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

by

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PRELIMINARY

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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. We study the careers of MBAs who graduated between 1990 and 2006 from a top U.S. business school and how career dynamics differ by gender. Although male and female MBAs have nearly identical labor incomes at the outset of their career, 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 reasons for the large and rising gender gap in earnings: differences in training prior to MBA graduation; differences in career interruptions; and differences in weekly hours. These three determinants can explain the bulk of gender differences in earnings across the years following MBA completion. The presence of children is the main contributor to the lesser job experience, greater career discontinuity and shorter work hours for female MBAs. It appears that many MBA mothers, especially those with well-off spouses, decide to slow down within a few years following their first birth. The pecuniary penalties from shorter hours and any job discontinuity among MBAs are enormous.

Positions in the business and financial sectors have commanded exceptionally high earnings in recent years and have attracted extraordinary talent.<sup>1</sup> 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 who obtained their BA from a selective institution, those continuing for an MBA within ten years of graduation increased from 4.3 percent to 7.1 percent in the two decades after 1972.<sup>2</sup> At the same time, the share of MBAs earned by the female graduates of selective undergraduate institutions increased by more than a factor of three.<sup>3</sup> The fraction female among graduating MBAs has exceeded 30 percent for each of the past 25 years and today stands at 43 percent.<sup>4</sup>

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 increased eight-fold from 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 why women underperform in the corporate and financial sectors. Even women who self-select into MBA programs may differ from their

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<sup>1</sup> Philippon and Reshef (2008) demonstrate the growth of the financial sector across the past century.

<sup>2</sup> 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 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 we also exclude those who obtained an MBA without having graduated from a U.S. university. By limiting the undergraduate institutions to selective ones, we attempt to hold student quality constant over the two decades.

<sup>3</sup> Using the NSCG and restricting the sample to BAs from selective universities and colleges gives 0.127 in 1970-73 and 0.395 in 1990-93 for the fraction female.

<sup>4</sup> According to data from NCES, the fraction of MBAs going to women has exceeded 0.3 since 1984. The fraction has been lower in the top MBA programs. It exceeded 0.3 at Harvard Business School starting around 2000 (HBS website) and has only just exceeded 0.3 at the University of Chicago GSB (UC GSB administrative data). The fraction female among *all* MBAs increased from 1970 to 2006 by a factor of ten, rising from 4 percent to 43 percent (*Source*: Department of Education, NCES, *Digest of Education Statistics*, includes all masters in business fields).

male peers and be less attracted to (or less prepared for) the more remunerative finance-related jobs, choosing instead “softer” careers in marketing or human resources management. Some experimental evidence suggests that women disproportionately lack a taste for the high-pressure, highly-competitive work environments found in top finance and corporate jobs (Niederle and Vesterlund 2007). Female MBAs may be less comfortable than their male colleagues in negotiating aggressively for additional pay and promotions and may even fear (possibly realistically) backlash from such behavior (Babcock and Laschever 2003). 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. Finally, it is possible that implicit or explicit gender discrimination persists in the corporate and financial sectors (Bertrand, Chugh, and Mullainathan 2005). Talented female MBAs may find it difficult to get recognized in work environments that are still heavily male-dominated.<sup>5</sup>

This paper speaks to the relative importance of these alternative explanations for the continuing and substantial gender gap in career outcomes for highly-educated workers 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 Graduate 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.

The main conclusion from our work is that female MBAs have not done as well as male MBAs in the labor market. That finding should not come as a surprise. The more startling findings concern why they have not done as well.

At the outset of their careers male and female MBAs have nearly identical labor incomes. Their earnings, however, soon diverge. Among those with positive earnings the male annual earnings advantage reaches 30 log points five years after MBA completion and almost 60 log points at ten to 16 years after MBA completion. The share of female MBAs not working at all

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<sup>5</sup> For example, Bell (2005) 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 5 paid” positions and remunerate these female executives more than non-women led firms do.

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.

Three proximate reasons are responsible for the large and rising gender gap in earnings that emerges within a few years of MBA completion: differences in training prior to MBA graduation; differences in career interruptions; and differences in weekly hours. These three determinants can explain the bulk of the gender differences in earnings across the years following MBA completion, but their relative importance changes with years since MBA completion. We use our sample to explore this evolution by analyzing the gender gap by years after the MBA and by comparing women without any career interruptions, with and without children, to men.

Male and female MBAs begin their careers with somewhat different training. Men take more courses in finance during the MBA program and earn higher GPAs. Gender differences in grades and course selection are statistically significant but not very large: women have a mean GPA of 3.25 compared with 3.38 for men and they take about half a class less in finance. But because of a strong positive correlation between MBA training and post-MBA earnings, these variables account for a non-trivial share of the gender gap in earnings. On average across all years following MBA completion, the gender difference in MBA GPA accounts for nearly 6 log points of the gender gap in earnings and each additional finance classes increases earnings by about 8 log points.

The large growth in the gender gap in earnings for MBAs during the first 15 years of their careers is mainly a consequence of gender differences in career interruptions and weekly hours worked. Women take more career interruptions and work shorter hours. About a decade following MBA completion, the actual job experience of men and women differs by six months; women work 52 hours per week, men 58 hours. Although these differences in cumulative work experience and contemporary hours worked appear to be modest, the remuneration disparity they entail is exceptionally large. We will demonstrate that *any* career interruption—a period of six months or more out of work—is very 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. Women may not be treated that differently from men, but 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 only a 1.5 month deficit. Similarly woman with children typically work 24 percent fewer weekly hours than the average male; while woman without children work only 3.3 percent fewer hours.

Although we cannot rule out that mothers reduce their labor supply in response to unfair treatment, actual or perceived, in the corporate world, our data do not provide direct evidence for this view. Mothers seem to actively choose jobs that are family friendly and avoid jobs with long hours and greater career advancement possibilities. MBA mothers, it would appear, decide to slowdown within a few years following their first birth. The women in our sample who have children are, if anything, positively selected on predicted earnings based on MBA performance as well as on actual cumulative earnings up through the two years prior to their first birth.

Our finding that a combination of human capital and labor supply factors can account for most of the gender gap in earnings among MBAs is in line with the findings 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. And our finding of a large increase in the gender gap over the first ten to 15 years in the careers of MBAs corresponds 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., Loprest 1992; Manning and Swaffield 2008).

## A. Background

The shift of talent to the corporate and financial sectors in the past three or so decades can be seen in the career choices made by graduates from top undergraduate institutions. 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 were working in the financial sector in 2005, again 15 years later. 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 also large rising from 11.7 percent to 22.5 percent, although the levels are lower than for the men.<sup>6</sup>

The reason for the shift of talent into the financial and corporate sectors is clear: high and rising compensation for highly-educated workers in these sectors. The premium to working in the financial sector among Harvard graduates, for example, is a whopping 195 percent and the premium to working in the corporate sector (executive and management jobs) is 25 percent relative to the average of other occupations (Goldin and Katz 2008). It is no wonder that exceptional talent has been flowing in the corporate and finance direction.

The career paths of female MBAs appear to differ significantly from the paths of comparable women with other professional and graduate degrees. Evidence on the working lives and family transitions of women who received BAs from Harvard University between 1969 and 1992 shows that about two-thirds went on to obtain a professional or doctoral degree. Among this group, the women who earned an MBA had the lowest labor force participation rates 15 years after obtaining their BA, the lowest share working full-time and full-year, took the greatest amount of (non-educational) time off from employment, and forfeited the most income because of their lapses from paid work (Goldin and Katz 2008). The differences are largest for those with children.<sup>7</sup> Among the youngest of the cohorts in the Harvard and Beyond project, those graduating college around 1990, only 75 percent of mothers with MBAs were working 15 years after Harvard graduation compared with 96 percent of those with MDs, 89 percent of those with

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<sup>6</sup> We include individuals employed in financial services, in executive and management positions, and in consulting, marketing, and sales as working in the corporate and financial sectors. See Goldin and Katz (2008) on the findings from the Harvard and Beyond project, which surveyed undergraduates from the classes of 1969 to 1973, 1979 to 1982, and 1989 to 1992.

