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ABSTRACT

In the United States, much of the gap in earnings between men and women is due to the persistent gap for high wage earners. This paper explores changes in the gender wage gap for MBAs graduating from a large public university over 30 years. We document large gender wage gaps on average, which grow in the course of men's and women's careers. Comparing graduates at identical career stages across time periods to address composition concerns, we show that the raw gender wage gap has shrunk by 33 to 50 percent over the last two decades. Additionally, the temporal pattern of the gap has fundamentally shifted: while gaps only emerged over time in earlier decades, significant gaps now emerge immediately. Convergence in labor supply factors, particularly hours worked, explains much of the narrowing gap, alongside shifts in industry composition. However, unexplained wage gaps persist for recent graduates from the very start of their careers, suggesting different underlying mechanisms across cohorts. These findings highlight both progress in gender wage equity among business professionals and concerning patterns that emerge earlier in careers than in previous decades.

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Introduction

In the early 2000s, new research revealed a significant wage gap between men and women in business careers–a gap that emerged over their careers. Based on retrospective surveys that ended in 2006, Bertrand, Goldin, and Katz (2010) showed that while men and women typically earned close to parity in their first job after completing the MBA, the gap expanded from that point onward. After 10 to 16 years the raw unadjusted gender pay gap grew to 60 log points, or 82 percent.

Other studies have replicated the large wage gender gap for some professions but not others. Bütikofer, Jensen, Salvanes (2018) provide further evidence using Norwegian data. They document that despite Norway's renowned generous family leave policies and extensive childcare facilities, the gender wage gap grows over time for women with children in both business and legal professions but not in medicine or STEM fields. They interpret these results in light of Claudia Goldin's thesis (Goldin, 2014, 2021) that such careers mandate 'greedy work', which is not easy to reconcile with the demands of family.

The gender wage gap declined significantly in the 1980s in the United States. However, since then, the shrinking of the overall wage gap has slowed down. One reason, as documented by Francine Blau and Lawrence Kahn, is that the gender wage gap has declined more slowly for highly skilled occupations. Blau and Kahn (2017) point out that while educational achievements have converged for men and women in the United States, factors remain that contribute to the persistent gender wage gap, particularly at higher income levels. Some of the factors they emphasize include the possibility of discrimination (including statistical discrimination which occurs when gendered occupational choice is associated with lower pay), as well as psychological factors and societal norms.

Recent work by Altonji et al. (2025) provides important historical context for understanding gender wage gap trends among highly educated workers. Examining college-educated workers born between 1931 and 1984, they find that much of the convergence in earnings between early cohorts (1931-1950) was due to a declining "residual component", i.e. the portion of the wage gap unexplained by observable factors. However, this residual component remained stable for cohorts born between 1951 and the late 1970s, after which it resumed its decline. Their findings suggest that the dynamics of gender wage gaps among highly educated workers have varied considerably across birth cohorts, with periods of convergence alternating with periods of stagnation.

Figure 1 shows the evolution of wages for MBA graduates from a large public university over the first 13 years after receiving their MBA degree. Based on a survey of MBA graduates from 1990 through 2019, the results confirm that the pay gap between men and women MBAs is quite small at graduation but grows significantly over time.[1] Figure 1 also confirms that the gender gap is largest at higher income levels. Thirteen years after graduation, men earn about 30 percent more than women with the same degree. The gap is even larger at the upper end of the wage distribution. At the ninetieth percentile for men or women, the male wage 13 years after graduation is 75 percent higher.

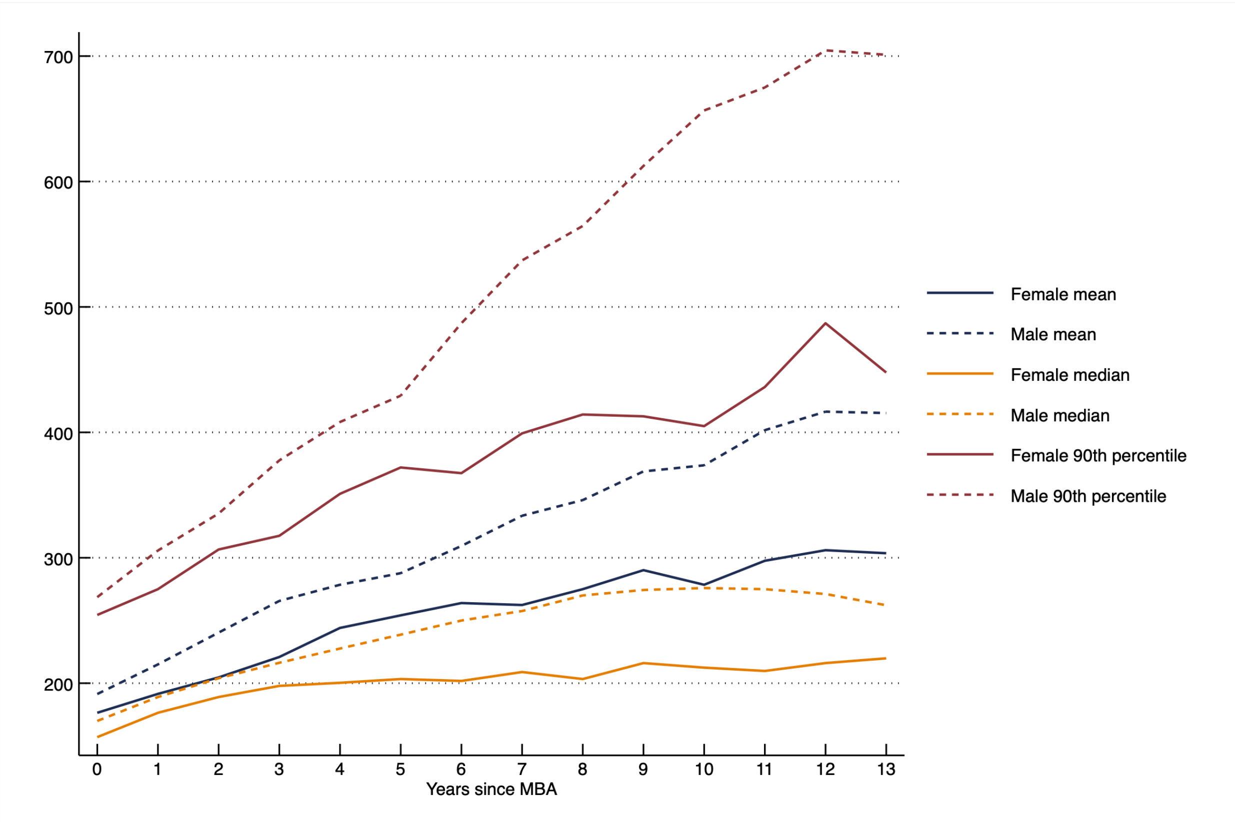

Figure 1: Male and Female Mean, Median, and 90th Percentile Annual Salaries (Thousands of 2022 Dollars) by Years since MBA. Nominal earnings in each year are converted into real earnings in 2022 dollars using the Consumer Price Index for All Urban Consumers (CPI-U).

Two questions naturally arise from a review of this literature. The first question is whether circumstances have changed. Nearly twenty years after Bertrand, Goldin, and Katz's (which we will refer to as BGK) landmark study of US business graduates, has the wage gap between men and women professionals narrowed? A second question is: do the reasons for this gap remain the same, or are there other explanations that remain to be discovered? Goldin (2014, 2021) and Bertrand et al. (2010) argue that much of the explanation for the gap among women professionals stems from the intersection of the desire for family and the fact that these kinds of careers require what Goldin (2014, 2021) refers to as "greedy work". Goldin (2014, 2021) argues that in occupations characterized by "greedy work", individuals who work fewer hours are heavily penalized due to the non-linear, convex relationship between hours worked and pay.

Answering these questions requires comparing patterns across two distinct time periods: that of BGK, and the years since. This comparison introduces a key methodological challenge: how to separate true temporal changes from differences in sample composition. When

[1] These results are magnified when we measure earnings inclusive of equity payouts. See Figures A1 and A2.

comparing career outcomes across different time periods, earlier cohorts are often observed predominantly in their later career years while more recent cohorts are observed primarily in their early career years. Our data illustrate this challenge clearly. The distribution of respondents by years since MBA graduation differs between pre-2006 and post-2006 graduates. The earlier cohort is heavily weighted towards long-term graduates, with most observations reflecting respondents with decades of post-MBA experience. In contrast, the later sample is heavily weighted towards recent graduates (see Figure A3). To address this composition bias, our primary analysis focuses on comparing graduates with identical years of post-MBA experience across the two time periods.

This paper makes three contributions to the literature on the gender pay gap. Using data on women and men MBAs graduating from a large public university over 30 years, we begin by exploring whether the raw (before adding controls) gender gaps identified by BGK through 2006 also exist in our sample. We find that the answer is yes. Using a survey instrument and specification similar to Bertrand et al. (2010)[2], we are able to reproduce their results for the period up to and including 2006. In this earlier period, the average unadjusted gender wage gap is 28 log points, or 32 percent. Over time, the gap grows from 9 percent at graduation to 37 percent 10 years after graduation. We also find that there is a large penalty attached to taking any time off from the labor force. A no work spell of six months or more is associated with a reduction in wages of 19 to 25 log points— similar to what was found by BGK.

Second, we explore whether gender wage gaps for business professionals have narrowed. We find that the raw gender wage gap has narrowed and now exhibits a very different pattern. The raw gender gap shrinks by thirty-three to fifty percent, to 14.5 log points without controlling for any labor supply factors. However, there is now a consistent raw gender wage gap from the very beginning of MBA careers, which was not present in earlier decades. Figure 2 shows the changes for the MBA respondents in our sample. The figure on the left shows the growing gender wage gap for all women and men MBAs who graduated before or in 2006. As seen in the figure, after 13 years, women on average were earning less than 300,000 dollars in 2022 dollars, while men on average were earning over 400,000 dollars. The figure on the right shows the same graph for all MBA graduates who graduated after 2006. In 2022 dollars, the gap has shrunk by thirty-three percent after 13 years. Yet a significant gap emerges at a much earlier stage in women's careers.

Do these changing patterns reflect significant progress or regrettable backsliding? In this paper, we explore the reasons for the existence as well as the reduction in the gap. The

[2]Our specification is identical to the BGK specification with two exceptions: first, we excluded the share of finance classes taken by respondents due to limited data; and second, we added a control for compensation prior to entering the MBA program.

reduction in the wage gap is explained primarily by a convergence of labor supply factors such as hours worked. Yet persistent differences remain, including the emergence of an early career wage gap in the later period which cannot be explained by observables.

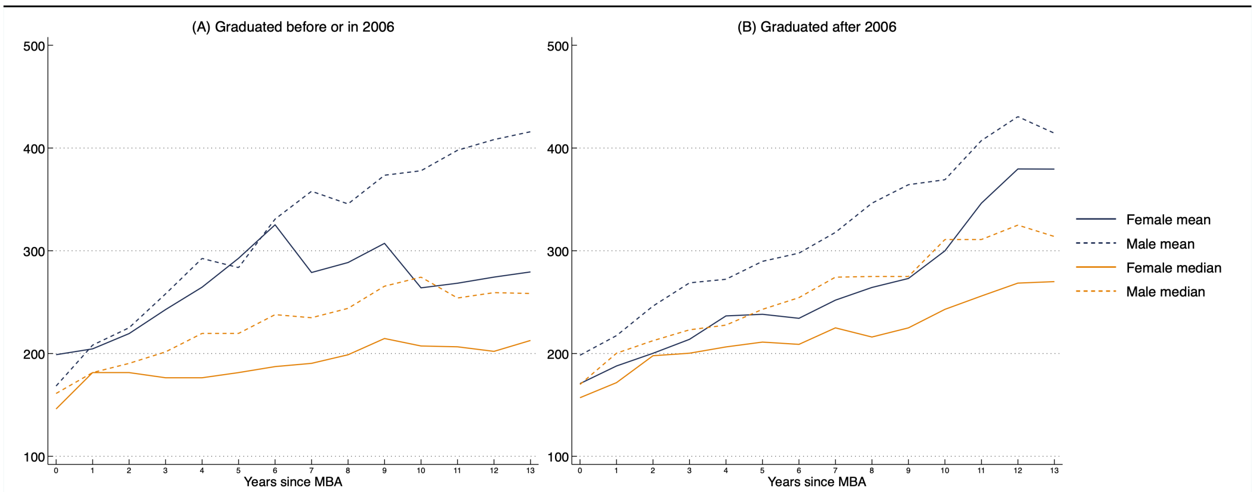

Figure 2: Male and Female Mean and Median Annual Salaries (Thousands of 2022 Dollars) by Years since MBA by Cohort. Nominal earnings in each year are converted into real earnings in 2022 dollars using the Consumer Price Index for All Urban Consumers (CPI-U).

The third contribution of the paper is to identify additional factors not quantified by previous studies. We explore the role of sexism, the availability of affordable childcare, and the prevalence of so-called "greedy work". We focus on these three additional factors because these factors are plausibly important but have not been systematically incorporated into previous analyses that seek to explain the gender wage gap for high paying women professionals.

We show that these three factors (sexism, childcare availability, and greedy work) do not play a large role in explaining wage differentials but do matter indirectly by affecting labor supply decisions for MBAs. Quantitatively, the most important of these three are greedy work and background sexism. In this paper, we show how hours of work and work interruptions of six months or more are in turn influenced by sexism and greedy work.

When we seek to understand why women MBAs put in fewer hours, have a higher rate of self-employment, and are more likely to take time off from work, we find that all of these differences are associated with women who have children. Our results point to the very real dilemma posed in Goldin's book, Career and Family (2021): it is indeed difficult to have it all. Yet gender wage differences have shrunk over the last three decades, as women with children have made the decision to remain in the labor force. In the earlier period, we can fully explain the remaining gender wage gaps through differences in hours worked and occupation choices. In the later period, however, there remain unexplained wage gaps from the very beginning of an MBA's career.

There is a vast literature that explores the possibility of gender discrimination. Several experiments have shown unequivocally that mothers are much less likely to be hired, while fathers are instead more likely to be hired (Correll et al., 2007; England et al., 2016). BGK (2010) conclude that "Of course, the evidence does not rule out discrimination since women facing such career barriers still may give family reasons for job changes." In the business world, female representation at the highest levels remains low. In the United States, female CEOs in the S&P 500 account for only 8 percent of all CEOs.

Gender disparities in business careers may have antecedents even during business education itself. Krishna and Orhun (2022) document significant gender performance differences in undergraduate business school courses, finding that women's grades are 11% of a standard deviation lower in quantitative courses while men's grades are 23% of a standard deviation lower in non-quantitative courses. Notably, they find that female instructors substantially reduce these performance gaps in quantitative courses by providing counter-stereotypical role models. While their focus is on academic performance during education rather than labor market outcomes, their findings suggest that gender stereotypes and representation may shape trajectories even before graduates enter the workforce. Our analysis examines whether these patterns translate into wage disparities in the post-MBA labor market and how such disparities have evolved over time.

