2005. See Goldin and Katz (2008) on the Harvard data and Philippon and Reshef (2009), more generally, for an analysis of the growth of the financial sector across the past century.

² The 2003 National Survey of College Graduates (NSCG) is used to obtain the fraction of BAs graduating from Research University I and Liberal Arts I colleges (Carnegie classifications) from 1970 to 1973 and from 1990 to 1993 who received an MBA within ten years of graduating. In this manner we exclude those who obtained an MBA in mid-career through an executive MBA program and those who obtained an MBA without having graduated from a U.S. university.

³ Using the NSCG and restricting the sample to BAs from selective universities and colleges gives 12.7 percent in 1970-73 and 39.5 percent in 1990-93 for the fraction female among those earning MBAs.

⁴ In fact, the fraction female among all graduating MBAs has exceeded 30 percent for each of the past 25 years (*Source*: U.S. Department of Education, NCES, *Digest of Education Statistics*, includes all masters in business fields). The fraction has been lower in the top MBA programs. It exceeded 30 percent at Harvard Business School starting around 2000 (HBS website) and has only just exceeded 30 percent at the University of Chicago Booth School of Business (UC Booth administrative data).

increased from just four in 1992 to 34 in 2004, according to Wolfers (2006), but women still represent only 1.3 percent of the CEO-year observations in his sample.

Various explanations have been proposed for women's underperformance in the corporate and financial sectors. Experimental evidence suggests that women have less taste for the highly-competitive environments in top finance and corporate jobs (Niederle and Vesterlund 2007), and female MBAs may be less willing to aggressively negotiate for pay and promotion (Babcock and Laschever 2003). MBA women may be subject to implicit or explicit gender discrimination (Bertrand, Chugh, and Mullainathan 2005), and even talented female MBAs may encounter difficulty getting recognized in male-dominated workplaces.⁵ Women may also fall behind because of the career-family conflicts arising from the purportedly long hours, heavy travel commitments and inflexible schedules of most high-powered finance and corporate jobs.

This paper speaks to the relative importance of these alternative explanations of the gender gap in career outcomes for highly-educated personnel in the U.S. corporate and financial sectors. We study the careers of MBAs who graduated between 1990 and 2006 from a top U.S. business school—the Booth School of Business of the University of Chicago—and how career dynamics differ by gender. We explore the evolution of the gender gap in earnings and labor supply for young professionals employed primarily in corporate, consulting and financial services jobs.

We find that at the outset of their careers male and female MBAs have nearly identical labor incomes. Their earnings, however, soon diverge. The male annual earnings advantage reaches 30 log points five years after MBA completion and almost 60 log points ten to 16 years after MBA completion. The share of female MBAs not employed also rises substantially in the decade following MBA completion with 13 percent of the women not working at all at nine years after MBA completion as compared with 1 percent of the men.

Most interesting is why female MBAs have not done as well as their male peers. We

⁵ See also Bell (2005), who finds that women-led firms (e.g., firms where the CEO or the chairman of the board is a women) have a higher share of female executives in the other “top five paid” positions and remunerate these female executives more than non-women led firms do.

identify three proximate reasons for the large and rising gender gap in earnings that emerges within a few years of MBA completion: differences in business school courses and grades, differences in career interruptions, and differences in weekly hours worked. These three determinants combined can explain 84 percent of the 31 log point raw gender gap in earnings pooling across all the years following MBA completion. Because the relative importance of each factor changes with years since MBA completion, we explore the evolution in the earnings gap by sex by time since obtaining the MBA. We also compare women without any career interruptions and any children to all men.

Male and female MBAs begin their careers with somewhat different training. Men take more finance courses and have higher GPAs in business school. Gender differences in grades and courses are not large but contribute to the earnings gap because of large labor market returns to these components of MBA training. The large growth in the gender gap in earnings for MBAs during their first 15 years out is mainly a consequence of gender differences in career interruptions and weekly hours worked. Women have more career interruptions and work shorter hours, including more work in part-time positions and self-employment. Although these differences are modest, the remuneration disparity they entail is exceptionally large. The relationship between income and time off is highly non-linear for those in our sample. *Any* career interruption—a period of six months or more out of work—is costly in terms of future earnings, and at ten years out women are 22 percentage points more likely than men to have had at least one career interruption. Deviations from the male norm of high hours and continuous labor market attachment are greatly penalized in the corporate and financial sectors.

The presence of children is the main contributor to the lesser job experience, greater career discontinuity and shorter work hours for female MBAs. Across the first 15 years following the MBA, women with children have about an eight month deficit in actual post-MBA experience compared with the average man, while woman without children have a 1.5 month deficit. Similarly women with children typically work 24 percent fewer weekly hours than the average male; women without children work only 3.3 percent fewer hours. Women in our sample with children are not negatively selected on predicted earnings; MBA mothers are, if anything, positively selected on business school performance and earnings in the first few years

following MBA completion. By estimating panel data models with individual fixed-effects, we can observe exactly when women with children shift into lower hours positions and leave the labor force. The careers of MBA mothers slow down substantially within a few years following their first birth. But almost no decline in labor force participation and only a modest decline in hours worked are apparent in the two years before the first birth.

MBA mothers seem to actively choose jobs that are family friendly and avoid jobs with long hours and greater career advancement possibilities. The dynamic impact of a first birth on women's labor market outcomes greatly depends on spousal income. New MBA mothers with higher-earnings spouses reduce their labor supply considerably more than mothers with lower-earnings spouses. In fact, the first birth has only a modest and temporary impact on earnings for MBA women with lower-earnings spouses.

Our finding that human capital and labor supply factors can account for most of the gender gap in earnings among MBAs comports with that of Black, Haviland, Sanders and Taylor (2008) for a broader group of U.S. college-educated women between 25 and 60 years old in the 1993 NSCG. Our finding of a large increase in the gender gap during the first ten to 15 years in the careers of MBAs is similar to other studies exploring the dynamics of the gender earnings gap for new lawyers (Wood, Corcoran, and Courant 1993) and for broader samples of young workers (e.g., Light and Ureta 1995; Loprest 1992; and Manning and Swaffield 2008).⁶

II. University of Chicago MBA Survey and Sample

Our data come from a web-based survey we conducted of University of Chicago MBAs from the graduating classes of 1990 to 2006.⁷ The participants were asked detailed questions about each of the jobs or positions they had since graduation, including earnings (both at the beginning and end of a given position), usual weekly hours worked, job function, sector, size of firm, and type of firm. The earnings questions asked for total annual earnings, before taxes and

⁶ Weinberger (2009) presents somewhat contrasting evidence on the career dynamics of the gender gap for college graduates, using samples largely restricted to those remaining in full-time work.

⁷ The survey was taken between November 2006 and June 2007. Only full-time MBA graduates were included; part-time MBAs and executive MBAs were excluded.

other deductions, in the first and last year at each job.⁸ The responses to the earnings questions and usual weekly hours worked in each position were collected in discrete bins that were transformed into real-valued variables (at the mid-point of each bin).⁹ Respondents were also asked why they had left a position and the reasons they took a subsequent job. Each position, or spell with an employer, lasting six months or more constituted a separate “stage,” and all stages were surveyed for the variables just listed. Information was gathered on all post-MBA spells of non-employment (periods of six months or longer in which an individual was not working for pay) and the reasons for these spells.

The survey responses were converted into an (unbalanced) individual-year panel dataset. Individual earnings in a given year were computed by linear extrapolation based on earnings in the first and last year of a given stage and the length of that stage. Administrative data from the University of Chicago were matched to our individual-level survey data providing information on MBA courses and grades, undergraduate school, undergraduate GPA, GMAT scores, and demographic information (age, ethnicity, and immigration status). Respondents were also asked about their current marital status and, for those currently married or living with a partner (we will use “married” for both), about their spouse’s educational attainment, employment status and earnings. All respondents were asked whether they had any children (biological or adopted), the year of birth of each child, and the allocation of childcare responsibilities in pre-school years between themselves, their spouse, other family members, home care, and day care.

Among the MBAs in these classes with known e-mail addresses about 31 percent responded to the survey.¹⁰ Of this group 2,485 (or 97 percent) were matched to University of

⁸ Employees were asked to include salary and bonuses; the self-employed were asked for total earnings.

⁹ Possible answers to the earnings question were < \$50K, \$50-\$75K, \$75-\$100K, \$100-\$150K, \$150-\$200K, \$200-\$300K, \$300-\$400K, \$400-\$500K, \$500-\$750K, \$750K-\$1MM, \$1-\$2MM, and > \$2MM. We converted the answers into a real-valued earnings variable at the mid-point of each earnings bin; we assigned earnings of \$25K to those that responded earning less than \$50K and earnings of \$3MM to those who indicated earning more than \$2MM. Nominal earnings in each year were converted into real earnings in 2006 dollars using the Consumer Price Index for all Urban Consumers (CPI-U). The response bins for usual weekly hours worked were < 20 hours, 20-30 hours, 30-40 hours, ... , 90-100 hours, and > 100 hours.

¹⁰ Because e-mail addresses can fail without generating a return e-mail, the 31 percent response rate should be considered a lower bound. The survey was sent to each MBA’s “life-time” University of

Chicago administrative records. These 1,856 men and 629 women form the basis of our sample. The University of Chicago has awarded about 570 MBAs annually since 1990 and 24 percent of these have gone to women. The figure is considerably lower than the national average of MBAs earned by women, which was about 40 percent for the same period, although it is less out of line with the University of Chicago's closest competitors.¹¹

The respondents do not differ much from the non-respondents based on the observables. Respondents are, to a slight degree, disproportionately female and U.S. citizens, and they had somewhat better undergraduate and graduate records than the non-respondents. We find about the same gender differences in pre-MBA background, MBA course selection and MBA grades in the full sample of 1990-2006 graduates as in the sub-sample of those that participated in our survey. The women in our survey are slightly positively selected on their undergraduate GPA compared with their male peers, and the survey respondents for both genders are somewhat positively selected on GMAT scores and MBA GPA.¹²

Relative to the male MBAs, the women are a bit younger at graduate school entry and more often U.S. citizens; they did better as undergraduates but less well on the GMAT. Because the University of Chicago MBA program offers a flexible curriculum, considerable variation exists in course selection. Women take relatively fewer finance and accounting classes but relatively more marketing classes. Because of a school policy imposing a maximum mean grade per class, the Chicago MBA program has not been subject to much grade inflation and, in consequence, the MBA grades are reasonably comparable over time and reflect performance in the program. Women have slightly lower graduate GPAs across all fields of study with the largest gender gap in grades found in finance courses.

At the time of the survey, the female MBAs in the sample were less apt to be married than their male counterparts (0.65 versus 0.81). If married, female MBAs were far less likely to have a husband with fewer years of schooling than they. Female MBAs were less likely to have

Chicago e-mail address and, when available, to his or her e-mail addresses listed in the Business School's alumni directory.

¹¹ Among Harvard Business School MBAs for the same period, 31 percent were female.

¹² See on-line Appendix Tables A1 and A2 for comparisons of survey respondents and non-respondents.

any children by the year they exited the program (4 percent versus 16 percent), and they remained less likely to have children by the time of the survey (42 percent versus 60 percent). Among the sub-sample of survey respondents that we can observe nine years after the MBA program, 45 percent of women were still childless compared with 30 percent of men. Female MBAs were more apt to have taken any time off work since receiving their MBA (27 percent versus 10 percent). And 11 percent of the women across all cohorts were not working at the time of our survey as compared to just 2 percent of the men.¹³

Weekly hours are high for almost all MBA positions. Hours are highest in investment banking and consulting, the sectors where almost two-fifths of our sample took their first post-MBA jobs (13 percent and 26 percent, respectively).¹⁴ The average investment banker put in a whopping 74 hours per week, the average consultant 61 hours per week. Also reaching close to the 60 hours per week mark are those employed in venture capital and sales and trading.¹⁵

The share of MBAs working in the high hours sectors declines rapidly in the years following graduation. The share working as consultants was 26 percent initially but 17 percent four years after graduation and 12 percent at seven years or more after. MBAs also shift out of investment banking with only 6 percent still working as investment bankers at seven or more years after graduation. Employment shares in investment management, company finance, and product management remain stable in the 15 years following graduation, and MBAs increasingly move into general management as their careers progress.

III. Descriptive Dynamics

A. Labor Supply

We briefly explore aspects of labor supply to set the stage for the analysis of the gender

¹³ Summary information on the career and family characteristics of the survey respondents overall and by sex are given in on-line Appendix Table A3.

¹⁴ In contrast, only about one-fifth of MBA graduates worked in either consulting or investment banking prior to entering the MBA program.

¹⁵ See on-line Appendix Table A4 for mean weekly hours for the most common job functions in our MBA sample.

earnings gap. Early in their careers labor force participation among the MBAs in our Chicago alumni sample is extremely high and similar by gender (Table 1). But the gender gap in labor force participation widens as careers progress. No more than 1 percent of males are not working in any given post-graduation year as compared with 13 percent of women in year nine and 17 percent of women ten or more years since their MBA.¹⁶ Differences are yet more pronounced comparing the fraction of men and women working full-time and full-year in a given year (Table 1).¹⁷ The fraction of men working full-time, year-round, ranges between 92 and 94 percent in all years following graduation. Although 89 percent of women are full-time and full-year immediately following graduation, 78 percent are six years out, 69 percent nine years out, and 62 percent ten or more years out.¹⁸ For women with at least one child, 52 percent work full-time and full-year ten or more years after MBA completion and the figure is about the same (50 percent) for women with two or more children.

Gender differences in labor force participation translate into differences in actual post MBA labor market experience. The fraction of men who had at least one career interruption (a period of six months or more without working) is 4 percent a year after graduation and 10 percent by ten years out. In contrast, the fraction of women with at least one post-MBA career interruption is 9 percent a year after graduation but 32 percent by year nine and 41 percent ten to 16 years after graduation. Among all women in the sample just 4 percent had children upon receiving their MBA, but more than one-half (56 percent) did nine years out.

