Child Care Subsidies and the Labor Force Outcomes for Working Married Mothers

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Abstract: Working married mothers often make work-related accommodations to help rear their young children, which may include reducing work hours, taking a pay cut, or dropping out of the labor force. These actions may exacerbate negative labor force outcomes for working married mothers and wage differences between working spouses. Since the high cost of paid child care may lead to these work-related accommodations, child care subsidies, like the Child Care Development Fund (CCDF) for low-income families, may prevent these accommodations from occurring and improve labor force outcomes for married working mothers. Using unique data from the CCDF administrative records and Social Security Administration's Detailed Earnings Records linked to the Current Population Survey, Annual Social and Economic Supplement (CPS ASEC), this study estimates the average treatment effect of CCDF subsidy receipt on whether working married mothers remain in the labor force and whether receipt reduces spousal pay differences four years later. Using propensity score matching (PSM) as well as inverse probability weighting with regression adjustment (IPWRA) to account for selection effects, there is robust support that CCDF receipt increases the probability that working married mothers stay in the labor force. There also is support from the doubly robust IPWRA models that CCDF receipt helps working married mothers earn a more equitable proportion of the household's total earnings.

∗ Source: U.S. Census Bureau, Current Population Survey, 2008-2015, Annual Social and Economic Supplements; CCDF Administrative Records, 2007-2014; Social Security Administration's Detailed Earnings Record, 2007-2018.

Introduction

Research has shown that the gender pay gap tends to increase dramatically between men and women around the time of parenthood (Budig and England 2001), as the spousal earnings gap widens around the time of the birth of the first child up until the children reach school age (Chung et al. 2017). Mothers often encounter wage penalties for making work-related accommodations to help rear their children (Gangl and Ziefle 2009). These accommodations include reducing work hours, taking a pay cut, or dropping out of the labor force altogether during the early child-rearing years (Parker 2015; Staff and Mortimer 2012). While these accommodations may not be as viable for single mothers as the primary breadwinners, working mothers in opposite-sex marriages may be more likely to make these accommodations and rely on their working husbands as being the primary breadwinners (Cohn, Livingston, and Wang 2014). However, this produces unequal gender-related labor force outcomes, as the mothers who dropped of the labor force may find it more difficult to find a new job later in life, being perceived as less committed to work (Correll et al. 2007), or be penalized with lower relative earnings (Hotchkiss et al. 2017). Indeed, the work-related accommodations of married mothers, who often perceive these actions as necessary and not voluntary (see Damaske 2011; Stone 2007), lead to negative labor force outcomes and exacerbate the broader gender wage gap problem in society.

While there are many factors behind these work-related accommodations that may lead to the motherhood wage penalty or mothers dropping out of the labor force, including a lack of workplace provisions to help parents balance their work and family roles (Stone 2007), one understudied factor may be cost of paid child care. Expensive child care can greatly reduce household take-home pay and potentially “price out” working married mothers from the labor market, especially those in low-income populations (Cohany and Sok 2007; Cohn, Livingston, and Wang 2014). Indeed, some even suggest that rising child care costs may be contributing to the small uptick in stay-at-home mothers since the 1980s (Desilver 2014). In 2018, annual paid child care costs in the United States ranged from $18,442 in the South to $26,102 in the Northeast, with the cost of center-based child care often exceeding the annual income of families in poverty for areas with high costs of living, such as Washington, D.C. (Child Care Aware of America 2019). By reducing the cost of child care, working mothers may have a greater opportunity to maintain their full-time working hours, stay in the labor force, and reduce the gender wage gaps that commonly follow motherhood.

Childcare subsidies, like the Child Care Development Fund (CCDF), provide an opportunity to reduce the costs of paid child care and improve labor force outcomes for working mothers (Enchautegui et al. 2016; Giannarelli et al. 2019). Since 1990, the federally funded CCDF block grant program has provided child care subsidies for millions of working low-income families, and research has shown the labor force benefits of the subsidy program. A number of studies have shown higher employment rates among single mothers who were subsidy recipients (Bainbridge, Meyers, and Waldfogel 2003; Berger and Black 1992; Blau and Tekin 2007; Brooks et al. 2002; Enchautegui et al. 2016; Meyers, Heintze, and Wolf 2002; Tekin 2005). Using survey and administrative data, Forry and Hofferth (2011) found fewer child care–related work disruptions among subsidy recipients compared to non-recipients. Ha (2009) found that long term subsidy use is associated with an increase in the mothers' earnings. Zanoni and Weinberger (2015) found that mothers who are either unemployed or on the upper margins of eligibility benefit the most from the program. There are some studies that found null effects of subsidy use on earnings and employment (see Michalopoulos, Lundquist, and Castells 2010), but in general, many studies find that families, specifically low income mothers, experience positive labor force outcomes from subsidy programs like CCDF.

However, there are limitations in this area of the inquiry. Most of these studies focus on the employment of single mothers, since they compose a vast majority of subsidy recipients (Davis, Krafft and Forry 2017).[1] However, less is known about married mothers, a group who compose a majority (two-thirds) of stay-at-home mothers (Cohn, Livingston, and Wang 2014), and who may make work accommodations given the presence of a working spouse as well as societal pressure to stay at home to raise children.[2] Many studies also rely on either survey data or state-specific administrative records, but few studies link generalizable survey data and administrative data on the nation level (for exceptions, see Enchautegui et al. 2016). Finally, few studies focus on subsidy receipt and wage gaps between spouses, particularly across time, so the effects of childcare subsidies on gender equality labor force outcomes remain understudied.

This study seeks to examine whether the reduction of child care costs via child care subsidies help to improve labor force outcomes for working married mothers. Specifically, it examines the effect of CCDF childcare subsidy receipt on whether the working married mothers with young children stay in the labor force and whether the wage differences with their spouse are lower relative to non-CCDF households. Both outcomes are measured longitudinally, four years after observed CCDF receipt. The unique data from this study come from the CCDF administrative records provided by the Department of Health and Human Services (HHS), Social

[1] There are single unmarried mothers who may be living with a cohabiting partner who receive CCDF, but the cohabiting partner typically is not included in the family unit used to determine eligibility for most states. Five states (Florida, Kansas, Louisiana, Nevada, and Virginia) always include the cohabiting partner in the family unit, while four states (Colorado, Montana, New Jersey, and Oklahoma) include the cohabiting partner if this person is contributing to the financial wellbeing of the child (see Minton et al. 2015: 22).
[2] About 60 percent of Americans say children are better off if a parent stays home to focus on the family. See Cohn, Livingston, and Wang (2014) for a review of stay-at-home mothers.

Security Administration's Detailed Earnings Records (SSA DER), and the Current Population Survey, Annual Social and Economic Supplement (CPS ASEC). Given the known selection effects into CCDF receipt, this study uses treatment effects estimators – including propensity score matching and inverse probability weighting with regression adjustment – to balance treatment and control groups on a variety of relevant observed covariates. This improves statistical inferences and isolates the unique role of child care subsidies on observed outcomes. In sum, the unique merging of administrative and survey data, along with the implementation of a variety of balancing estimators to measure treatment effects, provides a strong methodological contribution in addition to the substantive contribution of better understanding the understudied role of child care subsidies on the labor force outcomes of working married mothers.

CCDF and Selection Problems

The CCDF is a federally funded program that's administered at the state level and seeks to provide child care subsidies to low-income parents who need to work, attend training, or go to school. It was authorized under the Child Care Development Block Grant Act (CCDFBG) as part of Omnibus Budget Reconciliation Act of 1990 (U.S. Department of Health & Human Services 2021).[3] In 2014, approximately 1.4 million children across 870 thousand families received child care subsidized through the CCDF (Minton et al. 2015). Copayments vary based on eligibility criteria, but in 2014, a family of three earning $15 thousand dollars a year would typically pay a

[3] It is important to note that the CCDFBG is not the only source of subsidized child care in the United States. In addition to CCDFBG, funding for child care subsidies also came from the Temporary Assistance for Needy Families Program (TANF), the Social Services Block Grant (SSBG), and from other state/local sources during the time period of this study. Some of the families receiving subsidized child care via these alternative sources are included in the CCDF data of this study, but since they are not required to be reported to HHS, some families receiving subsidized child care from non-CCDF funding sources are excluded from the data, which is a limitation of the study.

