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IZA DP No. 16263

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ABSTRACT

Assessing the Fertility Effects of Childcare Cost Subsidies: Evidence from the Child and Dependent Care Tax Credit*

We examine the impact of the Child and Dependent Care Tax Credit (CDCTC) on fertility and parental investment in children. The CDCTC aims to support working parents but its availability only to families with children incentivizing having more children or increasing investment in existing ones. Using the Panel Study of Income Dynamics and the National Center for Health Statistics' Natality data, we analyze the effects of state-level CDCTC policies on fertility and birth outcomes. Results indicate that the CDCTC increases labor force participation rates for married mothers, potentially suppressing fertility rates. Additionally, it has a positive effect on gestational age.

JEL Classification: I38, J13

Keywords: fertility, birth outcomes, child and dependent care tax credit

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1. Introduction

Low fertility rates, coupled with aging populations and concerns for long-run labor supply, have emerged as prominent demographic and social issues in most developed countries (e.g., Pronzato, 2017; Adserà and Ferrer, 2018; Kearney and Levine, 2021; Kearney et al., 2022). Consequently, policymakers, scholars, and the public have engaged in discussions regarding the potential of subsidizing childcare services to promote maternal labor supply and increase or stabilize birth rates (e.g., Miller 2019). In 2019, a significant portion (41 percent) of mothers served as the sole earners in their families or contributed at least half of their families' earnings (Glynn, 2021). Additionally, a majority (60 percent) of children aged 5 and under who are not in kindergarten spend at least some of their time in childcare (Cui and Natzke, 2021). However, the cost of childcare in the US remains prohibitively high. In 2018, the average monthly expense for center-based childcare for an infant or toddler was estimated to be $1,230, placing a significant financial burden on families (Workman and Jessen-Howard, 2018). For households with the median US income of approximately $63,000, childcare costs accounted for 23 percent of their income, over three times more than what the US Department of Health and Human Services defines as affordable childcare (no more than 7 percent of a family's annual household income) (Malik, 2019). As a result, childcare often ranks as one of the largest expenditures in a family's monthly budget, surpassing housing, transportation, food, and, in some states, even college tuition (ChildCare Aware, 2022).

The costs of childcare have been consistently increasing, with estimates suggesting a 48 percent rise in expenses between 2005 and 2019 (Herbst, 2023).

In contrast to many other high-income countries, the US has lacked a universal childcare program since the short-lived Lanham Act during World War II. The COVID-19 pandemic further exposed the fragility of the US childcare system, with many mothers forced to exit the labor force to care for their children when childcare centers closed, raising concerns regarding, among other issues, the ability of mothers to engage in work (Elias and D'Agostino, 2021).

In this paper, we focus on assessing the potential fertility effects of one specific policy aimed at reducing childcare costs—the Child and Dependent Care Tax Credit (CDCTC)[2] --- a tax credit in the US tax system which subsidizes childcare costs incurred while working. As the largest tax program in the US specifically targeting childcare costs, it facilitated over 5 million households to claim $2.8 billion in expenses during fiscal year 2020.[3] In addition to the federal CDCTC, which is non-refundable, by 2019, 25 states and Washington, D.C. had also implemented their own CDCTCs, some of which are refundable.

To identify the effect of the CDCTC on fertility and child quality, we leverage the variation in state-level CDCTC implementation. We use both individual-level data from the Panel Survey of Income Dynamics (PSID) from 1968 to 2019 and the US National Center for Health Statistics' (NCHS) Natality data from 1970 to 2019. To account for known biases in parameter estimates from the two-way fixed-effects (TWFE) model (Goodman-Bacon, 2021), in addition to the TWFE estimator, we use the estimator developed by Calloway and Sant'anna (2021) to estimate the average treatment effect in the presence of staggered treatment (which in our

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[2] The CDCTC is also referred to as the "dependent care tax credit" or the "child and dependent care tax credit".

[3] https://www.taxpolicycenter.org/statistics/credit-type-and-amount (accessed 6/12/2023).

case is the state-level CDCTC implementation). Data from 2020 are excluded due to the potential impact of the COVID-19 recession on fertility decisions (Kearney and Levine, 2022). We find that the presence of a state CDCTC has no discernible effect on fertility, a result consistently observed across both datasets. This result can be attributed to the positive effect of the CDCTC on certain measures of women's labor market attachment. Furthermore, the results show that the presence of the CDCTC has improved the quality of children at birth, measured by average birth weight and average gestational age of newborns, as well as maternal smoking rates during pregnancy, although statistical significance is only observed for the effect on average gestational age.

This study makes significant contributions to the existing literature by being the first to examine the effect of the CDCTC on fertility and birth outcomes using longitudinal data and state-level variation in CDCTC implementation over an extensive timeframe. While previous research on the CDCTC has predominantly focused on its effect on women's labor supply, we are the first, to our knowledge, to comprehensively investigate its potential effects on both the quantity and the quality of births. Additionally, we explore potential mechanisms that may explain our findings.

Our work has several policy implications. Perhaps most importantly, given the below replacement fertility currently experienced in the US, it is important for policymakers to understand which policies hold potential for increasing fertility. The Earned Income Tax Credit (EITC), one of the most effective anti-poverty programs currently in the US, targets a lower income segment of the population than the CDCTC is and does not specifically subsidize childcare, despite some limited research examining the effects of the EITC on fertility, with generally small to no observed effects.[4] Our findings, along with the existing literature on the EITC, highlight that tax credits not explicitly designed for fertility purposes maybe not effectively address this issue. Instead, policymakers may benefit from exploring more targeted fertility policies. Furthermore, our results provide evidence to states that have not implemented a CDCTC, suggesting that while potentially desirable for other reasons, it should not be regarded as a fertility instrument. Importantly, our results do not indicate a negative effect of the CDCTC on fertility, despite its positive impact on the labor force participation of married mothers. In addition, we present some evidence that the CDCTC may improve the quality of children as measured by birth outcomes.

The rest of this paper is organized as follows. We provide a brief overview of the CDCTC, followed by a literature review on both the CDCTC and maternal labor supply, as well as the broader literature on the effects of pronatalist policies on birth outcomes. Subsequently, we outline the theoretical framework underpinning our empirical strategy. While the CDCTC is not explicitly defined as a pronatalist policy, our theoretical model highlights the possibility of reduced fertility costs for women living in states with a CDCTC. We then detail our data, empirical strategy, results, threats to identification, and conclude with key insights.

2. Description of the CDCTC

The CDCTC is a tax credit designed to cover a portion of an individual's child and dependent care expenses related to employment. The primary goal of the CDCTC upon introduction was to assist working mothers, particularly single mothers, in

[4] For a more detailed review of this literature, see the Literature Review section.

covering the costs of childcare while they pursued employment. Hence, the credit is contingent upon using childcare to support work (or schooling). Eligible children must be aged 13 or younger. For married couples, both the taxpayer and their spouse must have earned income (unless one spouse is a full-time student) to claim the credit. Single parents, on the other hand, must be employed to be eligible for the credit.

The amount that a family can claim through the CDCTC depends on four factors. First, there is a limit on the total amount of allowable expenses a family can claim. The expense limit is $3,000 for families with one eligible child in care and $6,000 for families with two or more eligible children in care. Second, the claimed amount cannot exceed the earned income of the taxpayer or their spouse with the lower income. Third, because the federal tax credit is not refundable, a family cannot receive more benefits than the amount they owe in federal income taxes. However, as noted earlier, some states have made their CDCTC refundable. Finally, the credit is graduated on a sliding scale. Currently, families with an Adjusted Gross Income (AGI) of $15,000 or less are eligible for a credit equal to 35 percent of eligible expenses. The rate decreases as AGI increases above $15,000 until it reaches 20 percent for families with AGIs above $43,000 (see Figure 1). Thus, in theory, families with AGI of $15,000 or less are eligible for a maximum credit of $2,100 per eligible child, while families with incomes above $43,000 are eligible for a maximum credit of $1,200 per eligible child. According to the Congressional Research Service, the average credit claimed in 2020 ranged between $500 and $600.

