

## **Re-Visiting the Family Gap in Pay in the United States**

**Ipshita Pal  
Jane Waldfogel**

**Columbia University**

**August 5, 2014**

### **Abstract**

Previous studies have examined the family gap in pay – the differential in hourly wages between women with children and women without children - at a point in time, across groups, or across countries, but we know little about whether, and how, the family gap has changed over time. We provide new evidence on this question for the United States from 1977 to 2007, using data from the 1978, 1988, 1998, and 2008 March Current Population Survey and a consistent set of methods to adjust for selection into motherhood and employment. We find that for women overall, after accounting for selection into motherhood, the penalty to motherhood in 2007 is similar to 1977. However, the results differ by race/ethnicity, education level, and marital status; most importantly, we find that the magnitude of the family gap has declined in recent decades for married mothers, but increased for never married mothers.

Keywords: family gap, gender gap, motherhood penalty, women's pay

J16; J31

The family gap in pay – the differential in hourly wages between women with children and women without children – has drawn considerable attention from economists and sociologists. A series of increasingly rigorous studies have examined the magnitude of the gap at particular points in time, as well as disparities in the gap across groups and across countries. Yet, we know surprisingly little about *whether, and how, the family gap in pay has changed over time.*

We provide new evidence on this question for the U.S. over the period 1977 to 2007, using comparable data on nationally representative samples of women from the 1978, 1988, 1998, and 2008 rounds of the March Current Population Survey (CPS) and applying to each year of data the same methods to adjust for bias associated with selection into motherhood and selection into employment. To briefly preview the results, we find that for women overall, accounting for selection into motherhood, the penalty to motherhood in 2007 is similar to what it was in 1977. This overall conclusion is unchanged even after taking changes in part-time employment, occupation, and industry into account.

Results are not uniform, however. We find persistent family penalties for Non-Hispanic White women and Black women, but not for Hispanic women. Results by education level also reveal considerable heterogeneity. Most strikingly, we find no significant family penalties at any year for those with less than a high school education, in contrast to the other education groups for whom significant penalties are seen in all four years. Finally, examining trends by marital status, we find a marked decline in the family gap for married mothers over the past two decades, a period when married fathers' involvement in child care and household work has been increasing. In contrast, we find a sharp increase in the magnitude of the family gap for never married

mothers in the 1980s and 1990s, a period when welfare reforms pushed many low-skilled single mothers into the labor market.

### **1. Prior Research on the Family Gap in the United States**

One of the earliest explicit estimates of the differential in hourly pay between women with children and women without children appeared in *Women's Quest for Economic Equality*, by Victor Fuchs (1988). Using Census data from 1960 and CPS data from 1986, Fuchs estimated that women with children earn 7-9% less than childless women. Researchers in the 1990s found gaps of similar magnitude, with mothers' hourly wages trailing those of non-mothers by roughly 10-15% (Sanders Korenman and David Neumark 1992; Jane Waldfogel 1997).

Studies since the 1990s have estimated increasingly sophisticated models, and examined differences in the family gap between groups.<sup>1</sup> Many studies use the National Longitudinal Survey of Youth (NLSY) or Young Women (NLSYW), employing both pooled OLS as well as fixed effects models (Hiromi Taniguchi 1999; Michelle Budig and Paula England 2001; Deborah Anderson, Melissa Binder, and Kate Krause 2002; Charles Baum II 2002; Sarah Avellar and Pamela Smock 2003; Catalina Amuedo-Dorantes and Jean Kimmel 2008) to analyze the effect of children on women's wages. Concerned that fertility may be endogenous to the wage equation (if lower-earning women select into childbirth or if women time childbirth to coincide with periods of slow wage growth), some researchers have made use of instrumental variables (IV) models to gauge the causal effect of children on wages (Sanders Korenman and David Neumark 1992;

---

<sup>1</sup> There are also many studies that examine the family gap in other countries, and across countries (see e.g. Erin Todd 2001; Susan Harkness and Jane Waldfogel 2003; Wendy Sigle-Rushton and Jane Waldfogel 2007; Markus Gangl and Andrea Ziefle 2009).

Catalina Amuedo-Dorantes and Jean Kimmel 2008; Katie Winder 2008). Researchers have frequently used Heckman selection correction models to correct for selection into employment (Sanders Korenman and David Neumark 1992; Catalina Amuedo-Dorantes and Jean Kimmel 2005; Rebecca Glauber 2007; Markus Gangl and Andrea Ziefle 2009) since the women most likely to be affected by the motherhood wage penalty are also more likely to remain out of the labor force, thereby biasing down the magnitude of the wage penalty in uncorrected models. The use of increasingly sophisticated models has improved the rigor of research in this area, but has also made it difficult to compare estimates across studies.

Over the last decade, researchers have increasingly looked at variation in the motherhood penalty between groups.<sup>2</sup> Studies have obtained mixed results as to how the motherhood wage penalty varies by education and skill level. Some researchers have found the penalty to be smaller (Hiromi Taniguchi 1999; Erin Todd 2001) or even absent (Deborah Anderson, Melissa Binder, and Kate Krause 2003; Catalina Amuedo-Dorantes and Jean Kimmel 2005;) at the highest end of the educational attainment distribution and larger in the middle (Anderson et al 2003, Todd 2001). Contrary to these findings, other researchers have found no penalties for the least educated mothers (Deborah Anderson, Melissa Binder, and Kate Krause 2002) and the largest penalties for women with the highest skill levels (Elizabeth Ty Wilde, Lily Batchelder, and David Ellwood 2010). With regard to differences in the motherhood penalty by race and ethnicity, there is some evidence that Hispanic mothers face no penalty (Rebecca Glauber 2007) or smaller penalties than other groups (Michelle Budig and Paula England 2001); Black mothers also tend to face smaller penalties (Jane Waldfogel 1997; Rebecca Glauber 2007; but see also

---

<sup>2</sup> See also recent review by Margaret Gough and Mary Noonan (2013).

Deborah Anderson, Melissa Binder, and Kate Krause 2003). With regard to variation by marital status, some evidence has linked marriage to a larger motherhood penalty (Michelle Budig and Paula England 2001; Rebecca Glauber 2007; David Loughran and Julie Zissimopoulos 2009).<sup>3</sup>

Few studies have examined changes in the family gap over time. Jane Waldfogel (1998a) presents parallel analyses of data from the NLSY and NLSYW in 1980 and 1991 (as well as more limited data from the CPS for prime age workers in 1978, 1988, and 1994) and concludes that the family gap was rising over that period, even as the overall gender pay gap was narrowing. Sarah Avellar and Pamela Smock (2003) also use the NLSYW (1975-1985) and the NLSY (1986-1998) and find a 3% motherhood wage penalty in both time periods.

In this paper, we examine the family gap over a longer period of time – using data from 1977 to 2007.<sup>4</sup> To assure comparability over time, as detailed in the next section, we use a consistent source of data, the March CPS, and apply the same methods in each year to adjust our estimates for selection into motherhood and employment. We examine the role played by part-

---

<sup>3</sup> Michelle Budig and Melissa Hodges (2010) included interactions of marital status with the number of children at different income quantiles and found that never married women earned lower penalties (compared to both the married and the divorced/separated) in the bottom quantiles only, while ever-married women at the top earnings quantiles earned a motherhood bonus. See also Alexandra Killewald and Jonathan Bearak (2014) for a re-analysis using unconditional quantile regressions and the original researchers' response in Budig and Hodges (2014).

<sup>4</sup> In unpublished work, Rebecca Glauber (2013) carries out a similar analysis for the period 1980-2010. She finds the motherhood penalty increased for unmarried mothers and decreased for married mothers over this period.

time employment, occupation, and industry and how that may have changed over time. And, we examine the extent to which the family gap differs by race/ethnicity, education level, and marital status, and how that variation may have changed over time.

The period we examine is an interesting one, because it is a period when the overall gender gap in pay declined. At the end of the 1970s, women's earnings averaged 62% of men's, but by 2008 this figure had risen to 80%. The most pronounced decrease in the gender gap was for women in the 25-to-34 age range, whose median weekly earnings relative to men's rose from 68% in 1979 to 89% in 2008 (Bureau of Labor Statistics 2009a, b). There was substantial variation in the trends in the gender gap by race and ethnicity, but all groups of women gained (Bureau of Labor Statistics 2008). However, we do not know if these trends in the gender gap were accompanied by comparable changes in the family gap.

## **2. Data and Methods**

Our data are drawn from the March Current Population Survey (CPS), a nationally representative survey of the non-institutionalized population in the U.S.<sup>5</sup> The CPS is the source of official labor force statistics and is administered monthly. We use the March CPS, which provides retrospective data on earnings in the prior year as well as comprehensive data on individual characteristics and family demographics.

We use data from the March 1978, 1988, 1998, and 2008 surveys, which provide information on earnings in 1977, 1987, 1997, and 2007 respectively. Our selection of these years is guided by the fact that they are a decade apart and occur at roughly similar points in the

---

<sup>5</sup> Data used in this research is from Miriam King et al (2010), publicly available at <https://cps.ipums.org>. Statistical models may be accessed from the authors upon request.

economic cycle (National Bureau of Economic Research 2010). We end our analysis with 2007 because of the Great Recession which occurred immediately afterwards.<sup>6</sup>

Our primary analysis sample in each year consists of women age 25 to 44 years who worked in the prior year and reported some income from employment.<sup>7</sup> Restricting analysis to prime-age workers is standard and ensures that estimates are not affected by including younger people who may still be enrolled in school or older people who may be starting to withdraw from the labor market.<sup>8</sup> We retain in our sample all types of workers except the self-employed (who represent 3-4% of our sample each year) and unpaid family workers (who represent less than 1% in each year's sample of working women).<sup>9</sup>

---

<sup>6</sup> We were not able to use data from 1968 March CPS because it does not include information on weeks or hours worked in the past year which is necessary to construct hourly wages.

<sup>7</sup> This represents 67% of women in the 25-44 age group in 1977, 78% in 1987, 79% in 1997 and 78% in 2007. See also Appendix A for sample divided by motherhood status.

<sup>8</sup> The March CPS contains data on children in the household, but not children ever born; thus among older women without children in the home, we cannot distinguish between those who did not ever have children and those who have children no longer living at home. We provide supplementary estimates where we test the sensitivity of our results to including younger or older workers. See Appendix C.

<sup>9</sup> We carried out supplementary analyses to test the sensitivity of our results to including the self-employed and, in results not shown but available on request, found that our overall results were unchanged.

Our focal outcome variable is the natural log of *hourly wages*. We calculate the wage in each year by first creating a variable to denote the *total hours worked last year* (product of *weeks worked last year* and *usual hours worked per week last year*) and then dividing the *annual wage and salary income from last year* by this variable to arrive at the *hourly wage*. We adjust wages for inflation using the annual average CPI-U (as provided by the Bureau of Labor Statistics in Malik Crawford and Jonathan Church 2014: Table 24. “Historical Consumer Price Index for All Urban Consumers (CPI-U): U. S. city average, all items”). Unless otherwise noted, reported wage figures are in 2011 dollars. We exclude women who reported wages less than 45% of the federal minimum wage for the year (this proportion is roughly similar across the four years, 0.9-2.6% of working women).<sup>10</sup> After excluding those not working or with wages below the cut-off, our final wage samples represent 60% of women age 25-44 in the CPS in 1977, 71% in 1987 and about 72% in both 1997 and 2007 (details in Appendix A).

Our key independent variable is a dummy variable for *motherhood*, which we define based on the presence of own children under the age of 18 in the household.<sup>11</sup> Thus in all models, the reference category is women with no children under age 18 in the household. We refer to this

---

<sup>10</sup> The CPS data is top-coded so we did not have to exclude any women for high wages.

<sup>11</sup> We also estimated models allowing the effects of motherhood to vary by the number of children and found mostly linear effects.



latter group as non-mothers.<sup>12</sup> The proportion of mothers to non-mothers is roughly similar across the four years, with 61-67% mothers and 33-39% non-mothers.

There are several challenges to estimating the causal effect of children on women's wages. The first is selection into motherhood. Women who have children may differ from other women in ways that also affect their wages; if so, the failure to control for those differences will lead to biased estimates of the "effect" of children on women's pay.