$60 copay per month for child care (Minton et al. 2015: iv).[4] Despite this benefit, recipients only represent about 14 to 17 percent of the eligible pool, meaning there are millions more children that are eligible for CCDF but don't receive the subsidy (see Giannarelli et al. 2019; Shaw, Partika, and Tout 2019). Funding for CCDF has increased since the start of the COVID-19 pandemic in 2020, as working families struggled with work and with paid child care. The Cares Act in the spring of 2020 provided an additional $3.5 billion for the program, and the December stimulus package in late 2020 provided an addition $10 billion toward CCDF, with funding likely to continue increasing in the 2021 (North 2021). Presidential candidates have continued to push for new policies to make child care more affordable (see North 2019), and expanding child care subsidies to broader populations has been recommended by experts to reduce childhood poverty and help working mothers stay in the labor force (see Giannarelli et al. 2019).

Eligibility for CCDF is primarily based on three criteria: the age of your child(ren), your income level, and your work/schooling status. First, eligible children need to be under the age of 13, though some states may increase the age threshold to 19 if the child is either under court supervision or is physically or mentally incapable of caring for themselves (Minton et al. 2015:13). Second, the family's income cannot exceed 85 percent of the state median income, though this also can be waived on a case-by-case basis.[5] And third, the parents or guardians of the child either need to be working, attending job training, or attending school to be eligible. These are the guidelines established by the federal government, but states ultimately have some

[4] For comparative purposes, a family of three below the poverty level in 2014 (<$19,790) needing center daycare for an infant would pay $402 per month in the most affordable state (Mississippi) and $1,856 per month in the most expensive area (District of Columbia). See Child Care Aware of America (2015) for more cost comparisons.
[5] Often, this may be waived if, for example, the child is in need of protective services (see Minton et al. 2015: 12).

discretion when determining eligibility and can adjust income thresholds,[6] as well as introduce other criteria (e.g., minimum working hours, other types of income/program benefits, blended/step family status, etc.; see Minton et al 2015 for a full discussion on eligibility). Moreover, the criteria can change over time, as the Child Care and Development Block Grant Act of 2014 increased program flexibility with regard to qualifying activities of parents, income thresholds, co-payment amounts, and more (see U.S. Department of Health & Human Services 2021). The type of child care is not part of the eligibility criteria, but most subsidies pay for daycare centers.[7]

Clearly, the eligibility requirements produce a selection problem when comparing labor force outcomes of CCDF versus non-CCDF married parent households, but the analytical solution is not obvious. Two issues arise: 1) determining the appropriate universe/analytical sample; and 2) improving causal inference despite knowing that CCDF and non-CCDF households will differ vastly on various characteristics. First, while it is fairly simple to restrict the analytical sample to family households with both married parents in the labor force and have children under the age of 13, the varying income thresholds across localities, as well as additional potential criteria mentioned, make it difficult to enforce strict cut off values on select variables to be in universe. Moreover, many CCDF family households are single parent households (e.g., 92 percent in Maryland, 2007-2012, see Davis, Krafft and Forry 2017), so in order to get a larger sample of married CCDF family households, the survey and administrative record years will need to be pooled across years, leading to more analytical problems as

[6] Approximately half of state program allow families to deduct child support payments from earned income and a few states (South Dakota, Utah, and Wyoming) allow a certain amount of earned income (e.g., 4 percent in South Dakota) to be disregarded in the income eligibility requirements.
[7] For a more detailed breakdown of child care type served by CCDF, see the “FY 2018 Preliminary Data Table 3 - Average Monthly Percentages of Children Served by Types of Care” here: https://www.acf.hhs.gov/occ/data/fy-2018-preliminary-data-table-3-average-monthly-percentages-children-served-types-care

eligibility thresholds change from year-to-year. At this point, strict cut-offs in determining the analytical sample become hard to justify, as it may remove some CCDF households from high income states or with some exceptional criteria, reducing an already small subsample, and exclude non-CCDF households who would otherwise serve as important counterfactual control cases for these unique CCDF households. Alternatively, one may be too permissive with universe restrictions, allowing too many dissimilar non-CCDF cases in the analytical sample who may be given too much statistical weight despite having a low propensity toward receiving CCDF. And second, it is difficult to isolate the effect of CCDF on labor force outcomes when the CCDF households, often coming from disadvantaged backgrounds and eligible based on select criteria, may differ on a variety of social and economic indicators compared to non-CCDF households. Many married working parents have relatively high socioeconomic status, as 68 percent of dual-income married working parent households with young children earned $100 thousand dollars or more in 2020.[8] Research also tends to show how those who select into marriage are more likely to be college educated and less likely to be black (Aughinbaugh 2013; McLanahan 2004). Thus, the general population of working married parents most likely will come from advantaged backgrounds while CCDF working parents will come from more marginalized backgrounds. It is not a simple “apples-to-apples” comparison across groups, which inhibits causal inference, so advanced modelling techniques are necessary.

The potential solution is to implement a treatment effects estimator. A treatment effects framework mirrors the logic of an experimental design, with control cases representing the counterfactual, or unobserved potential outcome, had one not received the treatment. For

[8] See Table FG2 in the 2020 America’s Families and Living Arrangements tables package here: https://www.census.gov/data/tables/2020/demo/families/cps-2020.html

example, how likely would it be for the married mother CCDF recipient to stay in the labor force had she not received the subsidy? What would the wage differences between her and her spouse look like had she not received CCDF? The control cases would represent the counterfactual. However, since randomly assigning a treatment is not possible in non-experimental settings, treatment effects estimators help balance the treatment (i.e., CCDF receipt) and control (no CCDF receipt) groups on observed similar characteristics in order to isolate the treatment effect on the measured outcomes (i.e., staying in the labor force four years later, wage differences between spouses four years later). First, one runs a logit model predicting the treatment based on important observed characteristics that may impact selection. This highlights how a treatment effects approach models selection around the treatment variable, not the outcome variable like regression adjustment. After the logit model is run, a propensity score, or predicted probability, is outputted and used to balance the group. Balancing may be implemented by either matching treatment and control cases with similar[9] propensity scores (i.e., propensity score matching) or re-weighting the data by the inverse probability of treatment for treated cases and inverse probability of non-treatment for control cases (i.e., inverse probability weighting; also known as inverse probability of treatment weighting or propensity score weighting, see Lanza, Moore, and Butera 2013). In terms of understanding the latter, inverse probability weighting magnifies both control cases who otherwise have a high propensity of receiving the treatment as well as treatment cases who otherwise have a low propensity toward receiving a treatment, creating counterfactuals not easily observed in the data (Caldera 2019). This allows for better causal inference, comparing like-with-like when selection issues would otherwise make inferences

[9] Depending on the matching algorithm, a similar propensity score is either the matched case with closest propensity score (i.e., nearest neighbor matching) or within a defined threshold or tolerance level (e.g., +/- .1 propensity score across matched cases; i.e., caliper matching). See Khandker, Koolwal, and Samad (2010) for a discussion on various approaches to identify similar matched cases in propensity score matching.

more difficult. Either propensity score matching (PSM) or inverse probability weighting (IPW) may be used to estimate treatment effects, and the current study re-runs analyses with both estimators for robust inferences. Moreover, the IPW estimator will be paired with a regression adjustment (i.e., IPWRA; see Wooldridge 2010) to model around the outcome as well as the treatment, making it “doubly robust” since either the selection equation or the regression equation may be misspecified and inferences are still robust as long as at least one of the equations are correctly specified (Stata 2014).