Figure 2 illustrates the distribution of CDCTC recipients by income. For comparison purposes, we also include the same statistics for the EITC.[5] It is not surprising that there is limited overlap between those who claim the CDCTC and those who claim the EITC, given that the EITC primarily targets lower-income families and phases out completely once the AGI reaches a certain level while the federal CDCTC is not refundable which means it can provide little to no benefit to many low-income families. The figure indicates that middle- and upper-income families are more likely to use the CDCTC, while lower-income families are more likely to benefit from the EITC. Appendix Figure 1 displays the eligibility rate for the CDCTC by AGI for various years, while Appendix Figure 2 presents the take-up rates for the CDCTC by AGI for different years. These figures further emphasize that the CDCTC is most often used by middle- and higher-income families.

Shortly after the federal CDCTC was enacted, states began to implement their own CDCTCs. The initial group of states introduced their state CDCTCs between 1976 and 1977, almost immediately after the federal CDCTC came into effect. As shown in Figure 3, by 2019, 25 states and Washington D.C. had implemented their own CDCTC. Many of these state CDCTCs are structured as a percentage of the federal CDCTC. For example, in our sample period, Iowa had the lowest percentage of 5 percent, while Oregon offered a generous credit of 188 percent of the federal credit. Although the CDCTC is not refundable at the federal level, 12 states had refundable credits in 2019. In these cases, if the state CDCTC exceeds the state tax liability, taxpayers can receive a refund. Figure 4 depicts the generosity of state CDCTCs using a heat-map, with darker colors indicating

[5] Because the 2012 data are missing, we smoothed across adjacent years.

states and years with the most generous CDCTC. Over time, generosity has generally diminished because the CDCTC is not indexed to inflation.

Parents do not receive the tax credit until they file their taxes, which means they must pay for childcare upfront and wait up to a year to be reimbursed. Moreover, only certain expenses are eligible for the credit, and these tend to be more formal childcare arrangements. Therefore, lower-income families may be less likely to use the CDCTC, as they are more inclined to rely on family members, such as grandparents, for care (Laughlin, 2013). Conversely, those with higher incomes are more likely to benefit from the credit due to higher childcare expenses and a greater likelihood of paying for childcare. Those at the lower end of the income distribution are less likely to incur tax liability and hence less likely to be eligible for the tax credit. Early studies on the CDCTC have documented that making the CDCTC refundable would significantly increase the amount families spent on market-provided childcare (Michalopoulos et al., 1992). Newer studies suggest that making the credit refundable would enhance the likelihood of utilization among single parents (Pepin, 2022). Finally, evidence indicates that a ten-percentage point increase in the CDCTC leads to a 5-percentage point rise in the use of paid childcare (Pepin, 2021).

3. Literature Review

Policies, whether intentional or unintentional, can significantly impact family income and the costs associated with raising children. Extensive literature has been conducted on policies that influence fertility rates in developed countries, as comprehensively summarized by Lopoo and Raissain (2012), Lopoo and

Raissian (2018), and Bergsvik et al. (2021). Unlike several other nations, the United States government has not implemented specific pronatalist policies. However, several policies indirectly alleviate the financial burden of raising children, which could potentially lead to increased fertility rates, even if fertility enhancement was not their primary objective. These policies include welfare programs such as the Temporary Assistance for Needy Families (TANF) and its predecessor, Aid to Families with Dependent Children (AFDC), as well as the personal exemption in the federal income tax, the Child Tax Credit, the EITC, family leave provisions, and the CDCTC on which we focus in this paper. Most of these policies have been extensively studied in relation to their influence on fertility, except for the CDCTC. However, early research indicated that subsidizing childcare costs could potentially raise fertility rates (Blau and Robins, 1989).[6]

In the US tax code, two policies have received attention for their possible pronatalist effects. In one of the earliest US-based studies investigating the relationship between aspects of the tax code and fertility, Whittington et al. (1990) focus on the effects of personal exemption, which provides financial relief from the burden of taxation for low-income families with children. They find a positive and significant impact on fertility. However, Crump et al. (2011)

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[6] In the US, a large literature has focused on the effect of welfare payments (either through AFDC or since 1996 TANF) and various aspects of these programs (e.g., family caps) on fertility rates. The consensus of this literature is that there is a small, but weak relationship between welfare programs and fertility (see, e.g., Lopoo and Raissian (2018) and Moffitt and Ribar (2004)). The provision of maternity leave has also received attention for its potential fertility effects as it can lower the cost of childbearing when leave is available. Early research demonstrated a link between maternity leave and fertility (Averett and Whittington, 2001). More recent work has used the adoption of the Family and Medical Leave Act in the US in 1993 to identify the effect of leave on fertility and has found positive effects (Cannioner, 2014). Although the US has not mandated paid maternity leave at the federal level, several states including California, New Jersey, and Rhode Island among others have adopted paid leave. The effect of these paid leaves on fertility is still an open question, although Leboeuf (2019) provides preliminary evidence that California's introduction of paid family leaves decreased fertility which may operate through a positive effect on mother's labor supply.

challenge the findings of Whittington et al. (1990) by showing that when the child tax credit and the EITC are included along with the personal exemption, there is no significant relationship between the personal exemption and fertility in the long run, although they do not rule out short-run timing effects.

Another policy of interest is the EITC, a tax credit aimed at low- and moderate-income families that functions as a negative income tax. Because EITC benefits depend, in part, on family size, they have been used as an exogenous change in income. In a widely cited study, Baughman and Dickert-Conlin (2009) examine the effect of the EITC on fertility, exploring the 1991 federal EITC expansion, which provided substantially higher benefits for families with two or more children. Some states also had their own EITC programs, which were typically a percentage of the federal benefits. Using aggregate birth records from the Natality data between 1990 and 1999, Baughman and Dickert-Conlin (2009) report very little evidence that the EITC affects fertility, with the only significant result suggesting that the EITC may actually *reduce* the fertility of high-parity white women. They speculate that this finding could be the result of the quality-quantity trade-off that parents face with higher income. In contrast, Bastian (2017), using individual-level data from the PSID for the years 1980 – 2013 which covers a much longer period and more recent changes in EITC, reports that expanded EITC payments increase fertility.

To the best of our knowledge, only one unpublished paper has focused specifically on the CDCTC and its effects on fertility.[7] Huang (2017) uses data

[7] Jiang (2020) in his exploration of the effect of the CDCTC on maternal labor supply notes that he also estimates the effect of the state CDCTCs on fertility (both the number of children born and the number of eligible children) and reports no effect. However, his results are not included in the paper.

from the March supplement to the Current Population Survey (CPS) and restricts her sample to married women between the ages of 18 and 45 from 1994 to 2006. Huang studies both the Child Tax Credit (CTC) and the CDCTC. To identify the fertility effects of these policies, she focuses on one federal expansion to the CDCTC, the 2003 Bush tax cuts known as The Economic Growth and Tax Relief Reconciliation Act (EGTRRA) of 2001. Using a difference-in-differences framework, she compares the childbearing outcomes of married women who did not finish high school (who are less likely to be eligible for the CDCTC and the CTC) to those of women who graduated high school (and therefore likely to have incomes high enough to receive the federally non-refundable tax credits). She reports an 11 percent increase in the probability of having a child for the treatment group in the post-2003 period. To isolate the effect of the CDCTC from other provisions of the EGTRRA, she uses a triple-difference analysis by leveraging the fact that several states have also introduced their own version of the CDCTC, which allows for a third comparison between women living in states with a CDCTC to those who did not. She finds a positive and significant fertility effect of the CDCTC expansions in 2003 for higher-educated women. However, the choice of control group in Huang's study could be questionable, as women in her control group may still be affected by the CDCTC if they are married to high-earning men.

