

Female labor force participation

Heidi L. Williams
MIT 14.662
Spring 2015

Outline

- 1) [Goldin \(2006\)](#) Ely lecture
- 2) Compensating differentials:
[Goldin \(2014\)](#), [Bertrand et al. \(2010\)](#), [Goldin and Katz \(forthcoming\)](#)
- 3) Roy model: [Mulligan and Rubinstein \(2008\)](#)

1 Facts: [Goldin \(2006\)](#)

Goldin argues that the most significant change in labor markets over the past century was the increased participation of women in the labor market. Figure 1 summarizes historical trends in mens' and womens' labor force participation.

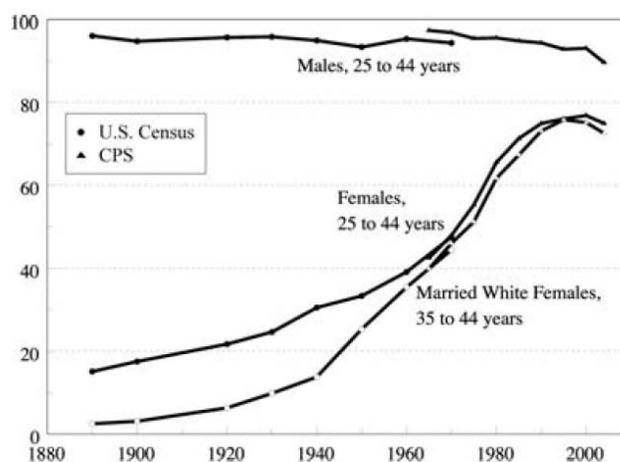


FIGURE 1. LABOR FORCE PARTICIPATION RATES FOR FEMALES AND MALES BY AGE AND MARITAL STATUS: 1890 TO 2004

Notes: All races, marital statuses, and education groups are included unless indicated otherwise. The labor force participation rate from 1890 to 1930 is the fraction of “gainful workers” in the relevant population. The difference between the Census and CPS for females is small, and somewhat larger for males.

Sources: 1890 to 1970, Goldin (1990) from U.S. Population Census; 1965 to 2004, March Current Population Survey (CPS).

Courtesy of Claudia Goldin and the American Economic Association. Used with permission.

Goldin argues there were four distinct phases in this shift, and argues that three factors in particular were important:

1. “Horizon”: whether, at the time of human capital investment, a woman perceives that her lifetime labor force involvement will be long and continuous or intermittent and brief
2. “Identity”: whether a woman finds individuality in her job, occupation, profession, or career
3. “Decision making”: whether labor force decisions are made fully jointly, if a woman is married or in a long-term relationship, or whether the woman is a “secondary worker” who optimizes her time allocation by taking her husband’s labor market decisions as given to her

Goldin argues that the transition of women over the last century was a change from static decision making with limited or intermittent horizons, to dynamic decision-making with long-term horizons; a change from agents who work because they and their families “need the money” to those who are employed at least in part because occupation and employment define one’s identity; and a change from “jobs” to “careers,” where the distinction concerns both horizon and human capital investment.

The four phases she delineates are the following:

1. Phase I: late nineteenth century to the 1920s. Female workers in the labor market (largely piece workers in manufacturing or services) were generally young and unmarried; women almost always exited the workforce at marriage.
2. Phase II: 1930 to 1950. Driven by increased demand for office and other clerical work due to the arrival of new types of information technologies and growth in high school education. Until 1940, few remained employed after marriage, partly due to marriage bars, regulations that forced single women to leave employment upon marriage and banned the hiring of married women.
3. Phase III: 1950 to mid-to-late-1970s. Driven partly by the creation of part-time employment, and partly by the elimination of marriage bars. But women were still largely secondary earners. Interviews for first jobs, even for women with college degrees, would often begin with “How well do you type?” (Anecdote about US Supreme Court Justice Sandra Day O’Connor being offered a first job as a legal secretary after no California law firm offered her a position as a lawyer.) Even though many women would eventually be employed for a significant portion of their lives, their expectations of employment when they were young were quite different: most woman had anticipated brief and intermittent employment in various jobs, not in a career.
4. Phase IV: beginning in the late 1970s. Goldin brings in a number of data series to illustrate the changes that occurred during Phase IV, because she argues that changes in labor force participation measures understate the amount of underlying change during this period.

She argues that women more accurately anticipated their future working lives, using data from the National Longitudinal Survey (NLS) of Young Women, which asked questions about expectations of paid employment at age 35. As shown in Figure 2, young woman in the 1970s began with expectations similar to the actual participation of their mothers' generation (around 0.3), but in the next ten years began to correctly anticipate - and slightly overstate - their future labor force participation rates.

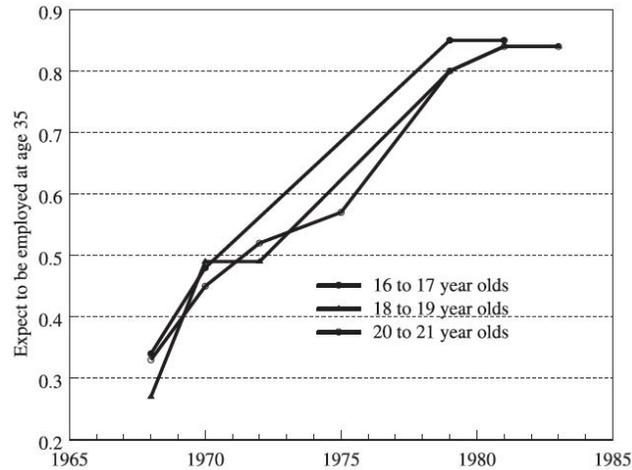


FIGURE 2. EMPLOYMENT EXPECTATIONS OF FEMALE YOUTH BY AGE: 1967 TO 1984

Notes: The NLS data are the response to whether an individual stated she expected to be in the paid labor force at age 35 and are given here for white women. The NLS data link the averages for each age group over time. Thus, the 14- to 15-year-olds in the NLS68 in 1968 became 16 to 17 years old in 1970 and are linked to the 16- to 17-year-olds in 1979 in the NLSY.

Sources: 1968 National Longitudinal Survey of Young Women (NLS68) and 1979 National Longitudinal Survey of Youth (NLSY). See Goldin (2005) for details.

Courtesy of Claudia Goldin and the American Economic Association. Used with permission.

Goldin argues that these revised expectations of future employment led young women to continue with college, as shown in Figure 3.

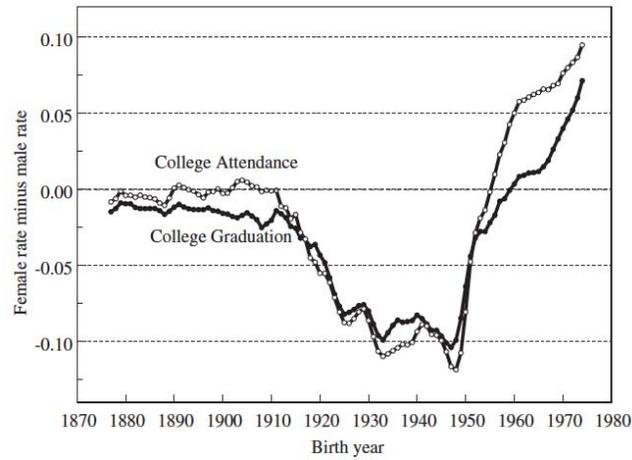


FIGURE 3. FEMALE MINUS MALE COLLEGE ATTENDANCE AND GRADUATION RATES: BIRTH COHORTS, 1877 TO 1974

Notes: The underlying data are the fraction of four-year college attendees or graduates by birth cohort and sex adjusted to 35 years of age for the U.S. born. College graduates are those with 16 or more completed years of schooling for the 1940–1980 samples and those with a bachelor’s degree or higher in the 1990–2000 samples. The underlying samples include all U.S.-born residents aged 25 to 64 years. For information on the age-adjustment regressions, see De Long et al. (2003, fig. 1) and Goldin et al. (2005).
Sources: 1940 to 2000 Census of Population Integrated Public Use Micro-data Samples (IPUMS).