In our research, due to our concerns regarding endogeneity, we measure only the impact of exposure to sexist norms early in life. We draw on recent work by Charles et al. (2018), who distinguish between "background sexism", based on the state in which a respondent spent their formative years, and "residential sexism" which is where a respondent currently resides. They measure state-level sexism using answers to the General Social Survey (GSS) and merge that with information on individuals who left one state and now reside in another. Since we are persuaded by their argument that background sexism is sufficiently exogenous since it is identified in childhood, while residential sexism is potentially endogenous, we only measure the impact of background sexism based on merging the results from responses to the GSS and our information on a survey respondent's state of birth or country of birth. We explore the direct impact of background sexism on both wage gaps and labor supply decisions (hours worked, self-employment, and career interruptions). Our results point to a significant impact of background sexism on hours worked. Surprisingly, its role is larger and more significant after 2006 rather than before. In our results, traditional views of women's roles as measured by population surveys where MBA women were raised have more impact in recent decades than previously.

We also measure the importance of greedy work for both wage outcomes and labor force participation decisions. Goldin (2014) posits that some professions like business and law have non-linear wage structures such that rewards come from being able to work very long hours. Goldin (2014) summarizes her theory as follows:

> What, then, is the cause of the remaining pay gap? Quite simply, the gap exists because hours of work in many occupations are worth more when given at particular moments and when the hours are more continuous. That is, in many occupations, earnings have a nonlinear relationship with respect to hours. A flexible schedule often comes at a high price, particularly in the corporate, financial, and legal worlds. . . Much has to do with the presence of good substitutes for individual workers when there are sufficiently low transaction costs of relaying information.

In this paper, we identify the characteristics of individual MBA workloads using the suggested components identified by Goldin (2014). We are able to identify across all MBAs whether the remaining gender pay gap can be associated with specific attributes associated with greedy work. While others, including Goldin (2014) and Bütikofer et al. (2018), provide further evidence in support of the greedy work hypothesis, ours is the first study to test and explicitly identify whether the gender pay gap within business professions can be explained by non-linear characteristics. Our results suggest that greedy work characteristics are in fact an important component of MBA salaries in the post-2006 period. The magnitude is large: if work is rated as greedy on a scale of 1 to 5, then a 1 point increase is associated with a wage percentage increase of 9 to 12 percent.

The third explanation for the remaining gender pay differences that we explore is the availability of childcare. We address whether lower-cost child care options mitigate the gap or affect labor supply decisions. Using answers to our survey, we find that availability of lower priced childcare does not have a significant impact. However, this result could be due to our imperfect measure of childcare costs.

In general, our results suggest that the convergence of hours worked for men versus women explain much of the shrinking of the gender wage gap after 2006. We find that other factors not previously tested matter also for wage gaps and labor supply differences. In particular, individuals who do greedy work spend more hours working, are paid more and less likely to leave the labor force or work for themselves. This means that greedy work affects compensation both directly and also indirectly through its impact on women's labor supply decisions. We also find a dramatic shift in the behavior of women with children, who are 60 percent less likely to withdraw from the labor force today relative to earlier decades in order to raise their children.

The potential for technological changes to reduce the penalties associated with workplace inflexibility has gained renewed attention in recent work. Harrington and Kahn (2025) examine how the rise of work from home arrangements may have reduced the motherhood penalty in the labor market. Leveraging variation in technological feasibility of remote work across college degrees prior to the pandemic, they find that for every 10% increase in work from home capability, mothers' employment rates increased by 0.78 percentage points relative to other women. Importantly, this effect is concentrated in degrees linked to careers with high returns to hours and inflexible demands, precisely the "greedy work" characteristics that Goldin emphasizes. This evidence provides a potential explanation for the temporal changes we observe, as the period since 2006 has coincided with significant technological advances enabling workplace flexibility in traditionally inflexible business careers.

The results reported in this paper have implications for the conversation on "leaning in", as coined by Sheryl Sandberg in her 2013 book. Our results show a remarkable reduction in the wage gap over time, particularly as the differences in hours worked between men and women have narrowed. Yet persistent differences remain in wages, hours worked, and the decision to take time off. While in previous decades wage differentials emerged slowly, now they are apparent from the very beginning of an MBA's career.

The remainder of this paper is organized as follows. Section I describes the survey, the framework for estimating wages and gender wage gaps. Section II explores changes over time. We show that the raw gap among all men and women MBAs in our sample has declined by thirty three to fifty percent since 2006. Section III tests for the changing importance of greedy work, background sexism, and child care options in explaining the gender pay gap. Section IV explores the determinants of hours worked, spells of no work, and self-employment, major determinants of the gender pay gap for business professionals. Section V discusses changes in the nature of the gender pay gap and Section VI concludes.

1. Survey and Framework

The results presented in this paper are based on an internet survey that was conducted in Fall 2022 of all MBA graduates from a large public university for whom the alumni office had email addresses. MBAs who graduated from 1991 to 2021 were included in the survey. The survey was sent to 16,240 graduates and we received survey responses from 2139, a response rate of 16 percent. We also note that of the total respondents 846 did not report any career stages at all. This response rate is lower than the 31 percent response rate received from the survey of University of Chicago graduates conducted by BKG.

Looking at the survey response patterns, Tables 1, 2, and 3 provide evidence on the validity of our retrospective survey data by comparing the observable characteristics of respondents and non-respondents. A key concern with our 16 percent response rate is whether selection into survey participation differs systematically in ways that could bias our estimates of the gender wage gap evolution. We examine this potential selection along observable dimensions of academic achievement.

Table 1 presents the pooled sample comparison. While we observe some statistically significant differences between respondents and non-respondents—notably in undergraduate institution quality and verbal GMAT scores —these differences are modest in magnitude. Critically, we find no significant differences in quantitative GMAT scores or undergraduate GPA, suggesting that respondents and non-respondents are balanced on key measures of quantitative ability and overall academic performance that correlate strongly with post-MBA earnings.

The within-cohort comparisons in Tables 2 and 3 provide further reassurance about the validity of our temporal comparisons. For the pre-2006 cohort (Table 2), the selection into survey response is remarkably minimal. Respondents and non-respondents are virtually identical in undergraduate GPA and quantitative GMAT scores. While we observe statistically significant differences in MBA GPA and the fraction of finance courses taken, these differences are economically small—the MBA GPA gap of 0.04 points and the one percentage point difference in finance coursework are unlikely to generate substantial bias in our wage gap estimates, particularly given that we control for these characteristics in our regression specifications.

The post-2006 cohort (Table 3) shows somewhat stronger selection, as respondents are more likely to come from elite undergraduate institutions and have higher undergraduate GPAs. However, even in this cohort, we find no selection on quantitative GMAT scores or verbal GMAT scores, and the MBA GPA difference remains economically modest, at 0.03 points, and statistically insignificant. Importantly, the direction of selection—if anything, toward higher-achieving graduates in the post-2006 respondent pool—would likely bias against finding a narrowing gender gap if high-achieving women in recent cohorts face similar career constraints as their predecessors. Overall, while we cannot rule out selection on unobservables, the balance on observable characteristics that predict career success suggests that differential survey response is unlikely to be driving our main findings about the changing nature of the gender wage gap in business careers.

The survey was extensive, asked retrospective information on every career move since graduation from the program. Survey respondents filled out details on base salaries and bonuses, hours worked, career interruptions, and children. A core set of questions were taken directly from the BKG survey, in order to facilitate replication. A number of new questions were added to this survey which allow us to explore issues related to greedy work. Taken by Goldin (2014) from questions in the O*Net survey, answers to the following five questions (on a 5 point likert scale with endpoints of 1= Never and 5 = Every day) are what define greedy work:

1. How often does this job require the worker to meet strict deadlines?

2. How much does this job require the worker to be in contact with others (face-to-face, by telephone, or otherwise) in order to perform it?
3. How often does this job require developing constructive and cooperative working relationships with others, and maintaining them over time?
4. To what extent is this job structured for the worker, rather than allowing the worker to determine tasks, priorities, and goals?
5. How much decision making freedom without supervision does the job offer?

The survey is a one time survey that asks respondents to report their complete retrospective work histories since receiving their MBA. For each period of work that is at least a six month period, respondents are asked broad details about their roles and compensation, including the questions about greedy work listed above. The survey is then converted to an annual panel.

Our primary specification will begin with a standard log wage specification where the dependent variable is log annual wages, including bonuses. In the initial specification, the only controls will be years of experience, a cohort × time fixed effect, and gender. Additional specifications will add pre-MBA performance as measured by pre-MBA compensation and rank of the undergraduate institution. We then add controls for performance during the MBA years. BGK use both MBA GPA and percentage of courses taken which were in finance as a control for the different compensation that is associated with these outcomes. We will control for MBA GPA but do not have sufficient observations for share of finance courses so exclude this control. This is the basic specification as reported by BGK for the period before and including 2006.

In Section III, we introduce the possibility of three additional factors that could affect wages: background sexism, childcare costs, and greedy work. To take into account background sexism, we adopt the approach of Charles et al. (2018). We modify the basic specification to take into account the impact of attitudes towards women working based on where an individual grew up. Following Charles et al. (2018), attitudes are measured based on annual responses in the General Sample Survey (GSS) to the following 8 yes-no specific questions about the role of women in the workplace (with greater endorsement indicating more sexism):

1. Do you approve or disapprove of a married woman earning money in business or industry if she has a husband capable of supporting her?
2. Do you agree or disagree with this statement? Women should take care of running their home and leave running the country up to men.
3. If your party nominated a woman for president, would you vote for her if she were qualified for the job?

4. Tell me if you agree or disagree with this statement: Most men are better suited emotionally for politics than are most women.
5. A working mother can establish just as warm and secure a relationship with her children as a mother who does not work.
6. A preschool child is likely to suffer if his or her mother works.
7. It is more important for a wife to help her husband's career than to have one herself.
8. It is much better for everyone involved if the man is the achiever outside the home and the women takes care of the home and family.

We compile answers by year and by state or country of origin to these questions, as reported to the GSS. The GSS indicates both state of origin as well as the country of origin for immigrants who did not reside in US states while young, and we use the answers by country of origin for those survey respondents. We then combine answers with detailed information on where MBA graduates were raised, based on MBA admissions information. For each graduate, we pair them with GSS responses in their state or country of origin t years earlier, where t is defined as 20 years since they received their MBA.

To measure the impact of greedy work, we compile an average response to the five characteristics identified by Goldin (2014) as indicative of greedy work. Respondents were asked to rate their employment for each phase of their careers along these five characteristics on a scale from 1 (never) to 5 (every day). We compile all these into one measure of greedy work, which varies over time as individuals change jobs.

2. Changes over the last 20 years in labor supply and earnings

Figure 1 showed a growing gender wage gap over the course of an MBA's career. Table 4 confirms that the average gender gap in pay for our entire sample was 35 percent (264,000 average annual income in dollars for men divided by 196,000 for women). In this section, we identify changes in labor supply and earnings by gender between 1990 and 2019. We begin by denoting broad trends in both labor supply and earnings by gender for the two periods under study.

Descriptive statistics for the 16,442 combined years and individuals who completed the survey are listed in Table 4. On average, men and women are almost exactly the same age at graduation. Male MBA graduates earned on average 35 percent more compensation than women, and worked 8 percent more hours than women. The nonlinear relationship is a crude indication of support for Goldin's (2014) discussion of the consequences due to greedy work: individuals working longer hours (by 8 percent) are disproportionately rewarded with higher pay (by 35 percent). More robust tests of the nonlinear relationship between hours worked and earnings will be reported in Sections III and IV.

Table 4 also reports that women in the sample had slightly fewer children (70 percent for women versus 83 percent for men) and were less likely to be married and more likely to be self-employed (8 percent versus 6 percent). We also report the changes in the averages over time in Table 5 as well as the changes by gender in Appendix Tables A1 and A2. Notable changes over time include age at graduation, hours worked and ease of child care arrangements. Post-2006, age at graduation is older, from an average of 30.55 years to 32.16 years. Weekly hours worked decline by almost 2 hours a week. Self-employment falls significantly, from 10 percent pre-2006 to 4 percent post-2006.

The gender-specific changes over time show a narrowing of the differences in hours worked between men and women but divergence in other respects. In the earlier pre-2006 period, women on average worked 5.5 hours a week less than men. Post-2006, the difference has narrowed to only 2.5 hours a week. The descriptive statistics in Appendix Tables A1 and A2 show that women's hours of work have not changed significantly in the later era; instead, a bigger trend is that men are working fewer hours. Pre-2006, men worked 52.73 hours; now they work on average 50.32 hours a week. Pre-2006, women worked 47.23 hours a week and have slightly increased to 47.8 hours a week. In contrast, the gap in marriage status has grown, from a roughly 9% gap in pre-2006 to a 15% gap in post-2006, with fewer women being married than men in our survey. The gap has also grown for the decision to have children, with a larger percentage of women relative to men reporting no children (9% gap pre-2006 versus 16% gap in post-2006). However, the sample of recent graduates is significantly younger, by at least 10 years, so these differences may only be temporary.

Tables 6 and 7 report the means of the key variables over the two periods of our sample for both genders. In Table 6, we see that the means for female MBAs have not changed significantly over the two time periods. The biggest differences are ages and work experience, which simply reflect that the later sample has more younger individuals with less work experience. Female MBAs have slightly better GMAT scores in the later period, in both the quantitative and verbal sections. One big difference is in the composition of industry employment, which has moved from government and public sector roles to better compensated tech roles.

The changes for male MBAs are similar to those for women. While most of the changes are statistically insignificant across the two periods, there are significant increases in the proportion of Male MBAs who identify with an Asian ethnicity. There are also slight increases in quantitative and verbal GMAT scores as well as pre-MBA compensation, of similar magnitudes as those for Female MBAs. There is also a significant decline in the MBA GPA for male MBAs, unlike females. Finally, there is an even bigger shift towards employment in technology, with less of a shift out of government and public sector roles, where male

MBAs were not significantly represented. Between the two time periods, 15 percent of the male respondents shifted to technology, relative to a 10 percent shift towards technology for women. Apart from the large shift towards employment in the tech industry (larger for men than for women), there is no indication of large shifts in the type of student who attends this institution, either over time or across genders.

Table 8 presents our first set of regression results. Each row reports the coefficient on gender in a regression of either log earnings or labor supply as the dependent variable. In this first set of results, we control only for cohort and time effects. To ensure comparability, regressions for each subsample include only other MBAs with the same number of years post graduation. Log annual earnings show a 12 log point gender wage gap at initial hiring which grows to 15 log points 6 years after graduation and 33 log points 10 years after graduation. Women are also significantly less likely to be working, with a 7 percent higher probability of not working after 9 years. On average, women work fewer hours than men at all stages of their career, with a 7 point log difference initially which falls and then grows to 9 log points 10 years after graduation. As indicated in column 4, on average the gap in time not working is more than half a year after 10 or more years of work. As reported by others, the wage penalty for taking off a little over half a year over the course of a career is steep. To better understand the sources of the significant gender wage and labor supply gaps in our sample, we will now turn to our more precise extensive regression analysis that utilizes the same comparison of like cohorts across the two time periods but adds a number of additional controls.