Our work differs from Huang's in several crucial aspects. First, Huang's research focuses solely on the effects of one specific federal expansion in CDCTC history, while we examine a much longer time period and leverage the variation in the CDCTC at the state level. Second, we use the PSID, which provides more detailed information on individuals and allows us to control for individual fixed effects. Third, we control for the EITC as well, which Crump et al. (2011) demonstrate could be important. Finally, we also consider the potential effects of the CDCTC on child quality at birth.

Two other recent papers merit discussion as they explore the impact of the CDCTC's on women's labor force participation (Jiang, 2020; Pepin, 2021). Because women's labor force participation and fertility tend to be negatively correlated, these studies are relevant to our own work. Pepin (2021) focuses on the effect of CDCTC benefits on the utilization of paid childcare and labor market outcomes using data from the March CPS from 2001 to 2009, focusing on parents aged 26 to 54 in households with children under 13 years old. She combines these data with data from the Survey of Income and Program Participation (SIPP) childcare Topical Module administered in 2002. Her identification strategy relies on the 2003 federal CDCTC expansion and the resulting differential changes in CDCTC generosity across states and family sizes. Using the increases in CDCTC generosity from the Bush Tax Cuts as an instrumental variable for CDCTC benefits, she estimates the effects of CDCTC benefits on childcare participation, annual employment, usual hours worked per week, and annual earnings for four groups: single mothers, single fathers, married mothers, and married fathers. Taken together, her results suggest that the CDCTC leads to increased use of paid childcare across all groups and increases in labor supply among married mothers.

Jiang (2020) takes a different approach to identifying the effect of the CDCTC on women's labor supply. Using the PSID data, which we also use in our analysis, for the years 1968-2015, he focuses on a sample of women aged 20-55 years. An advantage of the PSID data is that individuals are followed over time, allowing for the control of individual fixed effects. Jiang uses state and year fixed effects to account for common factors in a given year or state that would influence a woman's labor supply, and individual fixed effects to capture time-invariant heterogeneity in productivity or preferences for work. His preferred specification uses the state's maximum CDCTC as an instrument for the CDCTC amount that the individual would be eligible for based on their income, state of residence, and number of children. Because the PSID does not report childcare expenses, he assumes that individuals would have the expenses that would maximize their CDCTC benefits given their income and number of children. Jiang finds significant and sizable effects of the CDCTC on mother's labor force participation.

Our work distinguishes itself from these prior works in several important ways. First and most notably, we provide the first evidence on the effects of the CDCTC on both the quantity and quality of births.[8] To our knowledge, no study has examined the effect of the CDCTC on fertility using the full range of variation in the CDCTC over years or on quality of births. Yet, one might reasonably argue that the CDCTC is more likely to subsidize child quality over quantity because women need to work to be eligible, and we know that working women tend to have fewer children. Second, we use a longer period of data (1968-2019), which allows us to leverage CDCTC variation at the state level throughout its entire history until the COVID-19 pandemic. Finally, we employ the new estimation method proposed by Calloway and Sant'anna (2021), which accounts for the staggered implementation and potential heterogeneous effects of state-level CDCTCs.

[8] There is a literature on the effects of US childcare subsidies on child quality (see, for example, Herbst and Tekin, 2010; 2016) but most of that literature is focused on subsidies to low-income families, while CDCTC affects middle- and high-income families as well. To our knowledge, we are the first to look at the effect of CDCTC on measures of child quality.

4. Theoretical Motivation

The conceptual framework underpinning our investigation into the effect of the CDCTC on fertility is based on the seminal model developed by Becker (1960) and Becker and Lewis (1973). According to Becker's theory, the decision to have children is driven by parental demand for children (child services) which, like other goods demanded by parents, is affected by prices and income. The total cost of providing child services comprises of both direct costs, such as expenses related to food and shelter, and indirect costs, which include the mother's opportunity cost arising from reduced labor force participation. Policies that change the cost of children, therefore, will inevitably affect the demand for children. In particular, factors that raise (lower) the cost of child-rearing will lead to a decrease (increase) in the quantity of children demanded.

The term child services encompasses both the number of children and the "quality" of those children, typically measured by indicators such as spending per child on things such as nutrition, health, test scores or education. An inherent trade-off exists between the quantity and quality of children (Becker and Lewis, 1973). The quantity–quality trade-off posits that as family income rises, parents may shift their investments towards enhancing the quality of their existing children rather than having more children. This observation helps explain why families with higher incomes tend to have fewer children.

The CDCTC introduces both a substitution and an income effect. Because the CDCTC is only available to families with children, the introduction or the expansion of the CDCTC tax credit reduces the cost (price) of raising children for eligible families, thereby exerting a positive influence on fertility rates.

Additionally, the tax credit alleviates the tax burden for eligible couples with children, leading to an increase in net income. This increase in income, under the assumption that children are a normal good, should increase the demand for children, although it is possible that the quality effect may outweigh the quantity effect.

However, the CDCTC, which is conditional upon working, also creates an incentive for individuals to work more, and empirical evidence has indicated that the CDCTC increases women's labor force participation (e.g., Averett et al., 1997; Jiang, 2020; Pepin, 2021). Consequently, women may opt to have fewer children and potentially allocate greater resources to enhancing the quality of the existing ones. As such, the effect of the CDCTC on the quantity and quality of children is theoretically ambiguous and ultimately an empirical question.

5. Data

To analyze the effects of the CDCTC on the quantity and quality of children, we first require comprehensive data on the CDCTC itself. We collected information on the federal CDCTC from Statute: 26 USCS § 21. Additionally, we obtained data on the introduction and the maximum CDCTC benefit offered by each state (including Washington, D.C.) from the Nexis Uni database and HeinOnline. Our empirical analysis relies on two distinct datasets, in which we merge our manually collected CDCTC data by state and year.

PSID

Our first dataset is the PSID, a nationally representative survey that has been tracking households and their offspring since 1968. The original sample contained information on over 18,000 individuals living in 5,000 families. All individuals residing in the household are interviewed, and individuals born into these households are tracked throughout their lives, even if they subsequently leave the household. Individuals who marry into PSID households are observed while residing in those households and are not followed if they later separate from the households. Interviews were conducted annually until 1997 and biannually thereafter. The PSID contains a rich set of information regarding household and individual characteristics including employment, income, wealth, childhood development, education, and state of residence, allowing us to calculate annual CDCTC exposure. Our data are from 1968 to 2019 and our observations are at the household-by-year level. We use the PSID because it is the world's longest-running national household panel survey, predating the introduction of the CDCTC in 1976. Because of the longitudinal nature of the PSID, we can control for individual fixed effects which might bias our estimates if omitted.

NCHS Natality Data

We also utilize the US natality data files maintained by the NCHS, which record information collected from state birth certificates and provide documentation of each of the approximately 40 million births in the US. We use the Natality data between 1970 and 2019, inclusive.

Each birth certificate record contains essential information including birth year, birth month, mother's state of residence, age, race, marital status, and, in most states, education. Information on father's race and age is available when a father is listed. Additional information includes the number of previous births has had and the birth order of the focal child on the birth certificate. Notably, birth certificate data do not contain information on family income, which is potentially endogenous to CDCTC eligibility and participation.