Courtesy of Claudia Goldin and the American Economic Association. Used with permission.

Goldin also notes that a set of related demographic changes occurred during the same period for college women. As shown in Figure 4, the median age at first marriage increased by 2.5 years for female college graduates born between 1949 and 1956.

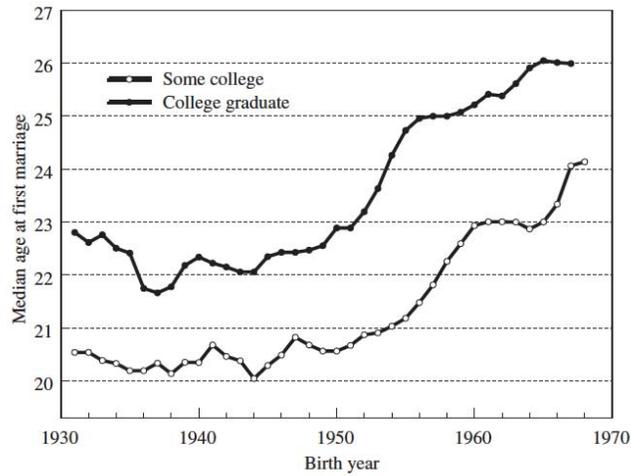


FIGURE 4. MEDIAN AGE AT FIRST MARRIAGE FOR BIRTH COHORTS OF FEMALE COLLEGE GRADUATES AND ATTENDEES: 1931 TO 1968 BIRTH YEARS

Notes: Three-year centered moving averages are shown.
Sources: Current Population Survey; Fertility and Marital History Supplement, 1990 and 1995.

Courtesy of Claudia Goldin and the American Economic Association. Used with permission.

Women also began to further their education in professional and graduate schools around 1970, as shown in Figure 5.

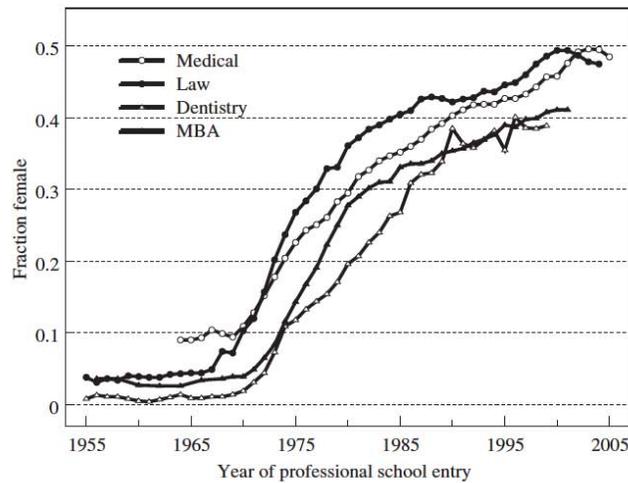


FIGURE 5. FRACTION FEMALE AMONG FIRST-YEAR STUDENTS IN PROFESSIONAL PROGRAMS: 1955 TO 2005

Sources: First-year law students from the American Bar Association Web site: <http://www.abanet.org/legaled/statistics/femstats.html>. First-year medical students (to 1994) from *Journal of the American Medical Association* (various years 1978 to 1998) and (from 1994 to 2005) from the American Association of Medical Colleges Web site <http://www.aamc.org/data/facts/2005/2005summary.htm>. First-year dentistry students extrapolated from dental degrees awarded lagged four years, from U.S. Department of Education, NCES (2005, table 257). Masters in business administration first-year students extrapolated from MBA degrees awarded lagged two years, from U.S. Department of Education, NCES (2005, table 278).

Courtesy of Claudia Goldin and the American Economic Association. Used with permission.

The earnings of women relative to men began to increase around 1980, after remaining flat since the 1950s, as shown in Figure 7.

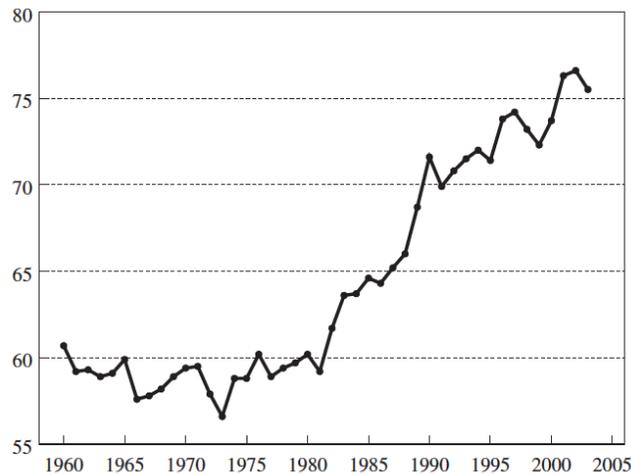


FIGURE 7. WOMEN'S EARNINGS AS A PERCENTAGE OF MEN'S EARNINGS: 1960 TO 2003

Notes: Based on median earnings of full-time, year-round workers 15 years old and over as of March of the following year. Before 1989, earnings are for civilian workers only.
Source: <http://www.census.gov/hhes/income/histinc/p40.html>.

Courtesy of Claudia Goldin and the American Economic Association. Used with permission.

Occupations shifted from “traditional” women’s occupations to a more varied group, as shown in Figure 8.

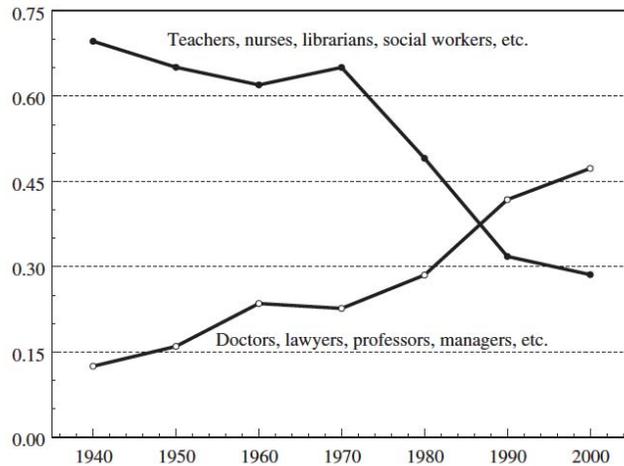


FIGURE 8. OCCUPATIONS OF COLLEGE GRADUATE WOMEN, 30 TO 34 YEARS OLD: 1940 TO 2000

Notes: The occupations in the two groups are: grade school teachers, nurses, librarians, social or religious workers, secretaries and other clerical workers; and doctors, lawyers, professors, managers, and scientists.