<sup>7</sup> Working with a partially overlapping sample of women who received BAs from Harvard University between 1988 and 1991, Herr and Wolfram (2008) find nearly identical results to those in the Harvard and Beyond project for labor force participation rates among those graduating college around 1990.

PhDs, and 82 percent of those with JDs; only those mothers without any post-graduate education were less likely to work 15 years out than mothers with MBAs (73 percent).<sup>8</sup>

## B. University of Chicago MBA Survey and Sample

To understand the claims and the facts about careers for women with MBAs, we conducted between November 2006 and June 2007 a web-based survey of University of Chicago MBAs from the graduating classes of 1990 to 2006.<sup>9</sup> 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. They were also asked why they had left a position and the reasons they took a subsequent job. Each of the positions, either as a separate job title or firm, that lasted six months or more constituted a separate “stage,” and all stages were surveyed by the variables just listed. Furthermore, 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 earnings question asked for total annual earnings, before taxes and other deductions, in the first and last year at the job (in U.S. dollars). Respondents were instructed to include salary and bonuses if employed, earnings if self-employed. The responses to the earnings questions and to questions on usual weekly hours worked in each position were collected in discrete bins that we transformed into real-valued variables (at the mid-point of each bin) in our empirical work.<sup>10</sup>

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<sup>8</sup> Mothers in our University of Chicago MBA sample are slightly more likely to work. About 77 percent were still working ten or more years after receiving their MBA.

<sup>9</sup> Only full-time MBA graduates were surveyed. Part-time MBAs and executive MBAs were excluded.

<sup>10</sup> 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 using 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. The response bins for the usual weekly hours worked questions ranged were <20 hours, 20-30 hours, 30-40 hours, ..., 90-100 hours, and >100 hours.



In the final section of the survey, respondents were asked a set of questions about their family background, including current marital status and, for those currently married (or living with someone), questions on their spouse's highest educational attainment, employment status and earnings. All respondents were asked whether they had any children (biological or adopted) and, if yes, 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.

To facilitate the empirical analysis, 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. The administrative records provide information on MBA courses and grades, undergraduate school, undergraduate GPA, GMAT scores, and demographic information (age, ethnicity, and immigration status).

The University of Chicago has awarded about 570 MBAs annually since 1990, and of these 24 percent—on average—were awarded to women. That 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.<sup>11</sup> Among the MBAs in these classes having apparently viable e-mail addresses about 31 percent responded to the survey, which was e-mailed to the group using both the MBA's "life-time" University of Chicago e-mail address and, when available, e-mail addresses from the alumni directory maintained by the Business School.<sup>12</sup> Of this group 2,485 (or 97 percent) were matched to University of Chicago administrative records. These 1,856 men and 629 women form the basis of our sample.

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<sup>11</sup> Among Harvard Business School MBAs for the same period, 31 percent were female, a number higher than that for the University of Chicago but lower than the national average.

<sup>12</sup> A viable e-mail address means that the address was listed and that the request did not bounce back. Because e-mail addresses can fail without having any mail bounce back, the 31 percent response rate should be considered a lower bound.

We provide summary statistics on the respondents and the non-respondents in Table A1 and on gender differences for a variety of pre-MBA characteristics in Table A2. The respondents are not much different from the non-respondents based on the observables. Respondents are, to a slight degree, disproportionately female and U.S. citizens, and they had better undergraduate and graduate records than the non-respondents (see Table A1).

Relative to the male MBAs, the women are slightly younger at graduate school entry and more often U.S. citizens; they did better as undergraduates but worse on the GMAT (Table A2). 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, these MBA grades have some informational content. Females have slightly lower graduate GPAs. The lower female grades extend across fields of study, but are particularly salient in finance and accounting courses and, to lesser degree, in economics and statistics.

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 (Table A2). The women in our survey are slightly more positively selected than males on their undergraduate GPA, and the survey respondents for both genders are modestly positively selected on GMAT scores and MBA GPA.

At the time of the survey, the female MBAs in the sample were less apt to be married (or living with a significant other) than their male counterparts (0.65 versus 0.81).<sup>13</sup> If married (or living with a significant other), female MBAs were much less likely to have a husband less educated (at most undergraduate degree) than they. Female MBAs were also less likely to have any children at the time they entered the MBA program (3 percent versus 9 percent) and by the year they exited the program (4 percent versus 16 percent). They remain less likely to have

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<sup>13</sup> Cross-sectional summary information on the career and family characteristics of our survey respondents overall and by sex are given in Table A3.

children at the time of the survey (42 percent versus 60 percent). Among the sub-sample of survey respondents that we can observe nine years out of 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 (0.27 versus 0.10), and whereas 11 percent of the women across all cohorts were not working at the time of our survey, just 2 percent of the men not working.

Almost two-fifths of our sample took their first post-MBA jobs in consulting and investment banking (26 percent and 13 percent, respectively).<sup>14</sup> The next three most common positions at graduation were investment management (9 percent), company finance (9 percent) and product management (8 percent). Finance jobs, both in investment banking and investment management, have accounted for a larger share of first positions in the more recent years.

The share of those working in consulting declines rapidly in the years following graduation: only 17 percent were still working as consultants four years after graduation and 12 percent were seven years or more after. MBAs also move away from investment banking as their careers progress: only 9 percent were still working as investment bankers four years after graduation and 6 percent were after seven years or more. On the other hand, the share working as general managers rises from 8 percent at four years after graduation to nearly 15 percent at seven years or more. In contrast, employment shares in investment management, company finance, and product management are quite stable in the 15 years following graduation.

Weekly hours are distinctly highest in investment banking and consulting, the two most frequent job functions at the start of careers. The average investment banker put in a whopping 74 hours per week, the average consultant 61 hours per week.<sup>15</sup> Also reaching close to the 60 hours per week average are those employed in venture capital and sales and trading. But hours are remarkably high among all functions for our sample of Chicago MBAs, with only the small

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

<sup>15</sup> See Table A4 data for mean weekly hours for the most common job functions in our MBA sample. We focus on job functions having at least 100 individual-year observations in the sample.

set of those working as managers (not *general* managers) putting in fewer than 50 hours per week on average (49.7 hours).<sup>16</sup>

## C. Descriptive Dynamics

### 1. Labor Supply

We begin with a summary of the early careers of the male and female MBAs in our Chicago GSB alumni sample (see Table 1). Labor force participation is extremely high for the men: at no point following graduation are there more than 1 percent of male graduates not working in a given year.<sup>17</sup> Slightly higher shares of women are not working in the years immediately following graduation (from 1 percent at one year out to 5 percent at five years out). The gender gap in labor force participation continues to widen as careers progress with 13 percent of women not in the labor force by year nine and 17 percent not in the labor force ten or more years since their MBA.

Differences in labor force participation by sex are even more pronounced comparing the fraction of men and women working full-time and full-year in a given year (Table 1).<sup>18</sup> The fraction of men working full-time, year-round, ranges between 91 and 94 percent in all years following graduation. Although 90 percent of women were employed full-time and full-year immediately following graduation, 80 percent were five years out, 70 percent nine years out, and 62 percent ten or more years out.<sup>19</sup> For women with at least one child, 52 percent were working full-time and full-year at ten or more years after MBA completion and the figure is about the same (50 percent) for women with more than one child.

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<sup>16</sup> The job function categories used in the survey are borrowed from the Business School Career Services Department. Although the difference between a manager and a general manager is not always clear, the “general manager” label tends to be reserved for higher-level positions in the corporate hierarchy.

<sup>17</sup> The only exception is the year of graduation because the MBA labor market is still clearing.