Tables 9 and 10 present the evolution of the gender wage gap with a full set of controls, decomposing earnings differences by years since MBA graduation for cohorts graduating before and after 2006. To account for potential composition differences between these cohort groups, where the pre-2006 sample is heavily weighted toward long-term graduates and the post-2006 sample toward recent graduates, we estimate separate regressions for each combination of cohort period and years since MBA. This approach allows us to compare individuals at identical career stages across different graduation eras, isolating true temporal changes from differences in sample composition.

Each cell in these tables represents a distinct regression with log earnings as the dependent variable. We progressively add controls, beginning with simple bivariate regressions that include only cohort-by-year fixed effects and a female dummy (the same as Table 8), and building toward specifications that control for pre-MBA characteristics, MBA performance, post-MBA work experience and career choices, and finally weekly hours worked.

Table 9 reveals fundamentally different patterns in the gender wage gap between the two periods. These differences are not evident from the previous regression results which pool all time periods. The stark differences are consistent with the visual changes in the figures reported earlier. For the pre-2006 cohort, the simple bivariate specification shows a classic pattern of an emerging and widening gap over career progression. The gender wage gap begins modestly and lacks statistical significance at MBA graduation (-0.086 log points) and year 1 (-0.050 log points). Neither of those differences are statistically significant. However, the gap steadily expands with career advancement, reaching statistical significance by year 9 (-0.212 log points) and continuing to widen substantially for those with 16 or more years of post-MBA experience (-0.437 log points). This pattern for the raw gender wage gap (without controls) aligns with theoretical predictions about the cumulative effects of differential returns to labor market attachment and career interruptions over time.

The post-2006 cohort exhibits a fundamentally different temporal evolution. The gender wage gap is immediately apparent and statistically significant from career inception, starting at -0.124 log points at graduation. Rather than widening substantially over time, the gap remains relatively stable through the early and mid-career years, fluctuating between -0.099 and -0.247 log points through year 9. Notably, for the limited observations available beyond year 10, the gap narrows substantially and loses statistical significance, reaching only -0.009 log points for those 16 or more years post-MBA.

The addition of controls substantially affects these patterns, particularly for the pre-2006 cohort. When we control for pre-MBA characteristics, MBA performance, and post-MBA work experience, the pre-2006 cohort shows little evidence of an unexplained wage gap across most career stages. The pattern for the post-2006 cohort remains more stable, with modest unexplained wage gaps persisting in early career years that generally dissipate beyond year 6, though small sample sizes in later years limit our ability to draw firm conclusions.

The inclusion of weekly hours worked further attenuates gender gaps while maintaining the overall temporal patterns. For the pre-2006 cohort, controlling for labor supply factors including work interruptions, work experience, and hours eliminates virtually all evidence of gender wage differences across career stages. This result suggests that labor supply differences in the pre-2006 period accounted for a large share of the observed wage gap. For the post-2006 cohort, the early-career wage gaps remain present but are generally smaller in magnitude and often insignificant (but not always). There is a puzzling positive wage gap one year out for the pre-2006 cohort, which remains unexplained.

Table 10 presents analogous results with a modified dependent variable that includes equity, which has become an increasingly important component of total compensation in business careers. The patterns mirror those found in base earnings but are generally more pronounced in magnitude. For the pre-2006 cohort, the bivariate specification shows an even steeper trajectory of wage gap expansion, reaching -0.608 log points for those 16+ years post-

MBA. For the post-2006 cohort, the early-career gaps are larger in magnitude when equity is included, starting at -0.170 log points at graduation, but the same pattern of stability through mid-career and narrowing in later years persists.

The progressive addition of controls again substantially reduces the gaps, particularly for the pre-2006 cohort. However, the post-2006 cohort continues to exhibit early-career wage gaps even with extensive controls, suggesting that observable characteristics explain less of the gender difference in total compensation for recent graduates than for their predecessors.

In both Tables 9 and 10, the raw gender wage gap becomes small and insignificant for the pre-2006 era with the addition of controls for MBA and post-MBA characteristics and hours worked. Controlling for pre-MBA characteristics does somewhat reduce the gender wage gap, indicating that there is some selection based on observables like GPA or quality of undergraduate institution or test scores into the MBA program. Even more important are the factors that differ with gender once students are in the MBA or afterwards–such as hours worked or industry of employment. For the pre-2006 period, adding these controls completely eliminates any significant gender wage gap. However, a significant gap remains for more recent decades.

In an online Appendix, we decompose the MBA and post-MBA controls associated with a reduction in the gender wage gap. We report the coefficient on the gender wage gap when adding each control separately one at a time. We address a key concern: whether the apparent temporal shift in gender wage gaps reflects genuine changes in how gender and compensation interact, or whether it instead reflects shifts in industry composition between the two periods. Our earlier descriptive analysis noted that both men and women have shifted substantially toward technology employment in the post-2006 period. If women and men differ in their industry distributions, and if gender wage gaps vary across industries, then compositional changes could account for some or all of the observed temporal patterns.

The results show that for both periods, differences in labor supply elements such as work interruptions, work experience, and hours worked play a role. In addition, industry affiliation and function also matter. These factors are enough to eliminate the statistical significance of the gender wage gap in the pre-2006 period, but not post-2006.

These results challenge the conventional narrative of unambiguous progress in gender wage equality among MBA graduates. Rather than simple convergence, we observe a fundamental shift in the temporal structure of gender wage gaps across cohorts. The pattern among pre-2006 graduates of minimal early gaps that widen substantially with career progression has given way to a different pattern: immediate but relatively stable gaps that may narrow in later career stages.

These granular results underscore the importance of accounting for the composition differences between our pre- and post-2006 samples. The pre-2006 cohort is observed with substantial representation across all career stages, while the post-2006 cohort is necessarily truncated at longer horizons. This compositional difference may explain some of the apparent "progress" in gender wage gaps if the most severe gaps emerge only after 13+ years in the workforce—a period for which we have limited post-2006 observations.

One question which naturally arises is whether this sample of MBA graduates is fundamentally different than the BGK sample. To test this, we present a set of regression results using the same specification and time period in Bertrand et al. (2010). This basic BGK specification for total log compensation (wages and bonuses are included) is reported in Tables 11 and 12. To facilitate comparison with Bertrand et al. (2010), which spanned MBAs graduating between 1990 and 2006, we conduct separate analysis for data pre- and post-2006. Without additional controls, the first column reports a gender wage gap of 28 log points, or 32 percent, for the pre-2006 period. This is the same unadjusted raw wage gap reported for the University of Chicago sample by Bertrand et al. (2010), which is a remarkable coincidence.

In our replication of Bertrand et al. (2010) we control for MBA GPA (in column (2)) and post-MBA work experience (in column (3)), which reduces the gap from 28 to first 12.6 then 3.5 log points. Columns (5) through (9) include controls for hours worked. This further reduces the gap. Controlling for hours worked in columns (5) through (8) reduces the gender gap to between 0.4 and 19.7 log points, as women are working fewer hours overall than men. Across all specifications that include work interruptions, defined as not working for a period of at least six months, the penalty is high. The coefficient on work interruptions varies from 18 to 29 log points across the first eight columns of the Table. A career cost of 29 log points for a work gap of at least six months is consistent with the results reported by Bertrand et al. (2010). They report a penalty of 22 to 29 log points for similar specifications.

For the sake of completeness, in column (9) we also include the same controls added by Bertrand et al. (2010) regarding the respondent's reasons for choosing their job. Both Bertrand et al. (2010) and Blau and Kahn (2017) express concerns about these additional controls. Bertrand et al. (2010) refer to these additional controls as "arguably even less exogenous" and do not feel that this is their preferred specification, and Blau and Kahn (2017) concur. Since neither Bertrand et al. (2010) nor Blau and Kahn (2017) place confidence in the results in this last column, we will not report further specifications using these sets of controls.

Table 12 presents the same set of results for the later period. This allows us to analyze how the raw gender gap changed and to analyze the impact of the additional controls. The overall unadjusted wage gap in column (1) is exactly 50 percent lower than it was in the previous period, falling from 28 to 14 log points. These results indicate a decline in the overall gender wage gap for more recent graduates, which can be seen visually in Figure 2. Our preferred specification is reported in column (8), which controls for MBA GPA, work experience and any no work spell, as well as hours worked. The results in column (8) indicate a statistically insignificant wage gap of 2.7 log points in the post-2006 period after controlling for pre-MBA, MBA, post-MBA, industry, and hours. All of the gap in the post-2006 period can be explained by labor supply characteristics, MBA differences, and industry affiliation in the BGK specification.

Why do the results differ from our analysis by years since MBA graduation, which shows a more persistent early gender wage gap in the post-2006 period? These results pool all cohorts and represent averages across MBA graduates of different vintages, while the earlier analysis allows us to separate and identify evolving gender wage gaps for different time periods post graduation. Across all specifications, we see a dramatic reduction in the raw gender wage gap for MBAs graduating after 2006. We now turn to Section III where we explore the role of additional factors.

3. Accounting for Greedy Work, Bias, and Child Care Costs

This section introduces a number of other factors that have been discussed as potentially important in explaining the gender wage gap for business professionals. We will add three measures: (1) self-reported answers to occupational characteristics that define greedy work (2) an exogenous measure of background sexism, and (3) self-reported measures of reduced cost childcare options. We described how we measure greedy work and background sexism in Section I. Our measure of lower cost childcare options is the percentage of childcare provided either by relatives or by employers.

In unreported extensions, we also included an interaction with gender to see if these variables varied with gender. However, since the interaction terms are not statistically significant (indicating that these additional factors affect men and women equally) we do not report that specification here. One additional control that we also add is whether or not graduates engage in self-employment. Our sample means show that women are more likely to be self-employed, presumably because this provides greater flexibility and control over working conditions. If self-employment is associated with compensation penalties, this could be an alternative source of gender pay gaps.

Table 13 reports the wage regressions for the pre-2006 period. The first row reports the coefficient on the gender wage gap for the pre-2006 period with a range of controls. Our BGK specification showed an insignificant gender wage gap of 3.5 log points controlling for Pre-

MBA, MBA and Post-MBA characteristics. The addition of self-employment status does not appreciably affect the pre-2006 gender wage gap. In the pre-2006 period, self-employment is associated with a large earnings penalty but smaller than work interruptions, with 12 to 26 log points lower earnings across different specifications. Adding background sexism, greedy work characteristics and childcare controls does not affect the coefficient on the pre-2006 gender wage. It remains small in magnitude and insignificant.

Table 14 reports the same sets of regression results for the post-2006 period. Across all specifications, the results indicate that in the post-2006 period the unexplained gender wage gap (which cannot be accounted for by differences in labor supply status or other factors) is close to zero. This does not mean that wage gaps are eliminated, but that all wage gaps can be explained by other variables in the post-2006 period, such as industry category, post MBA characteristics, work experience and time spent out of the labor force.

The remaining rows of Table 14 report the coefficients on greedy work, background sexism, and reduced cost of childcare. The evidence across different specifications suggests that the most important previously omitted consideration for understanding wage determination is greedy work. A one point (two standard deviation) increase in greedy work, which is categorized between 1 and 5, raises log wages by between 8.6 and 12.3 log points, as reported in columns 3, 4, 7 and 8. Individuals who work in professions that can be characterized by the rubric described in Section I as "greedy" earn significantly higher wages—after controlling for experience, GPA, hours, industry affiliation and other factors.

The evidence suggests that, particularly in the pre-2006 period, differences in log wages of MBAs can be traced to decisions about how many hours to work and whether to take time off. The labor supply characteristics that differ most between men and women are self-employment status, their likelihood of taking time off from work, which industry they work in, and the number of hours worked. Whether one's employment has "greedy" characteristics also affects the gender wage gap. In the next section, we explore the determinants of labor supply differences between men and women MBAs over the last four decades.

4. Labor Supply Determinants: Work Interruptions, Hours of Work, and Self-Employment

This section explores the determinants of work interruptions, working fewer hours, and the decision to be self-employed. We replace log compensation as the dependent variable with these three labor supply decisions as the dependent variables. Again, we explore both independently and together the impact of greedy work, bias, and childcare. While Section III estimated the direct effect of these factors on compensation, this section estimates the indirect effect operating through a reduction in labor supply.

The results are reported in Table 15. The first six columns explore the determinants of hours worked. As columns (1) and (2) indicate, much of the gender-specific differences in hours worked are associated with women who have children. Women with children report 9.9 log points lower hours worked, while there for women without children the reduction is 4.4 log points. In columns (3) through (6) we add controls for background sexism, greedy work, and reduced cost of childcare. Individuals who engage in greedy work report on average 10.3 log points higher hours of work per week. These greater hours worked are consistent with earlier evidence showing the significant wage premiums associated with greedy work. The evidence also suggests that having grown up in a region where respondents have more traditional values is associated with a reduction in weekly hours worked of 3.3 to 3.6 percent. Attitudes in the environment of one's youth have a permanent effect on labor supply choices later in life.

Columns (7) through (12) report the determinants of self-employment. The results show no gender-specific determinants of self-employment. There is also no significant association with greedy work, background sexism, or reduced cost of childcare. Self-employment, which is associated with a large negative wage penalty, is difficult to explain based on work or individual characteristics.

The last six columns report determinants of work interruptions. The results show in column (14) that work interruptions are equally likely for women with children and for those without. Our preferred specification in column (18) shows that work interruptions are more likely by 2.3 log points for women. The results also show that individuals engaged in work characterized as greedy are less likely to have work interruptions.

We redo the labor supply estimation for the pre- and post-2006 period. In the pre-2006 era, reported in Table 16, hours worked for female MBAs are lower by 9.1 log points. Individuals who do greedy work report 9.5 to 9.6 higher log points of hours worked per week. Neither background sexism nor reduced cost of childcare are associated with log weekly hours worked, either as sole predictors or in combination with the other two factors. Individuals whose work has greedy characteristics are much less likely to be self-employed. The negative association between greedy work and self employment may reflect one attraction of working for one's self. In the earlier period, women are significantly more likely (by 3.2 log points) to experience any no work spell. Greedy work is a significantly negative predictor, whereas the impact of reduced cost of childcare is not significant. In a reversal of other results, only women without children are significantly likely to engage in a no work spell.