In the context of this study, one can balance CCDF and non-CCDF households on important characteristics that may be associated with a higher propensity for CCDF, including income, education, race and Hispanic origin, full time work status, poverty status, other program receipts (e.g., food stamps), family characteristics, locality, year of receipt, and more. This solves the aforementioned problems of CCDF selection issues because: 1) Instead of having to determine arbitrary inclusion criteria for being in the analytical sample, the treatment effects estimators will be able to match similar cases via propensity scoring or re-weight cases to adjust for one’s propensity of receiving CCDF; and 2) By balancing CCDF and non-CCDF households on observed characteristics, selection concerns are reduced and it is easier to infer whether CCDF has an impact on labor force outcomes of working married mothers. Moreover, given how only a fraction of those eligible for CCDF actually receive child care subsidies (Giannarelli et al. 2019; Shaw, Partika, and Tout 2019), this suggests that there are potential control cases in the general population that are similar and may represent the counterfactual unobserved potential outcome of CCDF households had they not received the child care subsidy. In this way, a treatment effects approach is a viable means to address the known selection issues in the study.

Data & Methods

Data for the study come from three sources: CPS ASEC (2008-2015), CCDF Administrative Records (2007-2014), and the SSA DER-CPS (2007-2018). Conducted by the U.S. Census Bureau on behalf of the Bureau of Labor Statistics, the CPS ASEC is a nationally representative household survey performed every year in the month of March, and is a rich source of social as well as economic data on the United States population. The data serves as the primary sampling frame from which the analytical sample is drawn, and provides all the variable information for the study, except for child care subsidy information and earnings and labor force participation-related estimates. For whether a CPS household receives a childcare subsidy, I use the CCDF administrative data series, which contain annual information regarding whether a family received a CCDF subsidy, the copay amount, which month of subsidy receipt, number of children in the family receiving the subsidy, and more. The CCDF administrative data series also includes some, but not all, families receiving subsidized child care through non-CCDF funds (e.g., TANF, SSBG, and other state/local sources), so not all subsidized child care is captured in the measure, a limitation of the study. For earnings history, I use data from SSA DER-CPS, a restricted data set provided by the Social Security Administration to the U.S. Census Bureau of the earnings histories of CPS household members. The dataset contain W-2 tax form wages (the IRS requires employers to report wages paid to employees via W-2 forms), from 1973 up until 2018, providing longitudinal earnings and labor force participation data. I link all three data sources via the Census Bureau's personal identification key (PIK), a unique protected identifier produced by a PVS process (see Wagner and Lane 2014). Given that the CPS ASEC asks questions pertaining to the previous calendar year (i.e., reference year), I link all three sources via PIKs on the reference year (e.g., reference year = 2014: CPS ASEC 2015, CCDF 2014, SSA DER 2014), as well as retain earnings estimates from the SSA DER "outcome" year (four years after the reference year) for longitudinal dependent variables. In total, there are eight reference years pooled together (2007-2014),[10] which are pooled given the small percentage of married couple CCDF households in the CPS ASEC.

In order to be in the analytical sample, households must satisfy a set of criteria. First, the household must be a married opposite-sex couple household living with at least one (biological/step/adoptive) child younger than age 13. Second, both spouses need to be working full-time or part-time during the reference year and in the DER so that the study can measure spousal pay gaps and wife labor force retention. Third, the household needs paid child care during the reference year, either by taking a child care subsidy in the CCDF data or indicating they paid for child care in the CPS ASEC survey, with the latter requiring reported, not imputed, values. Fourth, the householder and the spouse need to have a PIK in order to be linked across the three data sources.[11] And fifth, all households needed to be residing in a state that includes a full population of CCDF recipients.[12] Some states in the CCDF administrative records only provided a sample, not full population, of their CCDF recipients, so it's possible to have CPS households using CCDF in these states and yet not be in the CCDF sample, making it appear that they are control cases when they are in fact treatment cases. Subsetting for full CCDF populations is recommended and often implemented when utilizing these data (see Shantz 2019).

[10] Because CPS sometimes re-interviews households across different months, if a household in one survey year showed up again in a following ASEC year that is part of the pooled estimate, the duplicate household in the second ASEC survey year is removed.

[11] Some CPS household members do not have PIKs, so PIK selection is adjusted for in the survey weights. This process includes estimating a logit model with PIK as the dependent variable and common demographic variables (age, race, gender, education) as the predictors. A propensity score is produced from the model and the inverse of propensity score is multiplied by the ASEC weight in order to adjust for PIK selection. These adjustments are done prior to subsetting for the analytical sample and using the treatment effects estimators.

[12] These are: Alabama, Arizona, Arkansas, Colorado, Delaware, Georgia, Hawaii, Idaho, Illinois, Kansas, Kentucky, Louisiana, Maine, Maryland, Michigan, Mississippi, Missouri, Montana, Nebraska, Nevada, New Hampshire, New Jersey, New Mexico, North Dakota, Ohio, Oklahoma, Oregon, Rhode Island, South Carolina, South Dakota, Tennessee, Texas, Utah, Vermont, West Virginia, Wisconsin, Wyoming, and the District of Columbia.

Dependent variables

The study focuses on two types of outcomes four years after the reference year: the wife remaining in the labor force and earnings gaps between spouses. For the former, this outcome is measured by whether the wife's earnings are found in the DER four years after they appeared in the reference year. If there are no earnings reported, it is assumed that the wife is not in the labor force.[13] In terms of spousal earnings gaps, this is measured by two separate dependent variables: the wife's proportion of household earnings and the husband-wife difference in log earnings. For the wife's proportion of household earnings, this is calculated from W-2 Box 1 total compensation reported to the IRS (wages, tips, and other compensation),[14] with the wife's total compensation as the numerator and the combined husband-wife total compensation as the denominator. The second spousal earnings gap measure, spousal difference in log earnings, is simply the log earnings of the wife subtracted from the log earnings of the husband, with larger values indicating larger pay gaps. Both measures are used to analyze gender pay discrepancies (for differences in log earnings, see Chung et al. 2017; for wife's proportion of household earnings, see Winslow-Bowe 2009), so both outcomes will be shown for robustness, though a greater focus is put on wife's proportion of household earnings given it's easy interpretability. These same pay gap variables also are measured for the reference year and used as matched covariates in their separate respective models. When examining the effect of the wife remaining in the labor force, the full analytical sample is used, while models examining pay gap differences

[13] There is, of course, the possibility of unreported income during the outcome year, or leaving the work force was specific for that year or not reflective of leaving the workforce in a long term sense. These are limitations of the dependent variable.

[14] In order to compare "like-with-like," wage earnings, not self employment earnings, are the focus of the study due to the inherent volatility in self employment income from year-to-year – it's difficult to infer whether changes in self employment income are due to work-related accommodations or the nature of their business -- as well as much larger pay discrepancies between men and women with regard to self employment earnings (see Lawter, Rua, Andreassi 2016).

four years later only include working spouses who remained in the labor force at both time points (wives who left the labor force four years later are dropped). All earnings are inflation-adjusted in 2018 dollars, which is the last outcome year observed.

Treatment & Covariates

The treatment variable is whether the CPS married couple household received a CCDF child care subsidy at any point during the reference year as evidenced by their presence in the CCDF administrative data. Even though amount of copays are not a focus of this study, many of the observed monthly copays were indeed low and align with what other researchers using CCDF data have found (Minton et al. 2015; Shantz 2019).