Sources: Integrated Public Use Micro-data Sample of the U.S. Federal Population Census, 1940 to 1960; March Current Population Survey 1970 to 2000.

Courtesy of Claudia Goldin and the American Economic Association. Used with permission.

Goldin’s discussion of the potential drivers of these Phase IV changes focuses on several factors. First, women in these cohorts observed the large increase in participation and full-time work of their predecessors, and extrapolated from that more accurate expectations for their futures. In doing so, they were better prepared to invest in their human capital. Marriage delay enabled women to take formal education more seriously, and she argues that one underlying driver of this marriage delay was the introduction of the contraceptive “pill.” While the pill was FDA approved in 1960, restrictive state laws were in place until the late 1960s and early 1970s.

2 Compensating differentials:

[Goldin \(2014\)](#), [Bertrand et al. \(2010\)](#), [Goldin and Katz \(forthcoming\)](#)

2.1 Goldin (2014)

Goldin’s 2014 AEA Presidential address follows on her Ely lecture, with a focus on the convergence in earnings between men and women. Figure 1 plots the earnings gender gap by age using synthetic birth cohorts (for college graduates working full-time full-year). The two striking findings from this graph are that each cohort has a higher ratio of female to male earnings than the preceding one, and that the ratio is closer to parity for younger individuals than for older individuals, up to some age, but the ratio increases again when individuals are in their forties. The main conclusion she draws from this is that differences in earnings by sex greatly increases during the first several decades of working life.

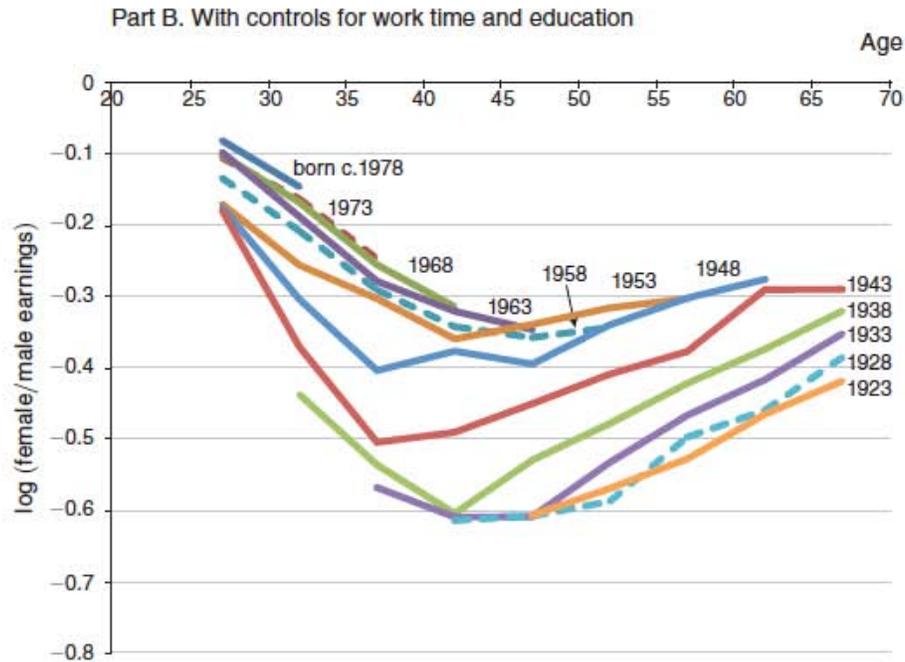
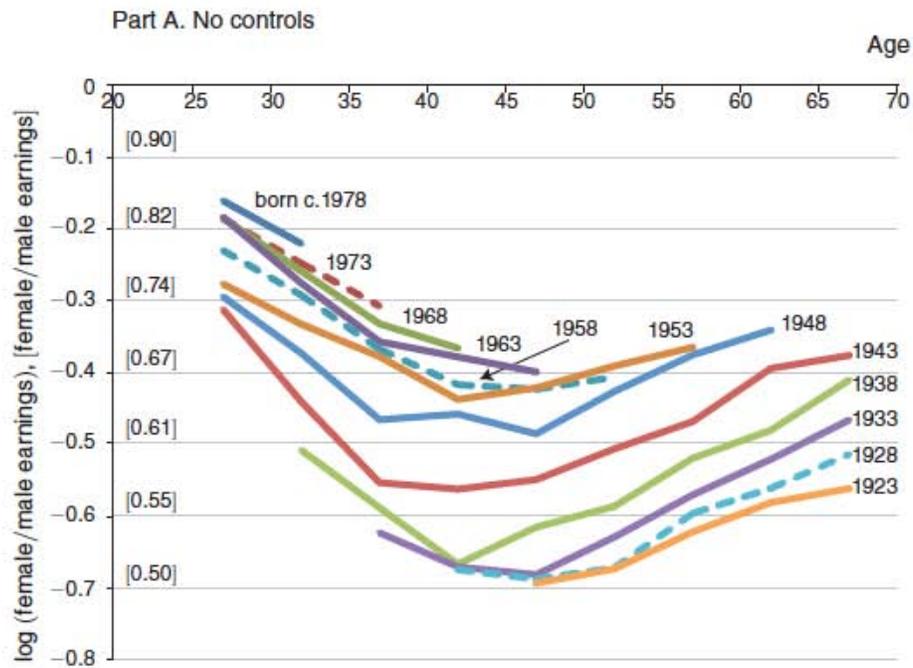


FIGURE 1. RELATIVE EARNINGS OF (FULL-TIME, FULL-YEAR) COLLEGE GRADUATE MEN AND WOMEN FOR SYNTHETIC COHORTS: BORN 1923 TO 1978

Notes: Sample consists of full-time (35+ hours), full-year (40+ weeks), college-graduate (16+ years of schooling), men and women (white, native-born, non-military, 25 to 69 years old), using trimmed annual earnings data (exceeding 1,400 hours \times 0.5 \times 2009 minimum wage) corrected for income truncation (top-coded values \times 1.5). Part B contains controls for education beyond 16 years, log hours, and log weeks. Age is entered in five-year intervals with an interaction with female. In each graph the lines connect the coefficients on the five-year intervals for each birth cohort.

Sources: US Census Micro-data 1970, 1980, 1990, 2000, and American Community Survey 2004 to 2006 (for 2005), 2009 to 2011 (for 2010).

Courtesy of Claudia Goldin and the American Economic Association. Used with permission.

Most studies of the gender wage gap produce estimates of an “explained” (by covariates) and “residual” (unexplained) portion. Goldin estimates such specifications in the 2009 to 2011 American Community Survey, and plots the residual gender difference by occupation against the log male wage in that occupation in Figure 2A. In almost all cases, the coefficient on female for each occupation is negative. She categorizes occupations into five broad sectors, which illustrates that business has the largest negative coefficients whereas technology and science have the smallest. She argues in the paper that these patterns are unlikely to be driven by selection.