Non-work spells are generally brief for both men and women, as indicated by the tabulations of cumulative years not working by years since graduation in Table 1. The average woman spends 0.28 years out of work by year six and 0.57 years out of work by year nine; for men, the equivalent figures are 0.07 at year six and 0.10 at year nine. Ten years or more post-MBA, mean cumulative years not working are 1.05 for women and just 0.12 for men.

¹⁶ The employment rate is relatively low for both men and women in the year of MBA graduation since the entry-level MBA market takes some time to clear.

¹⁷ Our survey did not include a question on “full-time” versus “part-time” work. We assign “full-time” (“part-time”) status to those who report working > [30-40] hours/week (at most [30-40] hours/week).

¹⁸ Our figure of 62 percent is close to that from an often-cited Catalyst study by Hollenshead and Wilt (2000), showing that 66 percent of the female graduates from 12 top MBA programs were working full-time (but not necessarily year-round) approximately ten to 16 years after receiving their MBA.

Weekly work hours are high for all MBAs and highest among the newly minted. Men in their first year out average 61 hours per week; women average 59 hours, despite being less likely to start in investment banking where hours are especially long.¹⁹ Hours of work decline for male and female MBAs in the years following graduation, but far more so for women. Three years after receiving their MBA, women work around 56 hours per week while men work around 60 hours; nine years out, women work around 51 hours per week, while men work around 57 hours.

Although hours of work are long for most MBAs, a substantial share of MBA women work part-time (defined as 30 to 40 hours or less per week). The incidence of part-time work among employed MBA women increases with years since graduation, from 5 percent during the first year to 22 percent at ten to 16 years out. Whereas about 17 percent of MBA women are not working at ten to 16 years out, another 18 percent [$0.22 \times (1 - 0.17)$] are working part-time.²⁰ Part-time work, therefore, is more prevalent than is non-employment for MBA women, even more than a decade after the MBA. But part-time positions are not common for those who remain in the corporate sector, especially in investment banking and consulting. One year after graduation, 4 percent of salaried women work part-time, 7 percent by year six, and 12 percent at ten years or more post-MBA. The reason such a large share of MBA women 10 to 16 years out can work part-time is because they are self-employed. In fact, of the 20 percent who are self-employed at 10 to 16 years out, 57 percent work part-time. When MBA women want to work part-time, they disproportionately employ themselves.

Immediately following graduation, 29 percent of self-employed women work part-time; 35 percent do by year six. Ten years or more post-MBA, 62 percent of self-employed women

¹⁹ See Landers, Rebitzer and Taylor (1996) on the role of similarly long hours for law associates at large U.S. law firms in the career dynamics of young lawyers.

²⁰ Gender differences in labor supply for Chicago Booth MBAs are quite similar to gender gaps around ten years after MBA completion for those in the 1989 to 1992 BA cohort of the Harvard and Beyond (H&B) sample who went on to get an MBA. The H&B male MBAs in these cohorts had a 98 percent employment rate as compared with an 82 percent employment rate for the H&B female MBAs in 2006. Conditional on being employed in 2006, the H&B male MBAs worked 55 hours per week on average with only 3 percent working part-time, and the H&B female MBAs worked 44 hours per week on average with 29 percent working part-time. A substantial gender gap in hours of work for those who received MBAs from 1990 to 2003 is also apparent for the 2003 NSCG with employed male MBAs working 49 hours per week on average as compared to 44 hours per week for employed female MBAs.

work part-time.²¹ In contrast, only 15 percent of self-employed men work part-time ten to 16 years out. The shares of working men and women who are self-employed are similar up to nine years following graduation (growing from less than 2 percent at graduation to 11 to 13 percent nine years out), but a surge in self-employment among MBA women occurs ten to 16 years out, with 20 percent of working women being self-employed compared with 14 percent for men.

By far the most common job function among self-employed part-timers is consulting. More than 30 percent of self-employed part-timers are consultants, whereas among full-timers only 18 percent are. For those who work in established firms, however, consulting offers less opportunity for part-time work: fewer than 3 percent of salaried part-timers are consultants.

In summary, MBAs in our sample are concentrated in job functions that generally have long hours. Hours decline with time since MBA for both men and women, in part reflecting a move out of investment banking and consulting and towards general management positions in corporations. But weekly hours worked drop considerably more for women, driven largely by a growing share working part-time, often self-employed. Women are increasingly more likely to be out of the workforce with years since MBA, although the average female MBA accumulates only half a year of non-employment in the first nine years after graduation. Part-time work for women is a more important factor than “opting out” behavior (non-employment) in explaining the lower incidence of full-time and full-year work for women than for men in the first 15 years after MBA completion.

B. Earnings

Labor market earnings are a key summary measure of career progress and ultimate success. We construct earnings for each calendar year by taking the annualized total earnings (including bonuses) from the stage worked at the end of that calendar year. In this manner, earnings per year are constructed as “full year” earnings in the last job held in that year and not

²¹ The share of part-timers is even higher among self-employed women with no employees: nearly 75 percent of them work part-time ten to 16 years out.

necessarily actual earnings for the year.²²

Earnings (expressed in 2006 dollars) advance substantially with time since MBA, as is clear from Figure 1. The growth is a hefty 8.9 percent average annual rate for all MBAs.²³ The average MBA earns \$126K at graduation (median is \$122K) and close to \$370K nine years out (median is around \$190K). Both the level and rate of change are greatest for those starting in investment banking, which attracts a substantial number of recent MBA graduates. Those starting their careers in investment banking earn more than \$170K at graduation (median is \$160K) and close to \$700K nine years out (median is \$470K), whether or not they are still employed in investment banking. Earnings levels and growth are similar for investment management. The consulting track, the other most prevalent career option among MBAs, is less remunerative than investment banking and investment management.²⁴

Mean earnings by sex are comparable directly following MBA receipt, but they soon diverge. Women earn \$115K on average at graduation and \$250K nine years out; men earn \$130K on average at graduation and \$400K nine years out. Median salaries by sex also diverge in favor of men with years since graduation but not by as much as do mean salaries. The median female MBA starts her career at the 34th percentile of the male distribution but after 15 years has fallen to the 19th percentile. The top half of the MBA wage distribution spreads out with time since MBA particularly for men.²⁵ The 90th percentile man earns over \$1 million at 10 to 16 years out as compared to \$438K for the 90th percentile women. The woman at the 75th percentile of the female earnings distribution begins at the 66th percentile of the male distribution but winds up at the 37th percentile by year 15. If we exclude the self-employed, the progression down the male distribution is far less severe and the 75th percentile woman, for example, is at the 56th

²² We have also averaged the annualized earnings of all working stages during the calendar year for those with multiple stages in a year (weighting each stage by its length). This definition also computes full-year earnings, which may differ from actual earnings for those employed only part of the year. There are no notable differences in the findings between the two earnings measures.

²³ The calculation assumes an average of 13 years for the ten to 16-year cell.

²⁴ On-line Appendix Table A5 has mean and median earnings, also for various quantiles, by sex, initial occupation, and years since MBA. All these tabulations are for those with positive earnings.

²⁵ Performance pay (bonuses) and the tournaments aspects of financial and corporate sector hierarchies are likely to contribute to the growing top-end dispersion of MBA pay with years since MBA. See Lemieux, MacLeod, and Paserman (2009) on the rising importance of performance pay to U.S. wage inequality and Frydman and Saks (2009) on the evolution of top-end corporate pay.

percentile by year 15.

Mean differences in earnings between men and women (conditional on only cohort \times year dummies) are given in Table 2 arrayed by years since receipt of the MBA. The 11 log point gender earnings gap at graduation jumps to 31 log points at five years out, 40 log points at nine years out and nearly 60 log points at ten or more years out (col. 2). The time profile of the earnings gap is roughly similar for the subset that starts a new job in that year (col. 3).

IV. Explaining the Gender Gap in Earnings

To understand why female MBAs have lower incomes than male MBAs, we estimate (log) annual earnings equations that pool all individual-year observations; the observations include *all* job stages previously held by the individual. The impact of the various factors discussed, including pre-MBA characteristics, MBA courses, post-MBA job experience, and non-working spells, on the gender gap in earnings, is explored. The estimation in Table 3 is done with and without controlling for weekly hours worked.

The raw gap in mean log earnings between men and women in the pooled sample is about 31 log points. The gender earnings gap shrinks slightly to 29 log points conditioning only on (cohort \times year) dummies (col. 1). The inclusion of pre-MBA characteristics, MBA GPA, and fraction of finance classes reduces the gender gap to 19 log points (col. 2). The difference in mean MBA GPA between men and women in the regression sample of 0.10 (3.40 versus 3.30) implies (using the estimated coefficient of 0.429 on MBA GPA in col. 2) that the gender difference in MBA grades alone can account for a gender earnings gap of 4 log points. Each additional finance class increases earnings by about 8 log points and women take about half a class less in finance than men.²⁶

Labor supply factors explain most of the remaining gender gap in earnings. The inclusion of a full set of dummy variables for weekly hours worked reduces the raw gender gap of 29 log points (col. 1) to 17 log points (col. 4). Adding hours worked to the specification

²⁶ Finance classes pay off even for those not starting in investment banking or investment management.

including pre-MBA characteristics and MBA performance lowers the remaining gender gap to 9 log points (col. 5). The gender earnings gap is reduced to just 6.4 log points (col. 6) with the further addition of a quadratic term for post-MBA years of actual work experience and a dummy variable for the presence of any post-MBA career interruption. Augmenting the model with (arguably even less exogenous) variables to control for reasons for choosing one's current job, job function, and employer type further reduces the coefficient on the female dummy to a (statistically insignificant) -3.8 log points (col. 9).²⁷

The estimates from our preferred specification in col. (6) of Table 3 can be used to obtain the earnings penalty from taking time out. The loss is 23 log points from taking *any* time out plus an additional amount from accumulating less post-MBA experience. An MBA observed six years after business school graduation with at least one non-employment spell in that period had an average employment spell of 4.97 years and thus an average non-employment spell of 1.03 years. The penalty from taking that amount of time off is 37 log points of which about two-thirds is due to the discrete earnings loss from taking *any* time off.²⁸ The earnings loss from time out is even greater using the estimates that do not hold hours constant (col. 3). The full earnings loss (among the employed), using those coefficients, is around 46 log points. The wage penalties we estimate (for the typical out-of-work spell at six years after MBA completion) are uniformly high across all career tracks: 36 log points in consulting, 45 log points in investment banking or investment management, and 45 log points in other functions.²⁹ The earnings loss from any career interruption is large in our MBA sample.

The models in Table 3 restrict the impact of career interruptions to be identical for men and women. Although it is possible that women are more heavily penalized for taking time out, estimates from separate earnings regressions by sex using the specification from Table 3, col. (6) do not support that suspicion. The wage penalty for men, using our standardized career

²⁷ The basic findings are almost identical for log hourly wage regressions as for log annual earnings regressions that include controls for weekly hours worked. See on-line Appendix Table A6 for log hourly wage regressions, comparable to the specifications in Table 3, for the full pooled sample.

²⁸ The penalty for an average non-work spell of an individual 6 years out from the MBA would be: $[(0.085 \times 4.967) + (0.005 \times 4.967^2) - 0.228] - [(0.085 \times 6) + (0.005 \times 6^2)] = 0.372$. Note that in the entire sample 27 percent of the women, but 10 percent of the men, took some time off.

²⁹ We re-estimated the specification in col. (6) separately for each of the subgroups.

interruption at six years out, is 45 log points whereas that for women is 26 log points. Taking any time out appears more harmful for men (26 log points) than for women (11 log points).³⁰ Similar calculations for a standardized career interruption based on the col. (3) specification, which does not hold hours constant, result in penalties for taking time out of 48 log points for men and 38 log points for women. For women, but less so for men, a career interruption usually goes hand in hand with a substantial reduction in weekly hours upon returning to work. The data do not indicate that MBA women lose more than MBA men for taking time out. It appears that everyone is penalized heavily for deviating from the norm.

Given that the coefficients from separate (log) earnings regressions for men and women are reasonably similar, we can partition the proximate impact of the various factors on the gender earnings gap using a standard decomposition framework applied to the regressions pooling men and women in Table 3.³¹ Our summary measure of the contribution of each explanatory variable to the overall mean gender earnings gap is simply the product of the gender difference in the sample means for that variable and the coefficient on that variable in our preferred specification (col. (6) of Table 3). The results of this decomposition echo the findings from adding factors across the Table 3 columns. The total (log) earnings difference women and men is -0.314. Of that, MBA performance differences (MBA GPA and finance classes) account for -0.078, differences in post-MBA job experience account for another -0.093, and differences in weekly hours also for -0.093. The dummy variable for female is -0.064 and all other factors (e.g., all cohort \times year effects, pre-MBA characteristic) make up the remaining 0.014 of the total -0.314. Thus, differences in just three factors—MBA performance, job experience, and hours— account for fully 84 percent of the gender gap in earnings pooled across all years since MBA completion.

Because differences in job experience and working hours between men and women are largely due to the presence of children, we also estimate the Table 3 earnings regressions including interactions of the female dummy with whether or not a woman has children.³² The

³⁰ A larger discrete earnings loss associated with having any career interruption for men than for women is also found in earnings regressions including person fixed effects and may reflect the much larger role of layoffs in men's sustained periods out of work.

³¹ See on-line Appendix Table A7 for the details of the decomposition.

³² See on-line Appendix Table A8.

raw earnings deficit relative to men (pooling men with and without children), conditional on only (cohort x year) dummies, is 45 log points for women with children and 22 log points for women without children. The -23 log point raw “impact” of children on women’s earnings is fully accounted for by reduced weekly hours and a higher incidence and duration of no-work spells.³³ Adding weekly hours, MBA performance, and career interruptions as control variables fully eliminates the child penalty in female earnings and narrows the gender earnings gap to 6 log points both for women with children and women without children.