In terms of covariates, the PSM and IPW equation of the IPWRA model require relevant variables that may relate to selection into CCDF, while the RA equation of the IPWRA model requires variables that may be related to the outcomes. The variables listed are used for both equations except when noted. Since CCDF households tend to come from low-income populations, who disproportionately are black and/or Hispanic and do not have a college degree (Semega et al. 2020), and the general target population of married households often come from advantaged backgrounds (Aughinbaugh 2013; Gurrentz 2018; McLanahan 2004), it is important to control for race and Hispanic origin, education, and socioeconomic characteristics. Race and Hispanic origin of spouses is divided into four categories: both white alone (non-Hispanic), both black alone (non-Hispanic), both Hispanic, and other (e.g., Asian, American Indian and Alaska Native, Native Hawaiian and Other Pacific Islander, interracial, interethnic, etc.). Education of spouses was broken down into four categories: both spouses have a Bachelor's degree, the wife is the only spouse who has a Bachelor's degree, the husband is the only spouse that has a Bachelor's degree, and neither spouse has a Bachelor's degree. Socioeconomic variables are measured by married couple household income (source: SSA DER), poverty status, and whether the household received food stamps during the reference year. In order to not violate the overlap assumption in the selection equations (i.e., each individual has a positive probability of receiving each treatment level), household income was broken down into four categories: income less than $25 thousand annually, $25-$50 thousand annually, $50-$75 thousand annually, and $75 thousand or more annually. For the RA equation of the IPWRA model, the continuous version of the household income variable (log transformed) is used since the overlap assumption is only necessary for the selection equations in treatment effects estimators. Nativity may also affect the ability to receive a childcare subsidy, so it is measured by whether either (or both) spouses are foreign born. Age differences between spouses may be associated with spousal wage gaps (Chung et al. 2017;), so age difference categories are broken down into six categorical variables that range from the husband being 7+ years older than the wife to the wife being 4+ years older than the husband. Also, work status and family characteristics may play a role in terms of both CCDF eligibility (see Minton et al. 2015), as well as the labor force outcomes of mothers (Kahn et al. 2014; Klerman and Liebowitz 1999; Staff and Mortimer 2012). Work status is a binary indicator of whether both spouses work full time (i.e., 35 hours or more per week). Family characteristics are measured by whether the family household is multigenerational (grandparents live in the household), whether the family household is blended (i.e., include stepchildren), the number of children who need paid childcare, and the age of the married couples' own children (non-mutually exclusive age categories: <3, 3-5, and 6-12).[15] Finally, survey year and divisional region of residence (nine categories) are included as covariates.[16]

[15] For example, a family household could potentially have a two-year-old, a four-year-old, and a seven-year-old, so they would =1 for each indicator.

[16] It would be ideal to use state indicators as covariates instead of divisional regional indicators given how different states have different CCDF eligibility requirements. However, it's difficult to balance on some state indicators

Analytical Strategy

First, I examine the social, demographic, and economic characteristics of CCDF compared to non-CCDF households, using replicate weights to test for significant differences. Differences suggest that these groups are unbalanced and may need to be matched/re-weighted to account for differences. Second, I estimate a bivariate and multivariate logit model predicting CCDF receipt, the latter of which produces the propensity score used later to adjust for selection in the PSM and IPWRA models. Third, I test whether covariates are balanced in the IPWRA models using *tebalance* command in Stata. Specifically, I use *tebalance overid* to test whether the covariates overall do not significantly vary across treatment groups, and I use *tebalance summarize* to examine whether variance ratio estimates are generally reasonable (values of 1 or 2, but not much larger, see Zhang et al. 2019). Fourth, I implement propensity score matching using *teffects psm* with robust standard errors to estimate the average treatment effect of CCDF on the wife remaining in the labor force and spousal earnings gaps four years after the reference year. Fifth, I re-run the same analyses using inverse probability weighting with regression adjustment, which reweights the data via inverse probability weighting, estimates treatment specific potential outcomes via regressions (i.e., a reweighted regression for treatment cases and a separate reweighted regression for control cases), and then estimates the average treatment effect by calculating the differences in means of these potential outcomes. IPWRA models are doubly robust in case either the selection equation or outcome equation are misspecified. ASEC sampling weights are adjusted for PIK selection and implemented as probability weights in the

across treatment groups, leading to relatively concerning weighted variance ratios and less confidence in causal inference.

IPWRA models and as a matched covariate in PSM.[17] Descriptive statistics are performed using SAS 9.4, while logit, PSM, and IPWRA models are performed using Stata 16.1.

Results

Table 1 shows the descriptive statistics of married working family households with young children in need of paid child care by CCDF receipt. This helps us assess whether the treatment and control groups are similar or whether they need to be balanced via treatment effects estimators on observed covariates. All characteristics shown are at time 1. As shown in Table 1, non-CCDF and CCDF households differ on a number of observed demographic, social, and socioeconomic characteristics. For example, while 71.1 percent of non-CCDF households have both spouses who are white alone (non-Hispanic), this is only true for 36.2 percent of CCDF households. There also are higher proportions of households with two black non-Hispanic spouses and households with two Hispanic spouses among CCDF recipients compared to non-CCDF recipients. Educational differences among groups also are evident, as 38.8 percent of non-CCDF households have both spouses with college degrees, while college degree attainment is significantly lower for CCDF households at 2.8 percent. In terms of family characteristics, a higher percentage of CCDF households are blended families that include stepchildren (38.4 percent vs. 10.6 percent), and CCDF households also tend to have a higher number of young children who need paid child care. Finally, some socioeconomic characteristics of CCDF households are significantly different from the non-CCDF households, which is expected given the income thresholds placed on CCDF eligibility. While only 1.9 percent of non-CCDF households make below $25 thousand dollars a year, 23.4 percent of CCDF households fall

[17] *Teffects psm* does not allow for sampling weights. Weighting a PSM model is somewhat controversial and guidelines are not always agreed upon, but Dugoff and colleagues (2014) recommend using the sampling weight as a matched covariate based on their analyses.

under this threshold. Approximately half (44.4 percent) of CCDF households make between $25 thousand and $50 thousand dollars annually, compared to only 7.5 percent of non-CCDF households. Moreover, 17.9 percent of CCDF households are in poverty and 36.8 percent are on food stamps, estimates much higher than 0.9 percent of non-CCDF households in poverty and 3.2 percent on food stamps. The spousal pay gap measures did not differ significantly by CCDF receipt. In sum, these two groups are significantly different and need to be rebalanced via propensity scores to compare "like with like."

[Insert Table 1 about here]

Table 2 presents bivariate and multivariate logit estimates predicting CCDF receipt. The multivariate logit estimates will later be utilized to produce the predicted propensity scores for rebalancing the treatment and control groups in the treatment effects models. Also, even though multicollinearity is not a concern when estimating propensity scores (McMurry et al. 2015), this may be a concern in the outcome regression equation of the IPWRA model, so collinearity diagnostics are implemented. Nonetheless, the variance inflation factors (VIFs) are reasonable, with a mean VIF of 2.6 and no individual estimate reaching the problematic VIF threshold of 10 or higher (Midi and Bagheri 2010).

Similar to Table 1, a number of demographic, social characteristics, and particularly socioeconomic factors predict CCDF receipt. Households with two white alone (non-Hispanic) spouses are less likely to use CCDF to subsidize their child care ($p<.01$), while households with two black alone (non-Hispanic) spouses are more likely (OR=3.71) to receive CCDF ($p<.001$). Also, households where either the wife or both spouses have a college degree are less likely to be subsidy recipients ($p<.001$ for either estimate). Blended families have an increased odds of 145 percent (OR=2.45) of being on CCDF compared to non-blended families ($p<.001$). The age of the married couples' own children also predicted CCDF receipt, as having a 3 to 5 year-old increased the odds of receiving a childcare subsidy by 96 percent compared to those who do not have a child in that age group (OR=1.96; $p<.001$). Number of children needing paid child care was a significant predictor in the bivariate model ($p<.001$), but not the multivariate model. Socioeconomic indicators, like household earnings ($p<.001$), poverty status ($p<.05$), and food stamps receipt ($p<.01$), all had significant effects on CCDF receipt in the multivariate model, as expected. Wife's proportion of household earnings at time 1 was not a significant predictor in the multivariate model.