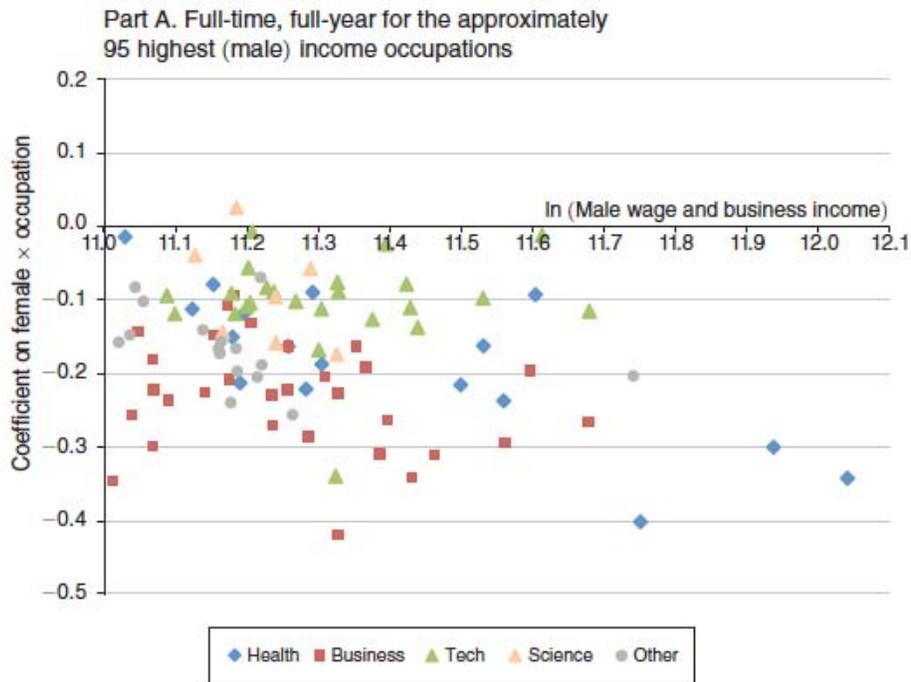


FIGURE 2A. GENDER PAY GAPS BY OCCUPATION: 2009 TO 2011

Notes: Sample consists of full-time, full-year individuals 25 to 64 years old excluding those in the military using trimmed annual earnings data (exceeding 1,400 hours \times 0.5 \times 2009 minimum wage). Regression contains age in a quartic, race, log hours, log weeks, education levels, census year, all occupations (469), and an interaction with female and occupation. Part A contains all full-time, full-year workers (2,603,968 observations); part B has those who graduated (BA) college (964,705 observations); part C has the group < 45 years old among those included in part A (1,333,013 observations). Each of the symbols in part A is an occupation for which the mean annual income for males exceeds \$60K (current \$) and is limited to occupations with at least 25 males and at least 25 females. For parts B and C the same occupations are graphed.

Source: American Community Survey 2009 to 2011.

Courtesy of Claudia Goldin and the American Economic Association. Used with permission.

She then outlines what she calls a “personnel economics theory of occupational pay differences.” The key starting point is the observation that individuals in some occupations work 70 hours a week and receive far more than twice the earnings of those who work 35 hours a week, but in some occupations they do not. She refers to this as some occupations exhibiting linearity with respect to time worked versus others exhibiting nonlinearity (convexity). Her claim is

that when earnings are linear with respect to time worked the gender gap is low; when there is nonlinearity the gender gap is higher.

While total hours worked are relevant, she notes that often what counts are the particular hours worked. The employee who is around when others are as well may be rewarded more than the employee who leaves at 11am for two hours but is hard at work for two additional hours in the evening.

In many workplaces, employees meet with clients and accumulate knowledge about them. If an employee is unavailable and communicating the information to another employee is costly, the value of the individual to the firm will decline. Equivalently, employees often gain from interacting with each other in meetings or through random exchanges.

Her key point is that whenever an employee does not have a perfect substitute, nonlinearities can arise. When there are perfect substitutes for particular workers and zero transaction costs, there is never a premium in earnings with the respect to the number or the timing of hours. If there were perfect substitutes earnings would be linear with respect to hours.

2.2 MBAs: [Bertrand, Goldin and Katz \(2010\)](#)

Despite the narrowing of the gender gap in business education, there is a growing sense that women are not getting ahead fast enough in the corporate and financial world. There is experimental evidence that women have less taste for the highly-competitive environments in top finance and corporate jobs. Women may also fall behind because of the career/family conflicts arising from the purportedly long hours, heavy travel commitments, and inflexible schedules of most high-powered finance and corporate jobs.

Although male and female MBAs have nearly identical earnings at the outset of their careers, [Bertrand et al. \(2010\)](#) find their earnings soon diverge, with the male earnings advantage reaching almost 60 log points a decade after MBA completion. The authors argue that three proximate factors account for the large and rising gender gap in earnings: differences in training prior to MBA graduation, differences in career interruptions, and differences in weekly hours.

2.2.1 Data

The authors conducted web-based surveys of University of Chicago MBAs from the graduating classes of 1990 to 2006. The participants were asked detailed questions about each of the jobs or positions they had since graduation, including earnings (both at the beginning and end of a given position), usual weekly hours worked, job function, sector, size of firm, and type of firm.

The authors collected administrative data from the University of Chicago to match to the survey data, providing information on MBA courses and grades, undergraduate school, undergraduate GPA, GMAT scores, and demographic information (age, ethnicity, and immigration status).

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

administrative records. These 1,856 men and 629 women form the basis of their sample. The respondents do not differ much from the nonrespondents based on the observables.

2.2.2 Empirical results

Table 1. Early in their careers, labor force participation for MBAs is extremely high and similar by gender. Hours decline with time for both men and women, in part reflecting a move out of investment banking and consulting and towards general management positions in corporations. But the gender gap in labor force participation widens as careers progress.

TABLE 1—LABOR SUPPLY BY GENDER AND NUMBER OF YEARS SINCE MBA GRADUATION:
DESCRIPTIVE STATISTICS

	Number of years since MBA graduation					
	0	1	3	6	9	≥ 10
Share not working at all in current year						
Female	0.054	0.012	0.027	0.067	0.129	0.166
Male	0.028	0.005	0.003	0.008	0.011	0.010
Share working full time/full-year (52 weeks and > 30 to 40 hours per week)						
Female	NA	0.89	0.84	0.78	0.69	0.62
Male	NA	0.93	0.94	0.93	0.93	0.92
Cumulative share with any no work spell (until given year)						
Female	0.064	0.088	0.143	0.229	0.319	0.405
Male	0.032	0.040	0.064	0.081	0.095	0.101
Cumulative years not working						
Female	0	0.050	0.118	0.282	0.569	1.052
Male	0	0.026	0.045	0.069	0.098	0.120
Mean weekly hours worked for the employed						
Female	59.1	58.8	56.2	54.7	51.5	49.3
Male	60.9	60.7	59.5	57.9	57.5	56.7
Share working part time (≤ 30 to 40 hours per week)						
Female	0.04	0.05	0.07	0.09	0.15	0.22
Male	0.02	0.02	0.02	0.03	0.03	0.04
Share working fewer than 52 weeks						
Female	NA	0.07	0.07	0.09	0.06	0.06
Male	NA	0.05	0.04	0.03	0.03	0.03

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

Courtesy of Marianne Bertrand, Claudia Goldin, Lawrence F. Katz, and the American Economic Association. Used with permission.

Figure 1. Mean earnings by sex are comparable directly following MBA receipt, but they soon diverge.