An analysis of the gender earnings gap by years since MBA graduation is given in Table 4. The (uncorrected) gender wage gap is 9 log points just after MBA completion. It rises to 25 log points three years out, to 38 log points at nine years out, and to 57 log points at ten to 16 years out.³⁴ But even the largest of these gender gaps in earnings is entirely eliminated by the inclusion of the observables, particularly job interruptions and hours of work. That detail, however, overlooks the changing importance of the various factors with time since MBA.

Within the first three years after receipt of the MBA the earnings gap between men and women expands by 16 log points. As much as a third of the increase appears to be due to growing labor market returns with experience to pre-MBA characteristics as well as MBA course performance. Gender differences in career interruptions and the accumulation of years of labor market experience do not expand much in the first three years in the labor market (as seen in Table 1), but the gender gap in hours worked is already an important factor for the gender earnings gap by year three (as suggested by comparing the gender gap estimates in rows 4 and 5 of Table 4). During the next six years (from year three to nine), the gender earnings gap grows by another 12 log points. At this juncture career interruptions become a more important factor and weekly hours also play a key role. The addition of controls for career interruptions reduces the 12.4 log point increase from year three to nine by 5.6 log points and the inclusion of controls

³³ In contrast, male MBAs with children have earnings that are 18 log point higher than childless males and this positive child earnings premium is only modestly reduced to 13 log points with the addition of controls for hours worked, career interruptions, and MBA performance.

³⁴ Because our sample is an unbalanced panel, the dynamics of the gender gap could reflect differential changes in sample composition by sex with years since MBA. We have replicated the analysis in Table 4 limiting the sample to those who completed their MBA prior to 1998, holding sample composition constant up to eight years out. The results are similar for the full sample and for the pre-1998 cohorts.

for weekly hours (in row 5) more than eliminates the remaining growth of the gender earnings gap. Of the increase in the gender earnings gap by 29 log points in the first nine years following MBA completion, 8 log points can be accounted for by adding pre-job characteristics and a further 19 log points by adding controls for career interruptions and hours of work.

A formal decomposition of the gender earnings gap at 0 years out and at 10 or more years out using the sex differences in means of the explanatory variables and the coefficients from the specification in line 5 of Table 4 shows that the contribution of MBA performance rises from 4 to 7 log points, of labor market experience from 0 to 11 log points, and of weekly hours from 2 to 29 log points over the first 15 years following MBA completion. These three proximate factors combined explain a 41 log point growth in the gender earnings gap (86 percent of the 48 log point total growth) from 0 years out to 10 to 16 years post-MBA. It is striking that a similar share (around 85 percent) of both the mean *level* of the gender earnings gap across all post-MBA years and of the *growth* of the gender gap over the first 15 years post-MBA can be accounted for by gender differences in MBA performance, labor market experience, and weekly hours.

Substantial earnings differences relative to men are apparent even for women who have taken no career break through ten years following MBA completion. The raw gender earnings gap widens by 25 log points in the first 10 years post-MBA from an initial 9 log points to 34 log points in year ten. Most (80 percent) of this total change can be accounted for by the increased importance of pre-job (MBA and pre-MBA) characteristics and by rising differences in weekly hours between all men and the group of women with no career breaks.

Even women with no career interruptions have children and some work fewer hours and are less available for career moves because of family reasons. Limiting the sample further to women without children and with no career interruptions by ten years out makes the career paths of the women in the sample similar to those of men. For that comparison, the gender earning gap starts out slightly larger than for all women but grows less rapidly. The gap in earnings between this sub-group of women and all men increases by 15 log points in the first ten years after the MBA. More than the entire increase in the gender pay gap by year ten can be accounted for by the greater importance of pre-MBA and MBA characteristics with years since MBA receipt.

Furthermore, we find no growth in the gender gap in weekly hours worked with years since MBA for the women in this sub-group.³⁵

V. Explaining the Gender Gap in Labor Supply

A major reason gender differences in earnings emerge and expand with time since MBA is due to differences in job experience and hours. Gender differences in labor supply grow substantially with years since completing an MBA even after the inclusion of cohort (MBA graduating class) effects, calendar year effects, and their interactions (see Table 2, cols. 4 to 8). Nine years out, a female MBA is about 12 percentage points less likely than a male MBA to be employed at all during the year (col. 5); and she will have spent half a year more than the average male out of work since MBA receipt (col. 4). Although only a 3 log point difference in weekly hours worked exists in the first post-MBA job, the difference grows to about 14 log points nine years out and to 20 log points at ten or more years after graduation (col. 8).

The reasons why gender differences in labor supply emerge are explored in Tables 5 and 6, which include a full set of (cohort \times year) dummies as well as controls for pre-MBA characteristics and MBA performance. The unit of observation is a survey respondent in a given year. Table 5 explores the role of children and Table 6 adds comparisons by spousal income.

The 8.4 percentage point gap in employment between men and women pooled across all post-MBA years, perhaps not surprisingly, is largely driven by women with children, as can be seen by comparing the first two columns of Table 5. A woman with at least one child is 20 percentage points less likely to work in a given year than the average man, whereas a woman without children is only 3 percentage points less likely to be employed than the average man (col. 2). A woman with at least one child has about 0.66 fewer years of actual labor market experience than the typical man in the sample, but the difference is only 0.13 year for a woman without children (col. 4). Although there is a 9 log point mean difference in weekly hours worked between employed men and women, it is 24 log points for women with kids and only 3

³⁵ On-line Appendix Table A9 contains regressions similar to those in Table 4 but for women with no career breaks in the first ten years following MBA completion and Table A10 has similar regressions for women with both no career breaks and no children by year ten.

log points for women without kids (col. 6). And the “impact” of children on female labor supply differs substantially by spousal earnings (Table 6).

Because our survey asked for spousal earnings only in the current year, we use spousal earnings as of the survey date as a proxy for spousal earnings in any prior year. We then separate women into those with “lower” earnings (less than \$100K per year) spouses, “medium” earnings (between \$100K and \$200K per year) spouses, and “high” earnings (more than \$200K per year) spouses. These spousal earnings categories are then interacted with an indicator variable for whether or not a woman has at least one child in a given year, thereby comparing the average man to six different groups of women.³⁶

The effect of motherhood on the likelihood that a woman is not working is more than twice as large if the woman has a high-earnings spouse rather than a lower-earnings spouse: these mothers are 30 percentage points less likely to work than the average man (Table 6, col. 1; $0.119 + 0.185$). Mothers with a medium-earnings spouse also work less than those with a lower-earnings spouse, but the difference is smaller and not statistically significant. Similarly, mothers with high-earnings spouses accumulate more than six months more in non-employment spells following MBA completion and, even when employed, have a workweek that is 19 log points shorter than mothers with low-earnings spouses (cols. 2 and 3).

Among women without children greater spousal earnings appear to *increase*, rather than decrease, labor supply. In fact, a woman without children married to high-earnings spouse is about as likely to work (the gap is only 2 percentage points), to accumulate post-MBA work experience, and to put in a long work week (women are actually higher by 3 log points) as the typical male in our sample. These findings suggest positive assortative mating based on preferences for work. The sharp reversal in labor supply patterns for MBA women by spousal income that occurs with motherhood seems most consistent with the notion that previously hard-working women slow down after their first birth if they have a high-earnings spouse.

Because spousal income may be endogenous to own labor supply choices and because we

³⁶ The Table 6 specifications include only women who were “married” at the survey date.

measure spousal income only in the survey year, we have replicated the analysis using spousal education levels. We contrast the labor supply of mothers married to men who are at least as educated as they (having MBA, JD, MD and related degrees, or PhD) to that of mothers with less-educated spouses. We find the same qualitative pattern of results as in Table 6.³⁷

MBA mothers whose spouses earn over \$150K indicate, in our survey, that they are responsible for 52 percent of their children's care as compared with only 32 percent for MBA mothers with lower-earnings spouses.³⁸ The difference is almost fully explained by their reported use of formal day care center services (12 percent with high-earnings spouses versus 31 percent with lower-earnings spouses). That is, MBA mothers with better-off husbands take a larger share of the responsibility for child care (relative to their spouses and others) than do other MBA women. Greater spousal income purchases more high-valued child-care time of the MBA mother relative to the time of nannies and other market child-care providers.

In summary, parental status accounts for the bulk of the difference in labor supply between male and female MBAs. The impact of children on female labor supply is strongly related to spousal income, with mothers in better-off households slowing down much more.³⁹

VI. Selection and Family Status

A large part of the difference between male and female earnings comes from job interruptions and most job interruptions are due to children. MBA women who become mothers might be selected on unobservables that could directly lead to lower earnings in the absence of children. But we uncover no evidence that MBA women who marry and have children are drawn from the lower part of the female earnings distribution (Table 7). To the contrary, we find that married women have slightly higher predicted earnings than unmarried women and those

³⁷ We also investigated how children affect male labor supply based on wives' earnings (and education), but found no significant impacts of the presence of children or of spousal income on male labor supply.

³⁸ When we use three types of earnings we term the > \$200K group "high," but when we use two groups, as we do here, we deem the > \$150K group "high."

³⁹ Women's decisions to get married, whom to marry, and whether or not to have children may be related to unobservable characteristics that directly impact earnings. We explore that possibility below.

with children have slightly higher predicted earnings than those without children, using a measure of predicted earnings based on pre-MBA characteristics and MBA performance.⁴⁰

MBA women who have children are not negatively selected in terms of predicted earnings levels and may even be positively selected. MBA mothers are, as well, positively selected on actual early career earnings. In unreported regressions, we find that the MBA women with a first birth three or more years following MBA completion earned about 4 log points more in the first two years following MBA completion than their female classmates who do not have children by our survey date.

VII. More on the Role of Children and Career Interruptions in the Dynamics of the Gender Gap

Because differences in earnings and employment between male and female MBAs appear to be largely associated with the presence of children, we use the (retrospectively-constructed) panel structure of the data to explore career dynamics after a first birth in Tables 8 and 9. The regressions include person fixed effects, (cohort \times year) dummies, a quadratic in age, and a set of indicator variables for the year surrounding the first child's birth (dummy variables for one or two years before the birth, the year of the birth, one or two years after the birth, three or four years after the birth, and greater than four years after the birth). The coefficients on these variables summarize the dynamics of labor supply and earnings responses to a first birth relative to the base period of three or more years prior to the first birth.⁴¹

MBA women reduce their labor supply on both the extensive and intensive margins after a birth. There is a large decline in labor force participation in the year of the first birth and a further reduction over the next four years. A woman's likelihood of not working in a year is about 13 percentage points higher in the two years immediately following her first birth than in the base period, increasing to 18 to 19 percentage points higher at three years following the birth and beyond (Table 8, col. 2). Similarly, weekly hours worked for the employed (col. 10)

⁴⁰ The predicted value of log (annual earnings) for all individuals is regressed on interactions of marital status and sex in one regression and, in a separate regression, on interactions of sex with whether an individual has a child. The predicted value of earnings is based on a full set of pre-MBA characteristics and MBA performance measures (see the notes to Table 7 for details).

⁴¹ The regression samples exclude individuals who had children prior to completing their MBA.

decrease sharply in the year of a first birth and continue to decline over the next four years, reaching a 24 log point deficit relative to the pre-birth base period. The reduction in weekly hours is associated with a large shift into part-time work and self-employment in the four years following a first birth.⁴² In contrast, there is no decline in labor force participation and only a modest (4 log points) decline in weekly hours worked in the one or two years before the first birth. MBA moms are, if anything, slightly more likely to work in the two years that precede the birth of their first child than in the base period of three or more years before their first birth.

Women's earnings (among those remaining employed) decline only modestly in the year of the first birth but decline sharply over the next several years especially around three to four years after the birth (Table 8, col. 4). A woman's earnings drop by about 30 log points relative to the pre-birth base period at three years or more after the birth. When we control for hours worked (col. 11), we find that annual earnings (essentially hourly wage rates) are unchanged in the two years immediately following the first birth but decrease by 6 to 7 log points after that.

Thus, earnings decline linearly with hours worked in the first two years after the first birth, but (hourly) wage penalties (associated with career interruptions) become evident for MBA women about three years after the birth. A woman's annual earnings (including the non-employed) fall modestly in the year of the first birth and continue declining over the next several years reaching a \$100K deficit relative to the base period by five years after the birth (col. 8).

The decreases in women's labor supply and earnings that expand three to four years after a first birth could reflect the impact of subsequent births. But we find large reductions in labor supply and earnings four years after a first birth even for women who do not have a subsequent birth.⁴³ In fact, we find the birth of a second child has little additional adverse effect on women's labor supply and earnings.

⁴² The share of MBA women working part-time increases from 5 percent two years before a first birth to 34 percent four years after a first birth with about half of this increase accounted for by women shifting into self-employment. Herr and Wolfram (2009) emphasize that corporate work environments contribute to MBA mothers' decisions to exit the labor force at motherhood. We find, in addition, that MBA mothers shift into self-employment, and also that self-employment enables part-time work.

⁴³ These findings derive from (unreported) regressions in which we add a dummy variable to the specifications in Table 8 for the two years immediately following the birth of a second child.

In contrast, MBA men with children see their earnings *increase*, not decrease, especially five years and more after birth of their first child (Table 8, cols. 3, 5, and 7). Male labor supply is virtually unaffected by fatherhood in our MBA sample (cols. 1 and 9).

Obvious reasons exist why women choose to cut back on work after giving birth. But MBA mothers may also be forced out, or at least out of the fast-track. Suggestive evidence exists, however, that the observed patterns of decreased labor supply and earnings substantially reflect women's choices given family constraints and the inflexibility of work schedules in many corporate and finance sector jobs. The differential impact of children on women's labor supply by her spouse's income (see Table 6) seems consistent with such an interpretation.