[Insert Table 2 about here]

Now that it is clear that receiving a child care subsidy via the CCDF is not randomly assigned and varies significantly based on a variety of demographic, social and economic indicators, it is important to rebalance these groups to make sure their characteristics are similar when estimating treatment effects. Fortunately, Stata's postestimation diagnostic test *tebalance* allows one to check whether covariates are balanced across treatment groups when re-weighted using IPW or IPWRA models.[18] Using *tebalance overid* in Stata to test for significant differences, the diagnostic test shows that the covariates in the IPWRA models are balanced across treatment groups and do not differ significantly. Moreover, using *tebalance summarize* in Stata, the variance ratios across treatment groups when re-weighted appear reasonable, with no estimate exceeding 2.6 across models. Ideally, the goal is to have a variance ratio close to 1 across treatment groups, but estimates close to 2 are considered acceptable as well (see Zhang et al. 2019). Using IPWRA models predicting wife's labor force participation at time 2, Figure 1

[18] *Tebalance* is not available for *teffects psmatch*.

shows the raw and weighted variance ratios across treatment groups for important socioeconomic indicators,[19] the same characteristics that were clearly different across groups in Tables 1 and 2. The raw variance ratios are as high as 17.4 for poverty status and exceed the value of 9 for food stamps receipt as well as household earnings below $25 thousand dollars annually. When re-weighted and balanced, we find the variance ratios to be 1.4 for poverty status, 1.5 for households earnings below $25 thousand a year, and 2.1 for food stamps receipt, much more acceptable estimates, suggesting balancing across treatment groups.

[Insert Figure 1 about here].

Now, that the covariates are balanced, Table 3 shows the effect of CCDF receipt on the labor force participation of the wife at time 2 as well as the spousal pay gap measures at time 2 (i.e., wife's proportion of household earnings and husband-wife difference in log earnings). In terms of wives still being in the labor force four years later, there is robust support that CCDF helps increase labor force retention of these married women with young children. Both treatment estimators, PSM and IPWRA, show positive significant effects (PSM: $p<.001$; IPWRA: $p<.05$). The .07 coefficient in the IPWRA models represents a seven percentage point difference in potential outcomes of the control vs. treated groups. Figure 2 shows that the estimated potential outcome for the control group is 91.3 percent of working married wives with children remaining in the workforce four years later, but this estimate is 98.3 percent for those who receive CCDF. In sum, when treatment and control groups are balanced and potential outcomes are estimated,

[19] Although other characteristics are important with regard to probability of receiving CCDF (e.g., like race/Hispanic origin or education), CCDF eligibility is explicitly tied to income levels and other program participation receipts (e.g., food stamps), making these characteristics particularly unbalanced across groups, so they are the main focus for Figure 1.

these results suggest that CCDF tends to increase the likelihood that married mothers remain in the workforce.

When examining the effect of CCDF on pay gap measures between spouses, the results differ in magnitude by the treatment effects estimator implemented. When using PSM, CCDF does not significantly predict wife's proportion of household earnings and only marginally predicts husband-wife differences in log earnings, the latter suggesting a small decrease in the earnings gap between spouses (coef = -0.13; $p < .10$). However, when using IPWRA, which is a doubly robust estimator that models around both the treatment and the outcome, estimates suggest that CCDF households have wives with higher relative earnings and lower spousal earning differences at time 2 (both DVs: $p < .01$). Estimating the predicted potential outcomes of wife's proportion of household earnings at time 2, Figure 2 shows that wives earnings in the control group represented 42.4 percent of the overall household earnings, but wives in the treatment group who received a childcare subsidy produced 49.7 percent of the households earnings, a fairly equitable earnings distribution across spouses in this group. Indeed, there is support, specifically when implementing the doubly robust IPWRA estimator, that CCDF leads to more earning equality across spouses compared to similar households that did not receive CCDF.

[Insert Table 3 about here]

[Insert Figure 2 about here]

Discussion & Conclusion

This study finds that selection concerns are a valid issue when studying targeted child care subsidy programs, like CCDF, but, nonetheless, when adjusting for selection and balancing across treatment groups, child care subsidies increase the likelihood that working married mothers remain in the labor force and decrease wage differences with their spouses. CCDF family households differ from non-CCDF family households on a number of characteristics, including race and Hispanic origin, education, and socioeconomic indicators. Given the targeted eligibility of low-income families, and certain disadvantaged racial, ethnic, and educational groups (e.g., black, Hispanic, high school educated) disproportionately composing those with low income (Semega et al. 2020), these differences are expected. These indicators, among others, are used in a multivariate logit model to predict CCDF, and the outputted propensity scores are later used to adjust for selection, either via matching in PSM or re-weighting in IPWRA models. Results suggest robust support that CCDF increases the retention of working married mothers in the labor force, as 98.3 percent of subsidy-receiving working mothers remained in the labor force four years later from observed receipt, compare to 91.3 percent of working married mothers without a child care subsidy. The effect of CCDF on spousal pay gap measures four years later substantively differed by treatment effects estimator, but the doubly robust IPWRA models, adjusting for both differences into treatment selection and around the outcome measure, find that child care subsidies significantly increase the probability that working married mothers earn a more equitable proportion of the household earnings, 49.7 percent, compared to working married mothers without child care subsidies, who earn an estimated 42.4 percent of household earnings. In other words, evidence from this study suggests that child care subsidies increase labor force retention and reduce spousal wage gaps for working married mothers, a group that is likely to make work accommodations when rearing young children (Parker 2015; Staff and Mortimer 2012).

When estimating the average treatment effect of CCDF on spousal pay gap measures four years later, why did the results of the PSM and IPWRA models differ somewhat in magnitude? It's possible the selection equation is misspecified and/or modelling around the outcome is necessary to account for suppressor effects. Recall that the IPWRA estimator adjusts for selection through inverse probability weighting and then estimates a multivariate regression model equation to adjust for observed differences related to the outcome. The benefit of IPWRA is that either the selection equation or outcome equation can be misspecified and the results are still valid as long as one of the equations is correct, making the estimator doubly robust. The variables in the selection models for PSM and IPW are the same, though adjusted differently, so it's possible the selection equation is incorrect, perhaps due to an omitted variable or measurement issue. However, the same variables are used in the regression equation of IPWRA as well, with the exception of household income, which is used as a continuous variable in the regression equation, but changing income into discrete categories in the regression equation to match the selection equation does not seem to account for the differences. Also, running an IPW without a regression adjustment produces null results, so differences are less likely due to the selection estimator type. Instead, it appears that there are suppressor effects that mask the significant relationship between CCDF and future spousal pay gap measures unless accounted for in an outcome regression model. It does not appear to be just one measure that is producing the suppressor effect. Adding education to the regression equation does make the IPWRA models go from not significant to significant, then adding family characteristics further strengthen the p-value, followed by the addition of other demographic variables that then resemble the final results. Thus, adjusting for selection alone is not sufficient. After re-weighting for selection, a multivariate outcome regression model is beneficial to account for suppressor effects and properly estimate the effect of CCDF on spousal pay gap differences. For this reason, this study strongly recommends IPWRA estimators when estimating treatment effects.