Results for the post-2006 era are reported in Table 17. As reported in column (1), the dummy for female is associated with a 4.5 percent reduction in hours worked, after controlling for pre-MBA and MBA characteristics, employer type, and cohort by year effects. Over these two periods, the data reveals a reduction of fifty percent in the gender hours differential. As shown in column (2), all of these differences in hours worked after 2006 are associated with having a child. Women with children work 7.4 log points fewer hours, after controlling for other factors. Both background sexism (which was not significant in the pre-2006 period) and greedy work have significant negative impacts on hours worked. The evidence shows that greedy work is associated with 11 log points more weekly hours worked, after controlling for other factors.

For self-employment, none of the three potential determinants emerge as statistically significant, either in separate or simultaneous regressions. As with the earlier period, observable factors do not easily explain the decision to be self employed. For any no work spell, only greedy work emerges as a significant (negative) factor associated with a no work spell.

The results in this section indicate that there is a significant gender gap in log weekly hours worked and work interruptions. The coefficient estimates explaining the differences have remained stable over the decades, and all of the gender gaps post-2006 are associated with women who have children. For self-employment decisions, however, there is no gender specific determinant. Both background discrimination and greedy work characteristics have played an important role in affecting the gender differences in hours worked.

5. The Changing Shape of the Gender Wage Gap over the Decades

In this penultimate section of the paper, we discuss the changing shape of the gender wage gap among this sample of post-MBA working professionals. Figures 1 and 2 showed that there is a persistent wage gap between men and women MBAs over the last several decades. Post-2006, the raw wage gap has shrunk by fifty percent, which shows remarkable progress. In addition, the shape of the wage gap has changed dramatically, and deserves reflection.

In the pre-2006 period, the gender wage gap was not apparent in the early years post-MBA, but only emerged after several years. In more recent decades, a significant wage gap is immediately apparent, and persists over time. This pattern is not only apparent from Figure 2, but is also confirmed by the point estimates reported in Tables 8, 9, and 10, which are based on balanced panels across the two cohorts.

The two periods exhibit a very different pattern. One possible reason could be due to the different composition of the two sets of survey respondents, which we have noted earlier in the paper. The distribution of respondents by number of years since their MBA is presented in Figure A3 The earlier cohort is heavily weighted towards long term graduates, with most observations reflecting respondents with decades of post-MBA experience. In contrast, the later sample is heavily weighted towards recent graduates. One question is whether this different sample mix could explain the different pattern of gender gaps. To test for this

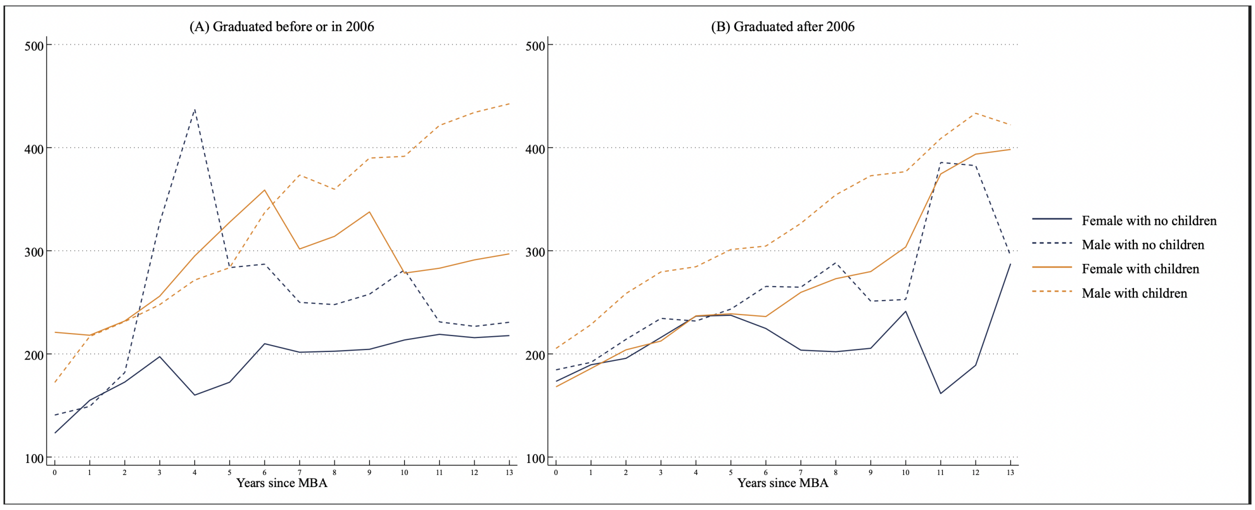

Figure 3: Annual Wages by Gender and Parent Status

possibility, we did the analysis earlier in the paper separating estimates into cohorts of equal number of years since graduation for both time periods. This allows us to compare the same cohort as defined by years since graduation over the different time periods. As we saw the difference in the pre- and post- 2006 cohorts is stable across specifications. In particular, the difference in the two cohorts remains when we control for the different characteristics of the two samples by comparing graduates with the same number of years post-MBA. This exercise suggests that the different patterns that emerge in terms of gender wage gaps are not due to the different characteristics of the two samples.

In the post-2006 period, the raw gender wage gap narrows by 33 to 50 percent (without the addition of controls). Yet labor supply differences persist, with women working fewer hours and continuing to take more time off from the labor force–both factors associated with the decision to have children. We explore the wage gaps associated with having children in Figures 3 and 4. We show wage and hours gaps both by gender and by parent status.

Figure 3 shows that–in addition to the narrowing gender wage gap noted in the paper–there is also a wage premium associated with having children. In both periods, men and women with children earn more than individuals who do not have children. These results are consistent with BGK, but inconsistent with the broader literature on the motherhood penalty. The narrowing of the wage gap is driven by a narrowing of wages within each of these two groups–parents versus non parents. We see that while the gender wage gap expanded prior to 2006 for parents, in the second period the gender wage gap narrows for parents.

Our regression results suggest that a major driver of the wage gap in the earlier period is hours worked. In the later period, the difference is less important. Consequently, we should see a narrowing of differences in hours worked over the two periods for parents. The graphs below show changes in hours worked for parents pre- and post- 2006. The figures are instructive: the narrowing of the hours gap is driven by a steady reduction in hours worked

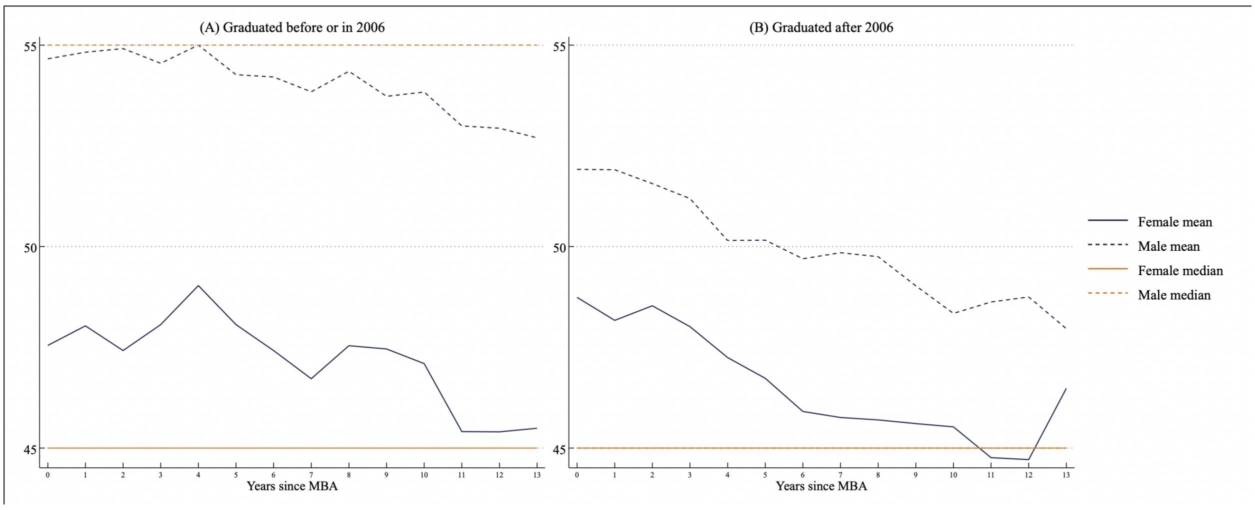

Figure 4: Hours Worked Per Week for Male and Female Parents

by men who are parents. Women with children are actually working longer hours relative to pre-2006. One striking result is that the median hours worked for both men and women parents have converged since 2006.

The empirical results across specifications point to the continuing challenge for women graduates in managing both career and family. The evidence is most striking in the determinants of labor supply, where differences persist in hours worked, labor force interruptions, and time in the workforce for women with children. Nevertheless, in the later period we cannot explain all of the remaining gender wage gap with differences in labor supply alone. A persistent wage gap which remains (in the cohort based regressions, not the BGK specification) after controlling for labor supply differences, industry, function, and other characteristics is a phenomenon which was not present in earlier years.

The convergence in hours worked for men and women over the decades is consistent with answers to other questions from the survey instrument. As we saw in Figure 4, the narrowing of the wage gap is consistent with a narrowing of the hours gap between men and women. Appendix Tables A3 and A4 ask respondents by gender about the frequency of family support for childcare before and after 2006. Respondents report a doubling of reliance on extended family. While only 3 percent of women relied on family for childcare at least once a week pre-2006, that number increases to 8 percent post-2006. For men, the percentage increases from 5 to 13 over the two periods. For both genders, over 60 percent of parents never relied on extended family for childcare pre-2006; post-2006 that number falls to 30 percent. For both men and women MBA graduates, relying on extended family to help with childcare has increased significantly.

Appendix Tables A5 and A6 document why both men and women stop working for pay. The results point to a massive shift away from child rearing. A much smaller percentage post-2006 takes time off for the reason of “home raising children”. For men, the percentage falls from 6 to 1 percent. For women, the percentage who report not working for pay in order to raise children declines from 44 percent pre-2006 to 15 percent post-2006. This large shift is consistent with the increasingly important role of low-cost childcare options in affecting labor supply decisions.

6. Conclusion

Our survey of MBA graduates from a large public university over the last 30 years points to progress in addressing the gender wage gap for high-earning professionals. In our survey, the reported raw gender pay gap falls by one third to one half of its previous high levels for students who graduated with an MBA after 2006. The raw gap, unadjusted for any controls, falls from 28 log points in the earlier period to 14 log points in the unbalanced panel and from 20 to 14 log points in the balanced panel. The pre-2006 cohort was followed for a much longer time period, so these results could be considered conditional–only additional future years will confirm these findings.

After accounting for work experience and individual background, the unexplained gender wage gap disappears in in the pre-2006 period but persists in more recent years. This gap is even larger when equity is taken into account. In the earlier period, differences in pay are driven by differences in labor supply factors, industry choice, and function. When these factors are controlled for, the gender pay gap disappears. In the later period, when there has been a convergence in hours worked for men and women, the remaining significant gender pay gap early in an MBA's career is cause for concern and deserves further study.

We also explore the impact of other factors in explaining the gender wage gap. In particular we measure the impact of background sexism, childcare availability, and so-called greedy work. To our knowledge, this is the first study to measure the impact of greedy work on gender wage gaps for working professionals. Background sexism, particularly in later years, plays a role in reducing hours of work, which in turn affects the gender wage gap.

We document different wage and labor supply outcomes associated with types of work that are known as "greedy". As first introduced by Goldin (2021), "greedy work" is characterized by long hours and low substitutability with other employees. Our results indicate that while men in our sample have maintained the same levels of greedy work as in the past, women have increased slightly the amount that they do. Individuals who do greedy work work more hours per week and are less likely to take time off, which means that greedy work is associated with higher wages.

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Table 1: Who Responded to the Survey

	Respondent	Non-respondent	p-value
Sample size	2139	14100	
Top 10 undergraduate	0.13	0.11	0.011
Top 10 to 20 undergraduate	0.09	0.08	0.042
Undergrad GPA	3.53	3.51	0.494
Undergrad GPA (missing)	0.82	0.85	0.000
Quantitative GMAT	46.91	46.94	0.845
Verbal GMAT	40.71	40.02	0.000
MBA GPA	3.56	3.53	0.000
Fraction finance classes	0.14	0.15	0.017

Table 2: Who Responded to the Survey (Pre-2006)

	Respondent	Non-respondent	p-value
Sample size	1706	8983	
Top 10 undergraduate	0.11	0.10	0.034
Top 10 to 20 undergraduate	0.10	0.08	0.023
Undergrad GPA	3.52	3.51	0.680
Undergrad GPA (missing)	0.78	0.78	0.961
Quantitative GMAT	47.00	47.01	0.900
Verbal GMAT	40.74	40.05	0.000
MBA GPA	3.56	3.52	0.000
Fraction finance classes	0.14	0.15	0.016

Table 3: Who Responded to the Survey (Post-2006)

	Respondent	Non-respondent	p-value
Sample size	433	5117	
Top 10 undergraduate	0.18	0.13	0.006
Top 10 to 20 undergraduate	0.09	0.08	0.853
Undergrad GPA	3.62	3.47	0.048
Undergrad GPA (missing)	0.98	0.98	0.893
Quantitative GMAT	45.47	46.21	0.165
Verbal GMAT	40.20	39.79	0.459
MBA GPA	3.57	3.54	0.022

Table 4: Descriptive Statistics

	Mean	Std. Dev.	Min	Max	Obs.
Earnings, in thousands of US dollars	243.94	294.01	25	3000	13,569
Male	264.17	320.67	25	3000	9,555
Female	195.80	210.14	25	3000	4,014
Age at MBA Graduation	31.44	3.79	25	55	14,173
Male	31.52	3.54	25	55	9,928
Female	31.27	4.33	26	51	4,245
MBA GPA	3.58	0.18	3.002	3.978	16,442
Male	3.58	0.18	3.002	3.978	11,563
Female	3.57	0.18	3.051	3.947	4,879
Actual post-MBA exp	12.82	7.96	0	39	16,442
Male	12.98	7.91	0	32	11,563
Female	12.43	8.08	0	39	4,879
Weekly hours worked	49.83	12.00	10	100	14,712
Male	50.95	12.12	10	100	10,388
Female	47.13	11.27	10	100	4,324
Self employed	0.07	0.25	0	1	16,442
Male	0.06	0.24	0	1	11,563
Female	0.08	0.27	0	1	4,879
At least one child	0.79	0.41	0	1	16,442
Male	0.83	0.37	0	1	11,563
Female	0.70	0.46	0	1	4,879
At least one child below the age of 3	0.12	0.33	0	1	16,442
Male	0.12	0.33	0	1	11,563
Female	0.11	0.32	0	1	4,879
Married at time of survey (2022)	0.71	0.45	0	1	16,442
Male	0.75	0.44	0	1	11,563
Female	0.63	0.48	0	1	4,879
Background sexism	-0.17	0.34	-1.6	2.2	16,442
Male	-0.18	0.34	-1.6	2.2	11,563
Female	-0.16	0.33	-1.2	1.6	4,879
Any no work spell	0.03	0.18	0	1	16,442
Male	0.02	0.16	0	1	11,563
Female	0.05	0.21	0	1	4,879
Greedy work	4.18	0.45	1	5	16,442
Male	4.19	0.45	1	5	11,563
Female	4.14	0.44	1.6	5	4,879
Reduced cost of childcare	6.33	12.53	0	100	16,442
Male	5.74	10.83	0	100	11,563
Female	7.72	15.75	0	100	4,879

Notes: The unit of observation is a survey respondent in a given post-MBA year. Earnings data for each year is linearly extrapolated from first-year and last-year earnings at each stage (job). *Any no work spell* is a dummy variable that equals 1 for a given individual in a given year if they experience a period of at least six months without work between MBA graduation year and that year. *Weekly hours worked* are binned: <20 hours, 20-30, 30-35, 35-40, 40-45, 45-50, 50-60, 60-70, 70-80, 80-90, 90-100, and >100 hours. *Background sexism* is based on the place (state or country if outside the U.S.) of the respondent's birth based on GSS data. *Greedy work* is the average of five Likert scale survey questions: (1) "How often does this job require you to meet strict deadlines?" (2) "How much does this job require the worker to be in contact with others?" (3) "How often does this job require developing constructive and cooperative working relationships with others, and maintaining them over time?" (4) "To what extent is this job structured for the worker, rather than allowing the worker to determine tasks, priorities, and goals?" (5). "How much decision making freedom, without supervision, does the job offer?". *Reduced cost of childcare* gives the fraction of childcare provided by family and/or subsidized by the respondent's employer.