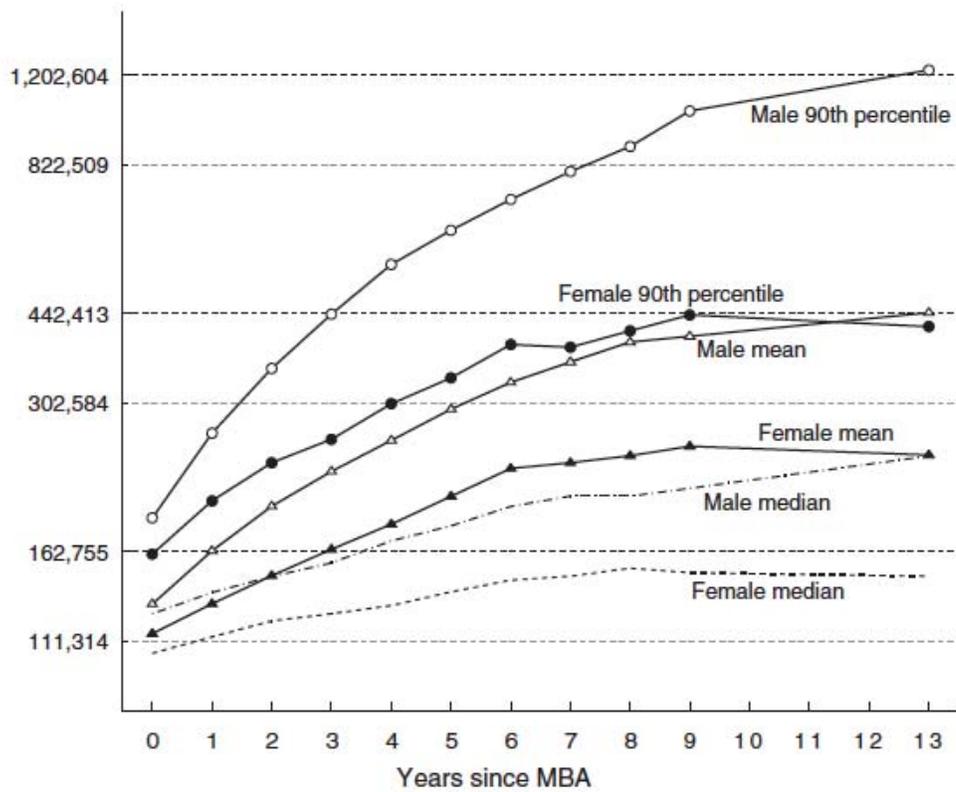


FIGURE 1. MALE AND FEMALE MEAN, MEDIAN, AND NINETYIETH PERCENTILE ANNUAL SALARIES (2006 DOLLARS) BY YEARS SINCE MBA

Notes: Web Appendix Table A5 contains the data points for a selected group of years since MBA. Nominal earnings in each year are converted into real earnings in 2006 dollars using the Consumer Price Index for All Urban Consumers (CPI-U). The vertical axis uses a natural logarithm (ln) scale.

Courtesy of Marianne Bertrand, Claudia Goldin, Lawrence F. Katz, and the American Economic Association. Used with permission.

Table 4. Differences in three factors - MBA performance (24%; GPA and finance courses), career interruptions and job experience (30%), and hours worked (30%) - account for 84 percent of the gender gap in earnings pooled across all years since MBA completion.

TABLE 4—GENDER WAGE GAP BY YEARS SINCE MBA

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

Courtesy of Marianne Bertrand, Claudia Goldin, Lawrence F. Katz, and the American Economic Association. Used with permission.

Perhaps unsurprisingly, children appear to be a main contributor to women’s labor supply changes. Women with children work 24% fewer hours per week than men or than women without children. The association between children and female labor supply differs strongly by spousal income, with MBA moms with high-earning spouses having labor force participation rates that are 18.5 percentage points lower than those with lesser-earning spouses.

Table 8. The authors use the (retrospectively-constructed) panel structure of the data to explore the effect of child on careers. The regressions include person-fixed effects, (cohort year) dummies, a quadratic in age, and a set of indicator variables for the year surrounding the first child’s birth (dummy variables for one or two years before the birth, the year of the birth, one or two years after the birth, three or four years after the birth, and greater than four years after the birth).

TABLE 8—IMPACT OF FIRST BIRTH ON EMPLOYMENT STATUS, SALARY, AND WORKING HOURS

	Not working		Log (annual earnings)		Annual earnings (0 if not working)		Log (weekly hours worked)	
	Male (1)	Female (2)	Male (3)	Female (4)	Male (5)	Female (6)	Male (7)	Female (8)
Year of birth of first child	-0.001 [0.007]	0.096 [0.032]***	0.008 [0.036]	-0.096 [0.054]	-2,315 [20,942]	-45,666 [20,936]**	-0.006 [0.010]	-0.126 [0.029]***
Years after birth of first child:								
1 or 2	-0.009 [0.007]	0.131 [0.036]***	0.040 [0.040]	-0.164 [0.066]**	5,117 [24,118]	-64,586 [26,335]**	-0.013 [0.011]	-0.168 [0.036]***
3 or 4	-0.007 [0.008]	0.178 [0.045]***	0.065 [0.049]	-0.292 [0.092]***	9,721 [29,915]	-99,397 [34,839]***	-0.011 [0.013]	-0.238 [0.049]***
5 or more	0.000 [0.0012]	0.190 [0.054]***	0.162 [0.060]**	-0.301 [0.119]**	62,581 [37,872]	-101,719 [44,384]**	0.000 [0.017]	-0.233 [0.071]***
Years before birth of first child:								
1 or 2	-0.006 [0.005]	-0.015 [0.021]	-0.008 [0.030]	-0.051 [0.041]	-7,830 [16,303]	-19,137 [15,226]	-0.005 [0.009]	-0.043 [0.023]
Observations	14,490	5,070	13,969	4,545	14,523	5,070	14,193	4,560
R ²	0.29	0.46	0.77	0.73	0.66	0.68	0.72	0.68

Courtesy of Marianne Bertrand, Claudia Goldin, Lawrence F. Katz, and the American Economic Association. Used with permission.

MBA men with children see their earnings increase, not decrease, especially five years and more after the birth of their first child (Table 8, columns 3 and 5). Male labor supply is virtually unaffected by fatherhood in this MBA sample (columns 1 and 7). MBA women reduce their labor supply on both the extensive and intensive margins after a birth. There is a large decline in labor force participation in the year of the first birth, and a further reduction over the next four years.

Goldin (2014) uses data on JDs graduating from University of Michigan Law School to document similar trends for lawyers.

2.3 Pharmacists: Goldin and Katz (forthcoming)

In contrast to MBAs and JDs, Goldin (2014) and - more extensively - Goldin and Katz (forthcoming) argue that pharmacy is an example of an occupation with fairly linear earnings with respect to hours worked and a negligible penalty to time out of the labor force. Managers of

pharmacies get paid more because they work more hours. Female pharmacists get paid less because they work fewer hours. But there is no “part time penalty.”

Goldin and Katz (forthcoming) study closely how pharmacy became the most egalitarian profession over the time period 1970-2010. The authors argue that three production and health-care changes are the forces behind the evolution of the pharmacy sector - technological changes increasing the substitutability among pharmacists, the growth of pharmacy employment in retail chains and hospitals, and the related decline of independent pharmacies.