The differential dynamic impacts of a first birth on women's labor market outcomes by husband's income are illustrated in Table 9, where we estimate separate regressions (using the Table 8 specifications) for married women by spousal earnings (more than or less than \$200K).⁴⁴ New MBA mothers with higher-earning spouses reduce their likelihood of working by 17 percentage points in the year of first birth (relative to the base period) and by 28 percentage points three to four years after the birth (col. 6). In contrast, MBA women with lower-earning spouses have an increased employment rate in the two years prior to a first birth and experience no noticeable change in the likelihood of employment (relative to the pre-birth base period) following the birth (col. 1). Weekly hours (conditional on employment) drop for both groups in the year of a first birth and in the four years following the birth (cols. 4 and 9). The total annual earnings decline (including those not working) associated with motherhood is large and persistent for MBA women with higher-earning spouses. The decline is quite modest for women with lower-earning spouses and does not persist beyond the first four years after the first birth.

Corroborating evidence arguing for some type of choice can be gleaned from the reasons MBA women give for not working, leaving their previous job, and for choosing a new job. The probability that a woman is not working for career-related reasons (which include "layoff" and

⁴⁴ These results are replicated in on-line Appendix Table A11 for spouses by education group rather than income.

“suitable job not available”) does not change post-birth (Table 10, col. 2). Instead, all of the reduction in labor force participation for MBA women following a first birth observed in Table 8 can be attributed to an increase in the likelihood of not working for family-related reasons (which include “do not need or want to work,” “home taking care of parents or other relatives” and “home raising children”) as seen in Table 10, col. (1).

What motivates mothers to choose their current job largely differs from what motivated them before they had children. Post-birth, women are 20 to 26 percentage points more likely to be in a job chosen for family-related reasons than in the pre-birth base period (Table 10, col. 3) and 13 to 21 percentage points less likely to have chosen their job for career-related reasons (col. 4). These changes in career orientation are not limited to when their children were infants but persist five or more years after the first birth.⁴⁵

Choice does not mean that earnings are not greatly affected, and large negative wage changes are associated with taking a new job for family-related reasons and for leaving a prior job for family-related reasons. Earnings decline 64 log points when the new job is chosen because of “flexible hours,” 20 log points when the new job is chosen because of an “opportunity to work remotely,” and 7 log points when the new job is chosen because of a “limited travel schedule.” The large role of family factors and desires for flexible hours in the job mobility decisions of women with children generates the striking differences in the wage changes by gender and parental status associated with job changes. Job changes in our MBA sample are income neutral for women without children and for men. But women with children lose nearly 18 log points in earnings when they shift jobs.⁴⁶

MBA mothers may emphasize family over career in choosing their jobs, but it is still possible that their jobs involve lower earnings and fewer career advancement opportunities because of differential treatment. This claim is difficult to evaluate directly. We examine the likelihood of leaving a given job, as well as the likelihood of leaving for family or career-related

⁴⁵ Family reasons for choosing a given job include: “flexible hours”; “opportunity to work remotely”; and “limited travel schedule.” Career reasons for choosing a given job include: “career advancement or broadening”; “compensation and other benefits,” and “prestige.”

⁴⁶ See on-line Appendix Table A12, panels A and B on wage changes and reasons for leaving a job.

reasons, *conditioning* on the stated reasons for originally choosing that job (Table 10, cols. 5 to 8). If MBA mothers were being sidelined in their current jobs, one might have expected them to be more likely to quit (or even be forced out) for career-related reasons. Yet, we find little evidence of that (cols. 5, 7 and 8). We do find that women are more likely to leave a job for family reasons in the two years before a birth (col. 6), suggesting some re-optimization of job choices in anticipation of children. Of course, the evidence does not rule out discrimination since women facing such career barriers still may give family reasons for job changes.

VIII. Summary and Conclusions

We have examined gender differences in the career dynamics of MBAs who graduated from a top U.S. business school—the Booth School of Business of the University of Chicago — from 1990 to 2006. Immediately following MBA completion male and female MBAs from this elite program have nearly identical labor incomes and weekly hours worked. But the gender gap in annual earnings expands considerably as their careers progress reaching almost 60 log points at ten to 16 years after MBA completion.

We identify three proximate factors that can explain the large and rising gender gap in earnings: (1) a modest male advantage in training prior to MBA graduation combined with rising labor market returns to such training with post-MBA experience; (2) gender differences in career interruptions combined with large earnings losses associated with any career interruption (of six or more months); and (3) growing gender differences in weekly hours worked with years since MBA. Differential changes by sex in labor market activity in the period surrounding a first birth play a key role in this process. The presence of children is associated with less accumulated job experience, more career interruptions, shorter work hours, and substantial earnings declines for female but not for male MBAs. The one exception is that an adverse impact of children on employment and earnings is not found for female MBAs with lower-earning husbands.

Are career-family tradeoffs faced by female MBAs in the corporate and financial sectors similar to those in other high-powered occupations? We have done an initial exploration of these issues using the Harvard and Beyond (H&B) project to examine the careers of Harvard graduates

from the undergraduate classes of 1969 to 1973, 1979 to 1982, and 1989 to 1992.⁴⁷ We find that female MBAs appear to have a more difficult time combining career and family than do female physicians, PhDs, and lawyers across all of these BA classes.⁴⁸

Fifteen years after obtaining their BA women who earned an MBA had the lowest labor force participation rates, the lowest share working full-time and full-year, and took the greatest amount of (non-educational) time off from employment compared with others having professional degrees and PhDs (Goldin and Katz 2008). Employment rates 15 years out for MDs exceeded 95 percent, for PhDs they were greater than 90 percent, for JDs they were around 90 percent, but they were 85 percent for MBAs.

Differences are greatest for those with children.⁴⁹ Less than 50 percent of the MBA women were both in the labor force (part-time or full-time) and had children 15 years out; in contrast, 65 percent of the MDs were and about 55 percent of the PhDs and JDs were. Just 30 percent of the MBA group were full-time, full-year in the workforce and had kids, whereas 43 percent of MDs were in that group and 38 percent of PhDs were. Female physicians take the briefest non-employment spells after having a child, followed by PhDs, then lawyers, and finally MBAs who take the greatest amount of time off for family reasons.⁵⁰

Log earnings regressions for 2005 annual earnings in the H&B sample using a specification similar to that in Table 3, col. (6), indicate larger earnings costs to career interruptions for MBAs than for MDs, JDs, or PhDs. The earnings penalty in 2005 for an 18 month career interruption for those in the Harvard graduating classes of 1989 to 1992, at around

⁴⁷ See Goldin and Katz (2008) for details.

⁴⁸ For analyses of gender earnings and promotion gaps, and career-family trade-offs, for professions, see Wood, Corcoran, and Courant (1993) on lawyers; Sasser (2005) and Reyes (2006) on physicians; Preston (2004) and Ginther and Kahn (2006) on science professionals; and Ginther (2006) on academics. In related work, Ellwood, Wilde, and Batchelder (2004) find larger negative impacts of childbearing on the wage trajectories of high skill (high AFQT) women than of less skilled (low AFQT) women.

⁴⁹ Working with a partially overlapping sample of women who received BAs from Harvard University between 1988 and 1991, Herr and Wolfram (2009) find nearly identical results to those in the H&B sample for labor force participation rates among those graduating college around 1990.

⁵⁰ Women with children in our MBA sample were slightly more likely to be employed than in the H&B sample (77 percent were working ten or more years after their MBA). If we restrict the H&B data to MBAs from top business schools the results are closer to the University of Chicago MBA sample.

six to 12 years after completing a graduate or professional degree, was 0.16 log points for MDs, 0.34 log points for JDs and PhDs, and 0.53 log points for MBAs. Furthermore, a large discrete and persistent earnings loss is associated with any career interruption for MBAs, while for MDs the cost of taking time off is fairly linear in foregone labor market experience.

We can only speculate about why different costs exist to taking time off and working lower hours across professions. Inherent differences in production technologies and in the organization of work may make the productivity costs to discontinuous experience and more flexible hours greater in the business and corporate sectors than in medicine or academia. The tournament nature of corporate and financial firm hierarchies and the up-or-out nature of major law firms and academic institutions may also contribute to their large costs of career interruptions relative to medicine. The economic benefits of re-organizing work to reduce the productivity costs of career interruptions and more flexible work options may be greater in professions where there is a larger share (or critical mass) of women in the talent pool. A tipping point may have been reached in fields where women have become a majority (or nearly the majority) of the young talent (such as medicine, veterinary medicine, optometry, pharmacy, and accounting) but not yet for MBAs and the business and financial sectors. It is also possible that there is more career commitment in those professions requiring greater upfront time investment, such as a PhD or an MD as opposed to an MBA. Additionally, female MBAs often have husbands with higher earnings than female PhDs and MDs allowing them the luxury to slowdown in the market and spend more time with their children. The career costs of that decision may not be evident until much later.

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Table 1
 Labor Supply by Gender and Number of Years since MBA Graduation: Descriptive Statistics

	<i>Number of Years since MBA Graduation</i>					
	0	1	3	6	9	≥ 10
	Share Not Working at All in Current Year					
Female	0.054	0.012	0.027	0.067	0.129	0.166
Male	0.028	0.005	0.003	0.008	0.011	0.010
	Share Working Full-time/Full-year (52 weeks and > 30 to 40 hours per week)					
Female	n.a.	0.89	0.84	0.78	0.69	0.62
Male	n.a.	0.93	0.94	0.93	0.93	0.92
	Cumulative Share with Any No Work Spell (until given year)					
Female	0.064	0.088	0.143	0.229	0.319	0.405
Male	0.032	0.040	0.064	0.081	0.095	0.101
	Cumulative Years Not Working					
Female	0	0.050	0.118	0.282	0.569	1.052
Male	0	0.026	0.045	0.069	0.098	0.120
	Mean Weekly Hours Worked for the Employed					
Female	59.1	58.8	56.2	54.7	51.5	49.3
Male	60.9	60.7	59.5	57.9	57.5	56.7
	Share Working Part-time (≤ 30 to 40 hours per week)					
Female	0.04	0.05	0.07	0.09	0.15	0.22
Male	0.02	0.02	0.02	0.03	0.03	0.04
	Share Working Fewer than 52 Weeks					
Female	n.a.	0.07	0.07	0.09	0.06	0.06
Male	n.a.	0.05	0.04	0.03	0.03	0.03

Notes:

Individuals who do not work at all in a given year are excluded from those “working part-time” and “working fewer than 52 weeks” and are included as zeros in the definition of “working full-time/full-year.”

Table 2
Gender Gap in Earnings and Labor Supply

<i>Number of years since receipt of MBA</i>	<i>Annual earnings</i>	<i>Log (annual earnings)</i>	<i>Log (annual earnings) first year in job</i>	<i>Cumulative years not working</i>	<i>Not working at all in current year</i>	<i>Annual weeks worked in current year^a</i>	<i>Annual hours worked in current year^a</i>	<i>Log (weekly hours worked)</i>
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
0	-16,943 [2,223]*	-0.113 [0.018]*	-0.110 [0.018]*	-0.001 [0.000]§	0.024 [0.009]§	-1.628 [0.530]*	-181.9 [46.7]*	-0.034 [0.012]*
1	-31,083 [3,999]*	-0.170 [0.022]*	-0.174 [0.050]*	0.022 [0.008]*	0.006 [0.004]	-0.907 [0.357]§	-111.7 [39.7]*	-0.036 [0.012]*
3	-65,799 [9,238]*	-0.260 [0.033]*	-0.189 [0.075]§	0.070 [0.017]*	0.023 [0.007]*	-2.059 [0.512]*	-260.9 [46.0]*	-0.074 [0.015]*
6	-97,662 [21,093]*	-0.320 [0.048]*	-0.272 [0.125]§	0.212 [0.041]*	0.059 [0.013]*	-4.665 [0.812]*	-363.5 [61.2]*	-0.083 [0.019]*
9	-152,002 [31,672]*	-0.402 [0.066]*	-0.360 [0.170]§	0.476 [0.079]*	0.116 [0.021]*	-7.029 [1.136]*	-622.6 [77.3]*	-0.138 [0.026]*
≥ 10	-195,576 [40,295]*	-0.583 [0.084]*	-0.604 [0.112]*	0.925 [0.143]*	0.155 [0.025]*	-8.812 [1.345]*	-789.9 [96.2]*	-0.195 [0.035]*
Cohort × year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,161	20,161	5,220	21,290	21,290	21,286	20,925	20,430
R-squared	0.11	0.15	0.21	0.14	0.08	0.08	0.09	0.07

^a Including zeros

Notes: The unit of observation is a survey respondent in a given post-MBA year. Each column corresponds to a different regression and each includes (cohort × year) dummies and interactions between a female dummy and dummy variables for the number of years since receipt of the MBA. The table reports the estimated coefficients on the interaction terms between the female dummy and years since receiving the MBA. “Annual earnings” is defined as total earnings before taxes and other deductions, including salary and bonus, and is coded as missing when the individual is not working. “Hourly wage” is computed by dividing annual earnings by (weekly hours worked × 52). Cols. (1) to (3) only include those with positive earnings. Col. (3) includes only the first year at a given job. Standard errors (in brackets) are clustered at the individual level; § significant at 5%; * significant at 1%.