Table 5: Mean Stats by Cohort

	Pre-2006	Post-2006	Diff.	P-value of diff.	Obs.
Earnings, in thousands of US dollars	260.15	230.05	30.10	0.000***	13569
Age at MBA Graduation	30.55	32.16	-1.61	0.000***	14173
MBA GPA	3.59	3.56	0.03	0.000***	17265
Actual post-MBA exp	18.37	7.53	10.84	0.000***	17265
Weekly hours worked	50.68	49.10	1.59	0.000***	14712
Self employed	0.09	0.04	0.06	0.000***	17265
At least one child	0.86	0.74	0.12	0.000***	16442
At least one child below the age of 3	0.01	0.22	-0.21	0.000***	16442
Married at time of survey (2022)	0.72	0.70	0.01	0.044**	16442
Background sexism	-0.12	-0.16	0.03	0.000***	17265
Any no work spell	0.03	0.03	0.00	0.111	17265
Greedy work	4.19	4.17	0.02	0.001***	17265
Reduced cost of childcare	5.54	7.08	-1.53	0.000***	17265

Notes: The unit of observation is a survey respondent in a given post-MBA year. Earnings data for each year is linearly extrapolated from first-year and last-year earnings at each stage (job). *Any no work spell* is a dummy variable that equals 1 for a given individual in a given year if they experience a period of at least six months without work between MBA graduation year and that year. *Weekly hours worked* are binned: $<$ 20 hours, 20-30, 30-35, 35-40, 40-45, 45-50, 50-60, 60-70, 70-80, 80-90, 90-100, and $>$ 100 hours. *Background sexism* is based on the place (state or country if outside the U.S.) of the respondent's birth based on GSS data. *Greedy work* is the average of five Likert scale survey questions: (1) "How often does this job require you to meet strict deadlines?" (2) "How much does this job require the worker to be in contact with others?" (3) "How often does this job require developing constructive and cooperative working relationships with others, and maintaining them over time?" (4) "To what extent is this job structured for the worker, rather than allowing the worker to determine tasks, priorities, and goals?" (5). "How much decision making freedom, without supervision, does the job offer?". *Reduced cost of childcare* gives the fraction of childcare provided by family and/or subsidized by the respondent's employer.

Table 6: Summary Statistics and Mean Differences (Female)

	Pre-2006	Post-2006	Difference	P-value
US Citizen	0.798	0.761	-0.037	0.466
Of Caucasian Ethinicity	0.562	0.540	-0.021	0.720
Of Asian Ethnicity	0.247	0.286	0.039	0.474
Attended a Top 10 Undergraduate Institution	0.213	0.155	-0.058	0.194
Attended a Top 10-20 Undergraduate Institution	0.079	0.130	0.052	0.183
Undergraduate GPA	3.520	3.538	0.018	0.341
Quantitative GMAT score	46.008	46.607	0.599	0.027
Verbal GMAT score	40.525	41.041	0.517	0.109
Age	51.583	38.544	-13.039	0.000
Log Pre-MBA Compensation	11.136	11.416	0.281	0.004
MBA GPA	3.566	3.574	0.008	0.730
Years of Work Experience	18.483	5.227	-13.256	0.000
Any No Work Spell	0.045	0.053	0.008	0.758
Background sexism	-0.124	-0.140	-0.016	0.659
Greedy Work	4.160	4.122	-0.038	0.467
Reduced Cost of Childcare	7.051	7.980	0.929	0.591
Industry: Accounting	0.011	0.003	-0.008	0.330
Consulting	0.191	0.161	-0.030	0.511
Consumer Products	0.079	0.090	0.011	0.737
Energy	0.022	0.031	0.009	0.671
Entertainment	0.011	0.012	0.001	0.928
Finance	0.191	0.087	-0.104	0.005
Government	0.045	0.009	-0.036	0.021
Healthcare	0.045	0.099	0.054	0.108
Manufacturing	0.000	0.006	0.006	0.457
Media	0.000	0.003	0.003	0.600
Natural Resources	0.000	0.000	0.000	.
Pharmaceutical	0.000	0.006	0.006	0.457
Public Sector	0.056	0.059	0.003	0.920
Real Estate	0.067	0.006	-0.061	0.000
Technology	0.135	0.230	0.095	0.051
Transporation	0.000	0.006	0.006	0.457
Other	0.022	0.037	0.015	0.497

Table 7: Summary Statistics and Mean Differences (Male)

		Pre-2006	Post-2006	Difference	P-value
US Citizen		0.701	0.726	0.025	0.473
Of Caucasian Ethinicity		0.558	0.470	-0.088	0.023
Of Asian Ethnicity		0.192	0.314	0.122	0.000
Attended a Top 10 Undergraduate Institution		0.170	0.112	-0.058	0.025
Attended a Top 10-20 Undergraduate Institution		0.085	0.092	0.007	0.750
Undergraduate GPA		3.514	3.509	-0.005	0.678
Quantitative GMAT score		46.907	47.228	0.322	0.027
Verbal GMAT score		40.419	40.722	0.303	0.176
Age		52.029	39.901	-12.128	0.000
Log Pre-MBA Compensation		11.155	11.536	0.381	0.000
MBA GPA		3.606	3.559	-0.047	0.001
Years of Work Experience		17.987	6.098	-11.889	0.000
Any No Work Spell		0.027	0.021	-0.005	0.647
Background sexism		-0.125	-0.165	-0.040	0.132
Greedy Work		4.163	4.144	-0.018	0.599
Reduced Cost of Childcare		4.862	6.846	1.984	0.021
Industry:	Accounting	0.004	0.002	-0.003	0.428
	Consulting	0.219	0.178	-0.041	0.175
	Consumer Products	0.049	0.046	-0.003	0.847
	Energy	0.022	0.047	0.025	0.102
	Entertainment	0.004	0.017	0.012	0.169
	Finance	0.143	0.124	-0.019	0.469
	Government	0.013	0.017	0.003	0.722
	Healthcare	0.071	0.080	0.008	0.692
	Manufacturing	0.022	0.008	-0.015	0.075
	Media	0.004	0.003	-0.001	0.757
	Natural Resources	0.004	0.002	-0.003	0.428
	Pharmaceutical	0.009	0.006	-0.003	0.661
	Public Sector	0.009	0.020	0.011	0.275
	Real Estate	0.049	0.032	-0.017	0.244
	Technology	0.219	0.309	0.091	0.010
	Transporation	0.004	0.002	-0.003	0.428
	Other	0.031	0.020	-0.011	0.327

Table 8: Gender Gap in Earnings and Labor

Number of years since receipt of MBA	Annual earnings (1)	Log annual earnings (2)	Log annual earnings first year in job (3)	Cumulative periods not working (4)	Not working at all in current period (5)	Log weekly hours worked (6)
0	-14.444**	-0.116***	-0.120***	0.017	0.029**	-0.067***
	(6.434)	(0.039)	(0.039)	(0.014)	(0.013)	(0.019)
1	-18.030***	-0.088***	-0.084***	0.033*	0.019	-0.041**
	(6.677)	(0.033)	(0.032)	(0.019)	(0.011)	(0.017)
3	-33.907***	-0.149***	-0.123***	0.048*	0.001	-0.055***
	(10.928)	(0.038)	(0.035)	(0.029)	(0.011)	(0.016)
6	-28.486	-0.147***	-0.119***	0.158***	0.039***	-0.078***
	(18.774)	(0.047)	(0.044)	(0.059)	(0.015)	(0.020)
9	-57.790*	-0.231***	-0.240***	0.351***	0.068***	-0.077***
	(29.698)	(0.065)	(0.062)	(0.115)	(0.020)	(0.024)
≥10	-119.350***	-0.331***	-0.305***	0.561**	0.019	-0.089***
	(33.946)	(0.071)	(0.073)	(0.235)	(0.013)	(0.025)
Cohort x year	X	X	X	X	X	X
R-squared	0.13	0.19	0.19	0.11	0.04	0.08
Observations	13210	13210	14080	15945	15945	14315

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 the salary and bonus, and is coded as missing when the individual is not working. Columns 1-3 only include those with positive earnings. Column 3 includes only the first year at a given job. Earnings data is collected for the first and last year in each stage (job). Earnings for all other years is linearly extrapolated. Standard errors (in parentheses) are clustered at the individual level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Gender Wage Gap by Years since MBA - Annual Earnings

	Number of years since MBA receipt							
	0	1	3	6	9	10	13	≥16
Simple bivariate								
Pre-2006	-0.086	-0.050	-0.135	-0.139	-0.212**	-0.275***	-0.298***	-0.437***
	(0.107)	(0.083)	(0.095)	(0.105)	(0.101)	(0.094)	(0.094)	(0.103)
N	221	247	255	256	255	257	255	2,193
Female frac.	0.281	0.283	0.278	0.277	0.275	0.280	0.282	0.284
Post-2006	-0.124***	-0.099***	-0.154***	-0.150***	-0.247***	-0.164*	-0.062	-0.009
	(0.040)	(0.035)	(0.040)	(0.049)	(0.086)	(0.095)	(0.150)	(0.130)
N	770	751	722	553	332	256	141	232
Female frac.	0.318	0.336	0.335	0.313	0.265	0.270	0.220	0.280
Control for pre-MBA characteristics								
Pre-2006	-0.048	0.038	0.017	-0.037	-0.113	-0.132	-0.117	-0.241**
	(0.133)	(0.104)	(0.115)	(0.123)	(0.108)	(0.111)	(0.098)	(0.105)
N	221	247	255	256	255	257	255	2,193
Female frac.	0.281	0.283	0.278	0.277	0.275	0.280	0.282	0.284
Post-2006	-0.091**	-0.082**	-0.120***	-0.116**	-0.237**	-0.169	-0.001	-0.085
	(0.043)	(0.037)	(0.042)	(0.054)	(0.098)	(0.113)	(0.196)	(0.166)
N	770	751	722	553	332	256	141	232
Female frac.	0.318	0.336	0.335	0.313	0.265	0.270	0.220	0.280
Control for pre-MBA, MBA, post-MBA characteristics								
Pre-2006	0.032	0.229	0.134	-0.037	-0.025	-0.052	-0.002	0.047
	(0.204)	(0.156)	(0.134)	(0.139)	(0.144)	(0.130)	(0.148)	(0.100)
N	221	247	255	256	255	257	255	2,193
Female frac.	0.281	0.283	0.278	0.277	0.275	0.280	0.282	0.284
Post-2006	-0.096**	-0.052	-0.115***	-0.066	-0.206*	-0.136	-0.406	0.349
	(0.046)	(0.039)	(0.043)	(0.056)	(0.113)	(0.142)	(0.458)	(0.251)
N	770	751	722	553	332	256	141	232
Female frac.	0.318	0.336	0.335	0.313	0.265	0.270	0.220	0.280
Control for pre-MBA, MBA, post-MBA characteristics, and hours								
Pre-2006	0.138	0.283*	0.087	-0.004	-0.093	-0.136	-0.088	0.035
	(0.197)	(0.145)	(0.143)	(0.169)	(0.166)	(0.145)	(0.160)	(0.100)
N	215	241	247	247	247	249	246	2,112
Female frac.	0.284	0.286	0.279	0.279	0.275	0.281	0.280	0.276
Post-2006	-0.086*	-0.055	-0.114**	-0.049	-0.178	-0.005	-0.297	0.391
	(0.046)	(0.037)	(0.044)	(0.056)	(0.119)	(0.153)	(0.545)	(0.380)
N	752	733	706	540	320	245	135	214
Female frac.	0.320	0.338	0.339	0.315	0.266	0.269	0.215	0.299

Notes: Each cell corresponds to a different regression. The dependent variable in each regression equation is log(annual earnings). The unit of observation is a survey respondent in a given post-MBA year. All regressions include (cohort ×year) dummies and a female dummy. For each regression, we report the beta coefficient on female, the standard error, sample size, and fraction of females in the sample. Pre-MBA characteristics include a dummy for US citizen, a Caucasian dummy, an Asian dummy, a dummy for top 10 undergraduate institution, and a dummy for top 10-20 undergraduate institution – based on *US News and World Report* rankings–, undergraduate GPA, age and its quadratic, verbal GMAT score, quantitative GMAT score, a dummy for pre-MBA industry, a dummy for pre-MBA job function, and log of pre-MBA compensation.MBA characteristics include only MBA GPA.Post MBA characteristics include years of work experience and its quadratic, any no work spell – a dummy indicating a period of at least 6 months within a year without work between receiving an MBA and that year–, industry dummies, job function dummies, and employer type dummies.Weekly hours worked dummies include: < 20 hours, 20-29, 30-39, 40-49, 50-59, 60-69, 70-79, 80-89, 90-99, and ≥ 100 hours. All models include missing dummies for each independent variable.