There are a number of limitations in this study. First, treatment effects estimators are still subject to omitted variable bias. Second, the outcome measure of staying in the workforce is simply whether the wife appeared in the Detailed Earnings Record four years, but there is, of course, the possibility of unreported income during the outcome year, or leaving the work force was specific for that year or not reflective of leaving the workforce altogether. Third, and related to the previous limitation, the study only measures short term outcomes, and the decision to only measure outcomes four years later is somewhat arbitrary. Studying the long term effects of child care subsidies on the labor force outcomes or working mothers would be beneficial. Fourth, while the study is able to creatively use earnings estimates longitudinally, the lack of time-varying CPS ASEC and CCDF variables is limiting. Fully longitudinal data would allow for change-over-change models, like within-person fixed effects models, which may be better to account for time-stable selection and adjust for changes over time, including changes in subsidy use and change in number of kids needing paid child care.[20] Fifth, the study restricts the sample to states that have a full population of CCDF recipients, but this limits generalizability since some of the larger states only provided CCDF samples. Full population CCDF records for all states would be ideal, though perhaps not feasible. In addition, the CCDF measure may not fully be representative of all subsidized child care recipients since families may receive government funding for child care from non-CCDF sources (e.g., TANF, other state/local sources) that are

[20] This may be possible by using the Survey of Income and Program Participation instead of the Current Population Survey, but this would greatly reduce an already limited number of CCDF cases in the analytical sample.

not required to be reported to HHS for the ACF-801 data used in this study.[21] Sixth, the study uses divisional region of residence as the locality covariate, not individual state of residence, due to issues of balancing state indicators across treatment groups. However, with a larger sample, it may be possible and certainly beneficial to use state indicators given it's importance to CCDF eligibility requirements. And finally, the study focuses on work accommodations that may occur after time 1 (e.g., staying in labor force, reduced relative pay), but the work accommodations of mothers may also take place prior to time 1 in ways that affects selection into the analytical sample. Stay-at-home mothers at time 1 are excluded from the study, but the decision to be a stay-at-home mother may have been due to the anticipated expenses of child care. Because of this, the control non-CCDF cases may be less likely to make work-related accommodations because these working married mothers already committed to staying in the workforce and maintaining their work hours despite the high expenses of childcare. In other words, this selection effect may underestimate the true average treatment effect of child care subsidies.

The current study provides a number of contributions related to Census products. The project highlights an innovative way to combine administrative records (CCDF & DER) with Census survey data (CPS). It serves to highlight the income dynamics of households, an important of focus of surveys like the Current Population Survey as well as the Survey of Income and Program Participation (SIPP). In particular, it uses the unique data housed at Census to understand and benefit populations of interest, including low-income groups who need paid child care. Finally, understanding how to better model CCDF variables may benefit other Census

[21] HHS allows states to pool CCDF and non-CCDF funded families together with their ACF-801 data submissions that compose the CCDF but does not *require* them to do so. In this way, there are some families served through other programs in the data, but not *all* families receiving subsidized child care are included.

projects hoping to incorporate the rich administrative record data, including the SIPP Gold Standard File, SIPP Synthetic Beta, and the Small Area Estimates Childcare Project.

In addition, the current study's substantive contribution of understanding the benefits of child care subsidies may also lead to important future avenues of research. As mentioned earlier, studying more long-term effects (e.g., 10-20 years later) of child care subsidies on the employment and earnings of working married mothers would be useful in gauging the broader labor force trajectory of this population over time. Moreover, with a larger sample of CCDF households, it may be beneficial to divide the subsidy treatment by absolute copay amount or relative copay amount (i.e., copay divided by household income) to examine the effects of high vs. low subsidization. Finally, another future area of study is the policy effect of child care subsidy expansion on childhood poverty and the labor force participation of all working parents. Simulation studies have suggested that increasing income eligibility requirements up to 150 percent of the poverty threshold would lead to an additional 270 thousand mothers joining the work force and 385 thousand child raised out of poverty (Giannarelli et al. 2019). If eligibility requirements become increasingly flexible, as current trends have suggested (North 2021; U.S. Department of Health & Human Services 2021), this may provide a natural experiment for understanding the far-reaching benefits of affordable child care on working families and their children. Indeed, the current study suggests that child care subsidies improve the labor force outcomes of working married mothers, so understanding how these benefits may extend to other populations is a viable future area of inquiry.

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Table 1. Descriptive Statistics of Total Sample and CCDF Subsample

Universe: Working Husband-Wife Households with Children (Ages 0-12) & Need Paid Childcare (Time 1)

	All (A)		Non-CCDF (B)		CCDF (C)				
Unweighted N:	11,500		11,000		450				
	Percent	SE	Percent	SE	Percent	SE	A vs. B	A vs. C	B vs. C
CCDF Recipient	4.50	0.41	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Both White Alone (non-Hispanic)	69.50	0.87	71.08	0.87	36.16	4.38		***	***
Both Black Alone (non-Hispanic)	7.86	0.49	6.82	0.46	29.81	4.41		***	***
Both Hispanic	7.48	0.50	7.10	0.50	15.63	3.10		**	**
Husband 1-3 Years Older	36.11	0.82	36.17	0.82	34.82	4.10			
Husband 4-6 Years Older	16.60	0.57	16.82	0.60	11.82	2.48		+	+
Husband 7+ Years Older	12.38	0.50	12.17	0.51	16.79	3.01			
Wife 1-3 Years Older	15.98	0.58	16.06	0.59	14.25	2.88			
Wife 4+ Years Older	5.14	0.37	4.96	0.37	8.87	2.62			
Both Have Bachelor's Degree	37.18	0.90	38.80	0.92	2.84	1.37		***	***
Wife Bachelor's Degree Only	18.48	0.65	19.03	0.65	6.92	1.98		***	***
Husband Bachelor's Degree Only	7.76	0.49	7.86	0.50	5.66	1.89			
Multigenerational Household	1.75	0.20	1.72	0.21	2.31	1.08			
Blended Family Household	11.83	0.52	10.58	0.51	38.39	4.05	+	***	***
Foreign Born Spouse(s)	13.67	0.60	13.70	0.62	12.95	2.86			
Own Children Under Age 3 (1=yes)	42.41	0.86	42.23	0.88	46.08	4.54			
Own Children Ages 3-5 (1=yes)	47.34	0.82	46.44	0.81	66.42	3.75		***	***
Own Children Ages 6-12 (1=yes)	54.91	0.84	54.40	0.85	65.71	4.07		**	**
Number of Children Needing Paid Childcare[a]	1.51	0.01	1.50	0.01	1.83	0.08		***	***
Both Spouses Work Full-Time	77.37	0.69	78.11	0.68	61.80	4.33		***	***

Source: U.S. Census Bureau, Current Population Survey, 2008-2015, Annual Social and Economic Supplements; CCDF Administrative Records, 2007-2014; Social Security Administration's Detailed Earnings Record, 2007-2018

Reference Groups: Other/Multiracial/Multiethnic Couple, Same Age, Neither Have Bachelor's, Neither Spouse Works Full-Time, Household Earnings $75K+, Regional Division: Pacific, Survey Year: 2008

Notes: All estimates are at time 1. Unweighted Ns are rounded for disclosure avoidance purposes.

a = Mean shown for continuous variable

N/A = Not applicable

+ p<.10; * <.05; ** p<.01; *** p<.001

Table 1. Descriptive Statistics of Total Sample and CCDF Subsample, Cont.