Table 3
Wage Regressions for Pooled Sample

	<i>Dependent Variable: Log (Annual Earnings)</i>								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Female	-0.287 [0.035]*	-0.190 [0.033]*	-0.146 [0.032]*	-0.173 [0.030]*	-0.094 [0.029]*	-0.064 [0.029]§	-0.054 [0.028]	-0.045 [0.026]	-0.038 [0.025]
MBA GPA		0.429 [0.054]*	0.406 [0.053]*		0.369 [0.051]*	0.351 [0.051]*	0.367 [0.049]*	0.341 [0.044]*	0.347 [0.043]*
Fraction finance classes		1.833 [0.211]*	1.807 [0.206]*		1.758 [0.199]*	1.737 [0.194]*	1.65 [0.193]*	0.464 [0.181]§	0.430 [0.180]§
Actual post-MBA exp			0.046 [0.075]			0.085 [0.071]	0.056 [0.068]	0.044 [0.066]	0.029 [0.064]
Actual post-MBA exp ²			0.010 [0.004]*			0.005 [0.004]	0.008 [0.003]§	0.006 [0.003]	0.007 [0.003]§
Any no work spell			-0.290 [0.067]*			-0.228 [0.062]*	-0.218 [0.061]*	-0.181 [0.056]*	-0.173 [0.054]*
Dummy variables:									
Weekly hours worked	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Pre-MBA characteristics	No	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes
Reason for choosing job	No	No	No	No	No	No	Yes	No	Yes
Job function	No	No	No	No	No	No	No	Yes	Yes
Employer type	No	No	No	No	No	No	No	Yes	Yes
Cohort × year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	12.156 [0.018]*	9.493 [0.585]*	8.809 [0.667]*	10.385 [0.151]*	8.08 [0.603]*	7.525 [0.694]*	8.229 [0.733]*	7.744 [0.521]*	8.324 [0.547]*
Observations	18,272	18,272	18,272	18,272	18,272	18,272	18,272	18,272	18,272
R-squared	0.15	0.31	0.34	0.26	0.40	0.41	0.43	0.53	0.54

Notes: The unit of observation is a survey respondent in a given post-MBA year. Pre-MBA characteristics include: a dummy for U.S. citizen, a “white” dummy, an Asian dummy, a dummy for “top 10” undergraduate institution and a dummy for a “top 10 to 20” undergraduate institution (from the *U.S. News & World Report* rankings), undergraduate GPA, a dummy for missing undergraduate GPA, a quadratic in age, verbal GMAT score, quantitative GMAT score, a dummy for pre-MBA industry and a dummy for pre-MBA job function. “Any no work spell” is a dummy variable that equals 1 for a given individual in a given year if the individual experiences a period of at least six months without work between MBA graduation and that year. “Weekly hours worked” dummies include: < 20 hours, 20 to 29, 30 to 39, 40 to 49, 50 to 59, 60 to 69, 70 to 79, 80 to 89, 90 to 99, and ≥ 100 hours. “Reason for choosing job” dummies include: Compensation and other benefits; Career advancement or broadening; Prestige; Culture/people/environment; Flexible hours; Reasonable total hours per week; Limited travel schedule; Opportunity to work remotely; Location; Other. “Employer type” dummies include: Public for-profit, < 100 employees; Public for-profit, 100 to 1,000 employees; Public for-profit, 1,000 to 15,000 employees; Public for-profit, > 15,000 employees; Private for-profit, < 100 employees; Private for-profit, 101 to 1,000 employees; Private for-profit, 1,000 to 15,000 employees; Private for-profit, > 15,000 employees; Not-for-profit; and Other. Standard errors (in brackets) are clustered at the individual level; § significant at 5%; * significant at 1%.

Table 4
Gender Wage Gap by Years since MBA

	<i>Number of Years since MBA Receipt</i>					
	0	1	3	6	9	≥ 10
1. With no controls	-0.089 [0.020]*	-0.154 [0.025]*	-0.253 [0.038]*	-0.308 [0.056]*	-0.376 [0.079]*	-0.565 [0.045]*
With controls:						
2. Pre-MBA characteristics	-0.080 [0.021]*	-0.136 [0.026]*	-0.204 [0.039]*	-0.248 [0.057]*	-0.320 [0.084]*	-0.479 [0.045]*
3. Add MBA performance	-0.054 [0.021]*	-0.103 [0.025]*	-0.154 [0.037]*	-0.180 [0.055]*	-0.257 [0.082]*	-0.446 [0.044]*
4. Add labor market exp.	-0.053 [0.021]§	-0.093 [0.025]*	-0.134 [0.037]*	-0.143 [0.055]*	-0.181 [0.082]§	-0.312 [0.044]*
5. Add weekly hours worked	-0.036 [0.020]	-0.073 [0.023]*	-0.073 [0.036]§	-0.079 [0.053]	-0.047 [0.078]	-0.098 [0.042]§
6. Add reason for choosing job	-0.033 [0.020]	-0.067 [0.023]*	-0.064 [0.035]	-0.075 [0.053]	-0.031 [0.079]	-0.066 [0.042]
7. Add job setting characteristics	-0.025 [0.019]	-0.060 [0.022]*	-0.064 [0.032]§	-0.080 [0.048]	0.002 [0.071]	-0.010 [0.037]

Notes: The dependent variable in each equation is log (annual earnings). Each cell corresponds to a different regression. The unit of observation is a survey respondent in a given post-MBA year. In the regression without any controls, the sample is restricted to those survey respondents with non-missing pre-MBA characteristics. All regressions include (cohort \times year) dummies and a female dummy. In each column, the sample is restricted to (individual \times year) observations that correspond to the number of years since graduation listed in that column. Each cell gives the estimated coefficient on the female dummy. The controls for Pre-MBA characteristics, Weekly Hours Worked, and Reason for Choosing a Job are the same as those described in the notes to Table 3. MBA performance includes overall MBA GPA and fraction of finance classes. Labor market experience includes a quadratic in actual experience since MBA graduation, a dummy variable for “any no work spell” and dummy variables for weekly hours worked. Job setting characteristics include job function dummies and “Employer type” dummies. “Employer type” dummies include: Public for-profit, < 100 employees; Public for-profit, 100 to 1,000 employees; Public for-profit, 1,000 to 15,000 employees; Public for-profit, > 15,000 employees; Private for-profit, < 100 employees; Private for-profit, 101 to 1,000 employees; Private for-profit, 1,000 to 15,000 employees; Private for-profit, > 15,000 employees; Not-for-profit; Other. Standard errors are in brackets; § significant at 5%; * significant at 1%.

Table 5
Determinants of the Gender Gap in Labor Supply: The Role of Children

<i>Dependent Variable</i>	<i>Not working</i>		<i>Actual post-MBA experience</i>		<i>Log (weekly hours worked)</i>	
	(1)	(2)	(3)	(4)	(5)	(6)
Female	0.084 [0.009]*		-0.286 [0.039]*		-0.089 [0.013]*	
Female with child		0.200 [0.024]*		-0.660 [0.094]*		-0.238 [0.031]*
Female without child		0.034 [0.007]*		-0.126 [0.031]*		-0.033 [0.012]*
Pre-MBA characteristics	Yes	Yes	Yes	Yes	Yes	Yes
MBA performance	Yes	Yes	Yes	Yes	Yes	Yes
Cohort × year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-0.175 [0.145]	-0.111 [0.126]	5.929 [0.618]*	5.757 [0.550]*	3.951 [0.462]*	3.914 [0.426]*
Observations	19,366	19,286	19,366	19,286	18,611	18,535
R-squared	0.07	0.11	0.98	0.98	0.14	0.16

Notes: The unit of observation is a survey respondent in a given post-MBA year. “Female with child” (“Female without child”) is a dummy variable that equals 1 if the respondent is a female and has at least one child (no child) in that year. Pre-MBA characteristics include: a dummy for U.S. citizen, a White dummy, an Asian dummy, a dummy for “top 10” undergraduate institution, a dummy for “top 10-20” undergraduate institution, undergraduate GPA, a dummy for missing undergraduate GPA, a quadratic in age, verbal GMAT score, quantitative GMAT score, a dummy for pre-MBA industry and a dummy for pre-MBA job function. MBA performance includes overall MBA GPA and fraction of finance classes. Standard errors (in brackets) are clustered at the individual level; * significant at 1%.

Table 6
Female Labor Supply and Spousal Income

	<i>Not working</i>	<i>Actual post-MBA experience</i>	<i>Log (weekly hours worked)</i>
	(1)	(2)	(3)
Female with child	0.119 [0.046]*	-0.420 [0.175]§	-0.169 [0.041]*
Female with child × spouse with high earnings	0.185 [0.061]*	-0.538 [0.240]§	-0.189 [0.078]§
Female with child × spouse with medium earnings	0.026 [0.059]	-0.148 [0.235]	-0.045 [0.063]
Female without child	0.047 [0.021]§	-0.162 [0.087]	-0.067 [0.025]*
Female without child × spouse with high earnings	-0.028 [0.023]	0.122 [0.088]	0.100 [0.034]*
Female without child × spouse with medium earnings	-0.011 [0.023]	0.100 [0.086]	-0.008 [0.030]
Pre-MBA characteristics	Yes	Yes	Yes
MBA performance	Yes	Yes	Yes
Spouse salary dummies	Yes	Yes	Yes
Cohort × year dummies	Yes	Yes	Yes
Constant	-0.138 [0.119]	5.795 [0.520]*	3.891 [0.426]*
Observations	17,655	17,655	17,010
R-squared	0.14	0.99	0.18

Notes: The unit of observation is a survey respondent in a given post-MBA year. The sample includes only women who were “married” at the survey date and also excludes women with missing information on spousal income; men are included regardless of marital status. “Female with child” (“without child”) is a dummy variable that equals one if the respondent is a female and has at least one child (no child) in that year. “Spouse with high earnings” is a dummy variable that equals one if the respondent reports that his/her spouse or significant other earns at least \$200,000 in the survey year, 0 otherwise. “Spouse with medium earnings” is a dummy variable that equals one if the respondent reports that his/her spouse or significant other earns at least \$100,000 and at most \$200,000 in the survey year, 0 if the respondent reports that his/her spouse or significant other earns at most \$100,000 or at least \$200,000 in the survey year. Pre-MBA characteristics include: a dummy for US citizen, a White dummy, an Asian dummy, a dummy for “top 10” undergraduate institution, a dummy for “top 10 to 20” undergraduate institution, undergraduate GPA, a dummy for missing undergraduate GPA, a quadratic in age, verbal GMAT score, quantitative GMAT score, a dummy for pre-MBA industry and a dummy for pre-MBA job function. MBA performance includes overall MBA GPA and fraction of finance classes. Standard errors (in brackets) are clustered at the individual level; § significant at 5%; * significant at 1%.

Table 7: Selectivity in Marriage and Childbearing

	<i>Dependent Variable: Predicted Log (Annual Earnings)</i>	
	(1)	(2)
Female, married	-0.066 [0.025]*	
Female, unmarried	-0.084 [0.029]*	
Male, married	0.052 [0.020]*	
Female with child		-0.073 [0.025]*
Female without child		-0.088 [0.022]*
Male with child		0.056 [0.016]*
Constant	-0.061 [0.018]*	-0.053 [0.012]*
Observations	2,317	2,310
R-squared	0.02	0.03

Notes: The unit of observation is a survey respondent. Each column corresponds to a different regression. The dependent variable in all regressions is predicted log (annual earnings) constructed as follows. In the sample of male respondents, log (annual earnings) at the individual \times year level is regressed on cohort \times year dummies. The residual from that regression is then regressed on pre-MBA characteristics and MBA performance. Predicted log (annual earnings) is the predicted value from that second regression. The controls for pre-MBA characteristics are the same as those described in the notes to Table 3. MBA performance includes overall MBA GPA and fraction of finance classes. “Female, married” (“Male, married”) is a dummy variable that equals one if the respondent is female (male) and married or living with a significant other at the time of the survey. “Female, unmarried” is a dummy variable that equals one if the respondent is female and is neither married nor living with a significant other at the time of the survey. “Female with child” (“Male with child”) is a dummy variable that equals one if the respondent is a female (male) who reports having at least one child at the time of the survey. “Female without child” is a dummy variable that equals one if the respondent is a female who reports being without child at the time of survey. Standard errors are in brackets; * significant at 1%.

Table 8
Impact of First Birth on Employment Status, Salary, and Working Hours

	<i>Not Working</i>		<i>Log (Annual Earnings)</i>		<i>Annual Earnings (conditional on working)</i>		<i>Annual Earnings (0 if not working)</i>		<i>Log(Weekly Hours Worked)</i>		<i>Log (Annual Earnings)^a</i>
	(1) Male	(2) Female	(3) Male	(4) Female	(5) Male	(6) Female	(7) Male	(8) Female	(9) Male	(10) Female	(11) Female
Year of birth of first child	-0.001 [0.007]	0.096 [0.032]*	0.008 [0.036]	-0.096 [0.054]	1,880 [21,228]	-32,690 [21,003]	-2,315 [20,942]	-45,666 [20,936]§	-0.006 [0.010]	-0.126 [0.029]*	0.016 [0.049]
Years after birth of first child: 1 or 2	-0.009 [0.007]	0.131 [0.036]*	0.040 [0.040]	-0.164 [0.066]§	7,817 [24,606]	-41,129 [27,000]	5,117 [24,118]	-64,586 [26,335]§	-0.013 [0.011]	-0.168 [0.036]*	-0.008 [0.060]
3 or 4	-0.007 [0.008]	0.178 [0.045]*	0.065 [0.049]	-0.292 [0.092]*	14,701 [30,833]	-60,050 [36,118]	9,721 [29,915]	-99,397 [34,839]*	-0.011 [0.013]	-0.238 [0.049]*	-0.069 [0.079]
5 or more	0.000 [0.0012]	0.190 [0.054]*	0.162 [0.060]§	-0.301 [0.119]§	69,385 [39,072]	-63,664 [50,035]	62,581 [37,872]	-101,719 [44,384]§	0.000 [0.017]	-0.233 [0.071]*	-0.079 [0.097]
Years before birth of first child: 1 or 2	-0.006 [0.005]	-0.015 [0.021]	-0.008 [0.030]	-0.051 [0.041]	-5,740 [16,341]	-21,501 [14,794]	-7,830 [16,303]	-19,137 [15,226]	-0.005 [0.009]	-0.043 [0.023]	-0.016 [0.037]
Observations	14,490	5,070	13,969	4,545	13,969	4,545	14,523	5,070	14,193	4,560	4,523
R-squared	0.29	0.46	0.77	0.73	0.68	0.72	0.66	0.68	0.72	0.68	0.79

^a Includes a vector of dummy variables to control for hours worked (i.e., < 20 hours, 20-29, 30-39, ... , 90-99, and ≥100 hours).