<sup>18</sup> Our survey did not include a question on “full-time” versus “part-time” work. We assign “full-time” (“part-time”) status to those that report working more than [30-40] hours/week (at most [30-40] hours/week).

<sup>19</sup> Our figure of 62 percent is close to that from Hollenshead and Wilt (2000), Catalyst study, 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.

These gender differences in labor force participation translate into gender differences in actual post MBA labor market experience. The fraction of men who have 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 increases from 9 percent a year after graduation to 32 percent by year nine, and to 40 percent at ten to 16 years after graduation.

Spells without work 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 0.22 years out of work by year five and 0.57 years out of work by year nine; for men, the equivalent figures are 0.06 at year five 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.

Weekly work hours are highest among newly minted MBAs. Men in their first year out average of 61 hours per week; women average 59 hours, despite being less likely to start in investment banking where hours are especially long.<sup>20</sup> Hours of work decline for both male and female MBAs in the years following graduation, but far more so for women. Four years after receiving their MBA, women work around 55 hours per week while men work around 59 hours; nine years after, women work around 51 hours per week, while men work around 57 hours.

Although hours of work are long for most MBAs, a large share of MBA women who were not working full-time, year-round worked part-time (defined as 30 to 40 hours per week or below). 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. While about 17 percent of MBA women were not working at ten to 16 years out, another 18 percent [ $0.22 \times (1 - 0.17)$ ] were working part-time.<sup>21</sup>

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<sup>20</sup> See Landers, Rebitzer and Taylor (1996) on the role of similarly long hours of work, for law associates at large U.S. law firms, in the career dynamics of young lawyers.

<sup>21</sup> These gender differences in labor supply for Chicago GSB MBAs are quite similar to the gender gaps at around 10 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

Part-time work is especially prevalent among self-employed women. One year after graduation, 29 percent of self-employed women are working part-time; the equivalent figures are 32 percent by year five and 56 percent by year nine. Ten years or more post-MBA, 62 percent of self-employed women are working part-time. The share of part-timers is even higher among self-employed women who have no employees: nearly 75 percent of them work part-time at ten to 16 years out. In contrast, self-employed men are less likely to work part-time: only 15 percent of self-employed men are working 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 about 1 to 2 percent at graduation to 11 to 13 percent nine years out), but there is a surge in self-employment among MBA women at ten to 16 years out, with 20 percent of working women being self-employed compared with 14 percent of working men.

Part-time work also exists among salaried women, but to a much lesser degree. One year after graduation, 4 percent of salaried women are working part-time; the equivalent figures are 8 percent by year five and 9 percent by year nine. Ten years or more post-MBA, 12 percent of salaried women are working part-time.

By far the most common job function among self-employed part-timers is consulting. Close to 30 percent of self-employed part-timers are consultants, compared with only 18 percent of full-timers. Consulting however offers much less opportunity for part-time work for those who work for established firms: less than 3 percent of salaried part-timers are consultants. Investment banking appears poorly suited to part-time work, be it through self-employment or a salaried position: only 1.5 percent of those working part-time are investment bankers, compared with 9.5 percent of those working full-time.

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percent employment rate as compared to 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.

Various commentators and advocates have asserted that MBA moms find it difficult to work part-time and, in consequence, drop out of the labor force. We find a non-trivial fraction of part-timers, but part-time positions are rare for those who remain in established corporations, especially in investment banking and consulting. MBA women achieve part-time work largely through self-employment.

In summary, MBAs work in a small number of job functions and these job functions are generally those with very long hours. Women are less likely to work in the finance jobs with the longest hours, but their average hours are still very high immediately after graduation. Hours decline with time since MBA for both men and women, reflecting in part a move out of investment banking and consulting and towards general management positions in corporations. But weekly hours worked drop considerably more for women, in part driven by a growing share working part-time. Women also become 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. But part-time work 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.

## 2. Earnings

Labor market earnings are a key summary measure of career success. We construct earnings for each calendar year by taking the salary earned in the stage worked at the end of that calendar year. In this manner, earnings per year are constructed as “full time” earnings and not necessary actual earnings for the year. We have also used a variable that averages earnings across all working stages during the calendar year for those with multiple stages in a year (weighting each stage by its length).<sup>22</sup> There are few differences between the results using either earnings measure.

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<sup>22</sup> This second definition also computes full-time earnings, which may differ from actual earnings for those employed only part of the year.

Earnings (expressed in 2006 dollars) grow substantially with time since MBA, as is clear from Table 2 and Figure 1. The growth is a hefty 8.9 percent average annual rate for all MBAs.<sup>23</sup> 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 substantial numbers of newly minted MBA graduates. Those starting their careers in investment banking earn on average \$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 profiles are similar (both mean and median) for investment management (not reported in the table). The consulting track, the other most prevalent career option among MBAs, is far less remunerative than investment banking and investment management. The average MBA starting in consulting earns about \$130K per year (median is the same) at graduation and about \$300K nine years out (median is \$190K).

Mean earnings by sex are comparable directly following MBA receipt, but they diverge every subsequent year. Women earn \$115K on average at graduation and \$250K nine years out; men earn \$130K on average at graduation and \$400K nine years out. Women's and men's median salaries also diverge in favor of men with years since graduation but not by as much as the divergence in mean salaries by sex.

Mean differences between men and women in earnings (conditional only on a full set of cohort  $\times$  year dummies) are given in Table 3 arrayed by the number of years since receipt of the MBA. The 11 log point gender earnings gap at graduation grows 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 of individuals that start a new job in that year (col. 3).

#### D. Explaining the Gender Gap in Labor Supply

Gender differences in labor supply expand substantially with years since completing an MBA even when adding controls for cohort (MBA graduating class) effects, calendar year

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



effects, and their interactions (Table 3, cols. 4 to 8). Nine years out, women are about 12 percentage points less likely than men to be working (col. 5) and have spent on average half a year more out of work since the MBA (col. 4). Only a 3 log point difference in weekly hours worked exists in the first post-MBA job but that difference grows to close to 14 log points nine years out and to 20 log points at ten or more years after graduation (col. 8).

The main reasons for gender differences in labor supply are detailed in Tables 4 and 5. All the regressions in Tables 4 and 5 include a full set of cohort  $\times$  year dummies, as well as a vector of controls for pre-MBA characteristics and MBA training. The pre-MBA controls include a quadratic in age, a U.S. citizen dummy, dummies for race, dummies for “top 10” and “top 10 to 20” undergraduate institutions (from the *U.S. News & World Report* ranking), undergraduate GPA, quantitative and verbal GMAT scores, as well as dummies for industry and job function in the last job prior to entering the MBA program. Our controls for MBA training and performance are the MBA GPA and the fraction of finance-related classes the individual took during the program.<sup>24</sup> The unit of observation in these regressions is a survey respondent in a given year.

The 8 percentage point gap in employment between men and women for our pooled sample after adjusting for pre-MBA characteristics, MBA performance, and cohort  $\times$  year dummies (Table 4, col. 1) is mainly due to the presence of children. A woman with at least one child is 20 percentage points less likely to work in a given year than the average man. In contrast, women without children are only 3 percentage points less likely to be employed than the average man (col. 2). A woman with at least one child has about 0.7 fewer years of actual labor market experience than the typical man in the sample; this difference is only 0.1 year for a woman without children (col. 4). Although there is a 9 log point mean difference in weekly hours worked between men and women (col. 5), it is 23 log points for women with kids and only 3 log points for women without kids.

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<sup>24</sup> For both these labor supply regressions and the subsequent earnings regressions, we experimented with including additional controls for the MBA training, such as field-specific grades and fraction of courses taken in other fields than finance. These additional controls did not have explanatory power once we controlled for GPA and fraction of finance classes.