Universe: Working Husband-Wife Households with Children (Ages 0-12) & Need Paid Childcare (Time 1)

	All (A)		Non-CCDF (B)		CCDF (C)				
Unweighted N:	11,500		11,000		450				
	Percent	SE	Percent	SE	Percent	SE	A vs. B	A vs. C	B vs. C
Household Earnings <$25K	2.88	0.32	1.91	0.26	23.35	3.52	*	***	***
Household Earnings $25K-$50K	9.12	0.49	7.45	0.46	44.44	3.85	*	***	***
Household Earnings $50K-$75K	18.70	0.65	18.54	0.66	21.95	2.82			
Wife's Proportion of HH Earnings[a]	41.81	0.33	41.68	0.34	44.54	2.20			
Spousal Diff. in Logged Earnings[a]	0.42	0.02	0.43	0.02	0.30	0.13			
In Poverty	1.71	0.25	0.94	0.19	17.87	3.40	*	***	***
On Food Stamps	4.71	0.41	3.20	0.35	36.83	4.01	**	***	***
Regional Division: New England	2.93	0.14	3.03	0.14	0.95	0.37		***	***
Regional Division: Mid-Atlantic	4.86	0.41	4.96	0.42	2.53	1.23		+	+
Regional Division: East North Central	24.59	0.85	24.55	0.89	25.39	3.98			
Regional Division: West North Central	9.30	0.52	9.24	0.54	10.59	2.65			
Regional Division: South Atlantic	12.87	0.57	13.09	0.60	8.32	1.90		*	*
Regional Division: East South Central	9.78	0.76	9.89	0.80	7.58	2.58			
Regional Division: West South Central	21.05	0.87	20.63	0.86	29.92	4.51		+	*
Regional Division: Mountain	11.62	0.53	11.63	0.54	11.52	2.49			
Survey Year: 2009	13.63	0.54	13.47	0.53	17.08	3.43			
Survey Year: 2010	11.00	0.44	10.69	0.44	17.46	3.10		*	*
Survey Year: 2011	12.22	0.51	12.29	0.53	10.76	2.35			
Survey Year: 2012	11.28	0.56	11.28	0.56	11.40	2.50			
Survey Year: 2013	12.16	0.57	12.34	0.60	8.46	1.94		+	+
Survey Year: 2014	11.37	0.62	11.44	0.63	9.70	2.41			
Survey Year: 2015	11.40	0.52	11.56	0.52	7.93	2.22			

Source: U.S. Census Bureau, Current Population Survey, 2008-2015, Annual Social and Economic Supplements; CCDF Administrative Records, 2007-2014; Social Security Administration's Detailed Earnings Record, 2007-2018

Reference Groups: Other/Multiracial/Multiethnic Couple, Same Age, Neither Have Bachelor's, Neither Spouse Works Full-Time, Household Earnings $75K+, Regional Division: Pacific, Survey Year: 2008

Notes: All estimates are at time 1. Unweighted Ns are rounded for disclosure avoidance purposes.

a = Mean shown for continuous variable

N/A = Not applicable

+ p<.10; * <.05; ** p<.01; *** p<.001

Table 2. Logit (Bivariate & Multivariate) Models of CCDF Receipt

Universe: Working Husband-Wife Households with Children (Ages 0-12) & Need Paid Childcare (Time 1)
Unweighted N: 11,500

	Bivariate Logit (w/o controls)				Multivariate Logit (w/ controls)			
	b	p	SE	OR	b	p	SE	OR
Both White Alone (non-Hispanic)	-0.88	***	0.17	0.41	-0.65	**	0.20	0.52
Both Black Alone (non-Hispanic)	1.27	***	0.19	3.56	1.31	***	0.25	3.71
Both Hispanic	0.59	**	0.20	1.80	-0.03		0.28	0.97
Husband 1-3 Years Older	-0.01		0.20	0.99	-0.38		0.26	0.68
Husband 4-6 Years Older	-0.33		0.23	0.72	-0.77	**	0.28	0.46
Husband 7+ Years Older	0.35		0.22	1.42	-0.18		0.28	0.83
Wife 1-3 Years Older	-0.09		0.23	0.91	-0.55	+	0.29	0.58
Wife 4+ Years Older	0.61	*	0.28	1.84	-0.16		0.36	0.86
Both Have Bachelor's Degree	-3.52	***	0.35	0.03	-1.87	***	0.37	0.15
Wife Bachelor's Degree Only	-1.91	***	0.22	0.15	-1.04	***	0.27	0.35
Husband Bachelor's Degree Only	-1.23	***	0.24	0.29	-0.35		0.28	0.70
Multigenerational Household	0.30		0.37	1.35	0.14		0.38	1.16
Blended Family Household	1.66	***	0.13	5.27	0.9	***	0.17	2.45
Foreign Born Spouse(s)	-0.06		0.16	0.94	-0.31		0.23	0.73
Own Children Under Age 3	0.16		0.12	1.17	0.19		0.17	1.21
Own Children Ages 3-5	0.82	***	0.13	2.28	0.67	***	0.17	1.96
Own Children Ages 6-12	0.47	***	0.13	1.61	0.44	*	0.19	1.55
Number of Children Needing Paid Childcare	0.58	***	0.08	1.79	0.12		0.10	1.12
Both Spouses Work Full-Time	-0.79	***	0.13	0.45	-0.01		0.17	0.99
Household Earnings <$25K	4.45	***	0.24	85.88	2.84	***	0.32	17.16
Household Earnings $25K-$50K	3.74	***	0.21	41.9	2.78	***	0.24	16.12
Household Earnings $50K-$75K	2.12	***	0.22	8.31	1.57	***	0.24	4.81
Wife's Proportion of HH Earnings	0.73	+	0.38	2.08	-0.01		0.33	0.99
In Poverty	3.13	***	0.22	22.85	0.65	*	0.30	1.92
On Food Stamps	2.87	***	0.15	17.66	0.64	**	0.21	1.90

Source: U.S. Census Bureau, Current Population Survey, 2008-2015, Annual Social and Economic Supplements; CCDF Administrative Records, 2007-2014; Social Security Administration's Detailed Earnings Record, 2007-2018.

Reference Groups: Other/Multiracial/Multiethnic Couple, Same Age, Neither Have Bachelor's, Neither Spouse Works Full-Time, Household Earnings $75K+, Regional Division: Pacific.

Notes: All estimates are at time 1. Unweighted Ns are rounded for disclosure avoidance purposes.

+ p<.10; * <.05; ** p<.01; *** p<.001

Table 2. Logit (Bivariate & Multivariate) Models of CCDF Receipt, Cont.

Universe: Working Husband-Wife Households with Children (Ages 0-12) & Need Paid Childcare (Time 1)
Unweighted N: 11,500

	Bivariate Logit (w/o controls)				Multivariate Logit (w/ controls)			
	b	p	SE	OR	b	p	SE	OR
Regional Division: New England	-1.23	***	0.35	0.29	-0.88	+	0.48	0.41
Regional Division: Mid-Atlantic	-0.74	+	0.42	0.48	0.34		0.61	1.40
Regional Division: East North Central	-0.04		0.26	0.97	0.18		0.35	1.19
Regional Division: West North Central	0.07		0.29	1.07	0.05		0.38	1.05
Regional Division: South Atlantic	-0.52	+	0.28	0.59	-0.68	+	0.40	0.50
Regional Division: East South Central	-0.33		0.33	0.72	-0.85	*	0.43	0.43
Regional Division: West South Central	0.30		0.26	1.35	-0.17		0.38	0.84
Regional Division: Mountain	-0.08		0.28	0.92	-0.02		0.36	0.98
Survey Year: 2009	0.22		0.22	1.25	0.04		0.24	1.04
Survey Year: 2010	0.47	*	0.22	1.61	0.10		0.24	1.10
Survey Year: 2011	-0.15		0.23	0.86	-0.28		0.26	0.75
Survey Year: 2012	-0.01		0.24	0.99	-0.24		0.30	0.79
Survey Year: 2013	-0.39	+	0.24	0.67	-0.39		0.28	0.68
Survey Year: 2014	-0.18		0.25	0.83	-0.26		0.30	0.77
Survey Year: 2015	-0.39		0.27	0.68	-0.56		0.34	0.57

Source: U.S. Census Bureau, Current Population Survey, 2008-2015, Annual Social and Economic Supplements; CCDF Administrative Records, 2007-2014; Social Security Administration's Detailed Earnings Record, 2007-2018.

Reference Groups: Other/Multiracial/Multiethnic Couple, Same Age, Neither Have Bachelor's, Neither Spouse Works Full-Time, Household Earnings $75K+, Regional Division: Pacific.

Notes: All estimates are at time 1. Unweighted Ns are rounded for disclosure avoidance purposes.