Notes: The unit of observation is a survey respondent in a given post-MBA year. Individuals who had children prior to completing their MBA are not included in the regressions. Each column corresponds to a different regression. All regressions include (cohort × year) dummies, person fixed effects, and a quadratic in age. Each row reports the coefficient on a dummy variable indicating the year of first birth or the number of years after or before the birth of the first child. Standard errors (in brackets) are clustered at the individual level; § significant at 5%; * significant at 1%.

Table 9

Impact of Birth of First Child on Female Employment Status, Salary, and Working Hours: by Spouse's Income Level in 2006

	Spouse Earns at Most \$200K in 2006					Spouse Earns More than \$200K in 2006				
	<i>Not Working</i>	<i>Log (annual earnings)</i>	<i>Annual earnings (conditional on working)</i>	<i>Log (weekly hours worked)</i>	<i>Annual earnings (0 if not working)</i>	<i>Not Working</i>	<i>Log (annual earnings)</i>	<i>Annual earnings (conditional on working)</i>	<i>Log (weekly hours worked)</i>	<i>Annual earnings (0 if not working)</i>
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Year of birth of first child	0.006 [0.040]	-0.003 [0.089]	-18,220 [23,492]	-0.141 [0.046]*	-9,659 [23,599]	0.170 [0.070]§	-0.043 [0.099]	-63,146 [64,143]	-0.088 [0.060]	-89,785 [62,741]
Years after birth of first child:										
1 or 2	0.003 [0.047]	-0.040 [0.102]	-22,952 [28,570]	-0.162 [0.054]*	-10,100 [28,203]	0.224 [0.081]*	-0.120 [0.124]	-84,144 [79,826]	-0.158 [0.077]§	-128,393 [78,332]
3 or 4	0.025 [0.064]	-0.100 [0.142]	-23,451 [41,993]	-0.238 [0.071]*	-13,151 [38,170]	0.281 [0.096]*	-0.264 [0.180]	-128,180 [109,853]	-0.206 [0.105]	-198,134 [105,466]
5 or more	0.013 [0.087]	0.069 [0.192]	-1,425 [56,470]	-0.234 [0.099]§	3,236 [49,555]	0.315 [0.107]*	-0.382 [0.233]	-135,986 [136,768]	-0.194 [0.153]	-216,101 [123,738]
Years before birth of first child:										
1 or 2	-0.066 [0.030]§	-0.047 [0.068]	-19,397 [16,397]	-0.082 [0.036]§	-1,574 [16,604]	0.018 [0.044]	0.078 [0.074]	-25,788 [37,108]	0.043 [0.048]	-38,502 [42,786]
Observations	1,841	1,674	1,674	1,672	1,841	1,422	1,198	1,198	1,190	1,422
R-squared	0.50	0.69	0.69	0.66	0.64	0.53	0.82	0.79	0.77	0.74

Notes: The unit of observation is a female survey respondent in a given post-MBA year. The sample includes those who were married at the survey date and excludes those who had children prior to completing their MBA. Each column corresponds to a different regression. All regressions include (cohort \times year) dummies, person fixed effects, and a quadratic in age. Each row reports the coefficient on a dummy variable indicating the year of first birth or the number of years after or before the birth of the first child. Standard errors (in brackets) are clustered at the individual level; § significant at 5%; * significant at 1%.

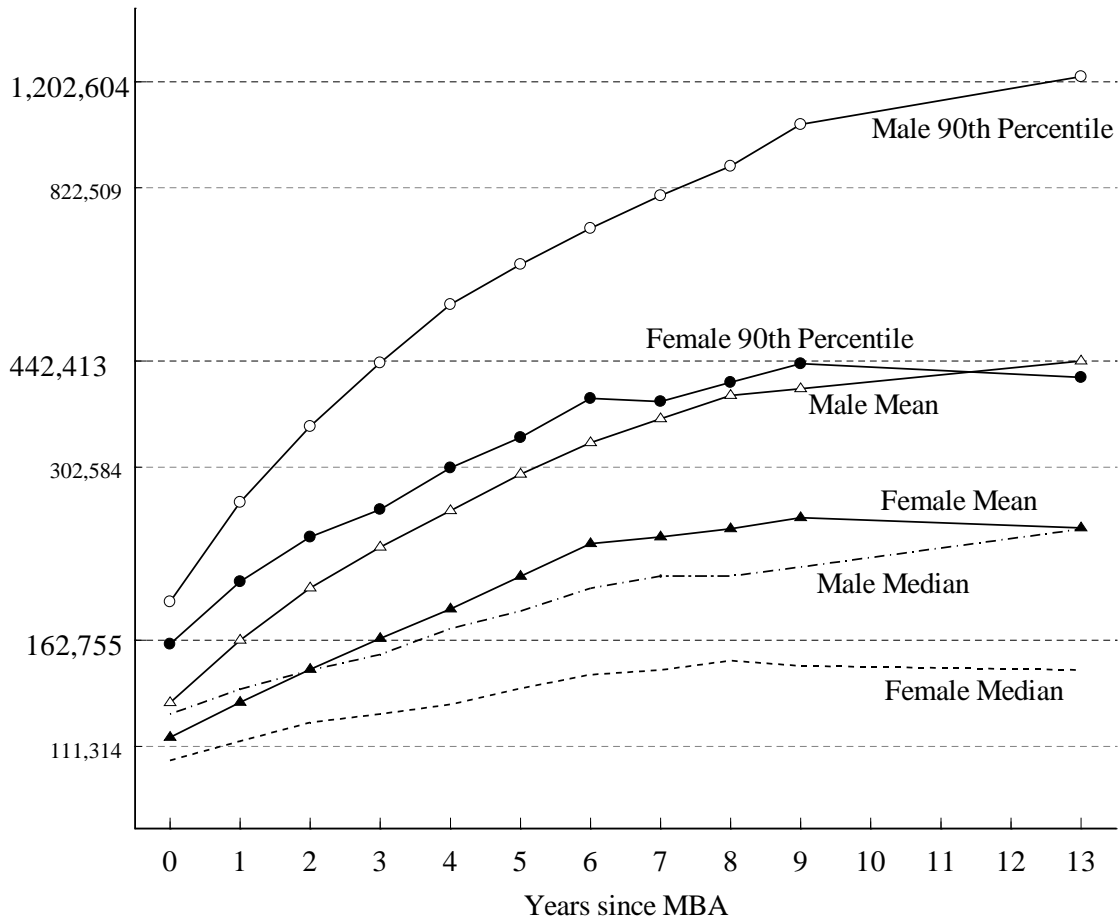
Table 10

Impact of Birth of First Child on Women's Reasons for Not Working, Choosing or Leaving a Job, and Job Characteristics

	<i>Not Working: Reasons</i>		<i>Choosing Job: Reasons</i>		<i>Leave Job</i>	<i>Leave Job: Reasons</i>			<i>Characteristics of Current Job Function</i>		
	<i>Family</i>	<i>Career</i>	<i>Family</i>	<i>Career</i>		<i>Family</i>	<i>Career</i>	<i>Career2</i>	<i>Mean hours</i>	<i>Fraction ≤ [30-40] hours</i>	<i>Fraction ≤ [40-50] hours</i>
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Year of birth of first child	0.119 [0.030]*	-0.011 [0.008]	0.125 [0.032]*	-0.080 [0.041]	-0.014 [0.035]	0.039 [0.022]	-0.014 [0.014]	-0.019 [0.021]	-0.018 [0.420]	-0.003 [0.004]	-0.019 [0.013]
Years after birth of first child:											
1 or 2	0.152 [0.034]*	-0.008 [0.010]	0.197 [0.040]*	-0.132 [0.051]*	-0.007 [0.031]	0.028 [0.017]	-0.019 [0.013]	-0.017 [0.019]	0.156 [0.491]	-0.004 [0.005]	-0.033 [0.016]§
3 or 4	0.200 [0.042]*	-0.009 [0.013]	0.256 [0.050]*	-0.214 [0.061]*	-0.043 [0.034]	0.035 [0.018]	-0.009 [0.016]	-0.017 [0.022]	0.552 [0.618]	-0.008 [0.006]	-0.053 [0.020]*
5 or more	0.233 [0.050]*	-0.018 [0.014]	0.231 [0.062]*	-0.135 [0.074]	-0.065 [0.038]	0.005 [0.019]	0.000 [0.019]	-0.007 [0.025]	1.068 [0.770]	-0.012 [0.007]	-0.066 [0.026]§
Years before birth of first child:											
1 or 2	-0.006 [0.016]	-0.004 [0.008]	0.040 [0.022]	-0.040 [0.032]	0.003 [0.027]	0.059 [0.017]*	-0.014 [0.013]	-0.040 [0.018]*	-0.483 [0.351]	0.004 [0.003]	0.014 [0.010]
Reason for choosing job dummies	No	No	No	No	Yes	Yes	Yes	Yes	No	No	No
Observations	5,070	5,070	4,577	4,577	5,070	5,070	5,070	5,070	5,070	5,070	5,070
R-squared	0.49	0.38	0.61	0.68	0.19	0.17	0.16	0.18	0.69	0.57	0.57

Notes: Unit of observation is a female survey respondent in a given post-MBA year. Individuals who had children prior to completing their MBA are not included in the regressions. Each column corresponds to a different regression. All regressions include (cohort \times year) fixed effects, person fixed effects, and a quadratic in age. Also included in columns (5) to (8) are dummies for the reasons for choosing current job. Each row reports the coefficient on a dummy variable indicating the year of first birth or the stated number of years after or before the birth of the first child. “Not Working: Reasons – Family (Career)” is a dummy variable that equals one if the respondent reports not working in that year and the reason for not working is family (career) related. Family reasons include: “Do not need or want to work”; “Home taking care of parents or other relatives” and “Home raising children.” Career reasons include: “Layoff” and “Suitable job not available.” “Choosing Job: Reasons – Family (Career)” is a dummy that equals one if the respondent reports family-related (career-related) reasons for choosing the job she/he is holding in that year. Family reasons include: “Flexible hours”; “Opportunity to work remotely”; “Limited travel schedule.” Career reasons include: “Career advancement or broadening”; “Compensation and other benefits” and “Prestige.” “Leave Job” is a dummy variable that equals one if the respondent reports leaving a job in that year. “Leave Job: Reasons – Family (Career)” is a dummy variable that equals one if the respondent reports leaving a job in that year and indicates family-related (career) reasons for leaving. Family reasons include: “Family reasons” and “Lifestyle (long hours, inflexible hours, extended travel schedule, etc).” Career reasons include: “Limited scope for career advancement and broadening” and “Limited scope for future earnings gain.” Career2 reasons also include: “Job did not match my strengths and interests” and “Issues with culture/people/environment.” “Fraction \leq [30-40] hours” is the fraction of (individual \times year) observations in that job function where hours worked are below 20, between 20 and 30, or between 30 and 40. “Fraction \leq [40-50] hours” is the fraction of (individual \times year) observations in that job function where hours worked are below 20, between 20 and 30, between 30 and 40 or between 40 and 50. See on-line Appendix Table A4 for more details. Standard errors (in brackets) are clustered at the individual level; § significant at 5%; * significant at 1%.

Figure 1
 Male and Female Mean, Median, and 90th Percentile (Ln) Annual Salaries (2006 dollars) by
 Years since MBA



Notes: On-line Appendix Table A5 contains the data points for a selected group of years since MBA. Nominal earnings in each year are converted into real earnings in 2006 dollars using the Consumer Price Index for All Urban Consumers (CPI-U).

On-Line Appendix Tables

Appendix Table A1
Who Responded to the Survey

	<i>MBA Classes 1990 to 2006^a</i>		
	<i>Respondent</i>	<i>Non-respondent^b</i>	<i>p-value</i>
Sample size	2,485	6,636	
Fraction female	0.25	0.23	0.063
Fraction US citizen	0.78	0.72	0.000
Fraction White	0.64	0.59	0.000
Fraction Asian	0.13	0.16	0.000
Age at entry	27.57	27.62	0.525
Top 10 undergraduate institution	0.13	0.13	0.880
Top 10 to 20 undergraduate institution	0.10	0.09	0.097
Undergrad GPA	2.68	2.65	0.456
Undergrad GPA (missing)	0.19	0.20	0.357
Total GMAT	668	655	0.000
Quantitative GMAT	43.31	42.79	0.000
Verbal GMAT	38.65	37.43	0.000
MBA GPA	3.35	3.31	0.000
Fraction finance classes	0.17	0.19	0.000

^a Includes only those who were matched to University of Chicago Booth School of Business administrative records (355 could not be matched).

^b “Non-respondent” also includes several hundred individuals who could not be contacted by e-mail.

Notes:

The unit of observation is an individual. The table compares mean pre-MBA characteristics and MBA performance between survey respondents and non-respondents. The last column reports a p-value on a test of comparison of means between the two groups. The top ten undergraduate institutions are Caltech, Columbia, Duke, Harvard, MIT, Princeton, Stanford, University of Chicago, University of Pennsylvania, and Yale; the top 20 undergraduate institutions add to this group: Brown, Cornell, Dartmouth, Emory, Johns Hopkins, Northwestern, Rice, University of Notre Dame, Vanderbilt, and Washington University (*Source: US News and World Report 2008, http://colleges.usnews.rankingsandreviews.com/usnews/edu/college/rankings/brief/t1natudoc_brief.php*). The Quantitative and Verbal GMAT scores are out of a total of 60; the Total GMAT score averages the percentage rankings of the two components and scales the average out of a total of 800.