The standard approach to addressing such selection in the family gap literature is to estimate multivariate ordinary least squares (OLS) regression models that include controls for the types of characteristics thought to affect both motherhood and wages – characteristics such as age, education, race and ethnicity, and so on. We adopt this approach in our first set of models, estimating the following equation(s) separately for each year:

$$\ln(Wage)_i = \beta_0 + \beta_1 Mother_i + \sum_j \beta_j X_{ji} + \varepsilon_i \quad (1)$$

where  $\ln(Wage)$  is the natural log of hourly wage (in 2011 dollars) for the  $i$ -th respondent;  $Mother$  is a dummy variable denoting whether a woman is a mother or not (as defined above);  $X$  is the covariate vector and includes  $j$  demographic, family, and human capital variables (*age* and *age squared*, and dummies denoting *educational attainment*, *marital status*, and *race and ethnicity*). We use four categories for educational attainment: less than high school,

---

<sup>12</sup> As mentioned, some women who we code as non-mothers may have had children in the past. Including such women among the non-mothers will attenuate differences between the mother and non-mother groups and lead us to under-estimate the magnitude of the family gap.

high school graduate, some college, and college graduate.<sup>13</sup> We use three categories for *marital status*: married, previously married, and never married. And we use the following categories for *race and ethnicity*: non-Hispanic White, non-Hispanic Black, and Hispanic.<sup>14</sup>  $\beta_1$  is our coefficient of interest in Eq.1 and provides an estimate of the percentage difference in wages between mothers and non-mothers in the given year.

A more refined approach to addressing selection, now quite commonly used although until recently not on this topic, is the estimation of propensity score models.<sup>15</sup> These models take

---

<sup>13</sup> Before 1992, information on educational attainment was collected by asking respondents their highest grade of school or year of college completed. Since 1992, the CPS has asked respondents their highest degree or diploma attained. This change led to some issues of comparability which we address following methods detailed by David Jaeger (1997, 1998).

<sup>14</sup> The *race* variable has gone through several changes over the years (Mary Bowler, Randy Ilg, Stephen Miller, and Ed Robinson 2003). We have created a *race* variable that is comparable across years and combined that with a *Hispanic* variable to create three race/ethnic categories. We combine the “Other” category (about 2.5-8% across the four years) into the Non-Hispanic White category. This allows us to get significantly better matched samples in our inverse probability of treatment weighted models.

<sup>15</sup> Marianne Simonsen and Lars Skipper (2006) use propensity score matching in a Danish sample (cross-sectional data from 1997). Miriam Beblo, Stefan Bender, and Elke Wolf (2008) use propensity score matching on German employment data. Most recently, Tarja Viitanen (2014) uses propensity score matching on longitudinal data from the UK’s National Child Development Study.

the same kinds of observed characteristics into account and adjust estimates for the likelihood of being in the “treatment” group (in this case, mothers). A major assumption underlying this approach is the ignorability of treatment assignment or conditional independence; that is, conditional on a set of observed covariates, the outcome is independent of treatment assignment. The propensity score of each woman is the probability of being a mother, conditional on observed pre-treatment covariates.<sup>16</sup> To obtain this, we first estimate a binary probit model with being a mother as a function of the set of confounding covariates that we believe affect selection into motherhood (as well as wages); these variables are either fixed over time or are assumed to be measured pre-treatment.

$$Mother_i = \beta_0 + \sum_j \beta_j X_{ji} + u_i \quad (\text{Selection Eq. 1})$$

where, *Mother* is the binary treatment (Mother or Non-Mother);  $X_j$  represents a vector of covariates that determine selection into motherhood and includes but is not limited to all covariates in the corresponding regression equation.

The predicted values from this probit regression give us propensity of being a mother. We use this propensity score to re-weight the sample using the method of inverse probability of

---

To our knowledge, no previous study in this literature has used the Inverse Probability of Treatment Weighting (IPTW) technique to correct for selection into motherhood.

<sup>16</sup>“If potential outcomes are independent of treatment status conditional on a multivariate covariate vector  $X$ , then the potential outcomes are independent of treatment status conditional on a multivariate scalar function of covariates, the propensity score” (Paul Rosenbaum and Donald Rubin 1983, 1984, 1985) .

treatment weighting (IPTW)<sup>17</sup>. After re-weighting, we test the covariate balance to ensure that there are no significant differences in means between treatment and control groups across all covariates.<sup>18</sup> We then run the adjusted regression (equation 1) using the re-weighted sample, which allows us to place more weight on those non-mothers who had a higher propensity score.

A common limitation of both standard OLS and IPTW regression models is that they adjust only for observable differences between groups. There may still be unobservable differences between women who become mothers and those who do not. For example, the

---

<sup>17</sup> Using the predicted values from the probit regression (Selection equation 1), i.e. the estimated propensity score,  $p$ , we create inverse probability of treatment weights as follows:  $1/p$  if  $Mother=1$  and  $1/(1-p)$  if  $Mother=0$ . (see for instance, Jared Lunceford and Marie Davidian 2004 for a discussion of the theoretical properties of the IPTW estimator).

<sup>18</sup> We modeled treatment (mother) in a variety of ways, using higher order terms as well as interaction terms in the selection equation to achieve covariate balance following standard diagnostic procedures for IPTW analysis (Stephen Cole and Miguel Hernan 2008; Stephen Morgan and Jennifer Todd 2008; Peter Austin 2011) and implemented it using the Stata module `psmatch2` (Edwin Leuven and Barbara Sianesi 2003). Other than the main covariates, we have tried two-way, three-way, and four-way interactions among them and inclusion of the following variables—region, whether residing in metropolitan area, nativity and citizenship status, in order to find models where each covariate is balanced. For our main results (Table 1), IPTW selection models are the best fitting models (using Akaike’s Information Criteria, AIC and Schwartz’s Bayesian Information Criteria, BIC) among such fully balanced models for each year. (See Balance Statistics in Appendix D)

former group may be less career-oriented. If so, even estimates from fully controlled or inverse probability of treatment weighted regression models could still be biased. However, this limitation cannot easily be addressed without an experiment that randomly assigns some women to motherhood (or a natural experiment or instrument that does something similar).

A second challenge to causal estimation is selection into employment. Women, and particularly those with children, do not always participate in the labor market, and thus at any single point in time, the wage sample will contain a selected group of wage-earners. If that selection is correlated with wages (e.g. if the mothers who work are those who face the smallest wage penalties), estimates that do not take it into account will be biased. The standard method in the family gap literature to address such bias is the use of a Heckman selection correction model (James Heckman 1979) and we apply that method here as well.

Recall that our wage sample is composed of women who worked (and had valid wages) in the previous year. Going back to our regression equation, Eq.1, we note that it is estimated only for this sample. To correct for selection into the wage sample, we need a variable that predicts this but is otherwise uncorrelated with the wage. We assume that the natural log of *other household income* (*OHY*, defined as the difference between total annual household income and the respondent's own annual income from wages) influences the woman's decision to work, but that once a woman is in the labor force, *OHY* has no impact on her wages. To correct for

selection into employment, we estimate the effect of motherhood on wages in a two-step process by first estimating the probability for a mother to be employed through a probit equation.<sup>19</sup>

$$\text{Selection } S_i = \beta_0 + \beta_1 \text{Ln\_OHY} + \sum \beta_j X_{ji} + u_i \text{-----(Selection Eq.2),}$$

A woman is selected into our wage sample only if  $S_i > 0$ . *OHY* is other household income as defined above and *X* is the same vector of covariates as in the wage regression equations.

While sample selection correction models have been widely used in this literature, they have limitations. They may not address all the factors associated with selection into employment and in particular those that are not observable. In addition, they rely on assumptions about the exogeneity of the predictors used in the selection regression (in our case, other household income), and their results may be sensitive to which predictors are included.<sup>20</sup> A further point to note is the quantity that they estimate – the wages that mothers *would* receive if they were in the labor market. While this is an interesting estimate, it is not the main estimate that we are concerned with here – which is the wages mothers *do* receive, relative to non-mothers. For this reason, we place less weight on the sample selection corrected estimates than on our IPTW estimates.

As is evident from this discussion, there are limitations to the methods we use to correct for selection into both motherhood and employment. However, for the purposes of this analysis,

---

<sup>19</sup> Sample selection causes bias because  $u_i$  and  $\varepsilon_i$  are correlated. Heckman (1979) showed that the sample selection bias can be analyzed as a form of omitted variable bias, where the omitted variable  $\lambda$  is the inverse mills ratio obtained from the participation equation.

<sup>20</sup> For example, when we estimated our sample selection correction models using the state unemployment rate as our exogenous predictor, we obtained different, and less stable, results.

the key element is that the methods we apply are consistent across the four data points. This maximizes comparability over time and increases confidence that our estimates may be capturing changes over time.

Although the primary question of interest in this analysis is the size of the family gap and whether and how it is has changed over time for women overall and for specific groups, we would also like to know what factors might explain the gap and changes in it over time. Researchers in this area (drawing in particular on the work of Gary Becker, 1981, 1985) have emphasized three possible (and not mutually exclusive) types of explanations. First, mothers and non-mothers may differ in terms of their human capital. In addition to differences that may precede and be associated with the selection into motherhood, there are likely to be differences that arise subsequent to, and as a result of, motherhood. Chief among these would be reductions in work experience and job-specific tenure, switches into part-time jobs, and reductions in effort or motivation. Second, mothers and non-mothers may work in different types of jobs, with mothers more likely to be concentrated in more family-friendly occupations or industries. Third, employers may discriminate against mothers, assuming or perceiving them to be less dedicated or career-focused.

We cannot observe employer discrimination in the CPS. Nor can we observe actual work experience, job-specific tenure, or work effort. We can however examine the role played by part-time work, as well as occupation and industry. We do so, in an additional set of models, by augmenting our regressions with controls for part-time work (defined in the CPS as less than 35

hours per week) as well as controls for occupation (seven categories; reference “professional and technical”) and industry (nine categories; reference “agriculture, forestry and fishing”).<sup>21</sup>

### 3. Results

Figure 1 about here: half page

Figure 1 displays the mean wages of mothers and non-mothers in our four annual samples (full descriptive statistics are provided in Appendix A). It is apparent that in the earliest years –

---

<sup>21</sup> We have used the following selection strategy in the IPTW selection models for results controlling for part-time/occupation/industry (Table 2), as well as for results by race/ethnicity (Table 3), education (Table 4), and marital status (Table 5). First, if we can find a selection model that provides strong balance across all covariates consistently for each year in a given panel, then we have preferred that selection model. If we have more than one such consistent selection model for a given panel, we have selected the one with the best fit, based on AIC and BIC fit statistics. Second, if there is no such consistent well-balanced model, we have used the best fitting one among the well-balanced ones for each year, and each panel. Finally, if there is no selection model that provides full balance across all covariates for a given year, and given panel, then we have used the one that gives the least mean bias for that year and panel. We have drawn upon the statistical literature on IPTW to design this system of choosing selection models but note that the literature does not prioritize one step over the other (Stephen Cole and Miguel Hernan 2008; Stephen Morgan and Jennifer Todd 2008; Peter Austin 2011). (Balance Statistics pertaining to Tables 2-5 and Appendix C available upon request)



1977 and 1987 - mothers have lower average wages than non-mothers (Fig 1) but the pattern is different in the later years – mothers nearly reach parity with non-mothers in 1997, and the difference seems negligible in 2007. But of course, these descriptive statistics do not tell us how earnings compare holding constant differences in characteristics between the groups.

Table 1 about here: full page

Table 1 shows results from our regression models controlling for selection into motherhood (Models 1-2) and selection into employment (Model 3). Results from Model 1 (OLS models with controls for age, age squared, educational attainment, marital status, and race/ethnicity) indicate a significant penalty to motherhood in each year. Comparing the OLS results across years, it appears the motherhood penalty has declined over the last four decades -- it is significantly lower in both 1997 and 2007 than it was in 1977 (Table 1).<sup>22</sup>

Results from our preferred model, Model 2 (IPTW), are similar in magnitude and suggest that there is nothing inherently different in the observed characteristics of mothers that explain their lower wages compared to non-mothers. We however do not see a significant decline in the overall motherhood penalty in our preferred models, such that for prime working age women as a

---

<sup>22</sup> The table notes indicate in which years coefficients are significantly different from those for 1977. We conduct Wald tests for equality of coefficients across models; to implement it in Stata, we use a ‘seemingly unrelated estimation technique’, which allows us to stack together two models and compare the coefficients as if they were estimates of the same model.

whole, the motherhood penalty is no smaller in 2007 than in 1977. Mothers continue to earn on average about 5-6% less than women without children.