6. Empirical Strategy

To identify the effect of the CDCTC on fertility, we leverage the substantial variation in the rollout of the CDCTC across states and over time. We use a generalized two-way fixed-effects (TWFE) difference-in-difference (DD) model that relates a woman's quantity and quality of birth to the variation in the presence of a CDCTC across states during the period 1968-2019. This approach requires the usual parallel trends assumption that the probability of having a child would have evolved similarly in states with and without a CDCTC if the policy had not been implemented. Under this assumption, the TWFE DD estimator identifies the causal effect of states' adoption of CDCTC on the quantity and quality of birth. Our TWFE DD model for analyzing the effect of the CDCTC on fertility using the PSID data is written as follows:

$$(1)\ Y_{ist} = \beta_0 + \beta_1 \text{ State CDCTC}_{s,t-2} + \beta_2 Z_{st} + \beta_3 X_{ist} + \delta_t + \eta_i + \varepsilon_{ist}$$

where Y_{ist} is the binary outcome of interest, indicating whether individual *i* in state *s* had an additional child between year *t-2* and year *t*. State CDCTC equals one if the state had a CDCTC in year *t-2*. We allow for a two-year lag to account for the fact that CDCTC is a tax credit received after filing taxes, resulting in a lag between the policy change and an corresponding birth. This also accommodates the biannual interviews conducted by the PSID after 1997. Z_{st} is a vector of state-level time-varying policy and economic variables, including state CDCTC refundability, maximum state-level EITC and its refundability, the state's maximum value of AFDC/TANF for a family of three, the state's maximum marginal tax rate (MTR), the state's minimum wage, number of hospital beds per state, state per-capita GDP, and the availability of state paid family leave. X_{ist} is a vector of individual-level characteristics, including race (white vs. non-white), marital status (married vs. not married), number of children, education (less than high school, high school or some college, college or more), a cubic function of age and, in certain specifications, the income of the male household head. δ and η are year and individual fixed effects, respectively. ε is the random error term.

β_1 is the main coefficient of interest and quantifies the change in fertility, measured as the increased likelihood (in percentage points) of having an additional child, resulting from a state's adoption of CDCTC. Because the model includes year fixed effects, individual fixed effects, and a comprehensive set of control variables, the effect of the CDCTC on fertility can be attributed to changes for individuals in states which adopted a CDCTC tax credit. While the federal CDCTC is generally more generous compared to most state-level CDCTCs, families receive the same amount of benefits from the federal CDCTC in a given year, conditional on their incomes. Consequently, the effects of the federal CDCTC are absorbed by the year fixed effects. We estimate the TWFE model using both a binary indicator of whether a state has a CDCTC and a continuous measure of the maximum of the state and federal CDCTC benefits to take advantage of the full range of variation. When estimating Equation (1) with TWFE, we cluster the standard errors by state.

Our model for the Natality data is slightly different due to the data's distinct structure. Specifically, all women in the Natality data have given birth, necessitating a denominator to calculate birth rate. To do so, we organize the data into cells and normalize them by a measure of the at-risk population.[9] We create this at-risk population by using weighted data from the 1960, 1970, 1980, 1990, 2000, and 2001-2019 Decennial Census 5% Public Use Microdata Samples (PUMS) to estimate cell sizes and then we linearly interpolate the values for the rest of the years in our sample. The birthrate can therefore be calculated as follows:

$$(2)\ \text{birthrate}_c = \frac{\#\ \text{births}_c}{\#\ \text{women at risk of pregnancy}_c}$$

where c indexes cells. These cells are defined by mother's age (20-24, 25-29, 30-34, 35-39), race (white, nonwhite), education (<= 12 years, 13-15 years, > 15 years), birth parity (first birth, second birth, higher-order birth), state, and year. We then use the following model to estimate the effects of the CDCTC on fertility rates using the Natality data:

$$(3)\ Y_{ct} = \beta_0 + \beta_1\ \text{State CDCTC}_{c,t-2} + \beta_2 Z_{st} + \beta_3 X_{ct} + \delta_t + \eta_c + \varepsilon_{ct}$$

where Y_{ct} is the birth rate for the c^{th} cell, *t* indicates the year, and *s* is the state. The covariates in X include race, marital status, educational level, birth order (first child, second child, third or higher child), and age group for mothers (20-24, 25-29, 30-34, 35-39) in cell c. The vector Z includes state level CDCTC refundability, maximum EITC benefit and its refundability, maximum welfare

[9] This is the same method used by Baughman and Dickert-Conlin (2009) in their analysis of the fertility effects of the EITC using the Natality data.

benefit, maximum income MTR, hospital beds, per capita GDP, and paid family leave. We strive to match X and Z as closely as possible for both the PSID and the Natality estimations. Given that we organize our data into cells and calculate within-cell birthrates for groups of various sizes, we weight our cell observations by cell size (i.e., the number of women in each cell). We cluster the standard errors by state when estimating Equation 3 with TWFE.

The TWFE estimator, according to Goodman-Bacon (2021), may yield biased estimates of the treatment effects when treatment timing is staggered or the effects of the treatment are heterogeneous with respect to treatment groups and time periods. To address these concerns, we use the CSDID estimator developed by Callaway and Sant'Anna (2021) for the TWFE model with multiple groups and time periods. This approach estimates the average treatment effect for each treatment-timing group, in each time period in which that group is treated, using a simple 2x2 DD estimator that compares the changes in outcomes for that group relative to a reference period to the same change in a control group (we use those states who have never been treated/adopted CDCTC as our control group). These group-time-specific estimates, limited to the set of "good" treatment-control pairs (excluding inappropriate comparison pairs), are then averaged to summarize the causal effects of the treatment. We exclude observations where the family moved across states over time because the CSDID method requires constant treatment status.[10] When using the CSDID estimator with the individual-level PSID data, we cluster the standard errors by state and individual ID. With the Natality data, the standard errors are clustered by state and group.

[10] For consistency, we use the sample of non-movers for all our estimations.

In addition to its effects on fertility, the CDCTC may influence parental investments in child quality. Not only does the CDCTC create an incentive to work, but it also creates an income effect for families provided they are using childcare. Unfortunately, although the PSID's child development survey collects variables that might be reasonable measures of child quality, they are limited to a specific set of years, rendering an analysis using these data infeasible.[11] However, maternal investments in her own health during pregnancy constitute another form of quality investment that may affect birth outcomes. We acknowledge certain issues with using birth outcomes. First, women may not be aware of their eligibility for the CDCTC at the time of pregnancy, especially for first births. Second, these investments are indirect, as they focus on maternal health, which is expected to have spillover effects on birth outcomes (e.g., higher birth weights, longer gestational age). Potential mechanisms include maternal smoking, better prenatal care, or a healthier diet. We use the Natality data to examine the effect of state CDCTCs on available measures of birth outcomes and maternal behavior: birthweight, gestational age, and maternal smoking.[12]

[11] Specifically, the Child Development Supplement (CDS) for the PSID which contains several quality indicators is only available in the years 1997, 2001, 2007, 2013 and 2019. However, individuals in the CDS in 2019 are not included in the PSID 2019 so that we cannot use them in our analysis. In addition, during the years 1997 to 2013, only 4 states introduced a CDCTC: Maryland (2000), Rhode Island (2001), Louisiana (2003) and Georgia (2006). Thus, we decide not to use these data for our analysis.

[12] In a parallel analysis to ours, Komro et al. (2019) conducted a study examining the impact of state EITC policies on birth outcomes demonstrating that state EITC benefits are linked to improved birth outcomes including a decrease in low birth weight and an increase in gestational age.