Table 10: Gender Wage Gap by Years since MBA - Annual Earnings with Equity

	Number of years since MBA receipt							
	0	1	3	6	9	10	13	≥16
Simple bivariate								
Pre-2006	-0.069	-0.082	-0.143	-0.196	-0.287**	-0.401***	-0.471***	-0.608***
	(0.108)	(0.097)	(0.117)	(0.132)	(0.127)	(0.118)	(0.128)	(0.112)
N	200	235	242	243	241	244	242	2,092
Female frac.	0.285	0.281	0.281	0.284	0.278	0.283	0.281	0.286
Post-2006	-0.170***	-0.133***	-0.204***	-0.214***	-0.275***	-0.196*	-0.121	0.103
	(0.050)	(0.041)	(0.048)	(0.058)	(0.094)	(0.109)	(0.166)	(0.168)
N	612	689	677	529	319	246	136	192
Female frac.	0.319	0.322	0.325	0.310	0.263	0.268	0.213	0.281
Control for pre-MBA characteristics								
Pre-2006	-0.050	0.005	-0.007	-0.125	-0.254*	-0.301**	-0.299**	-0.439***
	(0.140)	(0.117)	(0.129)	(0.152)	(0.135)	(0.137)	(0.134)	(0.122)
N	200	235	242	243	241	244	242	2,092
Female frac.	0.285	0.281	0.281	0.284	0.278	0.283	0.281	0.286
Post-2006	-0.149***	-0.106**	-0.161***	-0.146**	-0.249**	-0.165	0.025	0.014
	(0.052)	(0.042)	(0.049)	(0.064)	(0.113)	(0.134)	(0.250)	(0.364)
N	612	689	677	529	319	246	136	192
Female frac.	0.319	0.322	0.325	0.310	0.263	0.268	0.213	0.281
Control for pre-MBA, MBA, post-MBA characteristics								
Pre-2006	0.122***	0.264	0.179	-0.195	-0.138	-0.137	-0.042	-0.121
	(0.000)	(0.176)	(0.175)	(0.198)	(0.191)	(0.185)	(0.208)	(0.127)
N	200	235	242	243	241	244	242	2,092
Female frac.	0.285	0.281	0.281	0.284	0.278	0.283	0.281	0.286
Post-2006	-0.151***	-0.060	-0.138***	-0.054	-0.106	-0.015	0.046	10.508***
	(0.058)	(0.044)	(0.052)	(0.065)	(0.113)	(0.159)	(0.742)	(1.887)
N	612	689	677	529	319	246	136	192
Female frac.	0.319	0.322	0.325	0.310	0.263	0.268	0.213	0.281
Control for pre-MBA, MBA, post-MBA characteristics, and hours								
Pre-2006	0.311	0.316*	0.198	-0.250	-0.205	-0.307	-0.130	-0.101
	(0.238)	(0.176)	(0.202)	(0.232)	(0.222)	(0.202)	(0.255)	(0.133)
N	194	229	234	235	233	236	233	2,011
Female frac.	0.289	0.284	0.282	0.285	0.279	0.284	0.279	0.278
Post-2006	-0.133**	-0.070	-0.139***	-0.035	-0.123	0.106	-0.109	-9.148***
	(0.058)	(0.043)	(0.053)	(0.065)	(0.110)	(0.162)	(0.847)	(0.000)
N	599	675	663	517	308	236	131	176
Female frac.	0.322	0.326	0.329	0.313	0.266	0.271	0.214	0.301

Notes: Each cell corresponds to a different regression. The dependent variable in each regression equation is log(annual earnings with equity). The unit of observation is a survey respondent in a given post-MBA year. All regressions include (cohort ×year) dummies and a female dummy. For each regression, we report the beta coefficient on female, the standard error, sample size, and fraction of females in the sample. Pre-MBA characteristics include a dummy for US citizen, a Caucasian dummy, an Asian dummy, a dummy for top 10 undergraduate institution, and a dummy for top 10-20 undergraduate institution – based on *US News and World Report* rankings–, undergraduate GPA, age and its quadratic, verbal GMAT score, quantitative GMAT score, a dummy for pre-MBA industry, a dummy for pre-MBA job function, and log of pre-MBA compensation.MBA characteristics include only MBA GPA.Post MBA characteristics include years of work experience and its quadratic, any no work spell – a dummy indicating a period of at least 6 months within a year without work between receiving an MBA and that year–, industry dummies, job function dummies, and employer type dummies.Weekly hours worked dummies include: < 20 hours, 20-29, 30-39, 40-49, 50-59, 60-69, 70-79, 80-89, 90-99, and ≥ 100 hours. All models include missing dummies for each independent variable.

Table 11: BGK Specification (Pre-2006)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Female	-0.282***	-0.126*	-0.035	-0.053	-0.197***	-0.098	-0.004	-0.024	0.066
	(0.073)	(0.070)	(0.068)	(0.066)	(0.071)	(0.066)	(0.066)	(0.064)	(0.060)
MBA GPA		0.214	0.140	0.226		0.239	0.150	0.244	0.203
		(0.188)	(0.178)	(0.175)		(0.181)	(0.178)	(0.177)	(0.170)
Actual post-MBA exp			0.043**	0.037*			0.037*	0.028	0.017
			(0.020)	(0.020)			(0.021)	(0.022)	(0.024)
Actual post-MBA exp squared			-0.001	-0.001			-0.001	-0.001	-0.000
			(0.001)	(0.001)			(0.001)	(0.001)	(0.001)
Any no work spell			-0.286***	-0.294***			-0.204**	-0.229**	-0.098
			(0.100)	(0.098)			(0.091)	(0.096)	(0.098)
Weekly hours worked	-	-	-	-	X	X	X	X	X
Pre-MBA characteristics	-	X	X	X	-	X	X	X	X
MBA characteristics	-	X	X	X	-	X	X	X	X
Post-MBA characteristics	-	-	X	X	-	-	X	X	X
Industry		-	-	X	-	-	-	X	-
Job Function	-	-	-	-	-	-	-	-	X
Reason for choosing job	-	-	-	-	-	-	-	-	X
Cohort x year	X	X	X	X	X	X	X	X	X
Adjusted R-squared	0.15	0.33	0.38	0.42	0.24	0.38	0.42	0.45	0.50
Observations	6229	6229	6229	6229	6020	6020	6020	6020	6020

Notes: The unit of observation is a survey respondent in a given post-MBA year. Earnings data is collected for the first and last year in each stage (job). Earnings for all other years are linearly extrapolated. *Pre-MBA* characteristics include: a dummy for US citizen, a white dummy, an Asian dummy, a dummy for a top-10 undergraduate institution, and a dummy for a top 10-20 undergraduate institution (from the *US News and World Report* rankings), undergraduate GPA, a dummy for missing undergraduate GPA, age and its quadratic, pre-MBA industry, pre-MBA job function, and log pre-MBA compensation. *Post-MBA characteristics* include: years of post-MBA work experience (linear and quadratic) as well as , 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, and employer type: dummies include Public for-profit,<200 employees; Public for-profit, 200-1000 employees; Public for-profit, 1,000–20,000 employees; Public for-profit, >20,000 employees; Private for-profit, <200 employees; Private for-profit, 200-1000 employees; Private for-profit, 1,000–20,000 employees; Private for-profit, >20,000 employees; and Not-for-profit. *Weekly hours worked* are binned: <20 hours, 20-30, 30-35, 35-40, 40-45, 45-50, 50-60, 60-70, 70-80, 80-90, 90-100, and >100 hours. Earnings data is observed for the first and last year in each stage (job). Earnings for all other years are linearly extrapolated. Reasons for choosing a job include compensation and other benefits, career advancement or broadening, prestige, culture and environment, social impact, flexible hours, reasonable total hours per week, limited travel schedule, opportunity to work remotely, parental leave policies, location, and other. Standard errors (in parentheses) are clustered at the individual level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: BGK Specification (Post-2006)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Female	-0.140***	-0.106**	-0.071*	-0.063*	-0.133***	-0.095**	-0.062	-0.053	-0.073*
	(0.042)	(0.043)	(0.041)	(0.038)	(0.040)	(0.041)	(0.039)	(0.037)	(0.037)
MBA GPA		0.170	0.169	0.201*		0.144	0.144	0.175*	0.187*
		(0.109)	(0.107)	(0.105)		(0.104)	(0.103)	(0.102)	(0.098)
Actual post-MBA exp			0.059**	0.057**			0.039*	0.039*	0.044**
			(0.024)	(0.024)			(0.020)	(0.020)	(0.020)
Actual post-MBA exp squared			-0.003*	-0.003*			-0.002	-0.002	-0.002
			(0.002)	(0.001)			(0.001)	(0.001)	(0.001)
Any no work spell			-0.306***	-0.286***			-0.293***	-0.282***	-0.286***
			(0.084)	(0.074)			(0.075)	(0.066)	(0.079)
Weekly hours worked	-	-	-	-	X	X	X	X	X
Pre-MBA characteristics	-	X	X	X	-	X	X	X	X
MBA characteristics	-	X	X	X	-	X	X	X	X
Post-MBA characteristics	-	-	X	X	-	-	X	X	X
Industry		-	-	X	-	-	-	X	-
Job Function	-	-	-	-	-	-	-	-	X
Reason for choosing job	-	-	-	-	-	-	-	-	X
Cohort x year	X	X	X	X	X	X	X	X	X
Adjusted R-squared	0.14	0.24	0.29	0.32	0.19	0.29	0.33	0.35	0.38
Observations	7200	7200	7200	7200	6997	6997	6997	6997	6997

Notes: The unit of observation is a survey respondent in a given post-MBA year. Earnings data is collected for the first and last year in each stage (job). Earnings for all other years are linearly extrapolated. *Pre-MBA* characteristics include: a dummy for US citizen, a white dummy, an Asian dummy, a dummy for a top-10 undergraduate institution, and a dummy for a top 10-20 undergraduate institution (from the *US News and World Report* rankings), undergraduate GPA, a dummy for missing undergraduate GPA, age and its quadratic, pre-MBA industry, pre-MBA job function, and log pre-MBA compensation. *Post-MBA characteristics* include: years of post-MBA work experience (linear and quadratic) as well as , 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, and employer type: dummies include Public for-profit,$<$200 employees; Public for-profit, 200-1000 employees; Public for-profit, 1,000–20,000 employees; Public for-profit, $>$20,000 employees; Private for-profit, $<$200 employees; Private for-profit, 200-1000 employees; Private for-profit, 1,000–20,000 employees; Private for-profit, $>$20,000 employees; and Not-for-profit. *Weekly hours worked* are binned: $<$20 hours, 20-30, 30-35, 35-40, 40-45, 45-50, 50-60, 60-70, 70-80, 80-90, 90-100, and $>$100 hours. Earnings data is observed for the first and last year in each stage (job). Earnings for all other years are linearly extrapolated. Reasons for choosing a job include compensation and other benefits, career advancement or broadening, prestige, culture and environment, social impact, flexible hours, reasonable total hours per week, limited travel schedule, opportunity to work remotely, parental leave policies, location, and other. Standard errors (in parentheses) are clustered at the individual level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 13: Wage Regressions (Pre-2006)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	-0.035	-0.030	0.003	-0.014	-0.004	-0.001	0.027	0.012
	(0.068)	(0.066)	(0.067)	(0.066)	(0.066)	(0.066)	(0.066)	(0.064)
Any no work spell	-0.286***	-0.314***	-0.275***	-0.296***	-0.204**	-0.221**	-0.191**	-0.230**
	(0.100)	(0.102)	(0.101)	(0.100)	(0.091)	(0.092)	(0.094)	(0.098)
Self employed		-0.258**	-0.247**	-0.284**		-0.119	-0.127	-0.194*
		(0.119)	(0.115)	(0.111)		(0.120)	(0.114)	(0.111)
Background sexism			-0.040	-0.067			-0.014	-0.046
			(0.092)	(0.089)			(0.093)	(0.091)
Greedy work			0.050	0.074			-0.016	0.013
			(0.058)	(0.060)			(0.058)	(0.060)
Reduced cost of childcare			-0.005**	-0.005**			-0.004	-0.004
			(0.002)	(0.002)			(0.003)	(0.002)
Weekly hours worked	-	-	-	-	X	X	X	X
Pre-MBA characteristics	X	X	X	X	X	X	X	X
MBA characteristics	X	X	X	X	X	X	X	X
Post-MBA characteristics	X	X	X	X	X	X	X	X
Industry	-	-	-	X	-	-	-	X
Self-employed	-	X	X	X	-	X	X	X
Cohort x year	X	X	X	X	X	X	X	X
Adjusted R-squared	0.38	0.38	0.39	0.43	0.42	0.42	0.43	0.46
Observations	6229	6229	6229	6229	6020	6020	6020	6020

Notes: The unit of observation is a survey respondent in a given post-MBA year. Pre-MBA characteristics include: a dummy for US citizen, a white dummy, an Asian dummy, a dummy for a top-10 undergraduate institution, and a dummy for a top 10-20 undergraduate institution (from the *US News and World Report* rankings), [undergraduate GPA, a dummy for missing undergraduate GPA], age and its quadratic, [verbal GMAT score, quantitative GMAT score], pre-MBA industry, pre-MBA job function, and log pre-MBA compensation. *Any no work spell* is a dummy variable that indicates that a given individual in a given year experienced a period of at least six months without work between MBA graduation year and that year. Post-MBA characteristics include years of work experience and its quadratic, any no work spell – a dummy indicating a period of at least 6 months within a year without work between receiving an MBA and that year–, industry dummies, job function dummies, and employer type dummies. *Weekly hours worked* are binned: < 20 hours, 20-30, 30-35, 35-40, 40-45, 45-50, 50-60, 60-70, 70-80, 80-90, 90-100, and > 100 hours. *Background sexism* is an index derived from GSS data based on average beliefs about gender within the state or country that the respondent was born in. *Greedy work* is the average of five likert scale survey questions: (1) How often does this job require you to meet strict deadlines? (2) How much does this job require the worker to be in contact with others? (3) How often does this job require developing constructive and cooperative working relationships with others, and maintaining them over time? (4) To what extent is this job structured for the worker, rather than allowing the worker to determine tasks, priorities, and goals? (5) How much decision making freedom, without supervision, does the job offer? *Reduced cost of childcare* gives the fraction of time the respondent's child is cared for by company-provided childcare or extended family rather than by the respondent, his/her partner, or paid childcare. Earnings data is collected for the first and last year in each stage (job). Earnings for all other years are linearly extrapolated. Standard errors (in parentheses) are clustered at the individual level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 14: Wage Regressions (Post-2006)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	-0.071*	-0.060	-0.051	-0.046	-0.062	-0.056	-0.051	-0.044
	(0.041)	(0.039)	(0.038)	(0.036)	(0.039)	(0.038)	(0.038)	(0.036)
Any no work spell	-0.306***	-0.344***	-0.317***	-0.296***	-0.293***	-0.327***	-0.307***	-0.294***
	(0.084)	(0.086)	(0.088)	(0.078)	(0.075)	(0.078)	(0.080)	(0.071)
Self employed		-0.659***	-0.645***	-0.605***		-0.545***	-0.543***	-0.510***
		(0.085)	(0.086)	(0.083)		(0.089)	(0.088)	(0.085)
Background sexism			-0.061	-0.035			-0.016	0.002
			(0.049)	(0.048)			(0.048)	(0.048)
Greedy work			0.123***	0.117***			0.088***	0.086***
			(0.031)	(0.031)			(0.029)	(0.029)
Reduced cost of childcare			0.001	0.001			0.001	0.001
			(0.001)	(0.001)			(0.001)	(0.001)
Weekly hours worked	-	-	-	-	X	X	X	X
Pre-MBA characteristics	X	X	X	X	X	X	X	X
MBA characteristics	X	X	X	X	X	X	X	X
Post-MBA characteristics	X	X	X	X	X	X	X	X
Industry	-	-	-	X	-	-	-	X
Self-employed	-	X	X	X	-	X	X	X
Cohort x year	X	X	X	X	X	X	X	X
Adjusted R-squared	0.29	0.33	0.34	0.36	0.33	0.36	0.36	0.38
Observations	7200	7200	7200	7200	6997	6997	6997	6997