The impact of children on female labor supply differs by spousal earnings and the differences are large (Table 5). Since our survey asked for spousal earnings only in the current year, we use spousal current (survey date) earnings as a proxy for spousal earnings in any prior year.<sup>25</sup> We then separate women into those whose spouse has “low” earnings (less than \$100K per year), “medium” earnings (between \$100K and \$200K per year) and “high” earnings (more than \$200K per year). We interact these spousal earnings categories 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.

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 low-earnings spouse: these mothers are 30 percentage points less likely to work than the average man (Table 5, col. 1). Mothers with a medium-earnings spouse also work less than those with a low-earnings spouse, but the difference is much smaller and not statistically insignificant. Similarly, mothers with high-earnings spouses accumulate about 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).

Interestingly, greater spousal earnings increase, rather than decrease, labor supply among women without children. In fact, women without children married to high-earnings spouses are just about as likely to work (the gap is only 2 percentage points), accumulate post-MBA work experience at an almost identical rate, and put in a longer work week (by 3 log points) than 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 when they have a high-earnings spouse.

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<sup>25</sup> The sample sizes are smaller for the regressions in Table 5 than for those in Table 4 since the Table 5 specifications only include women who were married or living with someone at the survey date and also dropped women with missing information on spousal income. Men are included in Table 5 regardless of marital status.

Because spousal income may be endogenous to own labor supply choices and because we measure spousal income only in the survey year, we replicate the analysis in Table 5 by spousal education levels. We contrast the labor supply of mothers married to men who are at least as educated as they (MBA, JD, MD and related degrees, or PhD) to that of mothers with less-educated spouses. We find the same qualitative pattern of results with women with more-educated spouses working much less than those with less-educated spouses when children are present and the opposite pattern of (modestly) more work for women with more-educated spouses in the absence of children.

We also investigate the possibility of similar differences in labor supply between MBA men with children and MBA men without children and for asymmetries in male labor supply based on wives' earnings (and education). We found no significant impacts of the presence of children or of spousal income on male labor supply. Only women slow down and move off the "fast track" when they become parents and this is especially true for those with a spouse who can ensure the sustainability of high family income.

Complementary evidence from our survey confirms that MBA mothers with well-to-do husbands take a larger share of the responsibility for child care (relative to their spouses, other family members, or paid help) than do other MBA women with children. MBA mothers whose spouses earn over \$150K indicate being responsible for 52 percent of their children's care as compared with only 32 percent for MBA mothers with low-earnings spouses.<sup>26</sup> The difference is almost fully explained by the use of formal day care center (12 percent for mothers with high-earnings spouses versus 31 percent for mothers with low-earnings spouses).

Finally, we examine whether the impact of children on the labor supply of female MBAs differs by job function in their first post-MBA employment by separately estimating the regression specification in Table 4 for MBAs whose first job was in a function where average hours were above 57 hours (long hours) or below 57 hours (short hours). We do not find that first job characteristics matter differentially for the labor supply decisions of women with and

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<sup>26</sup> When we use three types of earnings we called the > \$200K group "high," but when we use two groups, as we do here, we term the > \$150K group "high."

without children.<sup>27</sup> MBA women with children have choices other than simply opting out, even when they start their careers in the most work-intensive and inflexible tracks.<sup>28</sup>

In summary, parental status accounts for the bulk of the difference in labor supply between male and female MBAs. Moreover, the impact of children on female labor supply is strongly related to spousal income, with mothers in better-off households slowing down much more.<sup>29</sup>

#### E. 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 the individual-year observations. 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 6 is done with and without controlling for weekly hours worked. The novelty of the estimation is our use of information on all job stages previously held by an individual.

The raw gap in earnings between men and women in the pooled sample is about 29 log points including only 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 sample of 0.13 (3.38 versus 3.25) 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 nearly 6 log points. Each additional finance class increases earnings by about 8 log points and women take about half

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<sup>27</sup> See Appendix Table A4 for a listing of the job functions with “long hours” and “short hours.” Mothers are about 21 percentage points less likely than men to work when they start in a long hours position as compared to 18 percentage points for those starting in a short hours position with a similar pattern of lower weekly work hours (by about 21 log points) for employed mothers than for men regardless of the type of starting position.

<sup>28</sup> This finding contrasts somewhat with Herr and Wolfram (2008) who conclude that corporate work environments contribute to MBA mothers’ decisions to exit the labor force at motherhood.

<sup>29</sup> Of course, neither marital nor parental statuses are randomly assigned and it is possible that women’s decisions to get married, whom to marry and whether or not to have children are related to unobservable characteristics that might directly impact earnings. We explore this possibility below.

a class less in finance than men.<sup>30</sup>

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 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 more endogenous 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).

The estimates presented in Table 6, col. (6) 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 having less post-MBA experience. In our sample an individual who received an MBA six years previously and had 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* amount of time off.<sup>31</sup> 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.

We also computed separate penalties for taking time out for those starting their career in consulting, investment banking and investment management, or other functions.<sup>32</sup> The wage penalties we estimate (for the typical out-of-work spell at six years after MBA completion) are uniformly high across career tracks: 36 log points in consulting, 45 log points in investment

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<sup>30</sup> Finance classes pay off even for those not starting in investment banking or investment management.

<sup>31</sup> 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 time off.

<sup>32</sup> We re-estimated the specification in col. (6) separately for each of the subgroups.

banking or investment management, and 45 log points in other functions. Furthermore, earnings penalties for time out are similarly large for the early (pre-1998 MBA) and more recent (1998 or later MBA) cohorts in our sample. The earnings loss from any career interruption is extremely large in our MBA sample.

The models in Table 6 restrict the impact of career interruptions to be the same for men and women, but it is possible that the costs differ by sex with women being more heavily penalized for taking time out. Running separate earnings regressions by sex using the specification from Table 6, col. (6) shows the opposite. The wage penalty for men, using our standardized career interruption at six years out, is 45 log points and for women it is 26 log points. Taking any time out appears more harmful for men (26 log points) than for women (11 log points).<sup>33</sup> Similar calculations based on the col. (3) specification, which does not hold hours constant, produces 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.

An analysis of the gender gap by years since MBA graduation is given in Table 7. The (uncorrected) gender wage gap is 9 log points just after MBA completion. It rises to 30 log points five years out, to 38 log points at nine years out, and to 57 log points for the ten to 16 years out group. Even the largest gender gap in earnings is entirely eliminated by the inclusion of the observables. But that detail 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. More than a third of this increase is due to the growing importance of pre-MBA characteristics as well as MBA courses and performance in them. Career interruptions and actual years labor market experience account for only 2 log points of the increase (or about 11 percent). The gender gap in hours worked is already an important factor by

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<sup>33</sup> The estimated coefficients on labor market experience and labor market experience squared are 0.054 and 0.012, respectively, in the men's regression and 0.177 and -0.003 in the women's regression. A larger discrete earnings loss associated with having any career interruption for men than for women is also found in earnings regressions that include person fixed effects.

year three, explaining about 25 percent of the increase. During the next six years, that is to year nine, the gender earnings gap grows by another 12 log points. At this juncture career interruptions become more important in explaining the gender earnings gap, accounting for almost half (5.6 log points) of the 12.4 log point increase from year three to year nine; the growing gender gap in weekly hours worked more than explains the other half. The explanatory power of pre-job characteristics reaches a plateau of a gender earnings gap of about 12 log points by year six. Overall, of the increased gap of 29 log points from year zero to year nine, 19 log points are due to differences in career interruptions and hours of work, whereas 8 log points are due to pre-job characteristics.

Because our full sample is an unbalanced panel, the individuals we observe in late-career are not the same as those we observe in early-career, and some of the dynamics of changes in the gender gap could reflect differential changes in the sample composition by sex with years since MBA completion. But such potential sample composition changes do not appear to affect our estimates. We have replicated the analysis in Table 7 and limited the analysis to those who completed their MBA prior to 1998, thus holding the student composition constant up to eight years out. The results are similar for the full sample and for the pre-1998 cohorts.