7. Results

Tables 1a and 1b present weighted summary statistics for our analysis samples. Table 1a pertains to the PSID data, with observations at the household-by-year level. We limit the age range for women in our sample to between 20 and 39 years to focus on the prime childbearing years. On average, 19.7 percent of households in our sample had a birth in the last two years, with an average of 1.62 children per household. Married couple households account for 72.4 percent of our sample, while 81.3 (15.4) percent of households report the household head's race as white (Black). Of our households, 27.8 percent are headed by a female. Turning our attention to the females in the household (household heads or spouses), we observe that 16.7 percent report having an education of less than high school, whereas 25.4 percent report having a college degree or more. Around 10 percent of our households reside in states with a CDCTC program, while a mere 0.3 percent live in states that offer paid family leave. Furthermore, 74.1 percent of women in our sample participate in the labor force, working an average of 1,577 hours per year. Appendix Figure A4 depicts a histogram of annual hours of work conditional on employment, showing an expected peak around 2,000 hours.

The sample means for the Natality data are presented in Table 1b. Panel A of Table 1b presents birth rates by women's characteristics. The overall birthrate is 13.8 births per 100 women, across all cells and years. As expected, the highest birthrate is for women ages 25 to 29. The birth rate for women giving birth to their first child is about 12 percent, while it is around 15 percent for women having higher-order births. Married mothers exhibit higher birth rates than unmarried mothers. Panel B of Table 1b presents state covariates averaged over the cells. The average maximum CDCTC benefit, expressed in 2017 dollars, is $2,520. We observe 21.3 percent of cells in a state with a CDCTC benefit. Finally, the average birth weight across all cells is 3,327 grams (equivalent to 7.3 pounds), and the average gestational age is 39 weeks. Across all cells, the smoking rate indicates that 11.2 percent of mothers smoked during pregnancy.

Before presenting our estimation results, we illustrate in Figure 5a the results of our Goodman-Bacon decomposition for the PSID data. This figure shows that over 80 percent of the comparisons come from treated versus never-treated groups. However, 9.9 percent of the comparisons involve earlier treated versus later treated groups, and 7.2 percent pertain to later treated versus earlier treated groups. The latter group presents an issue for the TWFE model, as these comparisons are inappropriate. Figure 5b displays the Goodman-Bacon decomposition results for the Natality data, revealing that 79.9 percent of the comparisons come from treated versus never-treated groups while 6.6 percent involve earlier treated versus later treated groups and 13.5 percent would be from later treated versus earlier treated groups. Once again, the latter group presents inappropriate comparisons. These graphs underscore the importance of using a new method to deal with the staggered treatment, which, in our case, corresponds to the staggered adoption of the CDCTC program by states.

Table 2 presents our main estimation results regarding the impact of the presence of a state CDCTC in year *t-2* on the probability of a birth in the household in year *t* using the PSID data (Panel A) and the Natality data (Panel B). For the PSID data, both the traditional TWFE estimator and the new CSDID estimator yield insignificant and mostly negative results (except for the positive but not statistically significant result of the CSDID model with covariates).

Similarly, for the Natality data, we find an insignificant effect of the presence of a state CDCTC on the probability of having a birth for both the TWFE and the CSDID models.[13]

We so far have not considered variations in the state generosity of the CDCTC. In the second and the fourth rows of Table 2, we present the results obtained by replacing the presence of a state CDCTC with the maximum CDCTC benefit in a state (maximum federal plus state CDCTC benefits). Given the current state of the econometrics literature on continuous and staggered differential treatment models, we present this analysis using the TWFE model only. We observe no significant effect of the maximum CDCTC benefits on fertility using either the PSID data or the Natality data.

To measure child quality, we use the Natality data, extracting information from the birth certificates regarding birth weight, gestational age, and maternal smoking during pregnancy. These data allow us to create average birthweight, average gestational age, and the fraction of women who smoke during their pregnancies. We then estimate Equation (3) with these measures as our outcome variables. The results from both the TWFE and CSDID methods are presented in Table 3. Because women may not be aware of the CDCTC until after giving birth, we present the results for all women in the top panel and for women who have already had one child in the bottom panel. For all women, the

[13] The results of the TWFE model with the full set of covariates for both datasets are shown in appendix Table A1. Compared to unmarried women, married women have a higher probability of having a birth, as expected. More highly educated women are more likely to have a birth. The more children a family has, the more likely a family is to have an additional birth and higher husband's income exerts the expected positive income effect. Having a refundable state CDCTC does not affect fertility.

TWFE results indicate no significant effects on gestational age, birthweight, or maternal smoking during pregnancy. For the sample of women who have already had their first birth, we find no significant effect of the CDCTC on these quality indicators. Conversely, the CSDID estimator reveals a small but statistically significant increase in gestational age for women in states with a CDCTC. These results hold true for the full sample of births and for the subsamples by whether the mother has already had her first child. Although the coefficients are not statistically significant, the signs of the coefficients on average birthweight and maternal smoking align with expectations, indicating an improvement in these outcomes. These results suggest that the CDCTC may function as a subsidy for certain aspects of child quality.

To assess whether the parallel trends assumption is satisfied, we conduct event study analyses using both estimation methods for both datasets. We start with the models where fertility is our outcome. Figure 6a presents an event study for the TWFE model using the PSID data and Figure 6b depicts an event study for the TWFE model using the Natality data. These figures largely support the assumption of no differential pretrends and generally indicate no effect of the CDCTC on fertility. Figures 6c and 6d illustrate the event studies for the CSDID estimator using the PSID and Natality data, respectively. The results align with those obtained using the TWFE model and indicate that the assumption of no differential pretrends is supported.

Subsequently, we examine the event studies for the models where gestational age, birth weight and maternal smoking are the outcomes. These models are only estimated for the Natality data as explained earlier. Figures 6e, 6f and 6g show these event studies for models estimated with the TWFE estimator, revealing that the assumption of no differential pretrends holds. Figures 6h, 6i and 6j display event studies for the same three outcomes using the CSDID estimator, further confirming the absence of differential pretrends for all outcomes.

One possible reason for our insignificant fertility results is that, in addition to incentivizing fertility, the CDCTC may also encourage women to work, as the benefits are exclusively available to working parents or those using childcare to attend school. To investigate this potential mechanism, we explore three time-use related outcomes in Table 4. These outcomes include a binary variable equal to 1 if the woman is working, annual hours of work conditional on employment, and years of schooling (because parents can also claim the CDCTC if they use childcare while attending school). This table has three panels. Panel A presents the effect of the presence of a state CDCTC on these outcomes for all women using both the TWFE and the CDSID estimator. The TWFE specification shows a significant effect on labor force participation which diminishes when employing the CSDID estimator. We find no significant effects of the CDCTC on hours of work or years of education with either the TWFE or CSDID estimator. Panels B and C focus on the effect of the presence of a state CDCTC on the outcomes for married and unmarried women, respectively. Based on the CSDID method, the presence of a state CDCTC significantly increases labor force participation for married women but not for single women. This is consistent with the findings of Pepin (2021) and Jiang (2020). The effects on hours of work or education are always insignificant regardless of women's marital status or our estimation method. Appendix Figure A3 presents a CSDID event study for labor force participation, further supporting the assumption of no differential pretrends.

In Table 5, we present the results on fertility and the birth outcomes for various subgroups, focusing on race (white/nonwhite), marital status (married/not married), education (less than HS, HS or some college, college or more), age (aged 20-29, aged 30-39) and the presence (or absence) of an eligible child (under age 13). All analyses are estimated with the CSDID estimator. We find no fertility effect for any subgroup using either the PSID or the Natality data (apart from a 10 percent significantly positive result for women with HS degrees using the PSID), consistent with the main results obtained from the overall sample. Furthermore, we observe that the presence of a state CDCTC increases gestational age across most subgroups, with a stronger effect observed for non-white and more educated mothers. Lastly, we find some evidence suggesting a reduction in maternal smoking, although the effect is small and only statistically significant for unmarried mothers.