Notes: The unit of observation is a survey respondent in a given post-MBA year. Pre-MBA characteristics include: a dummy for US citizen, a white dummy, an Asian dummy, a dummy for a top-10 undergraduate institution, and a dummy for a top 10-20 undergraduate institution (from the *US News and World Report* rankings), [undergraduate GPA, a dummy for missing undergraduate GPA], age and its quadratic, [verbal GMAT score, quantitative GMAT score], pre-MBA industry, pre-MBA job function, and log pre-MBA compensation. *Any no work spell* is a dummy variable that indicates that a given individual in a given year experienced a period of at least six months without work between MBA graduation year and that year. Post-MBA characteristics include years of work experience and its quadratic, any no work spell – a dummy indicating a period of at least 6 months within a year without work between receiving an MBA and that year–, industry dummies, job function dummies, and employer type dummies. *Weekly hours worked* are binned: $<$ 20 hours, 20-30, 30-35, 35-40, 40-45, 45-50, 50-60, 60-70, 70-80, 80-90, 90-100, and $>$ 100 hours. *Background sexism* is an index derived from GSS data based on average beliefs about gender within the state or country that the respondent was born in. *Greedy work* is the average of five likert scale survey questions: (1) How often does this job require you to meet strict deadlines? (2) How much does this job require the worker to be in contact with others? (3) How often does this job require developing constructive and cooperative working relationships with others, and maintaining them over time? (4) To what extent is this job structured for the worker, rather than allowing the worker to determine tasks, priorities, and goals? (5) How much decision making freedom, without supervision, does the job offer? *Reduced cost of childcare* gives the fraction of time the respondent's child is cared for by company-provided childcare or extended family rather than by the respondent, his/her partner, or paid childcare. Earnings data is collected for the first and last year in each stage (job). Earnings for all other years are linearly extrapolated. Standard errors (in parentheses) are clustered at the individual level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 15: Determinants of the Gender Gap in Labor Supply

	Log weekly hours worked						Self employment						Any no work spell					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Female	-0.110***		-0.109***	-0.102***	-0.109***	-0.101***	0.027		0.026	0.025	0.028	0.025	0.024*		0.024*	0.023*	0.025*	0.023*
	(0.024)		(0.023)	(0.023)	(0.024)	(0.023)	(0.028)		(0.028)	(0.028)	(0.028)	(0.028)	(0.013)		(0.013)	(0.013)	(0.013)	(0.013)
Female x post-2006 MBA grad	0.073**		0.074**	0.067**	0.073**	0.067**	-0.024		-0.024	-0.023	-0.024	-0.023	-0.003		-0.003	-0.002	-0.003	-0.002
	(0.029)		(0.029)	(0.028)	(0.029)	(0.028)	(0.029)		(0.029)	(0.029)	(0.029)	(0.029)	(0.017)		(0.017)	(0.017)	(0.017)	(0.017)
Female with child		-0.099***						0.022						0.023**				
		(0.020)						(0.022)						(0.011)				
Female without child		-0.044***						0.007						0.022**				
		(0.016)						(0.015)						(0.010)				
Background sexism			-0.033*			-0.036**			0.018			0.018			0.003			0.003
			(0.018)			(0.018)			(0.016)			(0.016)			(0.009)			(0.009)
Greedy work				0.103***		0.103***				-0.030**		-0.031**				-0.020***		-0.021***
				(0.016)		(0.016)				(0.014)		(0.014)				(0.007)		(0.007)
Reduced cost of childcare					-0.000	-0.000					-0.000	-0.000					-0.000	-0.000
					(0.001)	(0.000)					(0.000)	(0.000)					(0.000)	(0.000)
Pre-MBA characteristics	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
MBA charactersitics	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Employer type	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Cohort x year	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Adjusted R-squared	0.09	0.08	0.09	0.12	0.09	0.12	0.13	0.13	0.13	0.13	0.13	0.13	0.01	0.01	0.01	0.02	0.01	0.02
Observations	14575	14575	14575	14575	14575	14575	16309	16309	16309	16309	16309	16309	16309	16309	16309	16309	16309	16309

Notes: The unit of observation is a survey respondent in a given post-MBA year. The outcome variables of interest are log weekly hours worked, a dummy that indicates selfemployment, and a dummy that indicates a respondent experienced a period of at least six months of unemmployment in a given 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 US citizen, a white dummy, an Asian dummy, a dummy for a top-10 undergraduate institution, and a dummy for a top 10-20 undergraduate institution (from the *US News and World Report* rankings), [undergraduate GPA, a dummy for missing undergraduate GPA], age and its quadratic, [verbal GMAT score, quantitative GMAT score], pre-MBA industry, pre-MBA job function, and log pre-MBA compensation. MBA characteristics include MBA GPA. *Background sexism* is an index derived from GSS data based on average beliefs about gender within the state or country that the respondent was born in. *Greedy work* is the average of five likert scale survey questions: (1) How often does this job require you to meet strict deadlines? (2) How much does this job require the worker to be in contact with others? (3) How often does this job require developing constructive and cooperative working relationships with others, and maintaining them over time? (4) To what extent is this job structured for the worker, rather than allowing the worker to determine tasks, priorities, and goals? (5). How much decision making freedom, without supervision, does the job offer? *Reduced cost of childcare* gives the fraction of time the respondent's child is cared for by company-provided childcare or extended family rather than by the respondent, his/her partner, or paid childcare. *Employer type* dummies include: Public for-profit, $<$ 200 employees; Public for-profit, 200-1000 employees; Public for-profit, 1,000–20,000 employees; Public for-profit, $>$ 20,000 employees; Private for-profit, $<$ 200 employees; Private for-profit, 200-1000 employees; Private for-profit, 1,000–20,000 employees; Private for-profit, $>$ 20,000 employees; and Not-for-profit. Standard errors (in parentheses) are clustered at the individual level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 16: Determinants of the Gender Gap in Labor Supply (Pre-2006)

	Log weekly hours worked						Self employment						Any no work spell					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Female	-0.091***		-0.091***	-0.085***	-0.089***	-0.082***	0.024		0.023	0.019	0.026	0.021	0.032**		0.032**	0.030**	0.032**	0.030**
	(0.025)		(0.025)	(0.025)	(0.026)	(0.025)	(0.032)		(0.032)	(0.032)	(0.033)	(0.032)	(0.014)		(0.014)	(0.014)	(0.014)	(0.014)
Female with child		-0.113***						0.022						0.019				
		(0.029)						(0.039)						(0.015)				
Female without child		-0.062*						0.026						0.045**				
		(0.033)						(0.037)						(0.018)				
Background sexism			-0.025			-0.030			0.014			0.016			0.001			0.002
			(0.032)			(0.032)			(0.034)			(0.033)			(0.012)			(0.012)
Greedy work				0.095***		0.096***				-0.069***		-0.070***				-0.023*		-0.023*
				(0.031)		(0.031)				(0.026)		(0.026)				(0.013)		(0.013)
Reduced cost of childcare					-0.000	-0.000					-0.001	-0.001					-0.000	-0.000
					(0.001)	(0.001)					(0.001)	(0.001)					(0.000)	(0.000)
Pre-MBA characteristics	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
MBA characteristics	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Employer type	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Cohort x year	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Adjusted R-squared	0.18	0.18	0.18	0.20	0.18	0.20	0.17	0.17	0.17	0.18	0.17	0.18	0.03	0.04	0.03	0.04	0.03	0.04
Observations	6739	6739	6739	6739	6739	6739	7562	7562	7562	7562	7562	7562	7562	7562	7562	7562	7562	7562

Notes: The unit of observation is a survey respondent in a given post-MBA year. The outcome variables of interest are log weekly hours worked, a dummy that indicates selfemployment, and a dummy that indicates a respondent experienced a period of at least six months of unemployment in a given 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 US citizen, a white dummy, an Asian dummy, a dummy for a top-10 undergraduate institution, and a dummy for a top 10-20 undergraduate institution (from the *US News and World Report* rankings), [undergraduate GPA, a dummy for missing undergraduate GPA], age and its quadratic, [verbal GMAT score, quantitative GMAT score], pre-MBA industry, pre-MBA job function, and log pre-MBA compensation. MBA characteristics include MBA GPA. *Background sexism* is an index derived from GSS data based on average beliefs about gender within the state or country that the respondent was born in. *Greedy work* is the average of five likert scale survey questions: (1) How often does this job require you to meet strict deadlines? (2) How much does this job require the worker to be in contact with others? (3) How often does this job require developing constructive and cooperative working relationships with others, and maintaining them over time? (4) To what extent is this job structured for the worker, rather than allowing the worker to determine tasks, priorities, and goals? (5) How much decision making freedom, without supervision, does the job offer? *Reduced cost of childcare* gives the fraction of time the respondent's child is cared for by company-provided childcare or extended family rather than by the respondent, his/her partner, or paid childcare. *Employer type* dummies include: Public for-profit, < 200 employees; Public for-profit, 200-1000 employees; Public for-profit, 1,000–20,000 employees; Public for-profit, $> 20,000$ employees; Private for-profit, < 200 employees; Private for-profit, 200-1000 employees; Private for-profit, 1,000–20,000 employees; Private for-profit, $> 20,000$ employees; and Not-for-profit. Standard errors (in parentheses) are clustered at the individual level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 17: Determinants of the Gender Gap in Labor Supply (Post-2006)

	Log weekly hours worked						Self employment						Any no work spell					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Female	-0.045***		-0.044***	-0.042***	-0.045***	-0.040**	0.010		0.010	0.010	0.010	0.010	0.022**		0.021**	0.021**	0.022**	0.021**
	(0.016)		(0.016)	(0.016)	(0.017)	(0.016)	(0.011)		(0.011)	(0.011)	(0.011)	(0.011)	(0.010)		(0.010)	(0.010)	(0.010)	(0.010)
Female with child		-0.074***						0.021						0.033*				
		(0.025)						(0.018)						(0.018)				
Female without child		-0.027						0.003						0.015				
		(0.018)						(0.011)						(0.012)				
Background sexism			-0.045**			-0.045**			0.012			0.012			0.008			0.008
			(0.021)			(0.020)			(0.011)			(0.011)			(0.013)			(0.013)
Greedy work				0.110***		0.110***				-0.006		-0.006				-0.017**		-0.017**
				(0.015)		(0.015)				(0.013)		(0.013)				(0.007)		(0.007)
Reduced cost of childcare					-0.000	-0.000					-0.000	-0.000					-0.000	-0.000
					(0.001)	(0.001)					(0.000)	(0.000)					(0.000)	(0.000)
Pre-MBA characteristics	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
MBA characteristics	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Employer type	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Cohort x year	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Adjusted R-squared	0.06	0.06	0.06	0.10	0.06	0.10	0.09	0.09	0.09	0.09	0.09	0.09	0.01	0.01	0.01	0.01	0.01	0.01
Observations	7836	7836	7836	7836	7836	7836	8747	8747	8747	8747	8747	8747	8747	8747	8747	8747	8747	8747

Notes: The unit of observation is a survey respondent in a given post-MBA year. The outcome variables of interest are log weekly hours worked, a dummy that indicates selfemployment, and a dummy that indicates a respondent experienced a period of at least six months of unemployment in a given 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 US citizen, a white dummy, an Asian dummy, a dummy for a top-10 undergraduate institution, and a dummy for a top 10-20 undergraduate institution (from the *US News and World Report* rankings), [undergraduate GPA, a dummy for missing undergraduate GPA], age and its quadratic, [verbal GMAT score, quantitative GMAT score], pre-MBA industry, pre-MBA job function, and log pre-MBA compensation. MBA characteristics include MBA GPA. *Background sexism* is an index derived from GSS data based on average beliefs about gender within the state or country that the respondent was born in. *Greedy work* is the average of five likert scale survey questions: (1) How often does this job require you to meet strict deadlines? (2) How much does this job require the worker to be in contact with others? (3) How often does this job require developing constructive and cooperative working relationships with others, and maintaining them over time? (4) To what extent is this job structured for the worker, rather than allowing the worker to determine tasks, priorities, and goals? (5) How much decision making freedom, without supervision, does the job offer? *Reduced cost of childcare* gives the fraction of time the respondent's child is cared for by company-provided childcare or extended family rather than by the respondent, his/her partner, or paid childcare. *Employer type* dummies include: Public for-profit, $<$ 200 employees; Public for-profit, 200-1000 employees; Public for-profit, 1,000–20,000 employees; Public for-profit, $>$ 20,000 employees; Private for-profit, $<$ 200 employees; Private for-profit, 200-1000 employees; Private for-profit, 1,000–20,000 employees; Private for-profit, $>$ 20,000 employees; and Not-for-profit. Standard errors (in parentheses) are clustered at the individual level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix Figures

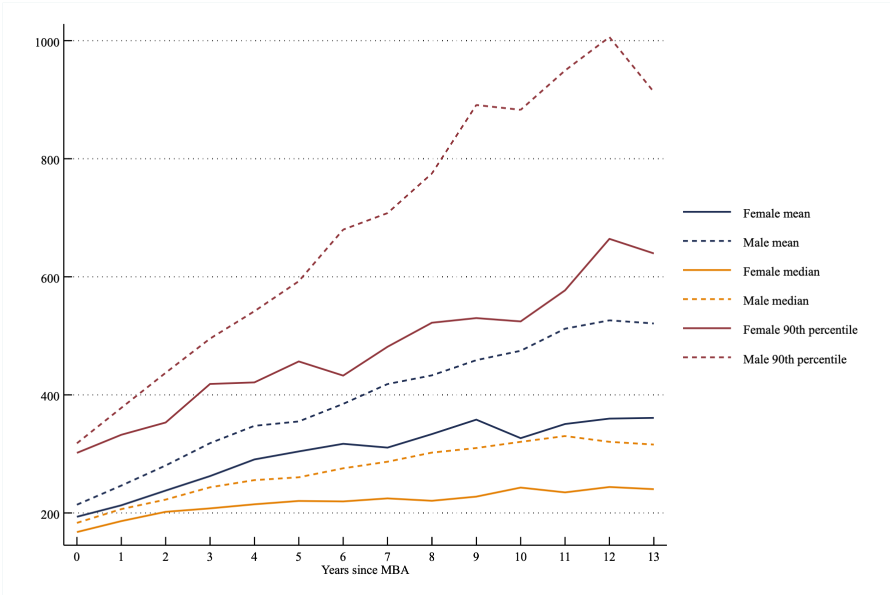

Figure A1: Male and Female Mean, Median, and 90th Percentile Annual Earnings Inclusive of Equity (Thousands of 2022 Dollars) by Years since MBA. Nominal earnings in each year are converted into real earnings in 2022 dollars using the Consumer Price Index for All Urban Consumers (CPI-U).