In Model 3 (Heckman correction), we turn our attention to selection into employment. There are three noteworthy results here. First, in all years, the penalty to motherhood becomes slightly more negative, confirming that failure to account for selection into employment leads to biased estimates. Second, consistent with this, the selection correction term, *lambda*, is statistically significant and positive in most models (indicating that the error terms in the selection equation and the main regression equations are positively correlated), suggesting that it is the women who face the smallest wage penalties who are most likely to be employed. Third, although they yield slightly more negative estimates, the Heckman results are consistent with the IPTW results in terms of the trend over time, again indicating that the motherhood penalties in 2007 are no smaller than in 1977.

So, the most striking result in Table 1 -- across both selection corrected models -- is the apparent stability in the family gap over time, culminating in a significant motherhood penalty in 2007 that we is not significantly different from the penalty in 1977.<sup>23</sup>

Table 2 about here: half page

---

<sup>23</sup> We also find that the motherhood penalty increased significantly between 1977 and 1987 -- from 6% to 11% in models that correct for selection into motherhood, and from 9.5% to 16% in models that correct for selection into employment; when we test the 1987 coefficient versus those of the last two years, we find a significant decline in the penalty from the exceptionally high 1987 level.

As discussed, we are not able to explore all the possible explanations for the family gap and change or lack of change over time, but we can examine the role of part-time work, occupation, and industry, and whether that has changed over time. Accordingly, in Table 2, we present estimates from augmented OLS and IPTW models, to which we have added controls for part-time, occupation, and industry.<sup>24</sup> We find, as expected, that the direct effect of motherhood is slightly lower when we control for part-time (since a portion of mothers' lower average wages is accounted for by their higher propensity to work in lower-paid part-time jobs), but this pattern is seen in each year of our data and does not seem to be changing over time. Subsequently controlling for occupation and for industry decreases the motherhood penalty in most of our preferred models as expected, and helps explain some of the family gap. However, after including part-time, occupation, and industry, the pattern over time in the family gap remains similar to what we observed in our main models – resulting in a similar overall motherhood penalty in 2007 and 1977.

Finally, we would like to know to what extent the family gap varies across groups and whether that variation has changed over time. We therefore repeat our main models (OLS and IPTW) for sub-groups defined first by race/ethnicity (Table 3), then by education (Table 4), and then by marital status (Table 5).

Table 3 about here; half page

---

<sup>24</sup> We do not include Heckman models here because those would have to account not just for selection into employment but also into part-time, occupation, and industry.

With regard to race/ethnicity, the results for non-Hispanic white women mirror the results for the overall sample; we find persistent significant negative penalties around 5.5-7.5% for non-Hispanic White women (although with a sharp increase to 13.5% in 1987). For non-Hispanic Black women, we find a similar persistent negative penalty of 7.6-8% (but a sharp increase to 12.8% in 1997). In contrast, among Hispanic women, there was no significant wage penalty in any year except 1997, when there is a significant 4.6% penalty to motherhood.

Table 4 about here; half page

As discussed earlier, previous research has obtained mixed results as to how motherhood penalties vary by education level. In our results, the only group exempt from motherhood penalties is the lowest education group (those with less than high school education). We find significant penalties for all other education groups and little clear evidence of a difference in magnitude between groups, except those with only a high school diploma who show a significant decline in the penalty over time. For college graduates, we find significant penalties in all years except 1977.

Table 5 about here; half page

Finally, results by marital status provide evidence that motherhood penalties have fallen significantly over time for married mothers. Penalties for previously married mothers do not

reveal a similar decline over time; and those for never married mothers rose sharply in the 1980s and 1990s.

#### **4. Supplementary Estimates**

We carried out several supplementary sets of analyses to test the robustness of our results (Appendix C). First, we re-estimated our main models for different age groups -- expanding the sample to include younger workers (adding those age 18-24) or older workers (adding those age 45-55) or both. Second, we re-estimated our main models including workers who were self-employed. These changes slightly altered the point estimates of the effects of motherhood, but they did not alter the main findings regarding trends over time.

#### **5. Discussion and Conclusions**

This paper had a modest goal – to re-visit the family gap in pay in the U.S. and determine whether it has changed over time. Using comparable data from the March CPS and contemporary methods to control for bias associated with selection into motherhood and employment, we find that for prime working age women as a whole, the family gap is no smaller in 2007 than it was in 1977. Holding constant differences in demographic and human capital characteristics, in our preferred IPTW models, women with children earn on average about 5-6% less than women without children in both years.

However, this overall story masks considerable heterogeneity in the size of the gap, and trends in the gap, by race/ethnicity, education, and marital status. Both non-Hispanic White and Non-Hispanic Black mothers have always received lower wages than otherwise comparable non-mothers, but the wage penalty reached its highest level in 1987 and 1997 respectively for these groups; Hispanic mothers historically did not face a motherhood penalty although we do find evidence of a penalty in 1997.

We also find divergence in motherhood wage penalties by education level. We find significant wage penalties to motherhood among women with a high school or more education, but not for those with less than a high school education. In future work, sample sizes permitting, it would be useful to examine differences by education level within race/ethnic groups since variation by the two sets of factors may be confounded.

Finally, we see heterogeneity in the motherhood wage penalties by marital status. For married women, the significant negative penalties to motherhood in the earlier decades are generally smaller in the most recent data. We find the opposite scenario for never-married women.

We were not able to take into account some key factors including women's work experience, job tenure, work effort, and motivation, and the role that changes in these factors may have played in the changing family gap. This is an important topic for future research. Although work effort and motivation are difficult to measure in large datasets, analyses using longitudinal data could shed light on the role that changes in work experience and job tenure have played.

While we cannot formally test explanations for what we find in terms of both change and lack of change in the family gap over time, we can posit a few possible explanations. First, there has been a change in women's labor force attachment patterns over the last few decades, with mothers returning to work sooner after childbirth now than they did in the 1970s. Among women with a first birth, only 22% were working 3 months after birth and about 40% were working 12 months after birth in 1976-80; these proportions increased to 44% and 64% respectively in 2005-07 (Lynda Laughlin 2011). Inasmuch as employment continuity as well as work experience are critical to wages, married mothers' increased labor force attachment should help explain the

narrowing of the family wage gap for that group. However, the most dramatic decreases in women's time away from the labor force following a first birth took place in the 1980s with only a very gradual progression afterwards, whereas in our analysis, the significant fall in the wage gap for married mothers occurs in the 1990s. This pattern in the data suggests that changes in labor force attachment post-birth may not have played a large role in reducing the family gap for this group, or perhaps did so with a lag.

Second, changes in men's roles could help explain the declining family gap for married women. Even though parenting has become more intensive, with both mothers and fathers spending more time in childrearing than they did in earlier decades, the increase for fathers has been greater, with fathers almost tripling their time in child care activities between 1965-85 and 2003-08 (Suzanne Bianchi 2011; Kim Parker and Wendy Wang 2013). Moreover, mothers' time in household work has declined sharply over time with a corresponding increase in father's household work time (Parker and Wang 2013). These shifts in the patterns of child rearing and household work might have helped close the wage gap between mothers and non-mothers by enabling mothers to conserve the effort that they would have earlier expended on non-market work. In addition, fathers' greater involvement in child care and household work may have facilitated mothers' increased labor force participation (Sara Raley, Suzanne Bianchi, and Wendy Wang 2012). Our results for married mothers are consistent with this explanation: when we restrict our analyses to married women only (Table 5), we find that the wage gap between mothers and non-mothers narrowed substantially from 8-9% in the 1970s and 1980s to 3% in the

1990s and 2000s, which roughly corresponds with the period when men's child care and household work involvement was increasing.<sup>25</sup>

Third, changes in the composition of the workforce could affect trends in the family gap. In particular, the 1996 federal welfare reform (following earlier federal and state reforms that begin in the late 1980s and early 1990s) pushed low income single mothers into the labor market in large numbers. If those newly entering the labor market had lower skills than the women who worked prior to welfare reform, this change in the composition of the workforce could have led to an increase in the family gap in the 1990s. We find some evidence of this in our results for Black and Hispanic women (who are more likely than non-Hispanic white women to be low income) (Table 3), and further evidence when we estimate our models separately for never married women (who are most likely to be affected by welfare policy) (Table 5).<sup>26</sup>

Finally, policies to help mothers reconcile work and family have been surprisingly rigid in the U.S. over the past few decades. The U.S. is the only developed country without any national paid leave policy or child care provision. Cross-national research shows that

---

<sup>25</sup> It is important to note that selection into marriage has changed, and the presence of a father, whether or not they are married, might affect the motherhood wage gap. In future work, it would be useful to explore differences between married, cohabiting, and non-partnered mothers.

<sup>26</sup> Another possibly relevant change in the composition of the workforce is the increase in highly skilled women opting out of the labor market in the 2000s. However, according to Heather Boushey (2008), this trend has been primarily driven by the weak economy and has affected both non-mothers and mothers, suggesting that it is not likely to explain changes in the wage gap between mothers and non-mothers.



motherhood wage penalties are likely to be relatively lower in countries with stronger work-family reconciliation policies (Janet Gornick and Marcia Meyers 2003; Joya Misra, Michelle Budig, and Stephanie Moller 2007; Joya Misra, Michelle Budig, and Irene Boeckman 2011).<sup>27</sup> There is also research showing that a moderate duration of paid parental leave has a positive effect on women's wages (Christopher Ruhm 1998), and that mothers who had leave coverage and used it to take leave and return to work received a premium almost large enough to offset the penalty from having a child (Jane Waldfogel 1998b). On the other hand, researchers testing the effect of the Family and Medical Leave Act (1994) – which provides only an unpaid leave of 12 weeks to eligible mothers in the US – have found no such positive wage effect (Jane Waldfogel 1999; Charles Baum II 2003). Given the importance of continued labor force attachment and better job matches on mothers' wages, the lack of strong work-family policies could explain to a large extent why the motherhood penalty has remained relatively stable in the U.S. over time.

Thus, it appears likely that many factors may help explain the recent changes and lack of changes in the family gap, and that the relevant factors may vary depending on the group considered. For married women, their own increased labor force attachment, but also changes in

---

<sup>27</sup> However, the specific bundle and design of such policies are likely to matter, as cross-national research finds family wage gaps in both the U.S. and the Nordic countries (Wendy Sigle-Rushton and Jane Waldfogel, 2007). In unpublished work, Michelle Budig, Joya Misra, and Irene Boeckman (2012) test the relationship of the motherhood penalty to specific policies in a cross national context. They find publicly available child care for 0-3 year olds as well as for children above age 3 to be associated with lower motherhood penalties; they also find a curvilinear relationship of the wage penalty with the duration of paid parental leave.

their husbands' behavior, seem to be relevant, while for unmarried women, the dramatic change in welfare policies in recent decades may be particularly consequential. Of concern, these changes appear to work in opposite directions, leading to reduced family gaps for married mothers but continued or possibly increased gaps for unmarried ones. If so, we may be entering a period of diminished inequality between mothers and non-mothers, but potentially increased inequality *among* mothers.

## References

- Amuedo-Dorantes, Catalina, and Jean Kimmel. 2005. "The Motherhood Wage Gap for Women in the United States: The Importance of College and Fertility Delay." *Review of Economics of the Household* 3(1): 17-48.
- Amuedo-Dorantes, Catalina, and Jean Kimmel. 2008. "New Evidence on the Motherhood Wage Gap". *IZA Discussion Papers* 3662.
- Anderson, Deborah J., Melissa Binder, and Kate Krause. 2002. "The Motherhood Wage Penalty: Which Mothers Pay it and Why?" *American Economic Review* 354-358.
- Anderson, Deborah J., Melissa Binder, and Kate Krause. 2002. "Motherhood Wage Penalty Revisited: Experience, Heterogeneity, Work Effort, and Work-Schedule Flexibility." *The Industrial and Labor Relations Review*. 56 273.
- Avellar, Sarah, and Pamela J. Smock. 2003. "Has the Price of Motherhood Declined Over Time? A Cross-Cohort Comparison of the Motherhood Wage Penalty." *Journal of Marriage and Family* 65 (3): 597-607.
- Austin, Peter C. 2011. "An Introduction to Propensity Score Methods for Reducing the Effects of Confounding in Observational Studies" *Multivariate Behavioral Research* 46(3):399-424.
- Baum II, Charles L. 2002. "The Effect of Work Interruptions on Women's Wages". *Labour* 16(1), 1-37.
- Baum II, Charles L. 2003. "The Effect of State Maternity Leave Legislation and the 1993 Family and Medical Leave Act on Employment and Wages." *Labour Economics* 10(5): 573-596.
- Beblo, Miriam, Stefan Bender, and Elke Wolf. 2008. Establishment-Level Wage Effects of Entering Motherhood. *Oxford Economic Papers –Special Issue: Women and Wages* 61 (suppl): i11-i34.
- Becker, Gary. S. .1985. "Human Capital, Effort, and the Sexual Division of Labor". *Journal of*

*Labor Economics* S33-S58.