8. Potential threats to identification

One potential threat to identification would be reverse causality. It is plausible that states with low birth rates may consider increasing childcare assistance through the CDCTC to stimulate fertility. However, upon investigating the motivations behind states adopting the CDCTC, we have found no evidence supporting the idea that states implemented the CDCTC to increase their fertility rates. Instead, states primarily implemented the CDCTC to support working mothers and lower their cost of childcare.[14]

To formally test this possibility, we aggregate our data into state-year cells and estimate Equation (1), where the outcome variable Y represents the proportion of women in a state who give birth. The main X of interest is whether the state offers a CDCTC in that particular year. Table 6 presents the results of this analysis, which indicate that, at the aggregate level, for both the Natality and the PSID data and at both the extensive and the intensive margins, there is no evidence that states adjust their CDCTC policy in response to changes in fertility rates. This suggests that reverse causality is not a significant threat to our identification strategy.

Another potential concern relates to whether changes in state CDCTCs are influenced by economic conditions or changes in other policies that also impact fertility. For example, if state CDCTCs are expanded during economic expansions and if people are more likely to have children during such periods, then estimates of the effect of CDCTC benefits on fertility would be biased upward. Conversely, if state CDCTCs act as substitute for other public assistance programs that encourage fertility and are expanded when other programs are cut, then our estimates of the effect of state CDCTC on fertility could be biased downward. In addition, the CDCTC may affect the demographic composition of a state.

To address this concern, we conduct formal tests examining the correlation between state CDCTCs and state-level demographics (using the PSID data), state

[14]See, for example: https://www.lao.ca.gov/Publications/Report/3417 (accessed 6/12/2023).

policies, and state economic conditions. Table 7 presents the results of regressing the presence of a state CDCTC on state-by-year characteristics, including maximum EITC, per capita GDP, minimum wage, welfare generosity, percentage white, percent married, percent less than high school, percent high school or some college, percent with college degree or more, average number of kids per family, average of household head, and average husband's income. We include these variables along with our full set of controls in our models to account for their potential correlation with birth quantity or quality.

Overall, the results in table 7 suggest that the presence of a state CDCTC is only correlated with a few of these outcomes. However, considering that all these factors may be correlated with quantity or quality of births, we control for them in our models to mitigate any potential biases.

By addressing these potential threats to identification, we strengthen the robustness and reliability of our findings, ensuring that our estimates accurately capture the causal relationship between state CDCTCs and fertility outcomes.

9. Conclusion

The CDCTC is a tax benefit provided by the government to alleviate the financial burden of childcare for families. Its potential influence on fertility rates arises from the reduction in financial strain associated with raising children, which may encourage more families to choose parenthood. However, it also increases a woman's probability of participating in the labor force which may offset any fertility effect.

In this study, we use an extensive dataset spanning almost five decades of state-level CDCTC data and draw from two prominent data sources: the individual-level PSID data and the NCHS Natality data. Our objective is to examine the effect of the CDCTC on both the quantity and the quality of births in the US. To achieve this, we use both the traditional TWFE models and the newly developed method by Callaway and Sant'anna (2021) to estimate a model that relies on variation in the timing of states' introduction of their CDCTCs. Our comprehensive approach allows us to provide valuable insights into the multifaceted ramifications of this policy.

Our results indicate no discernible effect of the CDCTC on the probability of having a birth. This finding may be attributed, in part, to the nature of the credit itself. As families typically incur childcare expenses on a weekly basis, the once-per-year receipt of the CDCTC may not directly influence fertility decisions. However, in line with the existing literature, our study reveals that the introduction of state-level CDCTCs has significantly increased the labor force participation of married women. This highlights the intricate interplay between childcare subsidies, labor market dynamics, and fertility choices.

Furthermore, our analysis demonstrates that the CDCTC has yielded improvements in certain birth outcomes, with the effect on gestational age being statistically significant. While other birth outcome indicators exhibit positive trends, statistical significance is not observed. These findings shed light on the potential positive impacts of the CDCTC on birth outcomes, warranting further research and discussion.

By addressing this previously unexplored aspect of the CDCTC, our research paper stands out as a pioneering endeavor that comprehensively examines the impact of this policy on both the quantity and quality of births. In doing so, we not only contribute significant insights to the ongoing discourse surrounding the effects of the CDCTC on various outcomes but also provide valuable input for important policy discussions concerning childcare subsidies, fertility rates, and birth outcomes. We hope our study can serve as a foundation for evidence-based policymaking related to the CDCTC, aiming to enhance the well-being of families and children across the nation.

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Figure 1: Structure of the Federal CDCTC over Time