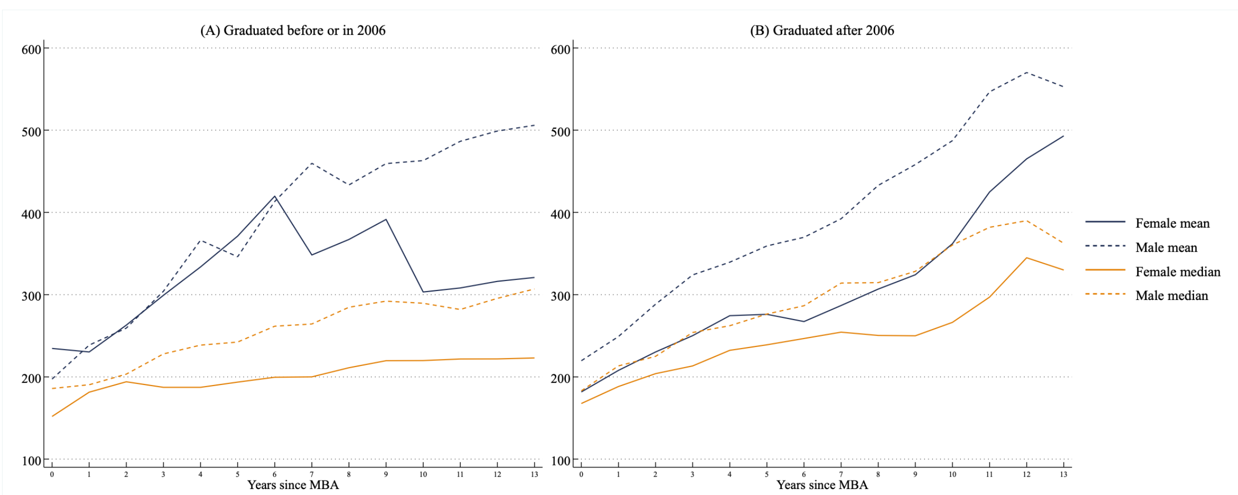

Figure A2: Male and Female Mean and Median Annual Earnings Inclusive of Equity (Thousands of 2022 Dollars) by Years since MBA by Cohort. Nominal earnings in each year are converted into real earnings in 2022 dollars using the Consumer Price Index for All Urban Consumers (CPI-U).

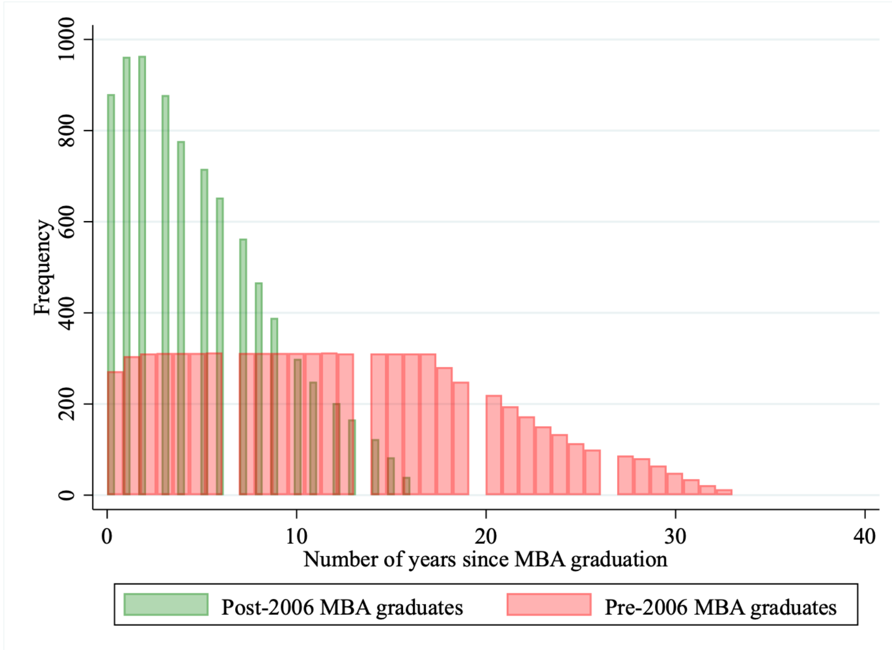

Figure A3: Distribution of Responses by Cohort

Appendix Tables

Table A1: Mean Stats by Cohort (Female)

	Pre-2006	Post-2006	Diff.	P-value of diff.	Obs.
Earnings, in thousands of US dollars	194.75	196.61	-1.86	0.796	4014
Age at MBA Graduation	30.22	32.07	-1.86	0.000***	4245
MBA GPA	3.57	3.57	0.00	0.723	4879
Actual post-MBA exp	19.45	6.89	12.56	0.000***	4879
Weekly hours worked	46.85	47.35	-0.50	0.152	4324
Self employed	0.12	0.05	0.07	0.000***	4879
At least one child	0.79	0.63	0.17	0.000***	4879
At least one child below the age of 3	0.00	0.20	-0.20	0.000***	4879
Married at time of survey (2022)	0.65	0.60	0.05	0.000***	4879
Background sexism	-0.14	-0.17	0.03	0.005***	4879
Any no work spell	0.05	0.05	0.00	0.438	4879
Greedy work	4.15	4.14	0.00	0.697	4879
Reduced cost of childcare	7.36	8.01	-0.66	0.152	4879

Notes: The unit of observation is a survey respondent in a given post-MBA year. Earnings data for each year is linearly extrapolated from first-year and last-year earnings at each stage (job). *Any no work spell* is a dummy variable that equals 1 for a given individual in a given year if they experience a period of at least six months without work between MBA graduation year and that year. *Weekly hours worked* are binned: < 20 hours, 20-30, 30-35, 35-40, 40-45, 45-50, 50-60, 60-70, 70-80, 80-90, 90-100, and > 100 hours. *Background sexism* is based on the place (state or country if outside the U.S.) of the respondent's birth based on GSS data. *Greedy work* is the average of five Likert scale survey questions: (1) "How often does this job require you to meet strict deadlines?" (2) "How much does this job require the worker to be in contact with others?" (3) "How often does this job require developing constructive and cooperative working relationships with others, and maintaining them over time?" (4) "To what extent is this job structured for the worker, rather than allowing the worker to determine tasks, priorities, and goals?" (5). "How much decision making freedom, without supervision, does the job offer?". *Reduced cost of childcare* gives the fraction of childcare provided by family and/or subsidized by the respondent's employer.

Table A2: Mean Stats by Cohort (Male)

	Pre-2006	Post-2006	Diff.	P-value of diff.	Obs.
Earnings, in thousands of US dollars	285.70	244.97	40.72	0.000***	9555
Age at MBA Graduation	30.68	32.20	-1.51	0.000***	9928
MBA GPA	3.61	3.56	0.04	0.000***	11563
Actual post-MBA exp	18.78	7.81	10.97	0.000***	11563
Weekly hours worked	52.18	49.86	2.32	0.000***	10388
Self employed	0.09	0.03	0.05	0.000***	11563
At least one child	0.88	0.79	0.10	0.000***	11563
At least one child below the age of 3	0.01	0.22	-0.21	0.000***	11563
Married at time of survey (2022)	0.74	0.75	-0.00	0.542	11563
Background sexism	-0.16	-0.20	0.03	0.000***	11563
Any no work spell	0.03	0.02	0.01	0.081*	11563
Greedy work	4.21	4.18	0.03	0.001***	11563
Reduced cost of childcare	4.71	6.66	-1.95	0.000***	11563

Notes: The unit of observation is a survey respondent in a given post-MBA year. Earnings data for each year is linearly extrapolated from first-year and last-year earnings at each stage (job). *Any no work spell* is a dummy variable that equals 1 for a given individual in a given year if they experience a period of at least six months without work between MBA graduation year and that year. *Weekly hours worked* are binned: $<$ 20 hours, 20-30, 30-35, 35-40, 40-45, 45-50, 50-60, 60-70, 70-80, 80-90, 90-100, and $>$ 100 hours. *Background sexism* is based on the place (state or country if outside the U.S.) of the respondent's birth based on GSS data. *Greedy work* is the average of five Likert scale survey questions: (1) "How often does this job require you to meet strict deadlines?" (2) "How much does this job require the worker to be in contact with others?" (3) "How often does this job require developing constructive and cooperative working relationships with others, and maintaining them over time?" (4) "To what extent is this job structured for the worker, rather than allowing the worker to determine tasks, priorities, and goals?" (5). "How much decision making freedom, without supervision, does the job offer?". *Reduced cost of childcare* gives the fraction of childcare provided by family and/or subsidized by the respondent's employer.

Table A3: Mean Childcare Stats by Cohort (Female)

	Pre-2006	Post-2006	Diff.	P-value of diff.	Obs.
How often do you rely on your extended family for childcare?					
Never	0.62	0.27	0.36	0.000***	229
Once a year or more, but not every month	0.23	0.36	-0.13	0.045**	229
Once a month or more, but not every week	0.03	0.22	-0.19	0.000***	229
Once a week or more, but not every day	0.03	0.08	-0.04	0.151	229
Every day	0.08	0.07	0.01	0.796	229
What share of childcare provided to your first child in their first year was provided through these channels?					
You	32.33	30.54	1.79	0.652	231
Partner	11.00	15.81	-4.81	0.017**	231
Paid childcare	42.00	38.15	3.85	0.440	231
Company-provided childcare	0.08	0.00	0.08	0.321	231
Extended family	8.03	9.62	-1.58	0.603	231
Prefer not to respond	6.56	5.88	0.68	0.855	231
What share of childcare provided to your second child in their first year was provided through these channels?					
You	27.49	30.05	-2.56	0.520	164
Partner	11.29	13.11	-1.81	0.494	164
Paid childcare	45.39	44.83	0.56	0.922	164
Company-provided childcare	0.04	0.04	-0.01	0.932	164
Extended family	7.94	7.54	0.40	0.902	164
Prefer not to respond	7.84	4.42	3.42	0.426	164
What share of childcare provided to your third child in their first year was provided through these channels?					
You	51.36	19.82	31.55	0.011**	22
Partner	13.64	10.00	3.64	0.405	22
Paid childcare	28.00	54.73	-26.73	0.042**	22
Company-provided childcare	0.00	4.55	-4.55	0.341	22
Extended family	5.64	10.91	-5.27	0.502	22
Prefer not to respond	1.36	0.00	1.36	0.341	22

Table A4: Mean Childcare Stats by Cohort (Male)

	Pre-2006	Post-2006	Diff.	P-value of diff.	Obs.
How often do you rely on your extended family for childcare?					
Never	0.63	0.33	0.31	0.000***	651
Once a year or more, but not every month	0.28	0.30	-0.02	0.659	651
Once a month or more, but not every week	0.02	0.19	-0.17	0.000***	651
Once a week or more, but not every day	0.05	0.13	-0.09	0.000***	651
Every day	0.01	0.05	-0.03	0.007***	651
What share of childcare provided to your first child in their first year was provided through these channels?					
You	17.13	16.33	0.79	0.644	657
Partner	45.40	42.25	3.15	0.271	657
Paid childcare	18.49	21.32	-2.82	0.229	657
Company-provided childcare	0.35	0.25	0.10	0.796	657
Extended family	3.51	6.25	-2.74	0.007***	657
Prefer not to respond	15.12	13.61	1.51	0.633	657
What share of childcare provided to your second child in their first year was provided through these channels?					
You	14.39	14.48	-0.08	0.957	468
Partner	47.79	42.46	5.33	0.117	468
Paid childcare	20.63	22.01	-1.38	0.624	468
Company-provided childcare	0.53	0.03	0.50	0.280	468
Extended family	2.27	5.10	-2.84	0.007***	468
Prefer not to respond	14.39	15.92	-1.53	0.676	468
What share of childcare provided to your third child in their first year was provided through these channels?					
You	11.46	12.61	-1.15	0.691	115
Partner	63.37	45.14	18.22	0.010***	115
Paid childcare	11.71	17.57	-5.86	0.230	115
Company-provided childcare	0.00	0.00	0.00	.	115
Extended family	1.27	5.76	-4.49	0.030**	115
Prefer not to respond	12.20	18.92	-6.72	0.333	115

Table A5: No Pay Stage by Cohort (Female)

	Pre-2006	Post-2006	Diff.	P-value of diff.	Obs.
Main reason why you were not working for pay during this stage					
layoff / job ended / company closed	0.22	0.29	-0.07	0.450	94
suitable job not available	0.06	0.16	-0.10	0.127	94
full-time student	0.00	0.02	-0.02	0.321	94
do not need or want to work	0.16	0.05	0.11	0.135	94
home raising children	0.44	0.15	0.29	0.005***	94
home taking care of parents or other relatives	0.00	0.02	-0.02	0.321	94
chronic illness or permanent disability	0.00	0.03	-0.03	0.159	94
retired	0.00	0.00	0.00	.	94
other	0.12	0.29	-0.17	0.050*	94
Would you have remained in your previous job if you had more flexibility (part time option, work from home)?					
Definitely would not	0.28	0.34	-0.06	0.571	94
Probably would not	0.22	0.10	0.12	0.150	94
Might or might not	0.06	0.08	-0.02	0.746	94
Probably would	0.06	0.06	-0.00	0.970	94
Definitley would	0.09	0.08	0.01	0.836	94
Don't know / Not applicable	0.28	0.34	-0.06	0.571	94

Table A6: No Pay Stage by Cohort (Male)

	Pre-2006	Post-2006	Diff.	P-value of diff.	Obs.
Main reason why you were not working for pay during this stage					
layoff / job ended / company closed	0.41	0.46	-0.05	0.541	142
suitable job not available	0.06	0.13	-0.07	0.150	142
full-time student	0.05	0.04	0.01	0.862	142
do not need or want to work	0.12	0.14	-0.02	0.682	142
home raising children	0.06	0.01	0.05	0.146	142
home taking care of parents or other relatives	0.05	0.01	0.03	0.268	142
chronic illness or permanent disability	0.00	0.00	0.00	.	142
retired	0.06	0.01	0.05	0.146	142
other	0.20	0.18	0.01	0.848	142
Would you have remained in your previous job if you had more flexibility (part time option, work from home)?					
Definitely would not	0.36	0.36	0.01	0.918	142
Probably would not	0.17	0.12	0.05	0.418	142
Might or might not	0.09	0.08	0.01	0.801	142
Probably would	0.06	0.12	-0.06	0.227	142
Definitley would	0.02	0.07	-0.05	0.121	142
Don't know / Not applicable	0.30	0.26	0.04	0.603	142