Becker, Gary. S. 1981. *A Treatise on the Family*. Harvard University Press.

Bianchi, Suzanne. M. 2011. Family Change and Time Allocation in American Families. *The ANNALS of the American Academy of Political and Social Science*, 638(1): 21-44.

Boushey, Heather. 2008. "Opting out?" The Effect of Children on Women's Employment in the United States". *Feminist Economics* 14(1) : 1-36.

Bowler, Mary, Randy E. Ilg, Stephen Miller, and Ed Robinson. 2003. "Revisions to the Current Population Survey Effective in January 2003." *Employment and Earnings* 50 (4).

Budig, Michelle J., & Melissa J. Hodges. 2010. Differences in Disadvantage: Variation in the Motherhood Penalty across White Women's Earnings Distribution. *American Sociological Review* 75(5): 705-728.

Budig, Michelle J., Joya Misra, and Irene Boeckmann. 2012. "How Cultural Attitudes and Work-Family Policies Combine to Predict Maternal Earnings Cross-Nationally." Paper presented at the Population Association of America annual meetings (San Francisco)

Budig, Michelle J., and Melissa J. Hodges. 2014. "Statistical Models and Empirical Evidence for Differences in the Motherhood Penalty across the Earnings Distribution." *American Sociological Review* 79(2) : 358-364.

Bureau of Labor Statistics. 2008. "Women's Earnings as a Percentage of Men's, 2008". *United States Department of Labor*.

[http://www.bls.gov/opub/ted/2009/ted\\_20091014.htm](http://www.bls.gov/opub/ted/2009/ted_20091014.htm) retrieved on January 03, 2013.

Bureau of Labor Statistics . 2009a. "Women's-to-Men's Earnings Ratio, 1979-2008". *United States Department of Labor* . <http://www.bls.gov/opub/ted/2009/jul/wk4/art05.htm> retrieved on January 03, 2013.

Bureau of Labor Statistics. 2009b. "Women in the Labor Force: A Databook". Report 1018.

*United States Department of Labor*

Cole, Stephen R. and Miguel A. Hernán. 2008. "Constructing Inverse Probability Weights for Marginal Structural Models." *American Journal of Epidemiology* 168(6): 656-664.

Crawford, Malik, and Jonathan Church. 2014. "CPI Detailed Report Data for May 2014".

*Bureau of Labor Statistics. United States Department of Labor.*

<http://www.bls.gov/cpi/tables.htm>

Fuchs, Victor. R. 1988. *Women's Quest for Economic Equality*. Harvard University Press.

Gangl, Markus, and Andrea Ziefle. 2009. Motherhood, Labor Force Behavior, and Women's Careers: An Empirical Assessment of the Wage Penalty for Motherhood in Britain, Germany, and the United States. *Demography* 46(2): 341-369.

Glass, Jennifer. 2004. "Blessing or Curse? Work-Family Policies and Mother's Wage Growth over Time." *Work and Occupations* 31(3): 367-394.

Glauber, Rebecca. 2007. "Marriage and the Motherhood Wage Penalty among African Americans, Hispanics, and Whites." *Journal of Marriage and Family*, 69(4), 951-961.

Glauber, Rebecca. 2013. "Increasing Inequality: Trends in the Motherhood Wage Penalty, 1980-2010." Paper presented at the Population Association of America Annual Meeting, New Orleans, April 12, 2013.

Gornick, Janet C. and Marcia K. Meyers. 2003. "Families that Work: Policies for Reconciling Parenthood and Employment". *Russell Sage Foundation*.

Gough, Margaret, and Mary Noonan. 2013. "A Review of the Motherhood Wage Penalty in the United States". *Sociology Compass* 7(4), 328-342.

Harkness, Susan and Jane Waldfogel. 2003. "The Family Gap in Pay: Evidence from Seven

- Industrialized Countries.” *Research in Labor Economics*, 22, 369-413.
- Heckman, James J. 1979. Sample Selection Bias as a Specification Error. *Econometrica: Journal of the Econometric Society* 153-161.
- Jaeger, David A. 1997. “Reconciling the Old and New Census Bureau Education Questions: Recommendations for Researchers”. *Journal of Business & Economic Statistics* 15(3) 300-309.
- Jaeger, David A. 2003. “Estimating the Returns to Education Using the Newest Current Population Survey Education Questions”. *Economics Letters* 78(3): 385-394.
- Killewald, Alexandra, and Jonathan Bearak. 2014. “Is the Motherhood Penalty Larger for Low-Wage Women? A Comment on Quantile Regression.” *American Sociological Review* 79(2): 350-357.
- King, Miriam., Steven Ruggles, J. Trent Alexander, Sarah Flood, Katie Genadek, Matthew B. Schroeder, Brandon Trampe, & Rebecca Vick. 2010. *Integrated Public Use Microdata Series, Current Population Survey: Version 3.0*. [Machine-readable database].  
Minneapolis: University of Minnesota.
- Korenman, Sanders, and David Neumark. 1992. “Marriage, Motherhood, and Wages”. *Journal of Human Resources* 27(2): 233-255.
- Laughlin, Lynda Lvonne. 2011. “Maternity Leave and Employment Patterns of First-Time Mothers: 1961-2008”. United States Department of Commerce, Economics and Statistics Administration, United States Census Bureau.
- Leuven, Edwin and Barbara Sianesi. 2003. PSMATCH2: Stata Module to Perform Full

- Mahalanobis and Propensity Score Matching, Common Support Graphing, and Covariate Imbalance Testing. Statistical Software Components S432001, Boston College Department of Economics, revised 19 Jul 2012.
- Loughran, David S., and Julie M. Zissimopoulos. 2009. "Why Wait? The Effect of Marriage and Childbearing on the Wages of Men and Women". *Journal of Human Resources* 44(2), 326-349.
- Misra, Joya, Michelle J. Budig, and Stephanie Moller. 2007. "Reconciliation Policies and the Effects of Motherhood on Employment, Earnings, and Poverty." *Journal of Comparative Policy Analysis* 9 (2) 135-155.
- Misra, Joya, Michelle Budig, and Irene Boeckmann. 2011. "Work-Family Policies and the Effects of Children on Women's Employment Hours and Wages." *Community, Work, and Family* 14(2):139-157.
- Morgan, Stephen L. and Jennifer J. Todd. 2008. "A Diagnostic Routine for the Detection of Consequential Heterogeneity of Causal Effects." *Sociological Methodology* 38(1): 231-281.
- National Bureau of Economic Research. 2010. "Business Cycle Dating Committee Report (September 20, 2010)". <http://www.nber.org/cycles/sept2010.html>
- Parker, Kim, and Wendy Wang. 2013. "Modern Parenthood: Roles of Moms and Dads Converge as they Balance Work and Family. *Pew Research: Social & Demographic Trends*.
- Raley, Sara, Suzanne M. Bianchi, and Wendy Wang. 2012. "When Do Fathers Care? Mothers' Economic Contribution and Fathers' Involvement in Child Care". *American Journal of Sociology* 117(5): 1422-1459.
- Rosenbaum, Paul R. and Donald B. Rubin. 1983. "The Central Role of The Propensity Score in

- Observational Studies for Causal Effects.” *Biometrika* 70(1), 41-55.
- Rosenbaum, Paul R. and Donald B. Rubin. 1984. "Reducing Bias in Observational Studies using Sub-Classification on the Propensity Score.” *Journal of the American Statistical Association*, 79(387), 516-524.
- Rosenbaum, Paul R. and Donald B. Rubin. 1985. "Constructing a Control Group Using Multivariate Matched Sampling Methods that Incorporate the Propensity Score”. *The American Statistician* 39(1): 33-38.
- Ruhm, Christopher J. 1998. "The Economic Consequences of Parental Leave Mandates: Lessons from Europe." *The Quarterly Journal of Economics* 113(1): 285-317.
- Sigle-Rushton, Wendy and Jane Waldfogel. 2007. “Motherhood and Women's Earnings in Anglo-American, Continental European, and Nordic countries”. *Feminist Economics*, 13(2), 55-91.
- Simonsen, Marianne and Lars Skipper. 2006. “The Costs of Motherhood: An Analysis Using Matching Estimators.” *Journal of Applied Econometrics*, 21(7), 919-934.
- Taniguchi, Hiromi. 1999. “The Timing of Childbearing and Women's Wages”. *Journal of Marriage and the Family*: 1008-1019.
- Todd, Erin. L. 2001. “Educational Attainment and Family Gaps in Women's Wages: Evidence from Five Industrialized Countries”. *Luxembourg Income Study*. Working Paper No. 246
- Viitanen, Tarja. 2014. “The Motherhood Wage Gap in the UK over the Life Cycle”. *Review of Economics of the Household* 12(2): 259-276.
- Waldfogel, Jane. 1997. “The Effect of Children on Women's Wages.” *American Sociological Review* 209-217.
- Waldfogel, Jane. 1998a. “Understanding the Family Gap in Pay for Women with Children”. *The*



- Journal of Economic Perspectives* 12(1): 137-156.
- Waldfogel, Jane. 1998b. "The Family Gap for Young Women in the United States and Britain: Can Maternity Leave Make a Difference?" *Journal of Labor Economics* 16(3): 505-545.
- Waldfogel, Jane. 1999. "The Impact of the Family and Medical Leave Act." *Journal of Policy Analysis and Management* 18(2): 281-302.
- Wilde, Elizabeth Ty, Lily Batchelder, and David T. Ellwood. 2010. "The Mommy Track Divides: The Impact of Childbearing on Wages of Women of Differing Skill Levels". *National Bureau of Economic Research* w16582
- Winder, Katie L. 2008. *Endogenous Fertility and the Motherhood Wage Penalty*. Technical Report, University of California, Merced.

## List of Figures and Tables

**Figure 1: Mean Wages of Mothers and Non-Mothers, 1977-2007**

**Table 1: Coefficients from Regression of Ln hourly wages (2011\$) on family, demographic and education variables for women aged 25-44**

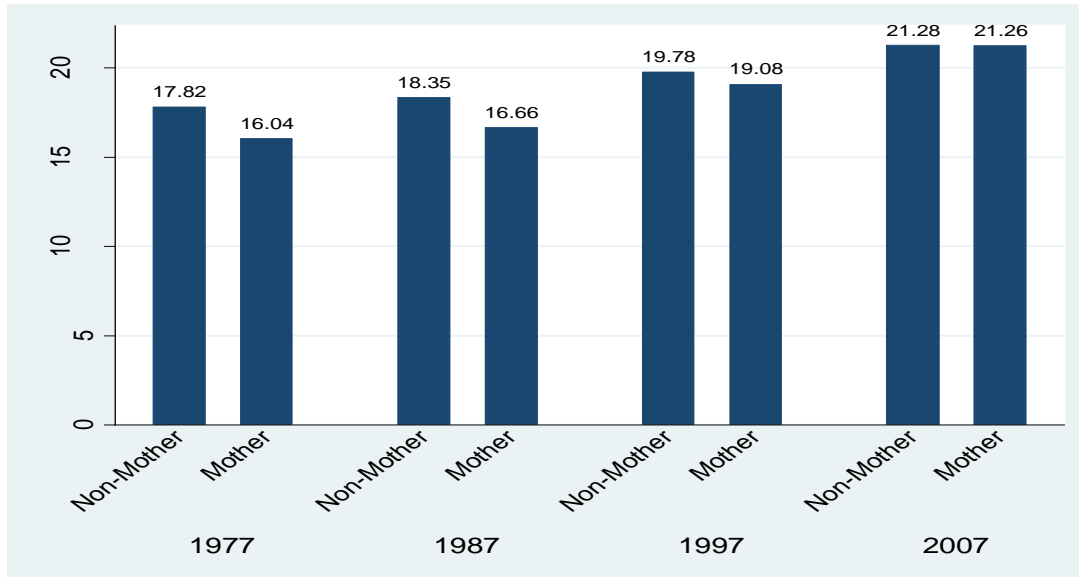
**Table 2: Coefficients from regression of Ln\_hourly wages (2011\$) on mother from OLS and IPTW models with controls for Part-time, Occupation, and Industry**