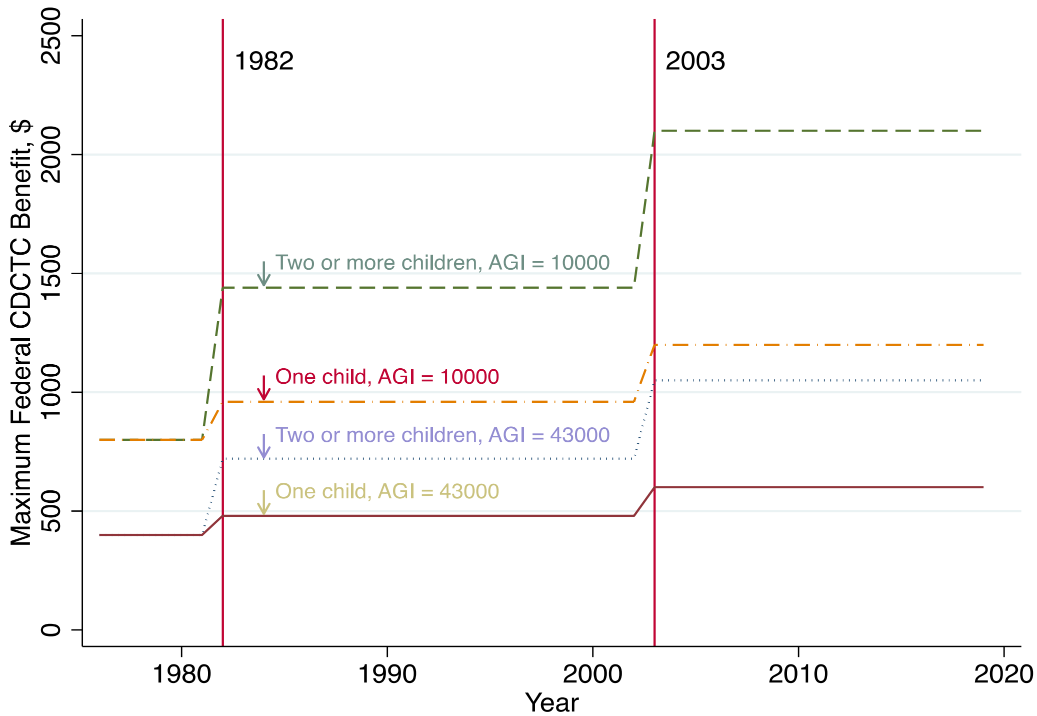
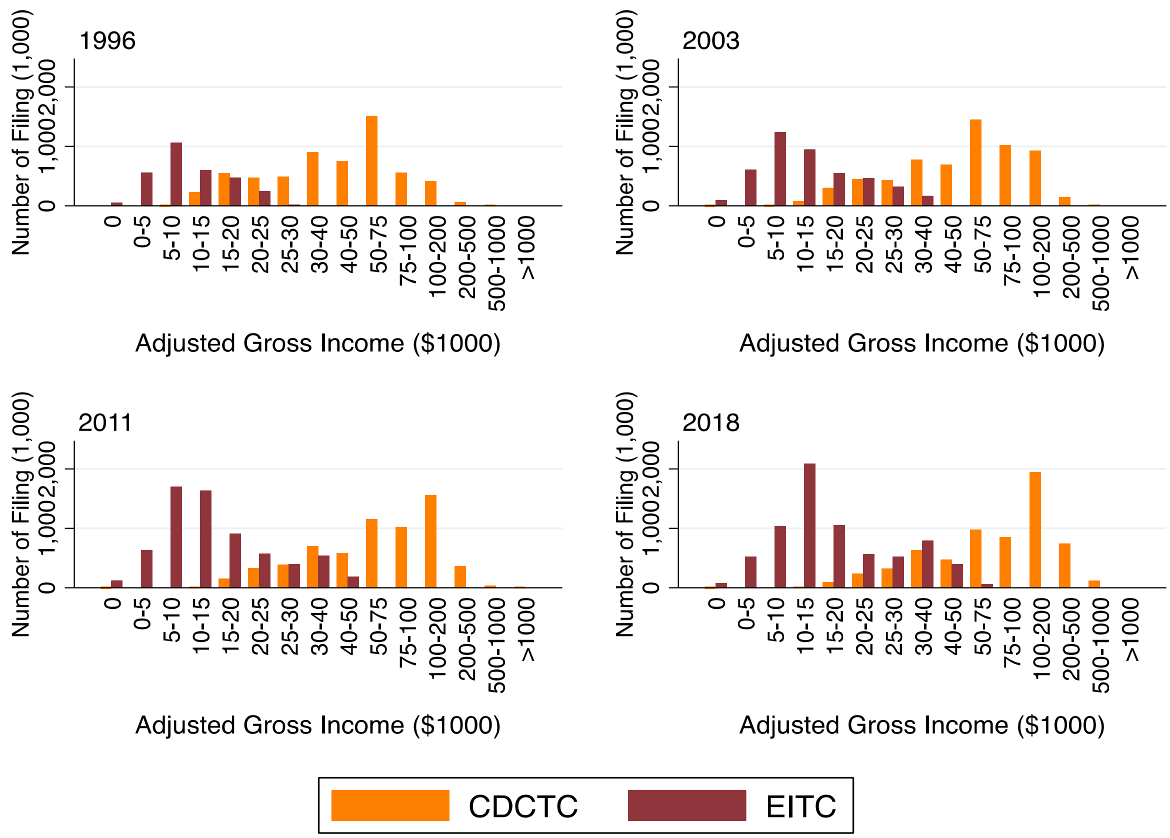
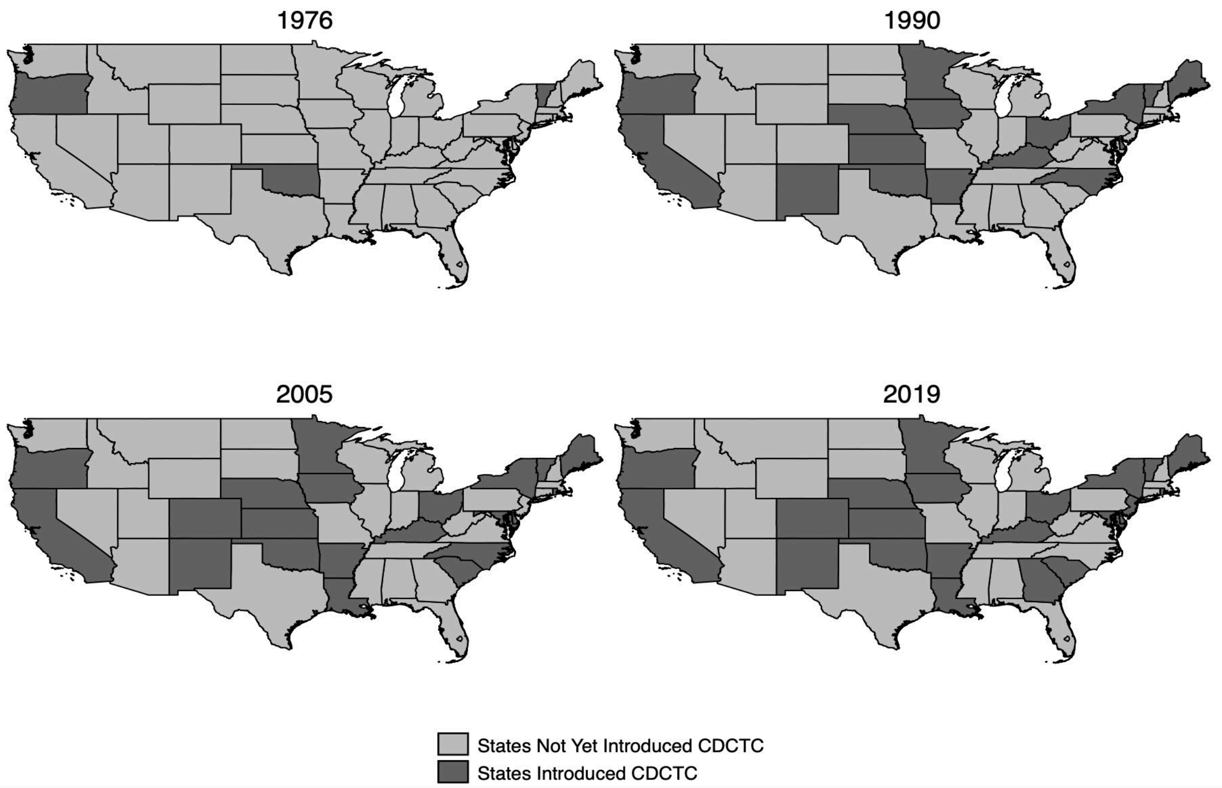


Figure 2: Distribution of Recipients of CDCTC Compared to EITC Recipients



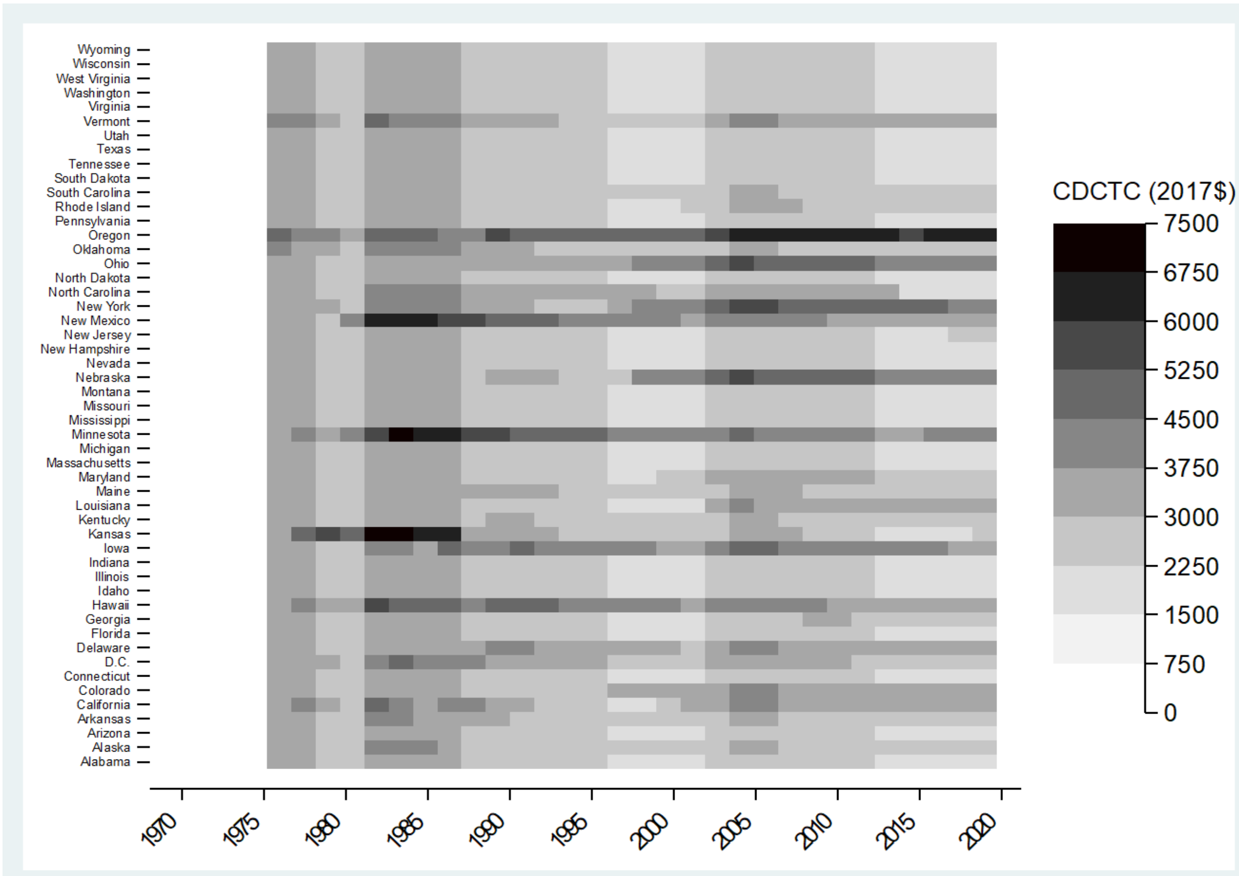
Source: Author's calculations from IRS and CPS data