Appendix Table A2

Gender Differences in Background, Test Scores, MBA Course Selection, and MBA Grades

	<i>All 1990-2006 Graduates</i>			<i>Survey Respondents</i>		
	<i>Females</i>	<i>Males</i>	<i>p-value</i>	<i>Females</i>	<i>Males</i>	<i>p-value</i>
	(1)	(2)	(3)	(4)	(5)	(6)
Sample size	2,185	6,936		629	1,856	
U.S. citizen	0.78	0.72	0.000	0.83	0.77	0.001
White	0.58	0.61	0.026	0.66	0.63	0.129
Asian	0.19	0.14	0.000	0.15	0.12	0.059
Age at entry	27.05	27.78	0.000	26.96	27.78	0.000
Top 10 undergraduate institution	0.14	0.12	0.062	0.15	0.12	0.091
Top 10 to 20 undergraduate institution	0.09	0.09	0.665	0.10	0.10	0.939
Undergrad GPA	2.79	2.62	0.000	2.87	2.61	0.000
Undergrad GPA (missing)	0.17	0.21	0.000	0.21	0.14	0.000
Total GMAT	642	664	0.000	654	673	0.000
Quantitative GMAT	41.14	43.49	0.000	41.77	43.81	0.000
Verbal GMAT	37.23	37.94	0.000	38.26	38.78	0.035
MBA GPA	3.23	3.34	0.000	3.25	3.38	0.000
Fraction MBA classes in:						
Finance	0.16	0.19	0.000	0.15	0.18	0.000
Accounting	0.13	0.15	0.000	0.13	0.14	0.003
Economics	0.15	0.15	0.842	0.15	0.15	0.928
Marketing	0.12	0.09	0.000	0.12	0.09	0.000
Statistics	0.06	0.06	0.000	0.06	0.06	0.005
Entrepreneurship	0.02	0.03	0.000	0.03	0.04	0.030
Average GPA in:						
Finance	3.03	3.27	0.000	3.04	3.31	0.000
Accounting	3.09	3.29	0.000	3.13	3.33	0.000
Economics	3.14	3.30	0.000	3.14	3.33	0.000
Marketing	3.26	3.30	0.002	3.30	3.34	0.085
Statistics	3.22	3.38	0.000	3.23	3.38	0.000
Entrepreneurship	3.21	3.33	0.000	3.26	3.37	0.007

Notes: The unit of observation is an individual. The table compares pre-MBA characteristics and MBA experience and performance between male and female individuals. Cols. (1) to (3) include all individuals who graduated from the MBA program between 1990 and 2006; cols. (4) to (6) are for those who responded to the survey. Cols. (3) and (6) report p-values of the test of equality of the means between females and males for each variable. Information on the top 10 and top 10 to 20 undergraduate institutions is given in the notes to Appendix Table A1.

Appendix Table A3
 Career and Family Statistics

	<i>All</i>	<i>Male</i>	<i>Female</i>
Career variables:			
First job post-MBA:			
Consulting	0.26 (0.44)	0.27 (0.44)	0.25 (0.43)
Investment banking	0.13 (0.33)	0.14 (0.34)	0.10 (0.29)
Investment management	0.09 (0.29)	0.10 (0.30)	0.06 (0.23)
Fraction of post-MBA working years in:			
Consulting	0.19 (0.33)	0.19 (0.34)	0.19 (0.33)
Investment banking	0.10 (0.27)	0.11 (0.28)	0.07 (0.24)
Investment management	0.11 (0.29)	0.12 (0.31)	0.07 (0.23)
Ever entrepreneur	0.15 (0.36)	0.16 (0.37)	0.11 (0.32)
Ever not working	0.14 (0.35)	0.10 (0.30)	0.27 (0.45)
Fraction post-MBA years not working	0.03 (0.10)	0.02 (0.07)	0.07 (0.16)
Currently not working	0.05 (0.21)	0.02 (0.15)	0.11 (0.32)
Total years not working	0.24 (0.92)	0.11 (0.44)	0.62 (1.60)
Average length of a working stage (years)	3.41 (2.89)	3.54 (3.00)	3.03 (2.50)
Average weekly working hours	58.29 (12.42)	59.15 (12.06)	55.75 (13.11)
Mean post-MBA annual earnings (2006 dollars)	228,236 (242,140)	249,938 (259,786)	164,417 (164,879)
Family variables:			
Married	0.77 (0.42)	0.81 (0.39)	0.65 (0.48)
Spouse with lower education	0.35 (0.48)	0.38 (0.49)	0.22 (0.42)
Number of children	1.11 (1.18)	1.23 (1.21)	0.77 (1.03)
Fraction without children	0.44 (0.50)	0.40 (0.49)	0.58 (0.49)

Notes: The unit of observation is a survey respondent. “Ever not working” is defined as having spent a period of at least six months since MBA graduation without working. “Annual earnings” is defined as total earnings, before taxes and other deductions, including salary and bonus. “Annual earnings” is missing when individual is not working. “Hourly wage” is computed by dividing annual earnings by (weekly hours \times 52). All family variables are measured as of the year the survey was conducted. Spouse with lower education is defined as a spouse with a BA degree, some college, a high school degree, or some high school.

Appendix Table A4
Hours Worked by Job Function

<i>Function</i>	<i>Mean hours</i>	<i>Mean hours (men only)</i>	<i>Fraction $\leq [30-40]$ hours</i>	<i>Fraction $\leq [40-50]$ hours</i>	<i>Fraction women</i>	<i>Individual \times year observations</i>
Accounting	52.1	51.4	0.06	0.55	0.24	161
Administration	53.2	55.3	0.08	0.38	0.19	161
Advertising	51.6	52.5	0.06	0.44	0.59	156
Business Development	55.8	55.9	0.04	0.29	0.17	842
Client Services	58.1	60.7	0.06	0.26	0.24	187
Commercial Banking	55.8	56.2	0.07	0.27	0.17	323
Company Finance	53.4	53.6	0.04	0.35	0.29	1693
Consulting	60.7	61.6	0.03	0.15	0.23	3643
Customer Relations	50.5	51.3	0.05	0.57	0.23	120
General Management	57.0	57.4	0.03	0.26	0.14	1869
Human Resources	51.0	56.4	0.16	0.40	0.71	126
Investment Banking	73.6	73.1	0.01	0.05	0.15	1871
Investment Management	57.8	58.7	0.03	0.24	0.15	2021
Law	58.3	58.1	0.06	0.25	0.19	188
Management	49.7	52.5	0.05	0.69	0.30	136
Multiple	59.0	59.0	0.09	0.26	0.22	515
Operations	50.8	51.0	0.11	0.48	0.13	227
Product Management	52.9	54.0	0.04	0.37	0.42	383
Project Management	52.4	52.1	0.08	0.48	0.26	1639
Real Estate	55.3	56.7	0.05	0.35	0.13	407
Research	52.2	54.7	0.09	0.36	0.30	275
Risk Management	54.5	54.0	0.01	0.25	0.14	265
Sales	54.0	53.6	0.03	0.36	0.30	161
Sales and Trading	59.3	58.1	0.02	0.16	0.18	491
Strategic Planning	53.7	55.1	0.04	0.40	0.30	691
Venture Capital	59.4	59.6	0.02	0.23	0.08	812
Other	55.8	55.9	0.10	0.31	0.54	740

Notes: Job function categories are from the Business School Career Services Department. The sample is restricted to those job functions where the number of (individual \times year) observations is ≥ 100 . “Fraction $\leq [30-40]$ hours” is the fraction of (individual \times year) observations where hours worked are: below 20, between 20 and 30, or between 30 and 40. “Fraction $\leq [40-50]$ hours” is the fraction of (individual \times year) observations where hours worked are: below 20, between 20 and 30, between 30 and 40 or between 40 and 50. “Fraction women” is the fraction of (individual \times year) observations where individual is a female.

Appendix Table A5

Earnings Trajectories (in 2006 dollars) by Years since MBA Graduation, Starting Job Function, and Quantiles

Years since graduation:	<i>Females</i>	<i>Males</i>	<i>All Survey Respondents</i>		<i>Start in Consulting</i>		<i>Start in I-Banking</i>	
	Mean (1)	Mean (2)	Mean (3)	Median (4)	Mean (5)	Median (6)	Mean (7)	Median (8)
0	114,928	130,156	126,356	122,076	129,623	129,032	173,740	160,612
1	130,321	162,785	154,691	129,032	143,649	140,307	248,639	232,411
3	163,835	227,143	212,043	146,342	176,254	154,601	352,911	314,019
6	230,084	330,114	307,451	175,000	246,169	180,645	500,979	380,645
9	252,421	400,488	367,601	186,766	299,331	196,109	691,156	468,120
10 plus	243,481	442,353	400,715	217,121	362,274	238,710	815,914	559,802

Years since graduation:	<i>Females</i>	<i>Males</i>	<i>Females</i>	<i>Males</i>	<i>Females</i>	<i>Males</i>
	Median (9)	Median (10)	75 th (11)	75 th (12)	90 th (13)	90 th (14)
0	105,882	125,000	140,078	151,261	160,612	186,766
1	113,404	136,520	149,416	180,130	200,765	266,808
3	125,000	154,601	172,734	250,000	260,006	439,626
6	143,874	196,109	208,712	350,000	387,097	711,463
9	148,432	211,573	211,765	361,290	382,420	800,000
10 plus	146,342	242,367	233,750	382,707	438,261	1,032,622

Notes:

Cols. (1) to (4) and (9) to (14): Mean and median annual earnings, and by percentile, by number of years since graduation for males and females or for all survey respondents with positive earnings. Columns (5) to (8) give means and medians for survey respondents whose first post-MBA job function was consulting or investment banking. All earnings numbers are given in 2006 dollars using the CPI-U as the price deflator.

Appendix Table A6
Hourly Wage Regressions

	<i>Dependent Variable: Log (Hourly Wage)</i>						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female	-0.193 [0.030]§	-0.148 [0.030]§	-0.102 [0.029]§	-0.068 [0.029]*	-0.05 [0.028]	-0.038 [0.025]	-0.029 [0.025]
MBA GPA			0.369 [0.051]§	0.349 [0.051]§	0.359 [0.050]§	0.332 [0.044]§	0.336 [0.044]§
Fraction finance classes			1.729 [0.198]§	1.705 [0.194]§	1.62 [0.193]§	0.472 [0.180]§	0.449 [0.179]*
Actual post-MBA exp				0.091 [0.074]	0.069 [0.071]	0.059 [0.068]	0.049 [0.066]
Actual post-MBA exp ²				0.005 [0.004]	0.007 [0.004]	0.005 [0.004]	0.006 [0.003]
Any no work spell				-0.216 [0.065]§	-0.200 [0.063]§	-0.158 [0.056]§	-0.150 [0.054]§
Dummy variables:							
Pre-MBA characteristics	No	Yes	Yes	Yes	Yes	Yes	Yes
Reason for choosing job	No	No	No	No	Yes	No	Yes
Job function	No	No	No	No	No	Yes	Yes
Employer type	No	No	No	No	No	Yes	Yes
Cohort × year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	4.156 [0.017]§	2.285 [0.609]§	1.582 [0.603]§	0.893 [0.717]	1.477 [0.780]	0.955 [0.548]	1.487 [0.597]*
Observations	18,272	18,272	18,272	18,272	18,272	18,272	18,272
R-squared	0.18	0.28	0.32	0.34	0.36	0.47	0.48

Notes: The unit of observation is a survey respondent in a given post-MBA year. Hourly wage is defined as annual earnings divided by (52 × usual weekly hours worked). Pre-MBA characteristics include: a dummy for U.S. citizen, a “white” dummy, an Asian dummy, a dummy for “top 10” undergraduate institution, a dummy for “top 10 to 20” undergraduate institution, undergraduate GPA, a dummy for missing undergraduate GPA, a quadratic in age, verbal GMAT score, quantitative GMAT score, a dummy for pre-MBA industry and a dummy for pre-MBA job function. “Any no work spell” is a dummy variable that equals 1 for a given individual in a given year if the individual experiences a period of at least six months without work between MBA graduation and that year. “Reason for choosing job” dummies include: Compensation and other benefits; Career advancement or broadening; Prestige; Culture/people/environment; Flexible hours; Reasonable total hours per week; Limited travel schedule; Opportunity to work remotely; Location; Other. “Employer type” dummies include: Public for-profit, < 100 employees; Public for-profit, 100 to 1,000 employees; Public for-profit, 1,000 to 15,000 employees; Public for-profit, > 15,000 employees; Private for-profit, < 100 employees; Private for-profit, 101 to 1,000 employees; Private for-profit, 1,000 to 15,000 employees; Private for-profit, > 15,000 employees; Not-for-profit; Other. Standard errors (in brackets) are clustered at the individual level; § significant at 5%; * significant at 1%.

Appendix Table A7

Decomposition of the Female-Male Log Earnings Gap by Explanatory Variables

	All Years since MBA Graduation			
	Raw Gender Log Earnings Gap = -0.314			
	Female Mean	Male Mean	Coefficient	Contribution
Female	1	0	-0.064	-0.064
Pre-MBA characteristics ^a				-0.014
MBA performance				-0.078
MBA GPA	3.299	3.396	0.351	-0.034
Fraction finance classes	0.159	0.184	1.737	-0.044
Labor market experience				-0.093
Actual post-MBA experience	4.610	5.098	0.085	-0.041
Actual post-MBA exp ²	36.419	42.932	0.005	-0.036
Any no work spell	0.127	0.055	-0.228	-0.016
Weekly hours worked dummies				-0.093
20 or less	0.016	0.001	-0.149	-0.002
20-30 (base group)	0.025	0.003	0.000	0.000
30-40	0.058	0.021	0.731	0.027
40-50	0.278	0.211	0.944	0.063
50-60	0.316	0.397	1.179	-0.095
60-70	0.173	0.217	1.356	-0.061
70-80	0.071	0.087	1.413	-0.023
80-90	0.040	0.034	1.338	0.009
90-100	0.017	0.018	1.595	-0.002
100 or more	0.005	0.011	1.596	-0.010
Cohort × year dummies				0.028

^a Pre-MBA characteristics = Demographics + Pre-MBA industry dummies + Pre-MBA function dummies; where demographics include U.S. citizen, race, rank of undergraduate college, undergraduate GPA, age, age squared, GMAT Quantitative, and GMAT Verbal.