**Table 3: Coefficients from regression of Ln\_hourly wages (2011\$) on mother from OLS and IPTW models, by Race/Ethnicity**

**Table 4: Coefficients from regression of Ln\_hourly wages (2011\$) on mother from OLS and IPTW models, by Education**

**Table 5: Coefficients from regression of Ln\_hourly wages (2011\$) on mother from OLS and IPTW models, by Marital Status**

**Figure 1: Mean Wages of Mothers and Non-Mothers, 1977-2007**



**Table1: Coefficients from Regression of Ln hourly wages (2011\$) on family, demographic and education variables for women aged 25-44**

	1977			1987			1997			2007		
	(1) OLS	(2) IPTW	(3) Heckman	(1) OLS	(2) IPTW	(3) Heckman	(1) OLS	(2) IPTW	(3) Heckman	(1) OLS	(2) IPTW	(3) Heckman
Mother	-0.086*** (0.011)	-0.062*** (0.017)	-0.095*** (0.017)	-0.095*** (0.009)	-0.109*** <sup>c</sup> (0.011)	-0.160*** <sup>b</sup> (0.015)	-0.057*** <sup>c</sup> (0.010)	-0.064*** (0.011)	-0.085*** (0.013)	-0.047*** <sup>b</sup> (0.009)	-0.053*** (0.010)	-0.068*** (0.010)
Age	0.062*** (0.010)	0.052*** (0.016)	0.062*** (0.010)	0.070*** (0.009)	0.082*** (0.015)	0.072*** (0.010)	0.079*** (0.011)	0.090*** (0.013)	0.077*** (0.011)	0.076*** (0.009)	0.081*** (0.012)	0.076*** (0.009)
Age <sup>2</sup> /1000	-0.840*** (0.147)	-0.707*** (0.234)	-0.001*** (0.000)	-0.873*** (0.134)	-1.040*** (0.217)	-0.001*** (0.000)	-0.955*** (0.152)	-1.091*** (0.187)	-0.001*** (0.000)	-0.916*** (0.132)	-0.992*** (0.166)	-0.001*** (0.000)
High School	0.207*** (0.012)	0.228*** (0.017)	0.213*** (0.016)	0.233*** (0.014)	0.246*** (0.017)	0.324*** (0.022)	0.261*** (0.018)	0.260*** (0.020)	0.345*** (0.027)	0.249*** (0.017)	0.269*** (0.021)	0.315*** (0.022)
Some College	0.335*** (0.014)	0.318*** (0.021)	0.342*** (0.018)	0.431*** (0.015)	0.458*** (0.018)	0.543*** (0.026)	0.442*** (0.018)	0.454*** (0.021)	0.543*** (0.031)	0.422*** (0.016)	0.439*** (0.020)	0.514*** (0.026)
College Graduate	0.526*** (0.014)	0.584*** (0.027)	0.537*** (0.022)	0.663*** (0.015)	0.656*** (0.021)	0.789*** (0.028)	0.779*** (0.018)	0.784*** (0.022)	0.902*** (0.036)	0.815*** (0.017)	0.821*** (0.021)	0.916*** (0.027)
Previously Married	0.014 (0.011)	0.030** (0.013)	0.021 (0.016)	-0.034*** (0.010)	-0.033*** (0.011)	0.003 (0.013)	-0.067*** (0.012)	-0.073*** (0.013)	-0.037* (0.014)	-0.078*** (0.011)	-0.067*** (0.013)	-0.036* (0.014)
Never Married	0.012 (0.015)	0.085* (0.050)	0.016 (0.016)	-0.030** (0.012)	-0.072*** (0.020)	-0.018 (0.013)	-0.064*** (0.013)	-0.082*** (0.019)	-0.044** (0.014)	-0.048*** (0.011)	-0.056*** (0.013)	-0.015 (0.013)
Non-Hispanic Black	0.010 (0.014)	-0.037 (0.024)	0.014 (0.015)	-0.043*** (0.013)	-0.042** (0.021)	-0.030* (0.014)	-0.021 (0.015)	0.003 (0.017)	-0.009 (0.016)	-0.011 (0.012)	-0.017 (0.015)	-0.003 (0.013)
Hispanic	-0.006 (0.014)	-0.040** (0.019)	-0.006 (0.014)	-0.045*** (0.013)	-0.070*** (0.018)	-0.057*** (0.014)	-0.070*** (0.013)	-0.069*** (0.016)	-0.085*** (0.014)	-0.067*** (0.011)	-0.075*** (0.014)	-0.074*** (0.011)
Constant	1.345*** (0.167)	1.505*** (0.276)	1.335*** (0.168)	1.042*** (0.154)	0.832*** (0.261)	0.828*** (0.166)	0.778*** (0.180)	0.568** (0.222)	0.610** (0.191)	0.892*** (0.158)	0.774*** (0.197)	0.690*** (0.167)
Lambda			0.031 (0.048)			0.308*** (0.057)			0.277*** (0.068)			0.252*** (0.053)
N	12,599	12,599	21,105	18,089	18,089	25,535	14,993	14,993	20,763	21,384	21,384	29,831
R-squared	0.127	0.148		0.170	0.169		0.199	0.206		0.214	0.211	

Standard errors in parentheses, robust standard errors in IPTW models; \*\*\* p<0.001, \*\* p<0.01, \* p<0.05 (two tailed tests); <sup>a b c d</sup> denote whether the coefficient on “Mother” is significantly different from 1977 in later years at p<0.001, p<0.01, p<0.05 and p<0.10 respectively. IPTW Selection Models are the best fitting models among fully balanced models for each year; 1978: mother = f (age, age\_sq, education, marital status, race, age\_sq\*race interactions, marital\*education interactions); 1988: mother = f(age, age\_sq, education, marital status, race, marital\*education interactions); 1998 and 2008: mother = f(age, age\_sq, education, marital status, race, marital\*education\*race two-way and three-way interactions)

**Table 2: Coefficients from regression of Ln\_hourly wages (2011\$) on mother from OLS and IPTW models with controls for Part-time, Occupation, and Industry**

	1977		1987		1997		2007	
	OLS	IPTW	OLS	IPTW	OLS	IPTW	OLS	IPTW
<b>Baseline</b>								
Mother	-0.086*** (0.011)	-0.062*** (0.017)	-0.095*** (0.009)	-0.109*** <sup>c</sup> (0.011)	-0.057*** <sup>c</sup> (0.010)	-0.064*** (0.011)	-0.047*** <sup>b</sup> (0.009)	-0.053*** (0.010)
<b>+ Part Time</b>								
Mother	-0.079*** (0.011)	-0.048** (0.018)	-0.073*** (0.009)	-0.083*** (0.013)	-0.046*** <sup>c</sup> (0.010)	-0.053*** (0.012)	-0.036*** <sup>b</sup> (0.009)	-0.035** (0.011)
<b>+Part Time +Occupation</b>								
Mother	-0.080*** (0.010)	-0.039* (0.016)	-0.073*** (0.009)	-0.079*** <sup>c</sup> (0.012)	-0.046*** <sup>c</sup> (0.010)	-0.050*** (0.012)	-0.035*** <sup>a</sup> (0.009)	-0.034** (0.011)
<b>+Part Time +Occupation + Industry</b>								
Mother	-0.069*** (0.010)	-0.038* (0.016)	-0.071*** (0.009)	-0.079*** <sup>c</sup> (0.012)	-0.042*** <sup>d</sup> (0.010)	-0.051*** (0.011)	-0.036*** <sup>c</sup> (0.009)	-0.035*** (0.010)
N	12,599	12,599	18,089	18,089	14,993	14,993	21,384	21,384

Standard errors in parentheses, robust standard errors in IPTW models; \*\*\* p<0.001, \*\* p<0.01, \* p<0.05 (two tailed tests); <sup>a b c d</sup> denote whether the coefficient on “Mother” is significantly different from 1977 in later years at p<0.001, p<0.01, p<0.05 and p<0.10 respectively; All models include the usual covariates – age, age\_squared, and dummies for education, race/ethnicity, and marital status. The first panel “Baseline” reports the main coefficients from Table 1 for ease of comparison.

Details about selection models pertaining to IPTW regressions – In the second panel “+ Part Time”, selection models for the 1978 and 1988 samples are moderately balanced models with the least mean bias while selection models for 1998 and 2008 are the best fitting ones amongst fully balanced models. 1978 and 1988: mother = f(age, age\_sq, education, marital status, parttime, race, age\_sq\*race, marital\*education, parttime\*education); 1998 and 2008: mother = f(age, age\_sq, education, marital status, race, parttime, marital\*education\*race two-way and three-way interactions, parttime\*marital) ; In the second panel “+Part Time + Occupation” and third panel “+Part Time + Occupation”, the following selection models provides strong balance in 2008 and moderate balance in the earlier years. 1978 and 1988: mother = f(age, age\_sq, education, marital status, parttime, occupation dummies, industry dummies, race, age\_sq\*race, marital\*education, parttime\*education); 1998 and 2008 mother = f(age, age\_sq, education, marital status, race, parttime, occupation dummies, industry dummies, marital\*education\*race two-way and three-way interactions, parttime\*marital)

**Table 3: Coefficients from regression of Ln\_hourly wages (2011\$) on mother from OLS and IPTW models, by Race/Ethnicity**

	1977		1987		1997		2007	
	OLS	IPTW	OLS	IPTW	OLS	IPTW	OLS	IPTW
<b>Non-Hispanic White</b>								
Mother	-0.100*** (0.012)	-0.075*** (0.019)	-0.107*** (0.010)	-0.135*** <sup>c</sup> (0.013)	-0.049*** <sup>b</sup> (0.012)	-0.058*** (0.015)	-0.047*** <sup>a</sup> (0.011)	-0.055*** (0.013)
N	9,802	9,802	14,365	14,365	11,093	11,093	15,273	15,273
<b>Non-Hispanic Black</b>								
Mother	-0.089*** (0.012)	-0.081*** (0.019)	-0.077*** (0.010)	-0.081*** (0.013)	-0.132*** (0.012)	-0.128*** (0.015)	-0.073*** (0.011)	-0.076*** (0.013)
N	1,412	1,412	1,920	1,920	1,630	1,630	2,578	2,578
<b>Hispanic</b>								
Mother	0.018 (0.033)	0.014 (0.032)	0.010 (0.029)	0.003 (0.031)	-0.041 (0.027)	-0.046* (0.027)	-0.038* (0.022)	-0.034 (0.025)
N	1,385	1,356	1,804	1,804	2,270	2,270	3,533	3,533

Standard errors in parentheses, robust standard errors in IPTW models; \*\*\* p<0.001, \*\* p<0.01, \* p<0.05 (two tailed tests); <sup>a b c d</sup> denote whether the coefficient on “Mother” is significantly different from 1977 in later years at p<0.001, p<0.01, p<0.05 and p<0.10 respectively; All models include the usual covariates – age, age\_squared, and dummies for education, race/ethnicity, and marital status.

Details about selection models pertaining to IPTW regressions – selection models are the following fully balanced models that are consistent across all four years in the given panel; **Non-Hispanic White**: mother =f(age, age\_sq, education, marital, age\*age\_sq\*education\*marital all two-way, three-way and four-way interactions); **Non-Hispanic Black**: mother =f(age, age\_sq, education, marital, education\*marital); **Hispanic**: mother =f(age, age\_sq, education, marital, education\*marital).