+ p<.10; * <.05; ** p<.01; *** p<.001

Table 3. Treatment Effects of CCDF on Women's Labor Force Participation And Earnings Gap Four Years Later

Universe: Working Husband-Wife Households with Children (Ages 0-12) & Need Paid Childcare (Time 1)

Treatment: CCDF

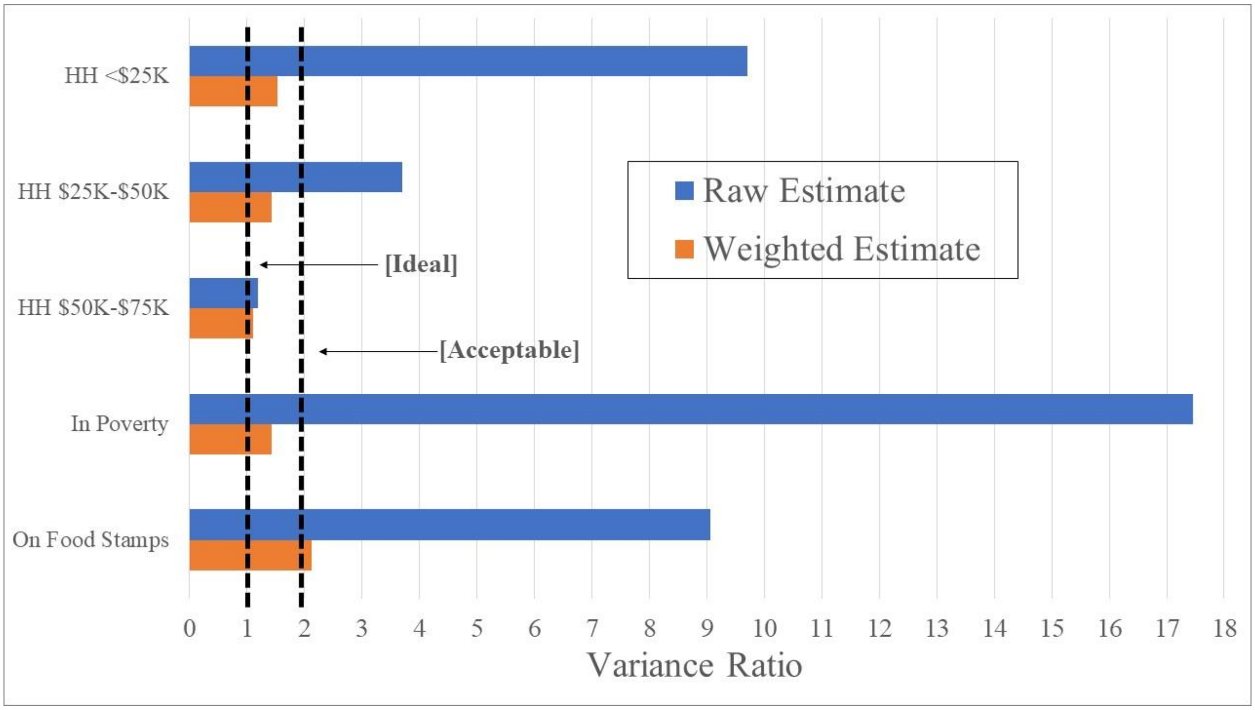
Outcome:	Wife Still in Labor Force (Time 2)			Wife's Proportion of Household Earnings (Time 2)			Spousal Difference (Husband-Wife) in Logged Earnings (Time 2)		
Unweighted N:	11,500			9,900			9,900		
Treatment Effects Estimator:	Coef.	p	SE	Coef.	p	SE	Coef.	p	SE
Propensity Score Matching (PSM)	0.04	***	0.01	0.02		0.02	-0.13	+	0.08
Inverse Probability Weighting w/ Regression Adjustment (IPWRA)	0.07	*	0.04	0.07	**	0.02	-0.58	**	0.19

Source: U.S. Census Bureau, Current Population Survey, 2008-2015, Annual Social and Economic Supplements; CCDF Administrative Records, 2007-2014; Social Security Administration's Detailed Earnings Record, 2007-2018.

Notes: 1) Unweighted Ns are rounded for disclosure avoidance purposes; 2) All models use robust standard errors (SE); 3) coef= average treatment effect coefficient; 4) PSM uses weighted means as outcome models, whereas IPWRA uses regression as the outcome model; 5) Control variables in the regression outcome equation of IPWRA are the same as those in the selection into CCDF model, though the continuous version of income in regression outcome model instead of standard categorical version used in selection model.

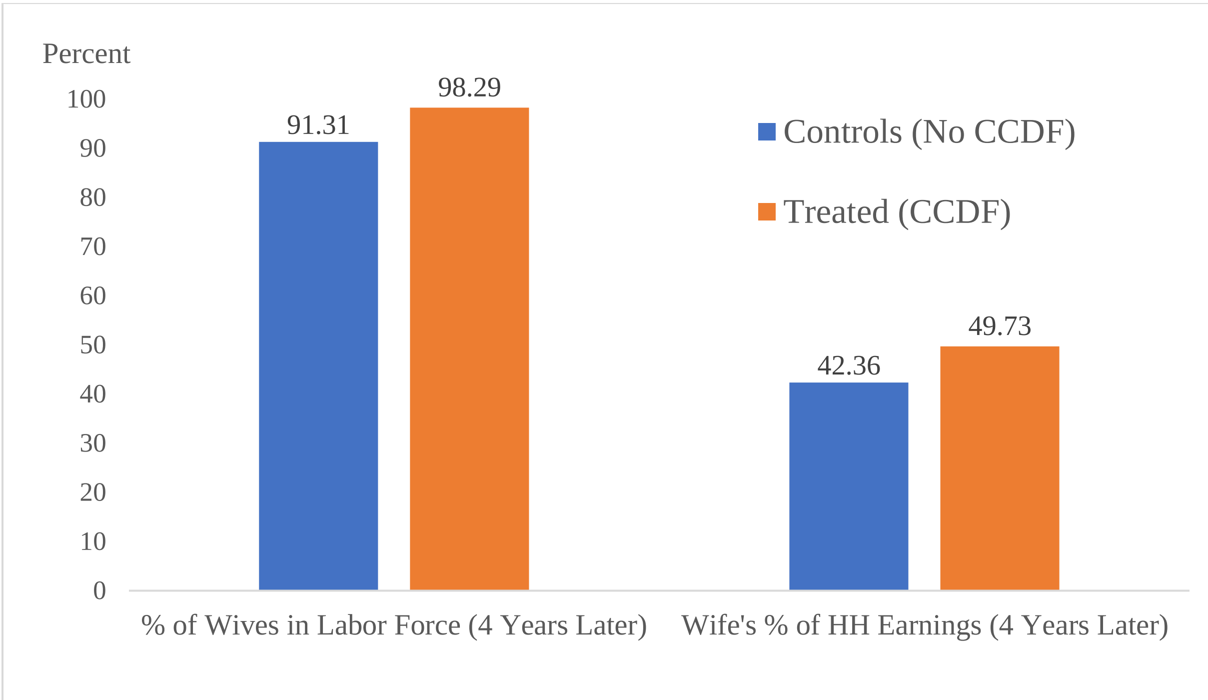
+ p<.10; * <.05; ** p<.01; *** p<.001

Figure 1. Variance Ratio Between Treatment Groups Before (Raw) and After (Weighted) Balancing, by Socioeconomic Characteristics



Source: U.S. Census Bureau, Current Population Survey, 2008-2015, Annual Social and Economic Supplements; CCDF Administrative Records, 2007-2014; Social Security Administration's Detailed Earnings Record, 2007-2018. Based on IPWRA model estimates predicting wife's labor force participation at time 2.

Figure 2. Predicted Potential Outcomes of CCDF on Labor Force Participation and Relative Earnings of Working Married Mothers



Source: U.S. Census Bureau, Current Population Survey, 2008-2015, Annual Social and Economic Supplements; CCDF Administrative Records, 2007-2014; Social Security Administration's Detailed Earnings Record, 2007-2018. Based on IPWRA model estimates.