Note: The coefficients and sample means by sex are for the specification shown in col. 6 of Table 3 pooling all years since MBA completion. Specifically, the model includes: pre-MBA characteristics, MBA performance, labor market experience, dummies for weekly hours worked, and (cohort × year) dummies. The contribution of variable j to the gender earnings gap is given by $(X_{jf} - X_{jm})B_j$ where X_{jf} and X_{jm} are respectively the female and male sample means for variable j for the regression sample and B_j is the estimated regression coefficient for variable j . The numbers in bold in the Contribution column are the sums of the contributions of the individual variables in that group of explanatory variables. The numbers in bold sum to the overall (raw) gender log earnings gap of -0.314.

Appendix Table A8
Wage Regressions with Female and Child Dummies

	<i>Dependent Variable: Log (Annual Earnings)</i>								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Female with child	-0.45 [0.069]*	-0.35 [0.060]*	-0.28 [0.058]*	-0.16 [0.054]*	-0.10 [0.049]§	-0.06 [0.049]	-0.03 [0.048]	-0.06 [0.045]	-0.04 [0.044]
Female without child	-0.22 [0.034]*	-0.13 [0.033]*	-0.09 [0.032]*	-0.18 [0.030]*	-0.09 [0.030]*	-0.06 [0.029]§	-0.06 [0.029]§	-0.04 [0.026]	-0.03 [0.026]
MBA GPA		0.43 [0.054]*	0.41 [0.054]*		0.37 [0.051]*	0.35 [0.051]*	0.37 [0.049]*	0.34 [0.044]*	0.35 [0.043]*
Fraction finance classes		1.81 [0.212]*	1.79 [0.206]*		1.76 [0.199]*	1.73 [0.195]*	1.65 [0.193]*	0.45 [0.182]§	0.42 [0.180]§
Actual post-MBA exp			0.05 [0.076]			0.09 [0.072]	0.06 [0.069]	0.04 [0.067]	0.03 [0.065]
Actual post-MBA exp ²			0.01 [0.004]§			0.01 [0.004]	0.01 [0.003]§	0.01 [0.003]	0.01 [0.003]§
Any no work spell			-0.30 [0.067]*			-0.23 [0.062]*	-0.22 [0.061]*	-0.19 [0.056]*	-0.18 [0.054]*
Dummy variables:									
Weekly hours worked	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Pre-MBA characteristics	No	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes
Reason for choosing job	No	No	No	No	No	No	Yes	No	Yes
Job function	No	No	No	No	No	No	No	Yes	Yes
Employer types	No	No	No	No	No	No	No	Yes	Yes
Cohort × year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	12.16 [0.018]*	9.43 [0.575]*	8.77 [0.669]*	10.37 [0.153]*	8.05 [0.606]*	7.49 [0.696]*	8.19 [0.733]*	7.72 [0.522]*	8.30 [0.546]*
Observations	18,205	18,205	18,205	18,205	18,205	18,205	18,205	18,205	18,205
R-squared	0.15	0.32	0.34	0.26	0.40	0.41	0.43	0.54	0.54

Notes: The unit of observation is a survey respondent in a given survey year. See also the notes to Table 3. Standard errors are in brackets; § significant at 5%; * significant at 1%.

Appendix Table A9

Gender Wage Gap by Years since MBA, for Females without Career Interruptions versus All Males

	<i>Number of Years since MBA Receipt</i>										
	0	1	2	3	4	5	6	7	8	9	10
1. With no controls	-0.088 [0.047]	-0.162 [0.053]*	-0.173 [0.061]*	-0.218 [0.068]*	-0.197 [0.071]*	-0.229 [0.073]*	-0.184 [0.078]§	-0.208 [0.083]§	-0.250 [0.087]*	-0.288 [0.093]*	-0.343 [0.097]*
With controls:											
2. Pre-MBA characteristics	-0.082 [0.052]	-0.122 [0.059]§	-0.106 [0.068]	-0.146 [0.074]§	-0.160 [0.079]§	-0.203 [0.081]§	-0.153 [0.088]	-0.159 [0.093]	-0.201 [0.097]§	-0.247 [0.103]§	-0.282 [0.106]*
3. Add MBA performance	-0.057 [0.051]	-0.082 [0.057]	-0.058 [0.066]	-0.088 [0.071]	-0.100 [0.075]	-0.140 [0.076]	-0.088 [0.084]	-0.092 [0.089]	-0.140 [0.093]	-0.176 [0.099]	-0.217 [0.103]§
4. Add labor market exp.	-0.057 [0.051]	-0.102 [0.057]	-0.087 [0.065]	-0.113 [0.070]	-0.118 [0.075]	-0.155 [0.077]§	-0.107 [0.084]	-0.124 [0.089]	-0.182 [0.093]	-0.214 [0.099]§	-0.261 [0.103]§
5. Add weekly hours worked	-0.050 [0.050]	-0.093 [0.055]	-0.075 [0.063]	-0.084 [0.068]	-0.075 [0.072]	-0.102 [0.075]	-0.085 [0.080]	-0.056 [0.084]	-0.116 [0.089]	-0.107 [0.095]	-0.100 [0.100]
6. Add reason for choosing job	-0.044 [0.050]	-0.082 [0.056]	-0.064 [0.063]	-0.084 [0.068]	-0.067 [0.072]	-0.102 [0.076]	-0.070 [0.081]	-0.046 [0.084]	-0.108 [0.088]	-0.099 [0.095]	-0.085 [0.099]
7. Add job setting characteristics	-0.040 [0.051]	-0.073 [0.055]	-0.044 [0.061]	-0.095 [0.066]	-0.060 [0.068]	-0.076 [0.071]	-0.066 [0.077]	-0.079 [0.080]	-0.116 [0.082]	-0.089 [0.089]	-0.070 [0.091]

Notes: The sample is restricted to the first ten years out for individuals who graduated at least ten years before. We include only females without a career interruption ten years post-graduation. See also the notes to Table 3. Standard errors are in brackets; § significant at 5%; * significant at 1%.

Appendix Table A10

Gender Wage Gap by Years since MBA, for Females without Children and without Career Interruptions versus All Males

	<i>Number of Years since MBA Receipt</i>										
	0	1	2	3	4	5	6	7	8	9	10
1. With no controls	-0.130 [0.068]	-0.210 [0.078]*	-0.223 [0.088]§	-0.221 [0.097]§	-0.158 [0.101]	-0.198 [0.104]	-0.137 [0.113]	-0.194 [0.119]	-0.235 [0.126]	-0.237 [0.133]	-0.279 [0.138]§
With controls:											
2. Pre-MBA characteristics	-0.151 [0.074]§	-0.194 [0.087]§	-0.172 [0.100]	-0.130 [0.107]	-0.097 [0.114]	-0.139 [0.116]	-0.077 [0.128]	-0.113 [0.136]	-0.159 [0.140]	-0.153 [0.148]	-0.141 [0.152]
3. Add MBA performance	-0.129 [0.073]	-0.163 [0.084]	-0.133 [0.096]	-0.084 [0.102]	-0.047 [0.107]	-0.090 [0.109]	-0.024 [0.122]	-0.059 [0.130]	-0.110 [0.135]	-0.094 [0.143]	-0.090 [0.148]
4. Add labor market exp.	-0.129 [0.073]	-0.182 [0.083]§	-0.161 [0.095]	-0.110 [0.101]	-0.067 [0.107]	-0.103 [0.109]	-0.040 [0.122]	-0.089 [0.129]	-0.156 [0.135]	-0.134 [0.142]	-0.136 [0.148]
5. Add weekly hours worked	-0.125 [0.072]	-0.173 [0.081]§	-0.157 [0.093]	-0.082 [0.098]	-0.050 [0.103]	-0.089 [0.106]	-0.065 [0.117]	-0.124 [0.123]	-0.172 [0.128]	-0.147 [0.136]	-0.125 [0.143]
6. Add reason for choosing job	-0.109 [0.071]	-0.161 [0.081]§	-0.149 [0.093]	-0.077 [0.098]	-0.046 [0.103]	-0.086 [0.108]	-0.049 [0.117]	-0.109 [0.123]	-0.154 [0.128]	-0.128 [0.136]	-0.103 [0.142]
7. Add job setting characteristics	-0.082 [0.071]	-0.153 [0.079]	-0.121 [0.090]	-0.072 [0.096]	-0.045 [0.096]	-0.047 [0.100]	-0.015 [0.110]	-0.103 [0.114]	-0.158 [0.117]	-0.112 [0.126]	-0.038 [0.129]

Notes: The sample is restricted to the first ten years out for individuals who graduated at least ten years before. We include only females without children and without a career interruption ten years post-graduation. See also notes to Table 3. Standard errors are in brackets; § significant at 5%; * significant at 1%.

Appendix Table A11

Impact of Birth of First Child on Female Employment Status, Salary, and Working Hours: by Spouse's Education Level

	Spouse Is Less Educated					Spouse Is As Or More Educated				
	<i>Not Working</i>	<i>Log (annual earnings)</i>	<i>Annual earnings (conditional on working)</i>	<i>Log (weekly hours worked)</i>	<i>Annual earnings (0 if not working)</i>	<i>Not Working</i>	<i>Log (annual earnings)</i>	<i>Annual earnings (conditional on working)</i>	<i>Log (weekly hours worked)</i>	<i>Annual earnings (0 if not working)</i>
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Year of birth of first child	-0.086 [0.057]	-0.028 [0.134]	909 [44,150]	-0.158 [0.049]*	27,227 [42,228]	0.145 [0.044]*	-0.045 [0.070]	-51,531 [36,032]	-0.102 [0.042]§	-72,015 [34,016]§
Years after birth of first child:										
1 or 2	-0.126 [0.063]§	-0.012 [0.148]	896 [52,830]	-0.139 [0.055]§	46,778 [48,058]	0.210 [0.051]*	-0.107 [0.089]	-62,063 [46,053]	-0.171 [0.059]*	-99,846 [43,235]§
3 or 4	-0.088 [0.099]	-0.098 [0.200]	-24,674 [71,447]	-0.226 [0.063]*	6,971 [65,573]	0.260 [0.060]*	-0.228 [0.122]	-85,510 [62,895]	-0.254 [0.080]*	-136,980 [58,035]§
5 or more	-0.179 [0.132]	-0.098 [0.275]	-67,470 [98,356]	-0.286 [0.097]*	11,636 [88,582]	0.283 [0.065]*	-0.189 [0.164]	-72,073 [82,226]	-0.258 [0.116]§	-130,666 [72,155]
Years before birth of first child:										
1 or 2	-0.095 [0.038]§	0.074 [0.089]	11,955 [31,464]	-0.052 [0.036]	38,708 [32,009]	0.004 [0.029]	-0.040 [0.053]	-35,854 [22,973]	-0.028 [0.034]	-39,946 [23,337]
Observations	881	814	814	808	881	2,625	2,281	2,281	2,276	2,625
R-squared	0.46	0.8	0.77	0.75	0.69	0.51	0.74	0.76	0.71	0.72

Notes: The unit of observation is a female survey respondent in a given post-MBA year. The sample includes those who were married at the survey date. Each column corresponds to a different regression. All regressions include (cohort × year) dummies, person fixed effects and a quadratic in age. Each row reports the coefficient on a dummy variable indicating the year of first birth or the number of years after or before the birth of the first child. Standard errors (in brackets) are clustered at the individual level; § significant at 5%; * significant at 1%.

Appendix Table A12: Wage Changes Associated with Job Changes

Panel A: By Gender and Parental Status	Log (entry salary) in stage t – Log (end salary) in stage $t-1$			
	Mean	Median	25 th percentile	75 th percentile
Overall	-0.012	0.000	0.000	0.336
Female:	-0.028	0.000	-0.260	0.336
With at least one child	-0.177	0.000	-0.357	0.336
No children	0.019	0.000	0.000	0.336
Male:	-0.008	0.000	0.000	0.336
With at least one child	-0.010	0.000	0.000	0.336
No children	-0.004	0.000	0.000	0.336
Panel B: By Reason for Job Change	Log (entry salary) in stage t – Log (end salary) in stage $t-1$			
	Mean	Standard Deviation	Number of Observations	
Reasons for choosing job in stage t :				
Career advancement or broadening	0.04	0.61	1514	
Compensation and other benefits	0.27	0.67	355	
Culture/people/environment	-0.02	0.60	230	
Flexible hours	-0.64	0.85	67	
Reasonable total hours per week	-0.21	0.60	83	
Location	-0.09	0.49	135	
Prestige	0.09	0.48	26	
Opportunity to work remotely	-0.20	0.88	20	
Limited travel schedule	-0.07	0.48	34	
Other	-0.53	0.99	211	
Missing response	-0.23	0.40	3	
Reasons for leaving job in stage $t-1$:				
Company was acquired	-0.23	0.83	164	
Limited scope for career advancement and broadening	0.07	0.64	617	
Issues with culture/ people/ environment	-0.08	0.69	244	
Limited scope for future earnings gain	0.33	0.73	224	
Family reasons	-0.23	0.79	80	
Involuntary separation	-0.23	0.71	191	
Lifestyle	-0.19	0.54	272	
Medical or health reasons	-0.82	1.16	2	
Company went out of business	0.05	0.78	134	
Needed to relocate	0.07	0.44	145	
Job did not match strengths and interests	0.02	0.63	259	
Other	0.01	0.69	333	
Missing response	-0.30	0.78	13	

Notes: The unit of observation is a working stage (stage t) that was immediately preceded by another working stage (stage $t-1$). For each observation, we compute the difference between log (entry salary) in stage t and log (end salary) in stage $t-1$. All salary figures are in 2006 dollars. In Panel A, observations are divided based on whether or not the individual had at least one child when stage t begins. In Panel B, observations are divided based on the reason for choosing job in stage t , or reason for leaving job in stage $t-1$.