1. Drug stores have increased in their scope and scale since 1970. These changes led to a greater share of corporate-owned pharmacies (e.g., CVS, Walgreens and Rite-Aid) and a lower share of owner-operated pharmacies, against a backdrop of evolution of retail chain stores. Owner-operated pharmacies demand more hours of work whereas in corporate-owned pharmacies the hours are more flexible. Changes in the healthcare sector led to an increase of pharmacists working in hospitals and mail-order pharmacies.
2. Demand-side substitutability. Pharmacists can access the prescriptions of clients through electronic systems administered by the Pharmacy Benefit Manager, so there is less cost/friction when pharmacists handoff clients.
3. Standardization of pharmacy products and services. Medicines have been increasingly produced by pharmaceutical companies, rather than being compounded in individual pharmacies. As a result, the idiosyncratic expertise of a particular pharmacist have become less important.

Over time, the demand for pharmacists has grown. The authors outline a compensating differentials framework along the lines of Goldin (2014) to clarify two cases. First, a demand side shift raising the demand for an amenity would imply an increase in the cost of the amenity and hence a likely decline in women’s relative earnings. In contrast, a supply side shift lowering the cost to firms of providing the amenity implies a decrease in the cost of the amenity and hence a likely increase in women’s relative earnings. They argue that the data and institutional context are more consistent with the latter than the former.

Unfortunately, the paper does little to tease apart the potential channels proposed by the authors. Doing so would seem to require either going beyond a case study of one profession, or using cross-geography variation in the three mechanisms.

Goldin (2014) concludes her paper by arguing that there are many occupations and sectors that have moved in the direction of less costly flexibility (physicians are a good example). But she stresses that not all positions can be changed.

3 Roy model: Mulligan and Rubinstein (2008)

Figure 1 of Mulligan and Rubinstein (2008) illustrates essentially the same graph as Goldin's Figure 7, but overlays a time-series plot of 90-10 wage inequality among men. Strikingly, the two series move together quite closely.

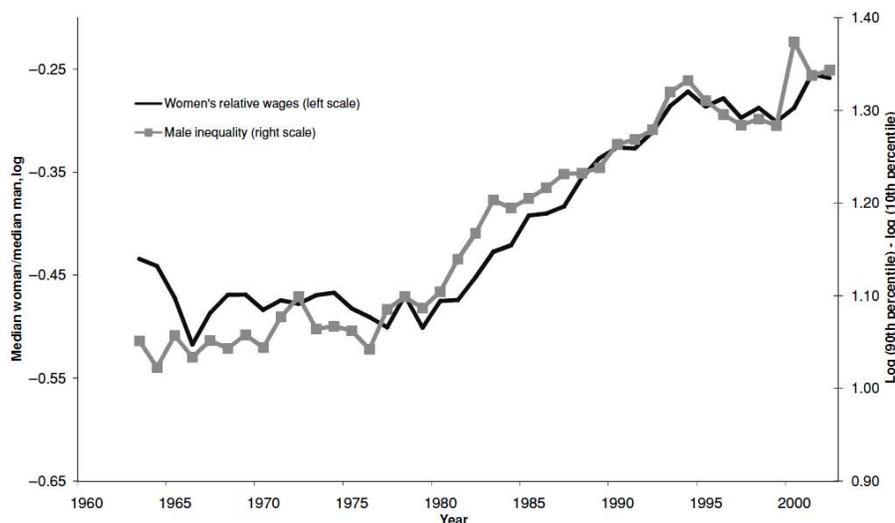


FIGURE I
Wage Inequality within and between Genders

The figure graphs time series of (a) the log of the ratio of the wage of the median working woman to that of the median working man (left scale, no markers), and (b) the log of the ratio of the wage of a man at the 90th percentile of the male wage distribution to that of a man at the 10th percentile (right scale, square markers). The calculations use our CPS wage sample of white persons aged 25–54, without trimming of outliers or adjusting topcodes.

© Oxford University Press. All rights reserved. This content is excluded from our Creative Commons license. For more information, see <http://ocw.mit.edu/help/faq-fair-use/>.

Mulligan and Rubinstein present a Roy-style model that offers an explanation for why these two series might move together. Their idea is that growing within-gender wage inequality over time indicates a shift in the demand for human capital that may induce women with less human capital to drop out of the labor force, and induce women with more human capital into the labor force. That is, even if the overall rate of female labor force participation stayed relatively constant over a given time period, changing within-gender wage inequality may induce a change in the composition of which women are working. Importantly, this means that changes in women's relative wage growth may in part reflect a change in the composition of the female workforce.

Although this idea is difficult to test empirically, a variety of evidence is presented in the paper which suggests this changing composition is important: Mulligan and Rubinstein argue that the majority of the apparent narrowing of the gender wage gap reflects changes in female workforce composition over time, with a shift from negative selection into the female workforce in the 1970s to positive selection into the female workforce in the 1990s. We'll first walk through their model and then review the main empirical results.

3.1 Model

The Mulligan-Rubinstein Roy model is motivated by wanting to understand self-selection of women into market and non-market work. Given this, they write out two equations to start:

a potential market wage equation and a nonmarket wage equation. Let woman i 's date t log reservation wage r_{it} be:

$$r_{it} = \mu_t^r + \sigma_t^r \epsilon_{it}^r \quad (1)$$

and let her date t log potential wage (if working) w_{it} be:

$$w_{it} = \mu_t^w + \gamma_t + \sigma_t^w \epsilon_{it}^w \quad (2)$$

As in the Borjas model, these expressions decompose wages into the part explained by observable characteristics (μ_t^w and μ_t^r) and the part explained by unobserved characteristics (ϵ_{it}^w and ϵ_{it}^r). The ϵ_{it}^w and ϵ_{it}^r terms are normalized to have mean zero and standard deviation 1: $\epsilon_{it}^w \sim N(0, 1)$ and $\epsilon_{it}^r \sim N(0, 1)$. Note that this implicitly assumes that the underlying skill distributions are time-invariant. The unobserved factors are weighted by either market (σ_t^w) or non-market (σ_t^r) prices.

Woman i will choose to work at time t ($L_{it} = 1$) $\iff w_{it} > r_{it}$, which is true $\iff \frac{\sigma_t^w \epsilon_{it}^w}{\sigma_t^r} - \epsilon_{it}^r > -(\frac{\gamma_t + \mu_t^w - \mu_t^r}{\sigma_t^r})$. Mulligan and Rubinstein focus on the case where ϵ_{it}^w and ϵ_{it}^r follow a standard bivariate normal distribution: $\begin{pmatrix} \epsilon_{it}^w \\ \epsilon_{it}^r \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}\right)$. Note that this assumes that the cross-sectional correlation between log reservation wages and log potential market wages, ρ , is constant over time.