**Table 4: Coefficients from regression of Ln\_hourly wages (2011\$) on mother from OLS and IPTW models, by Education**

	1977		1987		1997		2007	
	OLS	IPTW	OLS	IPTW	OLS	IPTW	OLS	IPTW
<b>Less than High School</b>								
Mother	-0.020 (0.026)	-0.009 (0.028)	-0.020 (0.029)	-0.027 (0.031)	-0.004 (0.036)	-0.010 (0.035)	-0.032 (0.030)	-0.002 (0.037)
N	2,168	2,168	1,725	1,725	1,258	1,258	1,545	1,545
<b>High School Diploma</b>								
Mother	-0.125*** (0.017)	-0.115*** (0.017)	-0.108*** (0.014)	-0.105*** (0.014)	-0.063*** <sup>b</sup> (0.017)	-0.051*** <sup>b</sup> (0.018)	-0.035*** <sup>a</sup> (0.018)	-0.038*** <sup>b</sup> (0.019)
N	5,544	5,544	7,583	7,583	4,703	4,703	5,388	5,388
<b>Some College</b>								
Mother	-0.102*** (0.024)	-0.121*** (0.029)	-0.114*** (0.019)	-0.117*** (0.019)	-0.107*** (0.018)	-0.107*** (0.018)	-0.083*** (0.016)	-0.074*** (0.016)
N	2,298	2,298	4,209	4,209	4,618	4,618	6,701	6,701
<b>College Graduate</b>								
Mother	-0.083*** (0.022)	0.026 (0.054)	-0.117*** (0.019)	-0.179*** <sup>a</sup> (0.031)	-0.034 (0.021)	-0.050* (0.027)	-0.055*** (0.018)	-0.061*** (0.020)
N	2,589	2,589	4,572	4,572	4,414	4,414	7,750	7,750

Standard errors in parentheses, robust standard errors in IPTW models; \*\*\* p<0.001, \*\* p<0.01, \* p<0.05 (two tailed tests); <sup>a b c d</sup> denote whether the coefficient on “Mother” is significantly different from 1977 in later years at p<0.001, p<0.01, p<0.05 and p<0.10 respectively; All models include the usual covariates – age, age\_squared, and dummies for education, race/ethnicity, and marital status.

Details about selection models pertaining to IPTW regressions – **Less than High School**: selection model is the best fitting one amongst the fully balanced selection models that are consistent across all four years, mother = f (age, age\_sq, marital, race, age\_sq\*race marital\*race); **High School Diploma**: selection models are the best fitting models amongst fully balanced models for each year; 1978: mother =f (age, age\_sq, race, marital, age\*race\*marital all interactions); 1988, 1998, and 2008: mother=f(age, age\_sq, race, marital, race\*marital); **Some College**: selection models are the best fitting models amongst the fully balanced ones for each year; 1978: mother =f(age, age\_sq, race, marital, age\*age\_sq\*race two-way and three way interactions); 1988: mother =f(age, age\_sq, race, marital, age\_sq\*marital, age\*age\_sq\*race two-way and three way interactions); 1998: mother =f(age, age\_sq, race, marital, marital\*age\_sq\*race two-way and three way interactions); 2008: mother =f(age, age\_sq, race, marital, , native, region, marital\*age\_sq\*race two-way and three way interactions); **College Graduate**: selection model for 1978 is the one showing least mean bias amongst the models with only one or two covariates not balanced, mother = f (age, age\_sq, race, marital, age\*marital, age\*race); selection model for each of 1988, 1998, and 2008 is the best fitting model amongst fully balanced ones for the given year; 1988: mother = f(age, age\_sq, race, marital, race\*marital, age\*race, ace\_sq\*race, age\_cube, age\_cube\*race, age\*marital, age\_sq\*marital, age\_cube\*marital); 1998:mother = f(age, age\_sq, race, marital, age\*marital\*race all up to three-way interactions) ; 2008: mother = f(age, age\_sq, race, marital, age\*marital\*race up to three-way interactions)

**Table 5: Coefficients from regression of Ln\_hourly wages (2011\$) on mother from OLS and IPTW models, by Marital Status**

	1977		1987		1997		2007	
	OLS	IPTW	OLS	IPTW	OLS	IPTW	OLS	IPTW
<b>Married</b>								
Mother	-0.075*** (0.013)	-0.081*** (0.013)	-0.091*** (0.011)	-0.091*** (0.011)	-0.030** <sup>c</sup> (0.013)	-0.034** <sup>c</sup> (0.013)	-0.027** <sup>b</sup> (0.013)	-0.027** <sup>b</sup> (0.013)
N	8,687	8,687	11,572	11,572	9,121	9,121	12,647	12,647
<b>Previously Married</b>								
Mother	-0.091*** (0.020)	-0.092*** (0.021)	-0.082*** (0.018)	-0.082*** (0.018)	-0.019 <sup>c</sup> (0.022)	-0.021 <sup>c</sup> (0.021)	-0.068*** (0.020)	-0.073*** (0.021)
N	2,333	2,333	3,356	3,356	2,657	2,657	3,615	3,615
<b>Never Married</b>								
Mother	-0.096** (0.041)	0.056 (0.091)	-0.125*** (0.027)	-0.209*** <sup>b</sup> (0.044)	-0.184*** <sup>d</sup> (0.024)	-0.182*** <sup>c</sup> (0.032)	-0.087*** (0.018)	-0.105*** <sup>d</sup> (0.023)
N	1,579	1,579	3,161	3,161	3,215	3,215	5,122	5,122

Standard errors in parentheses, robust standard errors in IPTW models; \*\*\* p<0.001, \*\* p<0.01, \* p<0.05 (two tailed tests); <sup>a b c d</sup> denote whether the coefficient on “Mother” is significantly different from 1977 in later years at p<0.001, p<0.01, p<0.05 and p<0.10 respectively; All models include the usual covariates – age, age\_squared, and dummies for education, race/ethnicity, and marital status.

Details about selection models pertaining to IPTW regressions – selection model for both **Married** and **Previously Married** is the following fully balanced model that is consistent across all years, mother = f (age, age\_sq, race, education, education\*race). **Never Married**: selection model for 1978 is the one that shows least mean bias amongst moderately balanced selection models, mother = f (age, age\_sq, race, education, age\*education, age\_cube, age\*race, age\_sq\*race, region, region\*race); 1988: mother = f (age, age\_sq, education, race, age\*education). Selection models for 1998 and 2008 in the Never Married panel are the best fitting ones amongst fully balanced models: mother = f (age, age\_sq, race, education, education\*race, education\*age) in both years.

## List of Appendices

**Appendix A: Percentage of women aged 25-44 employed and in the wage sample in 1977, 1987, 1997, 2007.**

**Appendix B: Descriptive Statistics of the four samples of women in 1977, 1987, 1997, and 2007**

**Appendix C: Supplementary Analysis Coefficients from regression of Ln\_hourly wages (2011\$) on mother from OLS and IPTW models after the inclusion of younger women, older women, or both**

**Appendix D: Balance Statistics for selection models used in IPTW regressions in Table 1**

**Appendix A: Percentage of women aged 25-44 employed and in the wage sample in 1977, 1987, 1997, 2007.**

	1977		1987		1997		2007	
	Mother	Non-Mother	Mother	Non-Mother	Mother	Non-Mother	Mother	Non-Mother
Total	15,811	5,294	17,012	8,523	13,676	7,087	20,915	8,916
Employed (% of total aged 25-44)	9,727 (61.5)	4,445 (84.0)	12,355 (72.6)	7,497 (88.0)	10,397 (76.0)	6,071 (85.7)	15,723 (75.2)	7,448 (83.5)
Employed and in Wage sample (% of total aged 25-44)	8,465 (53.5)	4,134 (78.1)	11,073 (65.1)	7,016 (82.3)	9,354 (68.4)	5,639 (79.6)	14,356 (68.6)	7,028 (79.4)

Employed = reporting >0 weeks worked last year

Employed and in the wage sample = Employed – (unpaid family workers + self-employed + reporting wages < 45% of Federal Minimum Wage)



**Appendix B: Descriptive Statistics of the four samples of women in 1977, 1987, 1997, and 2007**

	1977		1987		1999		2007	
	Mother	Non-Mother	Mother	Non-Mother	Mother	Non-Mother	Mother	Non-Mother
Age	33.874 (0.059)	31.780 (0.096)	34.361 (0.050)	32.962 (0.073)	35.290 (0.055)	33.877 (0.083)	35.657 (0.045)	33.578 (0.075)
Hourly Wages (\$)	4.322 (0.041)	4.801 (0.046)	8.415 (0.077)	9.267 (0.067)	13.620 (0.816)	14.115 (0.363)	19.592 (0.303)	19.609 (0.260)
Hourly Wages (2011\$)	16.044 (0.151)	17.822 (0.172)	16.662 (0.153)	18.348 (0.132)	19.081 (1.143)	19.775 (0.508)	21.258 (0.328)	21.275 (0.282)
Hours Worked	34.090 (0.122)	38.661 (0.125)	35.010 (0.104)	39.458 (0.104)	35.983 (0.111)	39.913 (0.125)	36.606 (0.086)	39.659 (0.111)
Weeks Worked	38.987 (0.179)	45.852 (0.186)	42.944 (0.140)	47.606 (0.122)	45.016 (0.136)	47.843 (0.135)	46.533 (0.098)	48.685 (0.109)
Annual Wages (\$)	5,803.182 (49.044)	8,594.243 (75.911)	13,024.270 (96.995)	17,921.586 (137.390)	21,091.336 (221.870)	26,463.294 (317.125)	32,649.337 (292.258)	37,457.690 (410.651)
Annual Wages (2011 \$)	21,541.412 (182.051)	31,901.831 (281.780)	25,788.055 (192.050)	35,484.740 (272.031)	29,548.962 (310.839)	37,075.075 (444.293)	35,424.532 (317.100)	40,641.595 (445.556)
Full time (%)	69.5	87.8	70.3	87.3	73.4	86.7	75.7	87
Part time (%)	30.5	12.2	29.7	12.7	26.6	13.3	24.3	13
<b>Education (%)</b>								
Less than High School	19.9	11.7	11.1	7.0	9.7	6.3	8.0	5.7
High School Diploma	48.2	35.5	46.1	35.2	34.7	25.8	26.3	22.9
Some College	17.3	20.2	22.9	23.9	31.8	29.2	33.0	27.9
College Graduate	14.7	32.6	19.8	33.9	23.8	38.8	32.7	43.5
<b>Marital Status (%)</b>								
Married	79.7	47.0	77.6	42.5	73.9	39.1	71.1	34.7
Previously Married	18.5	18.5	18.1	19.2	17.5	18.1	17.2	16.3
Never Married	1.8	34.5	4.3	38.3	8.6	42.7	11.7	49
<b>Race/Ethnicity (%)</b>								
White Non-Hispanic	76.2	81.0	77.8	81.9	71.9	77.4	72.3	69.7
Black Non-Hispanic	11.8	10.1	11.2	9.7	11.4	10.0	11.0	14.1
Hispanic	12.0	8.9	10.9	8.4	16.7	12.6	16.7	16.1
<b>Observations</b>	<b>8,465</b>	<b>4,134</b>	<b>11,073</b>	<b>7,016</b>	<b>9,354</b>	<b>5,639</b>	<b>14,356</b>	<b>7,028</b>

**Appendix C: Supplementary Analysis**

**Coefficients from regression of Ln\_hourly wages (2011\$) on mother from OLS and IPTW models after the inclusion of younger women, older women, or both**

	1977		1987		1997		2007	
	OLS	IPTW	OLS	IPTW	OLS	IPTW	OLS	IPTW
<b>Including Younger Women (Age: 18-44)</b>								
Mother	-0.086*** (0.009)	-0.053* (0.023)	-0.094*** (0.008)	-0.113*** <sup>d</sup> (0.024)	-0.055*** <sup>c</sup> (0.009)	-0.072*** (0.014)	-0.043*** <sup>a</sup> (0.009)	-0.059*** (0.010)
N	19,652	19,613	24,261	24,261	19,092	19,092	27,259	27,259
<b>Including Older Women (Age: 25-54)</b>								
Mother	-0.073*** (0.009)	-0.065*** (0.010)	-0.093*** <sup>d</sup> (0.008)	-0.103*** <sup>b</sup> (0.009)	-0.046*** <sup>d</sup> (0.009)	-0.063*** (0.010)	-0.040*** <sup>b</sup> (0.007)	-0.049*** (0.008)
N	17,121	17,121	23,110	23,110	21,063	21,063	32,243	32,243
<b>Including both younger and older women (Age: 18-54)</b>								
Mother	-0.078*** (0.008)	-0.050** (0.016)	-0.093*** (0.007)	-0.103*** <sup>c</sup> (0.015)	-0.046*** <sup>b</sup> (0.008)	-0.074*** (0.013)	-0.037*** <sup>a</sup> (0.007)	-0.054*** (0.008)
N	24,174	24,134	29,282	29,282	25,162	25,162	38,118	38,118

Standard errors in parentheses, robust standard errors in IPTW models; \*\*\* p<0.001, \*\* p<0.01, \* p<0.05 (two tailed tests); <sup>a b c d</sup> denote whether the coefficient on “Mother” is significantly different from 1977 in later years at p<0.001, p<0.01, p<0.05 and p<0.10 respectively; All models include the usual covariates – age, age\_squared, and dummies for education, race/ethnicity, and marital status.