What about the gender earnings gap for women who have had no career interruptions? Large earnings differences relative to men are apparent even for women who have taken no career breaks up to the post-MBA year considered (see Table A5). The total change in the earnings gap to year nine is 20 log points. Somewhat less than half of the total change is due to the increasing importance of pre-job (MBA and pre-MBA) characteristics and most of the remainder is due to differences in hours between men and women.

Even women with no career interruptions have children and some of these women will work fewer hours and be less available for career moves. Limiting the sample to women without children and with no career interruptions by ten years out makes the career-paths of the women in the sample more similar to those of men. For that comparison the gender earning gap starts out slightly larger than for all women, but it grows much more slowly (see Table A6). 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. This entire increase in the gender pay gap comes from the greater importance of pre-MBA and MBA characteristics with years since MBA receipt. Mechanically, given the construction of the sample, no part of the gender differences in earnings can be due to lesser job experience or to greater gaps in employment for the women. Furthermore, we find none is due to lower hours for this sample.

#### F. Selection and Family Status

Because we find that a large fraction of the difference between male and female earnings is due to job interruptions and most job interruptions are because of children, there may be a concern that MBA mothers are selected on unobservables that might directly lead to lower earnings even in the absence of children. But we find no evidence that MBA women who marry and have children are drawn from the lower part of the female earnings distribution (Table A7). We find, instead, that married women have slightly higher predicted earnings than unmarried females and women 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.<sup>34</sup> In other words, MBA women who have children are not negatively selected in terms of predicted earnings levels and may even be slightly positively selected. We also find evidence of positive assortative mating. Women who marry spouses more-educated than they are have slightly higher predicted earnings than women who marry less educated men.

We also explore whether women have children when their careers are slowing down. We restrict the sample to the years where all MBAs are childless and will remain childless for another two years. We then ask whether past earnings trajectories differ for the women and men who will become parents in the next two years compared with those that will remain without a child (Table A8). Cumulative earnings do not differ much for women who will remain childless compared with women who will give birth two years later. But the annual growth of earnings,

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<sup>34</sup> The predicted value of  $\log(\text{annual earnings})$  for all individuals is regressed on interactions of marital status and sex in one regression and on interactions of sex with whether an individual has a child in a separate regression. The predicted value of earnings is constructed as follows. Taking the sample of male respondents (individual  $\times$  year level),  $\log(\text{annual earnings})$  is regressed on (cohort  $\times$  year) dummies. The residual from that regression is then regressed on our full set of pre-MBA characteristics and MBA performance measures (see notes to Table A7).



averaged over the past three years, is 9 log points lower for women two years before their first birth relative to women who do not have a first birth in that period. The evidence suggests that MBA women have children when their earnings growth slows.

One possible picture that emerges from the combined cumulative earnings and earnings growth results is that soon-to-be-mothers may have performed above expectations earlier in their careers but then encounter some stumbling blocks. It could also be that soon-to-be mothers are over-achievers who become less aggressive in seeking promotions when they start planning their families.

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

Differences in earnings and employment between male and female MBAs appear to be largely, though not entirely, due to the presence of children. We now use the (retrospectively-constructed) panel structure of our data to explore in more detail what happens to an MBA's career after the arrival of children.

The regressions in Tables 8 and 9 examine the dynamics of a first birth's impact on employment outcomes. 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 birth of one's first child—dummy variables for one or two years before 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.

Women reduce their labor supply on both the extensive and intensive margins after a birth. More interestingly, the largest declines occur more than two years after the first birth, not immediately after. A woman's likelihood of not working in a year is about 9 percentage points higher in the two years immediately following her first birth than in the base period, increasing to a 13 to 14 percentage impact in the years following the birth (Table 8, col. 2). Similarly, hours worked for the employed (col. 10) decrease directly following the first birth (12 log

points), but the decrease is even greater after two years (an 18 log point decline relative to the pre-birth period). There is no apparent decline in labor force participation or hours worked one or two years before the birth, as one might have expected if the birth-timing decision was a consequence rather than a cause of career slowdown. In fact, MBA moms are more likely to work in the two years that precede the birth of their first child than in the base period.

Women's earnings also decline three to four years after a first birth and the decrease in relative earnings expands substantially in the first four years after the birth (Table 8, col. 4). A woman's earnings drop by "only" 13 log points one or two years after the first birth, but by about 25 log points relative to the 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 the first birth but decrease by 8 to 9 log points after that. Thus, earnings decline linearly with hours worked in the first two year after the first birth, but (hourly) wage penalties (associated with career interruptions) become evident for MBA women three years after the birth. Accounting for the increased likelihood of not working (and hence zero earnings), a woman's annual earnings drop by about \$45K in the two years following the first birth, and the impact grows to close to \$80K a year in subsequent years (col. 8). There is no evidence that these women's earnings declined significantly in the two years preceding a first birth, similar to our findings for labor supply.

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 also find large reductions in labor supply and earnings four years after a first birth even for women who do not have a subsequent birth.<sup>35</sup> We do not find the birth of a second child to have any additional effect on women's labor force participation and earnings, but we do uncover some evidence that weekly hours decline by an additional 4 log points following a second birth.

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

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<sup>35</sup> These findings derive from (unreported) regressions in which we add a dummy variable for the two years immediately following the birth of a second child to the specifications in Table 8.

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 largely reflect women’s choices (or family constraints) rather than direct labor market discrimination. One is that children differentially affect women’s labor supply and earnings depending on spouse’s income and education (as previously seen in Table 5 for labor supply).

The differential dynamic impacts of a first birth on women’s labor market outcomes by husband’s education are illustrated in the regressions in Table 9, where we estimate separate regressions (using the Table 8 specifications) for married women by spouse’s educational attainment.<sup>36</sup> A first birth is associated, if anything, with an increased likelihood of employment for MBA women with less-educated (and lower-earning) spouses (col. 1). In contrast, new MBA mothers with more-educated (and higher-earning) spouses reduce their likelihood of working in a year by 13 percentage points (relative to the base period) in the first two years following the birth and by 17 percentage points four years and more after the birth (col. 5). Weekly hours (conditional on employment) drop for both groups in the four years following a birth but more so for those with more-educated spouses (cols. 4 and 9). The total annual earnings decline (including those not working) associated with motherhood is large and persistent for MBA women with as or more educated spouses. The decline is more modest for women with less-educated spouses and shows up a few years after the first birth.

Other evidence that argues for choice can be gleaned from the reasons MBA women give for not working, leaving their previous job, and for choosing a new job (Table 10). The probability that a woman is not working for career-related reasons (which include “layoff” and “suitable job not available”) does not change post-birth (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

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<sup>36</sup> Interestingly, female MBAs with less educated spouses are 1.5 years older than those with as or more educated spouses at first birth (34.4 years old versus 32.9 years old).

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 15 to 20 percentage points more likely to be in a job chosen for family-related reasons (col. 3) and 10 to 18 percentage points less likely to have chosen their job for career-related reasons (col. 4). These changes in career orientation are not limited to the years when their children are infants but persist five years and more after the first birth.<sup>37</sup>

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 (Table A9, Panel B). Earnings declines of 64 log points are incurred 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 larger role of family factors and desires for flexible hours in the job mobility decisions of women with children than for other MBAs generates the striking differences in the wage changes by gender and parental status associated with job changes (Table A9, Panel A). Job changes in our MBA sample are income neutral for all men and for women without children. But women with children lose nearly 18 log points in earnings when they shift jobs.

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 discriminatory treatment. This claim is difficult to evaluate directly. Nevertheless, we find little evidence in support of it in our analysis of the job change patterns of women around the time of a first birth. We examine likelihood of leaving a given job, as well as the likelihood of leaving for family or career-related reasons, *conditioning* on the stated reasons for originally choosing that job (Table 10, cols. 5 to 8). If mothers were being sidelined in their current jobs, one might have expected them to be more likely to quit (or even be forced out), or at least more likely to quit for career-related reasons. Yet, we find no such evidence (cols. 5, 7 and 8). We do find that women

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<sup>37</sup> 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.”

are significantly more likely to leave a job for family reasons in the two years before a birth (col. 6). This finding suggests some re-optimization of job choices in anticipation of children.