Mulligan and Rubinstein focus on the case in which all men work but not all women work, implying that the actual gender gap γ_t differs from the gender gap observed in the data. They derive an expression for the observed gender gap as follows. Let $\nu_{it} = \frac{\sigma_t^w \epsilon_{it}^w}{\sigma_t^r} - \epsilon_{it}^r$. The derivation here is *very* similar to what we worked out before for the Borjas model; in particular, recall that $E(\epsilon_0|v) = \frac{\sigma_{0,v}}{\sigma_0^2} v$. The observed gender gap G_t can then be written as:

$$G_t = \gamma_t + E\left(\sigma_t^w \epsilon_{it}^w \middle| \frac{\sigma_t^w \epsilon_{it}^w}{\sigma_t^r} - \epsilon_{it}^r > -\left(\frac{\gamma_t + \mu_t^w - \mu_t^r}{\sigma_t^r}\right)\right) \quad (3)$$

$$= \gamma_t + \sigma_t^w E\left(\epsilon_{it}^w \middle| \nu_{it} > -\left(\frac{\gamma_t + \mu_t^w - \mu_t^r}{\sigma_t^r}\right)\right) \quad (4)$$

$$= \gamma_t + \sigma_t^w E\left(E(\epsilon_{it}^w | \nu_{it}) \middle| \nu_{it} > -\left(\frac{\gamma_t + \mu_t^w - \mu_t^r}{\sigma_t^r}\right)\right) \quad (5)$$

$$= \gamma_t + \sigma_t^w E\left(\frac{\sigma_{\epsilon_{it}^w, \nu_{it}}}{\sigma_{\nu_{it}}^2} \nu_{it} \middle| \nu_{it} > -\left(\frac{\gamma_t + \mu_t^w - \mu_t^r}{\sigma_t^r}\right)\right) \quad (6)$$

$$= \gamma_t + \frac{\sigma_t^w \sigma_{\epsilon_{it}^w, \nu_{it}}}{\sigma_{\nu_{it}}} E\left(\frac{\nu_{it}}{\sigma_{\nu_{it}}} \middle| \frac{\nu_{it}}{\sigma_{\nu_{it}}} > -\left(\frac{\gamma_t + \mu_t^w - \mu_t^r}{\sigma_{\nu_{it}} \sigma_t^r}\right)\right) \quad (7)$$

Recall that $\sigma_{\epsilon_{it}^w} = 1$, so that $\rho_{w\nu} = \frac{\sigma_{\epsilon_{it}^w, \nu_{it}}}{1 \cdot \sigma_{\nu_{it}}} = \frac{\sigma_{\epsilon_{it}^w, \nu_{it}}}{\sigma_{\nu_{it}}}$. We can rewrite $E\left(\frac{\nu_{it}}{\sigma_{\nu_{it}}} \middle| \frac{\nu_{it}}{\sigma_{\nu_{it}}} > -\left(\frac{\gamma_t + \mu_t^w - \mu_t^r}{\sigma_{\nu_{it}} \sigma_t^r}\right)\right)$ as $\frac{\phi(-\delta_t)}{1 - \Phi(-\delta_t)}$ where $\delta_t = \frac{\gamma_t + \mu_t^w - \mu_t^r}{\sigma_{\nu_{it}} \sigma_t^r}$. Interchanging $\phi(-\delta_t) = \phi(\delta_t)$ and rewriting $1 - \Phi(-\delta_t) = \Phi(\delta_t)$ implies that $E\left(\frac{\nu_{it}}{\sigma_{\nu_{it}}} \middle| \frac{\nu_{it}}{\sigma_{\nu_{it}}} > -\left(\frac{\gamma_t + \mu_t^w - \mu_t^r}{\sigma_{\nu_{it}} \sigma_t^r}\right)\right)$ can be simplified to $\lambda(\delta_t) = \frac{\phi(\delta_t)}{\Phi(\delta_t)}$. We then have:

$$G_t = \gamma_t + \sigma_t^w \rho_{w\nu} \lambda(\delta_t) \quad (8)$$

The second term in this expression is the selection bias term weighted by market prices σ_t^w . It is useful to derive an expression for $\sigma_{\epsilon_{it}^w, \nu_{it}}$. Because $\nu_{it} = \frac{\sigma_t^w \epsilon_{it}^w}{\sigma_t^r} - \epsilon_{it}^r$, we know that $\nu_{it} \sim N\left(0, 1 + \left(\frac{\sigma_t^w}{\sigma_t^r}\right)^2 - \frac{2\rho\sigma_t^w}{\sigma_t^r}\right)$. We can then derive $\rho_{w\nu}$ as follows:

$$\sigma_{\epsilon_{it}^w, \nu_{it}} = \text{cov}(\nu_{it}, \epsilon_{it}^w) \quad (9)$$

$$= \text{cov}\left(\frac{\sigma_t^w \epsilon_{it}^w}{\sigma_t^r} - \epsilon_{it}^r, \epsilon_{it}^w\right) \quad (10)$$

$$= \text{cov}\left(\frac{\sigma_t^w \epsilon_{it}^w}{\sigma_t^r}, \epsilon_{it}^w\right) - \text{cov}(\epsilon_{it}^r, \epsilon_{it}^w) \quad (11)$$

$$= \frac{\sigma_t^w}{\sigma_t^r} \text{var}(\epsilon_{it}^w) - \text{cov}(\epsilon_{it}^r, \epsilon_{it}^w) \quad (12)$$

$$= \frac{\sigma_t^w}{\sigma_t^r} - \rho \quad (13)$$

Substituting $\sigma_{\nu_{it}} = \sqrt{1 + \left(\frac{\sigma_t^w}{\sigma_t^r}\right)^2 - \frac{2\rho\sigma_t^w}{\sigma_t^r}}$ and the expression for $\sigma_{\epsilon_{it}^w, \nu_{it}}$ from above into $\rho_{w\nu} = \frac{\sigma_{\epsilon_{it}^w, \nu_{it}}}{\sigma_{\nu_{it}}}$, we have:

$$G_t = \gamma_t + \sigma_t^w \left(\frac{\frac{\sigma_t^w}{\sigma_t^r} - \rho}{\sqrt{1 + \left(\frac{\sigma_t^w}{\sigma_t^r}\right)^2 - \frac{2\rho\sigma_t^w}{\sigma_t^r}}} \right) \lambda(\delta_t) \quad (14)$$

Let b_t denote the $\left(\frac{\frac{\sigma_t^w}{\sigma_t^r} - \rho}{\sqrt{1 + \left(\frac{\sigma_t^w}{\sigma_t^r}\right)^2 - \frac{2\rho\sigma_t^w}{\sigma_t^r}}} \right) \lambda(\delta_t)$ expression, which is a selection bias term (weighted in the G_t expression by market prices σ_t^w). Selection bias will be positive only if the numerator in this expression is positive (that is, if $\frac{\sigma_t^w}{\sigma_t^r} - \rho > 0$). Hence, the sign of self-selection depends on the ratio of market to non-market prices ($\frac{\sigma_t^w}{\sigma_t^r}$) and the correlation between market and non-market skills (ρ). This analogues the Borjas model, where self-selection depending relative inequality and the correlation of ability in the two settings.

Mulligan and Rubinstein then look at how selection changes with changes in the ratio of market to non-market prices, and show that $\left. \frac{\partial b_t}{\partial \left(\frac{\sigma_t^w}{\sigma_t^r}\right)} \right|_{d\lambda_t=0} > 0$. This comparative static says that an increase in market prices relative to non-market prices increases selection bias: if b_t is negative, it becomes less negative; if b_t is positive, it becomes more positive. They also derive a second comparative static of how b_t changes with changes in $\lambda(\delta_t)$. The sign of this comparative static can be positive or negative: if self-selection is negative, increases in female labor force participation will increase female wages; on the other hand, if self-selection is positive, increases in female labor force participation will decrease female wages.

3.2 Data and estimation

Mulligan and Rubinstein use the March Current Population Survey (CPS) files in a series of empirical specifications; we here focus on their two main specifications: a Heckman two-step estimator, and an identification at infinity analysis. Recovering the latent gender gap - the goal of these exercises - is difficult, and neither of these strategies is perfect.