Details about selection models pertaining to IPTW regressions – **Including younger women: selection model** is the following moderately balanced model that is consistent across all years: mother = f (age, age\_sq, race, education, marital status, age\_sq\* race\*education\*marital status two-way, three-way, and four-way interactions). **Including older women:** selection models for 1978-1998 are those with least mean bias amongst moderately balanced models; 1978 and 1988 : mother=f(age, age\_sq, race, education, marital status, age\*age\_sq\* race\* \*marital status two-way, three-way, and four-way interactions), 1998: mother = (age, age\_sq, race, education, marital status, age\*age\_sq\*education, age\*age\_sq\*marital, race\*marital\*education, all two-way and three way interactions); selection model for 2008 is the best fitting one amongst fully balanced models: mother = f (age, age\_sq, race, education, marital status , age\*age\_sq\*education\*marital two-way, three-way, and four-way interactions).

**Including both younger and older women:** selection models for all years are the ones showing least mean bias amongst moderately balanced models. 1978 and 1988: mother = f(age, age\_sq, race, education, marital status, age\*race\*age\_sq marital\*education\*race all two-way and three way interactions), 1998: mother = f(age, age\_sq, race, education, marital status, race\*marital marital\*education, age\*age\_sq\*education age\*age\_sq\*marital age\*age\_sq\*race two-way and three way interactions), 2008: mother = f(age, age\_sq, race, education, marital status, age\*age\_sq\*education\*marital two-way, three-way, and four-way interactions).

**Appendix D: Balance Statistics for selection models used in IPTW regressions in Table 1**

**1977**

Variable	Unmatched Matched	Mean		%bias	%reduct  bias	t-test	
		Treated	Control			t	p> t
age	U	33.874	31.78	36.1		19.41	0.000
	M	33.229	33.242	-0.2	99.4	-0.18	0.858
age_sq	U	1.1771	1.0478	32.6		17.52	0.000
	M	1.1387	1.1392	-0.1	99.6	-0.09	0.925
2.race	U	.11754	.10087	5.3		2.79	0.005
	M	.13286	.14185	-2.9	46.1	-2.08	0.038
3.race	U	.12026	.08878	10.3		5.31	0.000
	M	.10796	.10633	0.5	94.8	0.42	0.674
2.race#c.age_sq	U	.13484	.11294	5.8		3.02	0.003
	M	.15093	.15948	-2.3	60.9	-1.64	0.100
3.race#c.age_sq	U	.13628	.09628	11.0		5.66	0.000
	M	.12188	.11935	0.7	93.7	0.54	0.587
2.marital	U	.18523	.18505	0.0		0.02	0.980
	M	.18708	.18828	-0.3	-558.2	-0.24	0.807
3.marital	U	.01819	.3447	-93.5		-58.63	0.000
	M	.12482	.12413	0.2	99.8	0.17	0.868
2.education	U	.48151	.3551	25.8		13.52	0.000
	M	.44256	.44211	0.1	99.6	0.07	0.943
3.education	U	.17271	.20223	-7.6		-4.03	0.000
	M	.17828	.17847	-0.0	99.3	-0.04	0.968
4.education	U	.14684	.32559	-43.0		-23.83	0.000
	M	.2049	.19982	1.2	97.2	1.01	0.314
2.marital#2.education	U	.08706	.07644	3.9		2.02	0.043
	M	.08452	.08471	-0.1	98.1	-0.06	0.955
2.marital#3.education	U	.03745	.04064	-1.6		-0.87	0.382
	M	.03858	.03854	0.0	98.5	0.02	0.985
2.marital#4.education	U	.01855	.03822	-11.9		-6.65	0.000
	M	.02513	.02493	0.1	99.0	0.10	0.918
3.marital#2.education	U	.00839	.10619	-43.0		-26.89	0.000
	M	.04112	.03999	0.5	98.8	0.46	0.649
3.marital#3.education	U	.00284	.07523	-38.0		-24.26	0.000
	M	.02325	.02628	-1.6	95.8	-1.55	0.121
3.marital#4.education	U	.00095	.13909	-56.2		-36.43	0.000
	M	.04799	.04594	0.8	98.5	0.77	0.442

-----  
 Summary of the distribution of the abs(bias)  
 -----

BEFORE MATCHING

Percentiles		Smallest		
1%	.0469858	.0469858		
5%	.0469858	1.646946		
10%	1.646946	3.878355	Obs	17
25%	5.801821	5.346767	Sum of Wgt.	17
50%	11.866		Mean	25.05004
		Largest	Std. Dev.	24.91049
75%	38.04592	43.04309		
90%	56.22976	43.04445	Variance	620.5327
95%	93.51765	56.22976	Skewness	1.252666
99%	93.51765	93.51765	Kurtosis	4.236589

AFTER MATCHING

Percentiles		Smallest		
1%	.0240071	.0240071		
5%	.0240071	.0496413		
10%	.0496413	.0722107	Obs	17
25%	.1201714	.0920279	Sum of Wgt.	17
50%	.3092701		Mean	.6908748
		Largest	Std. Dev.	.8410618
75%	.8327212	1.225399		
90%	2.266788	1.591881	Variance	.7073849
95%	2.882761	2.266788	Skewness	1.479461
99%	2.882761	2.882761	Kurtosis	4.110305

Sample	Pseudo R2	LR chi2	p>chi2	MeanBias	MedBias
Raw	0.245	3904.16	0.000	25.1	11.9
Matched	0.000	11.85	0.809	0.7	0.3

**1987**

Variable	Unmatched Matched	Mean		%reduct		t-test	
		Treated	Control	%bias	bias	t	p> t
age	U	34.361	32.962	24.6		16.38	0.000
	M	33.856	33.906	-0.9	96.4	-0.83	0.409
age_sq	U	1.2081	1.1239	21.6		14.36	0.000
	M	1.1798	1.1821	-0.6	97.3	-0.55	0.582
_Irace_2	U	.11216	.09664	5.1		3.30	0.001
	M	.12967	.13207	-0.8	84.5	-0.68	0.497
_Irace_3	U	.10946	.08438	8.5		5.49	0.000
	M	.10002	.09866	0.5	94.6	0.43	0.667
2.marital	U	.18134	.19213	-2.8		-1.82	0.069
	M	.18734	.18758	-0.1	97.7	-0.06	0.953
3.marital	U	.04272	.38312	-91.4		-65.30	0.000
	M	.17481	.17331	0.4	99.6	0.38	0.706
2.education	U	.46148	.35248	22.3		14.56	0.000
	M	.41907	.42255	-0.7	96.8	-0.67	0.502
3.education	U	.22884	.23874	-2.3		-1.53	0.125
	M	.23039	.23037	0.0	99.8	0.00	0.997
4.education	U	.19832	.33865	-32.1		-21.43	0.000
	M	.25495	.25131	0.8	97.4	0.80	0.426
2.marital#2.education	U	.08724	.08025	2.5		1.65	0.099
	M	.08524	.0862	-0.3	86.2	-0.33	0.743
2.marital#3.education	U	.04163	.05188	-4.9		-3.22	0.001
	M	.04573	.04558	0.1	98.5	0.07	0.944
2.marital#4.education	U	.02583	.03877	-7.3		-4.91	0.000
	M	.03182	.03142	0.2	96.9	0.22	0.826
3.marital#2.education	U	.02321	.11517	-36.8		-26.08	0.000
	M	.0583	.05819	0.0	99.9	0.04	0.966
3.marital#3.education	U	.00822	.08623	-37.4		-27.11	0.000
	M	.0367	.03809	-0.7	98.2	-0.70	0.482
3.marital#4.education	U	.0037	.16249	-60.1		-44.35	0.000
	M	.0674	.06492	0.9	98.4	0.95	0.342

Summary of the distribution of the abs(bias)

BEFORE MATCHING

Percentiles	Smallest	Obs	Sum of Wgt.
1%	2.337951		
5%	2.337951		
10%	2.524986	15	
25%	4.855586		15

50%	21.55187		Mean	23.97475
		Largest	Std. Dev.	25.19909
75%	36.8428	36.8428		
90%	60.0588	37.41349	Variance	634.9942
95%	91.42471	60.0588	Skewness	1.419974
99%	91.42471	91.42471	Kurtosis	4.457688

-----  
AFTER MATCHING  
-----

	Percentiles	Smallest		
1%	.004515	.004515		
5%	.004515	.0418332		
10%	.0418332	.0623197	Obs	15
25%	.0732117	.0732117	Sum of Wgt.	15
50%	.4577725		Mean	.46768
		Largest	Std. Dev.	.3302295
75%	.7862964	.7862964		
90%	.8753136	.8298718	Variance	.1090515
95%	.9379176	.8753136	Skewness	-.0903845
99%	.9379176	.9379176	Kurtosis	1.565034

Sample		Pseudo R2	LR chi2	p>chi2	MeanBias	MedBias
Raw		0.206	4975.80	0.000	24.0	21.6
Matched		0.000	16.47	0.351	0.5	0.5

1997

```

-----
> -----
> st
Variable          Unmatched |          Mean          %reduct |          t-te
> p>|t|          Matched | Treated Control    %bias  |bias| |          t
-----+-----+-----
> -----
age                U | 35.29  33.877    24.5    | 14.82
> 0.000           M | 34.674 34.752    -1.3    94.5 | -1.16
> 0.246
age                U | 35.29  33.877    24.5    | 14.82
> 0.000           M | 34.674 34.752    -1.3    94.5 | -1.16
> 0.246
age_sq             U | 1.2734 1.1863    21.8    | 13.15
> 0.000           M | 1.2358 1.2411    -1.3    93.9 | -1.15
> 0.252
2.race             U | .11375 .10037     4.3     | 2.55
> 0.011           M | .10883 .11017    -0.4    90.0 | -0.37
> 0.711
3.race             U | .16677 .12591    11.6    | 6.77
> 0.000           M | .15134 .1523     -0.3    97.6 | -0.23
> 0.816
2.marital          U | .17468 .18142    -1.8    | -1.05
> 0.296           M | .17667 .17947    -0.7    58.5 | -0.63
> 0.527
3.marital          U | .08606 .42738   -84.9   | -53.89
> 0.000           M | .22212 .21837     0.9    98.9 | 0.78
> 0.433
2.race#2.marital  U | .02662 .02181     3.1     | 1.83
> 0.067           M | .02449 .02463    -0.1    97.1 | -0.08
> 0.939
2.race#3.marital  U | .0372  .05391   -8.0    | -4.86
> 0.000           M | .04421 .04468    -0.2    97.2 | -0.20
> 0.842
3.race#2.marital  U | .03464 .02447     6.0     | 3.49
> 0.000           M | .03062 .0312     -0.3    94.2 | -0.29
> 0.769
3.race#3.marital  U | .01614 .05622   -21.6   | -13.75
> 0.000           M | .03221 .03182     0.2    99.0 | 0.19

```

> 0.849						
2.education	U	.34723	.25802	19.5		11.45
> 0.000						
> 0.794	M	.31428	.31288	0.3	98.4	0.26
3.education	U	.31783	.29172	5.7		3.36
> 0.001						
> 0.679	M	.3092	.30699	0.5	91.6	0.41
4.education	U	.23819	.38766	-32.7		-19.70
> 0.000						
> 0.707	M	.29287	.29485	-0.4	98.7	-0.38
2.race#2.education	U	.04362	.03298	5.5		3.23
> 0.001						
> 0.812	M	.03965	.04018	-0.3	94.9	-0.24
2.race#3.education	U	.04212	.03334	4.6		2.70
> 0.007						
> 0.761	M	.03862	.0393	-0.4	92.3	-0.30
2.race#4.education	U	.01775	.02713	-6.3		-3.86
> 0.000						
> 0.935	M	.02169	.02183	-0.1	98.5	-0.08
3.race#2.education	U	.05388	.03316	10.2		5.87
> 0.000						
> 0.878	M	.04608	.04645	-0.2	98.2	-0.15
3.race#3.education	U	.04319	.03369	4.9		2.89
> 0.004						
> 0.998	M	.03995	.03995	0.0	99.9	0.00
3.race#4.education	U	.02074	.03334	-7.8		-4.75
> 0.000						
> 0.937	M	.02541	.02526	0.1	98.9	0.08
2.marital#2.education	U	.06457	.06455	0.0		0.01
> 0.996						
> 0.671	M	.06411	.06532	-0.5	-5681.0	-0.42
2.marital#3.education	U	.06254	.05941	1.3		0.77
> 0.439						
> 0.743	M	.06098	.06189	-0.4	71.0	-0.33
2.marital#4.education	U	.02437	.04185	-9.8		-5.99
> 0.000						
> 0.848	M	.03137	.03176	-0.2	97.8	-0.19
3.marital#2.education	U	.03293	.08778	-23.2		-14.55