## H. Summary and Conclusions

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

We identify three primary 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 with post-MBA experience to such training; (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 accumulation of job experience, more career interruptions, and shorter work hours for female MBAs but not for male MBAs.

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 a preliminary 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.<sup>38</sup> We find that female MBAs appear to have a more difficult time combining career and family than do physicians, PhDs, and lawyers.<sup>39</sup>

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<sup>38</sup> See Goldin and Katz (2008) for details.

<sup>39</sup> For empirical analyses of gender earnings gaps and career-family trade-offs in specific professions, see Wood, Corcoran, and Courant (1993) on lawyers, Sasser (2005) and Reyes (2006) on physicians, Preston (2004) on science professionals, and Ginther (2006) on academics.

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. Log earnings regressions for 2005 annual earnings in the H&B sample using a specification, similar to that in Table 6, 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 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 more linear in foregone labor market experience.

We can only speculate about why different costs exist to taking time off and opting for 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 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 Graduation: Descriptive Statistics

	<i>Number of Years since Graduation</i>										
	0	1	2	3	4	5	6	7	8	9	≥ 10
	Share Not Working at All in Current Year										
Female	0.054	0.012	0.017	0.027	0.032	0.050	0.067	0.084	0.089	0.129	0.166
Male	0.028	0.005	0.002	0.003	0.007	0.004	0.008	0.008	0.006	0.011	0.010
	Share Working Full-time/Full-year (52 weeks and > 30 to 40 hours per week)										
Female	n.a.	0.89	0.85	0.84	0.82	0.79	0.78	0.76	0.72	0.69	0.62
Male	n.a.	0.93	0.93	0.94	0.94	0.91	0.93	0.94	0.93	0.93	0.92
	Share with Any No Work Spell (until given year)										
Female	0.064	0.088	0.116	0.143	0.161	0.193	0.229	0.259	0.287	0.319	0.405
Male	0.032	0.040	0.052	0.064	0.071	0.077	0.081	0.082	0.090	0.095	0.101
	Cumulative Years Not Working										
Female	0	0.050	0.077	0.118	0.157	0.215	0.282	0.366	0.426	0.569	1.052
Male	0	0.026	0.036	0.045	0.057	0.060	0.069	0.075	0.084	0.098	0.120
	Mean Weekly Hours Worked for the Employed										
Female	59.1	58.8	57.1	56.2	55.3	54.8	54.7	53.7	52.9	51.5	49.3
Male	60.9	60.7	60.2	59.5	59.1	58.6	57.9	57.6	57.6	57.5	56.7
	Share Working Part-time (≤ 30 to 40 hours per week)										
Female	0.04	0.05	0.06	0.07	0.08	0.10	0.09	0.10	0.11	0.15	0.22
Male	0.02	0.02	0.02	0.02	0.02	0.02	0.03	0.03	0.03	0.03	0.04
	Share Working Fewer than 52 Weeks										
Female	n.a.	0.07	0.08	0.07	0.08	0.09	0.09	0.07	0.10	0.06	0.06
Male	n.a.	0.05	0.05	0.04	0.04	0.06	0.03	0.03	0.04	0.03	0.03

*Notes:*

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

Number of years since graduation:	<i>Females</i>	<i>Males</i>	<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)	Median (3)	Median (4)	Mean (5)	Median (6)	Mean (7)	Median (8)	Mean (9)	Median (10)
0	114,928	130,156	105,882	125,000	126,356	122,076	129,623	129,032	173,740	160,612
1	130,321	162,785	113,404	136,520	154,691	129,032	143,649	140,307	248,639	232,411
2	146,616	196,208	121,184	146,237	184,111	139,516	159,823	151,261	306,221	280,156
3	163,835	227,143	125,000	154,601	212,043	146,342	176,254	154,601	352,911	314,019
4	182,103	258,785	129,412	169,657	240,861	154,601	196,798	160,085	410,985	332,016
5	204,702	294,934	136,957	180,645	274,186	168,093	221,059	170,311	470,608	369,076
6	230,084	330,114	143,874	196,109	307,451	175,000	246,169	180,645	500,979	380,645
7	235,733	359,822	146,342	204,878	332,762	186,766	263,166	196,109	565,927	398,419
8	242,528	391,075	151,261	204,878	357,991	191,739	288,272	191,739	635,775	434,572
9	252,421	400,488	148,432	211,573	367,601	186,766	299,331	196,109	691,156	468,120
10 or more	243,481	442,353	146,342	242,367	400,715	217,121	362,274	238,710	815,914	559,802

*Notes:*

Cols. (1) to (4): Mean and median annual earnings by number of years since graduation for males and females. Cols. (5) and (6): Mean and median annual earnings by number of years since graduation across all survey respondents. Remaining columns give means and medians for survey respondents whose first post-MBA job function was consulting (cols. 7 and 8) or investment banking (cols. 9 and 10).

Table 3  
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<sup>a</sup></i>	<i>Annual hours worked in current year<sup>a</sup></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]*	-181.94 [46.71]*	-0.034 [0.012]*
1	-31,083 [3,999]*	-0.17 [0.022]*	-0.174 [0.050]*	0.022 [0.008]*	0.006 [0.004]	-0.907 [0.357]§	-111.71 [39.74]*	-0.036 [0.012]*
2	-49,976 [7,072]*	-0.216 [0.027]*	-0.270 [0.056]*	0.038 [0.012]*	0.014 [0.005]§	-1.744 [0.423]*	-210.59 [41.76]*	-0.060 [0.013]*
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]*	-260.89 [45.99]*	-0.074 [0.015]*
4	-78,198 [11,334]*	-0.284 [0.036]*	-0.314 [0.067]*	0.099 [0.023]*	0.027 [0.009]*	-2.427 [0.559]*	-297.42 [49.04]*	-0.088 [0.016]*
5	-90,252 [15,011]*	-0.311 [0.042]*	-0.198 [0.081]§	0.154 [0.031]*	0.046 [0.011]*	-3.426 [0.695]*	-337.65 [52.63]*	-0.09 [0.017]*
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]*	-363.46 [61.16]*	-0.083 [0.019]*
7	-123,253 [24,038]*	-0.352 [0.053]*	-0.119 [0.105]	0.294 [0.052]*	0.077 [0.016]*	-5.101 [0.891]*	-438.56 [63.70]*	-0.094 [0.021]*
8	-149,901 [27,328]*	-0.375 [0.057]*	-0.476 [0.121]*	0.342 [0.062]*	0.082 [0.017]*	-6.152 [0.976]*	-487.39 [66.86]*	-0.097 [0.019]*
9	-152,002 [31,672]*	-0.402 [0.066]*	-0.36 [0.170]§	0.476 [0.079]*	0.116 [0.021]*	-7.029 [1.136]*	-622.55 [77.33]*	-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]*	-789.90 [96.23]*	-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

<sup>a</sup> 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  $\times$  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  $\times$  52). 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 4  
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>	
Female	0.084		-0.286		-0.089	
	[0.009]*		[0.039]*		[0.013]*	
Female with child		0.200		-0.660		-0.238
		[0.024]*		[0.094]*		[0.031]*
Female without child		0.034		-0.126		-0.033
		[0.007]*		[0.031]*		[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	-0.111	5.929	5.757	3.951	3.914
	[0.145]	[0.126]	[0.618]*	[0.550]*	[0.462]*	[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 5  
Female Labor Supply and Spousal Income

	<i>Not working</i>	<i>Actual post-MBA experience</i>	<i>Log (weekly hours worked)</i>
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 or living with someone at the survey date and also dropped 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 6  
Wage Regressions

	<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 <sup>2</sup>			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. The results are robust to limiting the sample to only survey respondents with non-missing pre-MBA characteristics. 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. “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  $\geq$  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; Other. Standard errors (in brackets) are clustered at the individual level; § significant at 5%; \* significant at 1%.