The Heckman two-step estimator follows directly from the Roy model (taking seriously the normality assumption). Mulligan and Rubinstein estimate a probit model of female labor force participation as a function of demographic characteristics (\mathbf{X}_{it}) and an excluded instrument (the number of children aged 0-6 interacted with marital status); \mathbf{Z}_{it} denotes \mathbf{X}_{it} together with the excluded instrument:

$$P_t(\mathbf{Z}_{it}) = \Phi(\mathbf{Z}_{it}\delta_t) = Prob(\text{work}|\mathbf{Z}_{it}, \text{female}) \quad (15)$$

$P_t(\mathbf{Z}_{it})$ are estimated as the fitted values from this probit equation, estimated on a sample of women; $P_t(\mathbf{Z}_{it})$ is set to 1 for men. Then, on the sample of employed men and women, they estimate log wages as a function of \mathbf{X}_{it} and the Inverse Mills Ratio $\lambda(\mathbf{Z}_{it}\delta_t) = \frac{\phi(\mathbf{Z}_{it}\delta_t)}{\Phi(\mathbf{Z}_{it}\delta_t)}$:

$$w_{it} = \mathbf{X}_{it}\beta_t + g_i\gamma_t + g_i\theta_t\lambda(\mathbf{Z}_{it}\delta_t) + u_{it} \quad (16)$$

Even if you don't use the Heckman two-step estimator in your own research, it is important that you are literate in this method and understand its strengths and weaknesses. In short, in the absence of an excluded instrument the Heckman correction lives off a functional form assumption: the Inverse Mills Ratio is a non-linear function of the same \mathbf{X}_{it} that are included linearly in the second (wage) regression. Here, Mulligan and Rubinstein use an instrument, but the exclusion restriction is not very plausible. These concerns are what motivate the second (identification at infinity) strategy.

The Roy model suggests that selection bias disappears for groups with characteristics \mathbf{X}_{it} such that practically all individuals work, even dropping the normality assumption. This observation motivates an identification at infinity method which estimates the wage equation on a sample *selected* such that almost all of the sample works. Mulligan and Rubinstein implement this method by estimating a probit equation for labor force participation separately by gender as a function from the \mathbf{X}_{it} 's above and a vector of coefficients for gender. The purpose of this probit model is to select which demographic groups to include in the wage equation: they include only men and women who are employed and who have demographic characteristics such that their predicted probability of employment α is close to one. In practice, they show results for several α 's. A selection-corrected gender wage gap is then calculated as the conditional gender wage gap for this selected sample. This method essentially predicts female labor force participation as a function of a bunch of stuff including schooling. But schooling is a choice variable, and we know that the selection of women vs. men into higher education levels has changed over time, so it seems unlikely that comparing (essentially) the wage gap between highly educated men

and highly education women over time is “taking care of” selection given the changing selection into education over time (differentially by gender).

3.3 Results

Mulligan and Rubinstein’s main results are summarized in Figure VI. The Heckman two-step and identification at infinity strategies give similar results: both suggest the latent gender wage gap has barely changed since 1975.

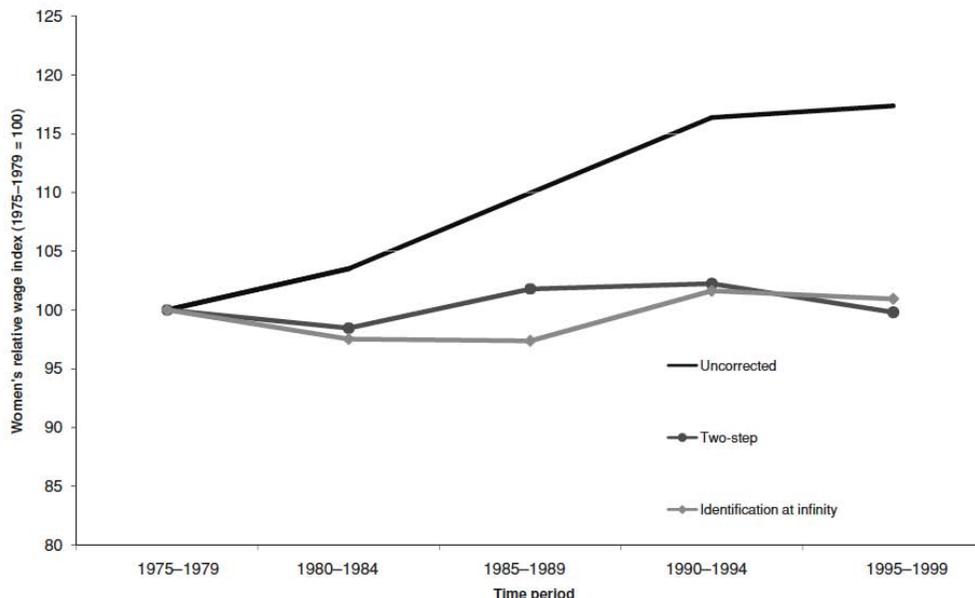


FIGURE VI
Gender Relative Wage Indices with and without Selection Corrections

The figure graphs three time series of indices of women’s wages as a ratio to men’s (1975–1979 = 100), net of demographic characteristics. The series differ according to the method for correcting selection bias. The calculations use our CPS sample of white persons aged 25–54, trimming outliers and adjusting topcodes as described in Appendix I.

¥ 'C! ZcfX' l b]j Yfg]mDfYgg"5``f][\hg'fYgYfj YX""H\]g'Vt'bh'bh']g'YI Wl XYX'Zfca 'ci f'7fYU]j Y
7ca a cbg']WbgY": cf'a cfY ']bZcfa Uh]cbz'gYY '\hd. ##cV# "a]h'YXi #\ Y'd#ZJe! ZJ]f! i gY#"

In terms of key take-aways, I would stress two. First, both of the empirical strategies here leave room for improvement, in the sense that assumptions underlying each approach seem unlikely to hold. Second, substantively this is an incredibly important question, and taken at face value this is a very thought-provoking set of results. If we think that in fact there has been little to no change in the latent gender wage gap over time, that provides a very different picture of how women are faring in the labor force relative to if we thought that womens’ wages were converging towards mens’ wages over time.

References

Bertrand, Marianne, Claudia Goldin, and Lawrence Katz, “Dynamics of the gender gap among young professionals in the corporate and financial sectors,” *American Economic Journal: Applied Economics*, 2010, 2 (3), 228–255.

Goldin, Claudia, *Understanding the Gender Gap: An Economic History of American Women*, Oxford University Press, 1990.

—, “Richard T. Ely lecture: The quiet revolution that transformed women’s employment, education, and family,” *American Economic Review*, 2006, *96* (2), 1–21.

—, “AEA Presidential Address: A grand gender convergence, Its last chapter,” *American Economic Review*, 2014, *104* (4), 1091–1119.

— **and Lawrence Katz**, “The most egalitarian profession: Pharmacy and the evolution of a family-friendly occupation,” *Journal of Labor Economics*, forthcoming.

Mulligan, Casey and Yona Rubinstein, “Selection, investment, and women’s relative wages over time,” *Quarterly Journal of Economics*, 2008, *123* (3), 1061–1110.

MIT OpenCourseWare
<http://ocw.mit.edu>

14.662 Labor Economics II
Spring 2015

For information about citing these materials or our Terms of Use, visit: <http://ocw.mit.edu/terms>.