> 0.000							
> 0.542	M		.05671	.0551	0.7	97.1	0.61
3.marital#3.education							
> 0.000	U		.03154	.12343	-34.9		-22.30
> 0.413	M		.06989	.0675	0.9	97.4	0.82
3.marital#4.education							
> 0.000	U		.01005	.19418	-63.8		-42.82
> 0.936	M		.07984	.08009	-0.1	99.9	-0.08
2.race#2.marital#2.education							
> 0.161	U		.01026	.00798	2.4		1.40
> 0.886	M		.00933	.00949	-0.2	93.0	-0.14
2.race#2.marital#3.education							
> 0.041	U		.0108	.00745	3.5		2.04
> 0.968	M		.00941	.00937	0.0	98.7	0.04
2.race#2.marital#4.education							
> 0.129	U		.00278	.00426	-2.5		-1.52
> 0.917	M		.00326	.00333	-0.1	95.4	-0.10
2.race#3.marital#2.education							
> 0.115	U		.01507	.01844	-2.6		-1.58
> 0.812	M		.01656	.01691	-0.3	89.5	-0.24
2.race#3.marital#3.education							
> 0.092	U		.01422	.01773	-2.8		-1.69
> 0.768	M		.01558	.016	-0.3	87.9	-0.29
2.race#3.marital#4.education							
> 0.000	U		.00385	.01561	-12.0		-7.71
> 0.759	M		.00877	.00844	0.3	97.2	0.31
3.race#2.marital#2.education							
> 0.675	U		.00973	.00904	0.7		0.42
> 0.792	M		.0095	.0098	-0.3	56.4	-0.26
3.race#2.marital#3.education							
> 0.002	U		.01016	.0055	5.3		3.03
> 0.950	M		.0083	.00837	-0.1	98.6	-0.06
3.race#2.marital#4.education							
> 0.329	U		.00342	.00443	-1.6		-0.98
> 0.936	M		.00376	.00382	-0.1	94.4	-0.08
3.race#3.marital#2.education							
> 0.000	U		.00545	.01365	-8.4		-5.29
> 0.998	M		.00873	.00873	0.0	100.0	0.00

```

3.race#3.marital#3.education  U | .0046 .01596 -11.3 | -7.20
> 0.000
                                M | .00949 .00914 0.3 96.9 | 0.31
> 0.753
3.race#3.marital#4.education  U | .0015 .01685 -16.2 | -10.76
> 0.000
                                M | .00748 .00734 0.1 99.1 | 0.14
> 0.889

```

```

-----
> -----
-----

```

Summary of the distribution of the abs(bias)

BEFORE MATCHING

```

-----
Percentiles      Smallest
1%      .0084854    .0084854
5%      .7096108    .7096108
10%     1.618651    1.309013   Obs          38
25%     3.127459    1.618651   Sum of Wgt. 38

50%     7.056611

                    Mean          13.4619
                    Std. Dev.    17.30577
                    Largest
75%     19.50909    32.66015
90%     32.66015    34.88589   Variance     299.4897
95%     63.82684    63.82684   Skewness     2.600443
99%     84.87646    84.87646   Kurtosis     10.236
-----

```

AFTER MATCHING

```

-----
Percentiles      Smallest
1%      .0031268    .0031268
5%      .0033124    .0033124
10%     .075324     .0466948   Obs          38
25%     .1158445    .075324     Sum of Wgt. 38

50%     .2935859

                    Mean          .3813295
                    Std. Dev.    .3611293
                    Largest
75%     .432776     .933759
90%     .933759     1.325409   Variance     .1304144
95%     1.343716    1.343716   Skewness     1.538519
99%     1.343716    1.343716   Kurtosis     4.595548
-----

```

```

-----
Sample | Pseudo R2   LR chi2   p>chi2   MeanBias   MedBias
-----+-----
Raw    | 0.188       3742.52  0.000    13.5       7.1
Matched | 0.000       4.37    1.000    0.4        0.3
-----

```

2007

```

-----
> -----
> st
Variable          Unmatched |      Mean          %reduct |      t-te
> p>|t|          Matched | Treated Control  %bias  |bias| |      t
-----+-----+-----
> -----
age                U | 35.657  33.578   35.5    | 25.07
> 0.000           M | 34.967  34.901   1.1    96.8 | 1.18
> 0.237
age                U | 35.657  33.578   35.5    | 25.07
> 0.000           M | 34.967  34.901   1.1    96.8 | 1.18
> 0.237
age_sq            U | 1.3003  1.1673   32.7    | 23.01
> 0.000           M | 1.256   1.252   1.0    97.0 | 1.03
> 0.303
2.race            U | .11034  .14143   -9.4    | -6.57
> 0.000           M | .12154  .12216   -0.2   98.0 | -0.19
> 0.846
3.race            U | .16704  .1615    1.5     | 1.02
> 0.305           M | .16498  .16752   -0.7   54.1 | -0.71
> 0.480
2.marital         U | .17205  .16292    2.4     | 1.67
> 0.094           M | .16983  .17085   -0.3   88.8 | -0.28
> 0.779
3.marital         U | .11682  .49018  -88.9   | -65.91
> 0.000           M | .23874  .24222   -0.8   99.1 | -0.84
> 0.400
2.race#2.marital U | .02396  .02775   -2.4    | -1.66
> 0.097           M | .02541  .0254    0.0   99.7 | 0.01
> 0.994
2.race#3.marital U | .04249  .08566  -17.7   | -12.87
> 0.000           M | .05733  .05771   -0.2   99.1 | -0.17
> 0.868
3.race#2.marital U | .03448  .02575    5.1     | 3.43
> 0.001           M | .03184  .03232   -0.3   94.4 | -0.28
> 0.776
3.race#3.marital U | .02487  .08509  -26.7   | -20.22
> 0.000

```

> 0.623	M		.04395	.04493	-0.4	98.4		-0.49
2.education	U		.26317	.22908	7.9			5.40
> 0.000	M		.25412	.25466	-0.1	98.4		-0.13
> 0.898								
3.education	U		.32997	.27945	11.0			7.49
> 0.000	M		.31526	.31485	0.1	99.2		0.09
> 0.928								
4.education	U		.32704	.43469	-22.3			-15.47
> 0.000	M		.3579	.35782	0.0	99.9		0.02
> 0.985								
2.race#2.education	U		.03671	.03813	-0.8			-0.52
> 0.605	M		.03767	.03773	-0.0	95.5		-0.03
> 0.973								
2.race#3.education	U		.04152	.0471	-2.7			-1.88
> 0.060	M		.04374	.044	-0.1	95.4		-0.13
> 0.896								
2.race#4.education	U		.02361	.04824	-13.3			-9.67
> 0.000	M		.03173	.03198	-0.1	99.0		-0.15
> 0.881								
3.race#2.education	U		.0496	.04525	2.0			1.39
> 0.163	M		.04856	.04932	-0.4	82.6		-0.36
> 0.717								
3.race#3.education	U		.04458	.04297	0.8			0.54
> 0.590	M		.04432	.04487	-0.3	65.7		-0.28
> 0.782								
3.race#4.education	U		.02563	.0488	-12.3			-8.89
> 0.000	M		.03219	.03322	-0.5	95.6		-0.60
> 0.550								
2.marital#2.education	U		.05259	.0498	1.3			0.87
> 0.387	M		.05219	.05295	-0.3	72.7		-0.35
> 0.725								
2.marital#3.education	U		.0675	.05507	5.2			3.51
> 0.000	M		.06349	.06336	0.1	99.0		0.05
> 0.957								
2.marital#4.education	U		.03385	.04425	-5.4			-3.77
> 0.000	M		.0374	.03778	-0.2	96.3		-0.21
> 0.835								

3.marital#2.education	U		.04402	.09789	-21.1		-15.46
> 0.000							
> 0.931	M		.06299	.06279	0.1	99.6	0.09
3.marital#3.education	U		.04347	.13219	-31.7		-23.79
> 0.000							
> 0.869	M		.07401	.0736	0.1	99.5	0.16
3.marital#4.education	U		.014	.23463	-70.9		-57.99
> 0.000							
> 0.128	M		.08277	.08688	-1.3	98.1	-1.52
2.race#2.marital#2.education	U		.00669	.00868	-2.3		-1.60
> 0.109							
> 0.902	M		.00752	.00762	-0.1	94.8	-0.12
2.race#2.marital#3.education	U		.00996	.01024	-0.3		-0.20
> 0.845							
> 0.877	M		.01002	.00987	0.1	47.6	0.15
2.race#2.marital#4.education	U		.00557	.00669	-1.4		-1.00
> 0.319							
> 0.946	M		.00598	.00603	-0.1	95.5	-0.07
2.race#3.marital#2.education	U		.01748	.02262	-3.7		-2.57
> 0.010							
> 0.922	M		.01947	.01961	-0.1	97.4	-0.10
2.race#3.marital#3.education	U		.01609	.02675	-7.4		-5.29
> 0.000							
> 0.944	M		.01994	.02003	-0.1	99.1	-0.07
2.race#3.marital#4.education	U		.00425	.03201	-20.9		-16.71
> 0.000							
> 0.915	M		.01335	.01347	-0.1	99.6	-0.11
3.race#2.marital#2.education	U		.01108	.00768	3.5		2.35
> 0.019							
> 0.739	M		.01009	.01042	-0.3	90.4	-0.33
3.race#2.marital#3.education	U		.00982	.00697	3.1		2.09
> 0.037							
> 0.889	M		.00894	.00907	-0.1	95.5	-0.14
3.race#2.marital#4.education	U		.003	.00583	-4.3		-3.12
> 0.002							
> 0.962	M		.00395	.00398	-0.0	99.0	-0.05
3.race#3.marital#2.education	U		.00822	.0239	-12.5		-9.40
> 0.000							
	M		.01351	.01349	0.0	99.9	0.02

```

> 0.986
3.race#3.marital#3.education  U | .00759  .0222  -12.1      | -9.08
> 0.000
                                M | .01249  .01245   0.0    99.7 |  0.03
> 0.972
3.race#3.marital#4.education  U | .00216  .0276  -21.1      | -17.25
> 0.000
                                M | .0095   .01053  -0.9    96.0 | -1.07
> 0.286

```

```

> -----

```

```

-----
Summary of the distribution of the abs(bias)
-----

```

```

-----
BEFORE MATCHING
-----

```

Percentiles		Smallest		
1%	.2837173	.2837173		
5%	.7501513	.7501513		
10%	1.26606	.78673	Obs	38
25%	2.446093	1.26606	Sum of Wgt.	38
50%	7.642407		Mean	14.70794
		Largest	Std. Dev.	18.94461
75%	21.09646	35.48853		
90%	35.48853	35.48853	Variance	358.8984
95%	70.94821	70.94821	Skewness	2.350004
99%	88.85711	88.85711	Kurtosis	8.887758

```

-----
AFTER MATCHING
-----

```

Percentiles		Smallest		
1%	.0069977	.0069977		
5%	.015915	.015915		
10%	.0306557	.0178048	Obs	38
25%	.0792273	.0306557	Sum of Wgt.	38
50%	.1489303		Mean	.3148394
		Largest	Std. Dev.	.3591833
75%	.356153	.9905276		
90%	.9905276	1.134696	Variance	.1290127
95%	1.134696	1.134696	Skewness	1.477275
99%	1.322415	1.322415	Kurtosis	3.992328

```

-----
Sample | Pseudo R2   LR chi2   p>chi2   MeanBias   MedBias
-----+-----
Raw    | 0.193       5219.23   0.000    14.7       7.6
Matched | 0.000       9.66     1.000    0.3        0.1
-----

```