Table 7  
Gender Wage Gap by Years since MBA

	<i>Number of Years since MBA Receipt</i>										
	0	1	2	3	4	5	6	7	8	9	≥ 10
1. With no controls	-0.089 [0.020]*	-0.154 [0.025]*	-0.213 [0.032]*	-0.253 [0.038]*	-0.274 [0.043]*	-0.299 [0.048]*	-0.308 [0.056]*	-0.331 [0.062]*	-0.358 [0.069]*	-0.376 [0.079]*	-0.565 [0.045]*
With controls:											
2. Pre-MBA characteristics	-0.080 [0.021]*	-0.136 [0.026]*	-0.172 [0.033]*	-0.204 [0.039]*	-0.221 [0.044]*	-0.257 [0.049]*	-0.248 [0.057]*	-0.271 [0.065]*	-0.296 [0.072]*	-0.320 [0.084]*	-0.479 [0.045]*
3. Add MBA performance	-0.054 [0.021]*	-0.103 [0.025]*	-0.129 [0.032]*	-0.154 [0.037]*	-0.166 [0.042]*	-0.189 [0.047]*	-0.180 [0.055]*	-0.200 [0.063]*	-0.234 [0.070]*	-0.257 [0.082]*	-0.446 [0.044]*
4. Add labor market exp.	-0.053 [0.021]§	-0.093 [0.025]*	-0.118 [0.031]*	-0.134 [0.037]*	-0.147 [0.042]*	-0.171 [0.047]*	-0.143 [0.055]*	-0.141 [0.063]§	-0.164 [0.070]§	-0.181 [0.082]§	-0.312 [0.044]*
5. Add weekly hours worked	-0.036 [0.020]	-0.073 [0.023]*	-0.069 [0.030]§	-0.073 [0.036]§	-0.079 [0.041]	-0.090 [0.045]§	-0.079 [0.053]	-0.054 [0.060]	-0.085 [0.067]	-0.047 [0.078]	-0.098 [0.042]§
6. Add reason for choosing job	-0.033 [0.020]	-0.067 [0.023]*	-0.058 [0.030]§	-0.064 [0.035]	-0.073 [0.040]	-0.089 [0.045]§	-0.075 [0.053]	-0.052 [0.060]	-0.086 [0.067]	-0.031 [0.079]	-0.066 [0.042]
7. Add job setting characteristics	-0.025 [0.019]	-0.060 [0.022]*	-0.051 [0.027]	-0.064 [0.032]§	-0.046 [0.037]	-0.065 [0.041]	-0.080 [0.048]	-0.070 [0.054]	-0.052 [0.060]	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. 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. 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. Weekly hours worked includes dummy variables for: < 20 hours, 20 to 30 hours, 30 to 40 hours, 40 to 50 hours, 50 to 60 hours, 60 to 70 hours, 70 to 80 hours, 80 to 90 hours, 90 to 100 hours, and  $\geq$  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. 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 (in brackets) are clustered at the individual level; § significant at 5%; \* 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)</i>
	(1) Male	(2) Female	(3) Male	(4) Female	(5) Male	(6) Female	(7) Male	(8) Female	(9) Male	(10) Female	(11) Female
Years after birth of first child:											
1 or 2	-0.009 [0.004]	0.091 [0.017]*	0.036 [0.017]§	-0.126 [0.030]*	6,900 [9,147]	-28,301 [11,023]§	6,233 [9,074]	-45,871 [10,327]*	-0.010 [0.005]	-0.118 [0.016]*	-0.014 [0.027]
3 or 4	-0.006 [0.005]	0.134 [0.020]*	0.061 [0.020]*	-0.251 [0.037]*	13,680 [10,757]	-45,928 [13,500]*	10,965 [10,640]	-78,805 [12,267]*	-0.007 [0.006]	-0.184 [0.020]*	-0.077 [0.033]§
5 or more	0.001 [0.006]	0.141 [0.022]*	0.157 [0.022]*	-0.254 [0.041]*	68,192 [12,019]*	-47,657 [15,176]*	64,031 [11,880]*	-78,238 [13,739]*	0.004 [0.007]	-0.172 [0.022]*	-0.088 [0.037]§
Years before birth of first child:											
1 or 2	-0.005 [0.004]	-0.047 [0.015]*	-0.010 [0.015]	-0.021 [0.025]	-6,471 [8,207]	-11,447 [9,323]	-6,936 [8,145]	-3,916 [9,231]	-0.003 [0.004]	-0.005 [0.014]	-0.021 [0.022]
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	0.45	0.76	0.73	0.68	0.72	0.66	0.68	0.72	0.67	0.79

*Notes:* The unit of observation is a survey respondent in a given post-MBA year. 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 number of years after or before the birth of the first child. Col. (11) also includes a vector of dummy variables to control for hours worked (i.e., < 20 hours, 20-29, 30-39, ... , 90-99 and ≥100 hours). Standard errors are in brackets; § 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 Education Level

	<i>Spouse Is Less Educated<sup>a</sup></i>					<i>Spouse Is As Or More Educated<sup>b</sup></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>	<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>
Years after birth of first child:										
1 or 2	-0.091 [0.037]§	0.000 [0.066]	514 [21,970]	-0.071 [0.030]§	35,504 [23,218]	0.132 [0.023]*	-0.084 [0.039]§	-35,976 [15,208]§	-0.119 [0.023]*	-61,435 [13,685]*
3 or 4	-0.048 [0.044]	-0.083 [0.083]	-25,142 [27,570]	-0.144 [0.038]*	-5,958 [28,053]	0.171 [0.028]*	-0.202 [0.049]*	-55,981 [18,965]*	-0.195 [0.029]*	-93,237 [16,700]*
5 or more	-0.131 [0.051]*	-0.081 [0.098]	-68,034 [32,841]§	-0.189 [0.045]*	-3,502 [32,116]	0.177 [0.034]*	-0.159 [0.059]*	-37,453 [22,755]	-0.189 [0.035]*	-78,124 [20,103]*
Years before birth of first child:										
1 or 2	-0.068 [0.032]§	0.083 [0.056]	11,670 [18,518]	-0.002 [0.025]	30,043 [20,189]	-0.053 [0.020]*	-0.024 [0.031]	-17,430 [12,035]	0.008 [0.019]	-11,726 [11,589]
Observations	881	814	814	808	881	2,625	2,281	2,281	2,276	2,625
R-squared	0.46	0.80	0.77	0.74	0.69	0.50	0.74	0.76	0.71	0.72

<sup>a</sup> Age at birth of first child is 34.4 years old for this sample.

<sup>b</sup> Age at birth of first child is 32.9 years old for this sample.

*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 number of years after or before the birth of the first child.

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)
Years after birth of first child:											
1 or 2	0.103 [0.025]*	-0.003 [0.007]	0.148 [0.031]*	-0.101 [0.039]*	-0.001 [0.029]	0.012 [0.016]	-0.013 [0.010]	-0.009 [0.016]	0.164 [0.343]	-0.003 [0.003]	-0.025 [0.012]§
3 or 4	0.147 [0.036]*	-0.004 [0.010]	0.202 [0.044]*	-0.180 [0.053]*	-0.037 [0.030]	0.017 [0.018]	-0.003 [0.012]	-0.008 [0.017]	0.560 [0.479]	-0.007 [0.004]	-0.045 [0.016]*
5 or more	0.172 [0.048]*	-0.013 [0.010]	0.169 [0.059]*	-0.096 [0.067]	-0.058 [0.034]	-0.016 [0.018]	0.008 [0.014]	0.003 [0.019]	1.078 [0.651]	-0.010 [0.006]	-0.057 [0.024]§
Years before birth of first child:											
1 or 2	-0.046 [0.013]*	0.000 [0.006]	0.001 [0.016]	-0.016 [0.024]	0.007 [0.025]	0.046 [0.017]*	-0.010 [0.012]	-0.034 [0.015]§	-0.477 [0.239]§	0.005 [0.002]§	0.020 [0.007]*
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	0.48	0.38	0.60	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. 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 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 Appendix A2 for more details. Standard errors (in brackets); § significant at 5%; \* significant at 1%.

Appendix Table A1  
Who Responded to the Survey

	<i>MBA Classes 1990 to 2006<sup>a</sup></i>		
	<i>Respondent</i>	<i>Non-respondent<sup>b</sup></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

<sup>a</sup> Includes only those who were matched to University of Chicago Graduate School of Business administrative records (355 could not be matched).

<sup>b</sup> “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](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) focus on those who responded to the survey. Cols. (3) and (6) report p-values to compare means between females and males. 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)	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 <math>\leq [30-40]</math> hours</i>	<i>Fraction <math>\leq [40-50]</math> hours</i>	<i>Fraction women</i>	<i>Individual <math>\times</math> 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:* Sample is restricted to those job functions where the number of (individual  $\times$  year) observations is  $\geq 100$ . “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

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 notes to Table 7.

Appendix Table A6

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 7.

Appendix Table A7: Who gets married? Who has kids?

	<i>Dependent Variable: Predicted Log (Annual Earnings)</i>		
	(1)	(2)	(3)
Female, married	-0.066 [0.025]*		
Female, unmarried	-0.084 [0.029]*		
Male, married	0.052 [0.020]*		
Female with spouse as or more educated		-0.110 [0.024]*	
Female with spouse less educated		-0.127 [0.038]*	
Male with spouse as or more educated		0.006 [0.017]	
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]*	-0.013 [0.014]	-0.053 [0.012]*
Observations	2,317	1,764	2,310
R-squared	0.02	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 firm  $\times$  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. 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. 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 spouse as or more educated” (“Male with spouse as or more educated”) is a dummy variable that equals one if the respondent is a female (male) living with someone that holds strictly more than a college degree. “Female with less educated spouse” is a dummy variable that equals one if the respondent is a female living with someone that holds at most a college degree. “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.

Appendix Table A8  
Earnings Trajectory and Birth of First Child

	<i>Log (cumulative earnings)</i>	<i>Log (cumulative earnings for last five years)</i>	<i>Average annual earnings growth over last five years</i>	<i>Average weekly hours worked over last five years</i>	<i>Log (cumulative earnings for last three years)</i>	<i>Average annual earnings growth over last three years</i>	<i>Average weekly hours worked over last three years</i>
Female, two years prior to first birth	-0.086 [0.041]§	-0.108 [0.042]*	-0.156 [0.068]§	-3.669 [1.138]*	-0.112 [0.042]*	-0.173 [0.064]*	-3.822 [1.153]*
Female, other years	-0.095 [0.033]*	-0.097 [0.033]*	-0.088 [0.036]§	-6.569 [0.840]*	-0.100 [0.034]*	-0.083 [0.033]§	-7.306 [0.842]*
Male, two years prior to birth of first child	0.026 [0.022]	0.035 [0.022]	-0.010 [0.027]	-0.251 [0.503]	0.034 [0.024]	-0.007 [0.028]	-0.215 [0.524]
Pre-MBA characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MBA performance	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort × year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	11.34 [0.557]*	10.69 [0.579]*	2.78 [2.012]	89.0 [17.99]*	10.39 [0.602]*	2.697 [2.012]	90.31 [18.33]*
Observations	11,042	10,998	8,787	19,394	10,955	8,823	19,397
R-squared	0.78	0.69	0.06	0.15	0.56	0.05	0.15

*Notes:* The unit of observation is a survey respondent in a given post-MBA year. The sample is restricted to up to two years preceding the birth of the first child for individuals with at least one child and includes all years for individuals without any children. “Cumulative earnings” is the sum of all post-MBA earnings to date; “Cumulative earnings for last five (three) years” is the sum of earnings between year  $t - 4$  ( $t - 2$ ) and year  $t$ ; “Average annual earnings growth over last five (three) years” is average annual earnings growth between year  $t - 4$  ( $t - 2$ ) and year  $t$ ; “Average weekly hours worked for last five (three) years” is the average of weekly hours worked between year  $t - 4$  ( $t - 2$ ) and year  $t$ . No annual earnings are assumed if the individual was not employed at all in a given year. “Female, two years prior to birth of first child” (“Male, two years prior to birth of first child”) is a dummy variable that equals 1 if the individual reports having her (his) first child born in year  $t + 2$ . “Female, other years” is a dummy variable that equals 1 in every other year for a female respondent. 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. 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%.

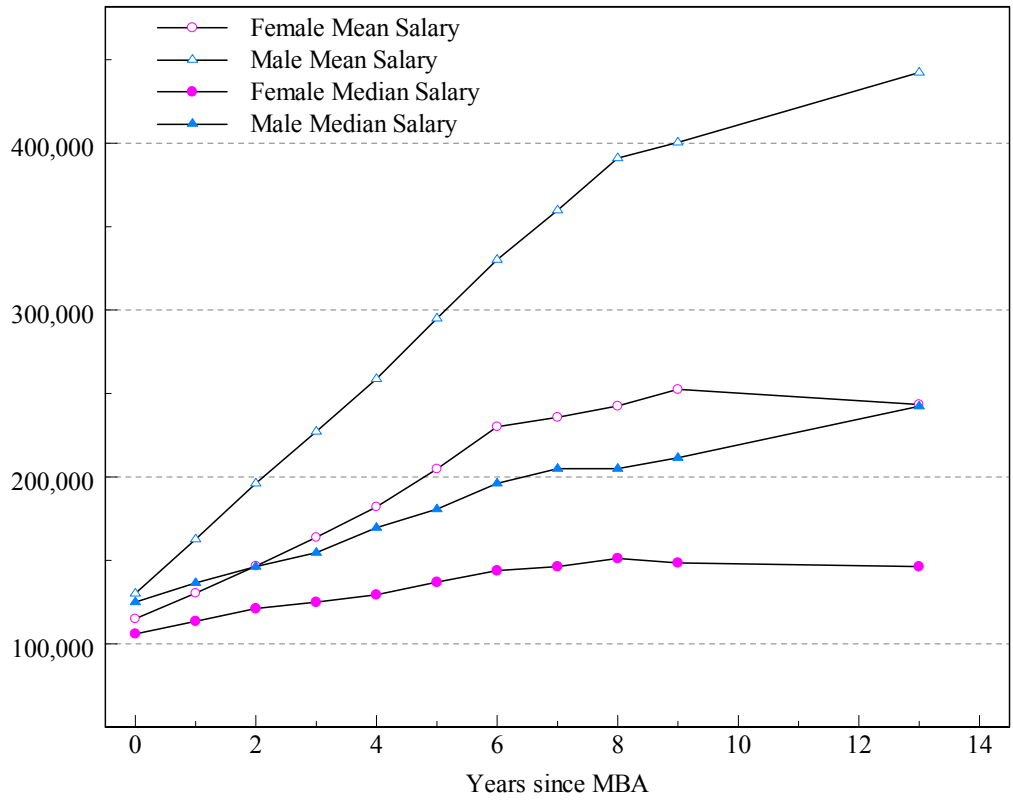


Table A9: Wage Changes Associated with Job Changes

Panel A: By Gender and Parental Status		Log (entry salary) in stage $t$ – Log (end salary) in stage $t-1$			
		Mean	Median	25 <sup>th</sup> percentile	75 <sup>th</sup> 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 has 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  $t-1$ .

Figure 1  
 Male and Female Mean and Median Salaries (2006 dollars) by Years since MBA



Notes: See Table 1.