Figure 3: State Level Introduction of the CDCTC over Time



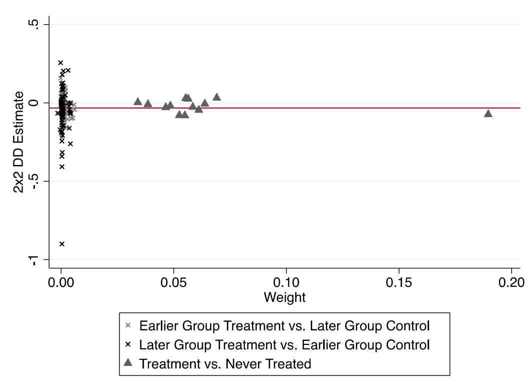
Source: Author’s calculations.

Figure 4: Heat Map of CDCTC generosity by State



Source: Author's calculations

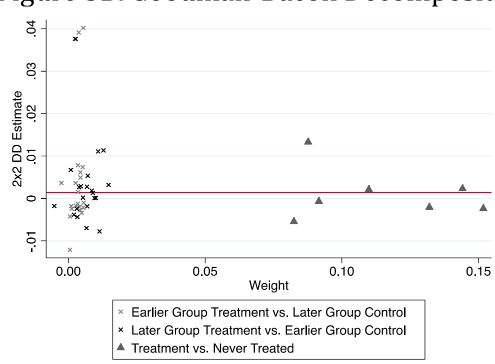
Figure 5A. Goodman-Bacon Decomposition for Fertility Using PSID



Diff-in-diff estimate: -0.033

DD Comparison	Weight	Avg DD Est
Earlier T vs. Later C	0.099	-0.043
Later T vs. Earlier C	0.072	-0.048
T vs. Never treated	0.829	-0.030

Figure 5B. Goodman-Bacon Decomposition for Fertility Using Natality



Diff-in-diff estimate: 0.001

DD Comparison	Weight	Avg DD Est
Earlier T vs. Later C	0.066	0.007
Later T vs. Earlier C	0.135	0.003
T vs. Never treated	0.799	0.001

T = Treatment; C = Control

Figure 6A. TWFE Event Study for Fertility using PSID Data

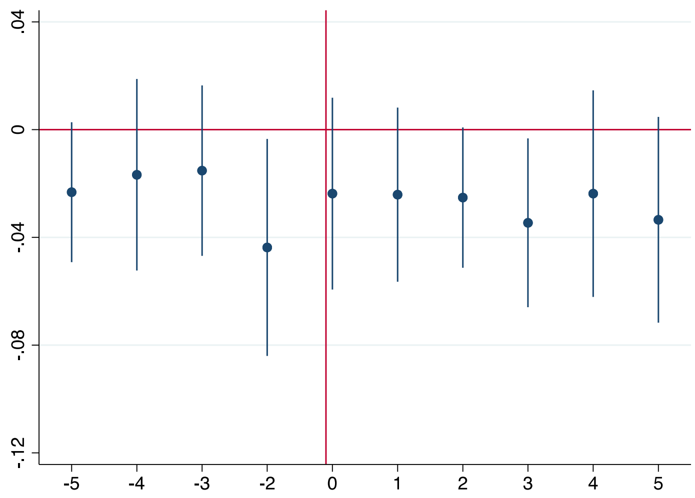
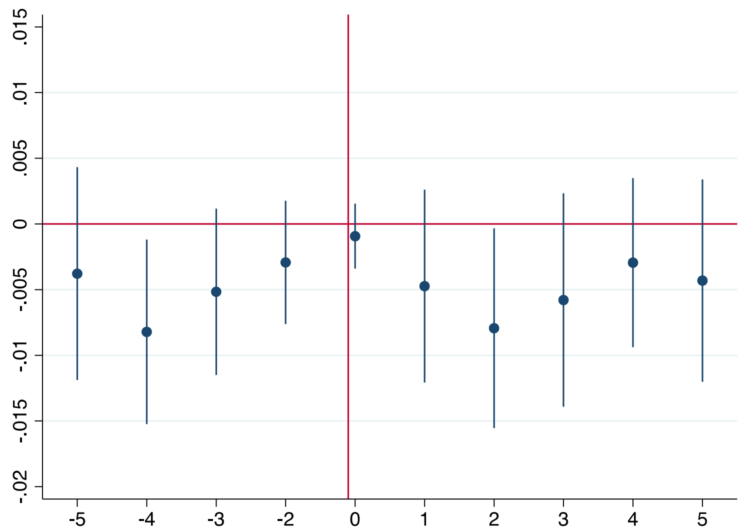


Figure 6B. TWFE Event Study for Fertility using Natality Data



Notes: These figures show the coefficients and the 95 percent confidence intervals from a TWFE event study regression where the outcome equals 1 if a birth occurred in year t+2. Treatment is defined as living in a state with a CDCTC at time t and the comparison group is comprised of women who live in a state without a CDCTC at time t. The x-axis measures time relative to treatment. Models include the full set of controls as shown in Table 1.

Figure 6C. CSDID Event Study for Fertility using PSID Data

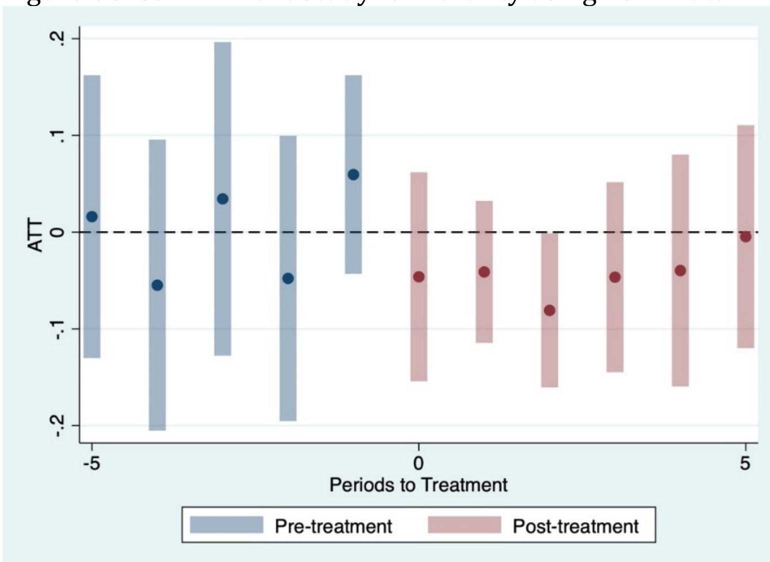
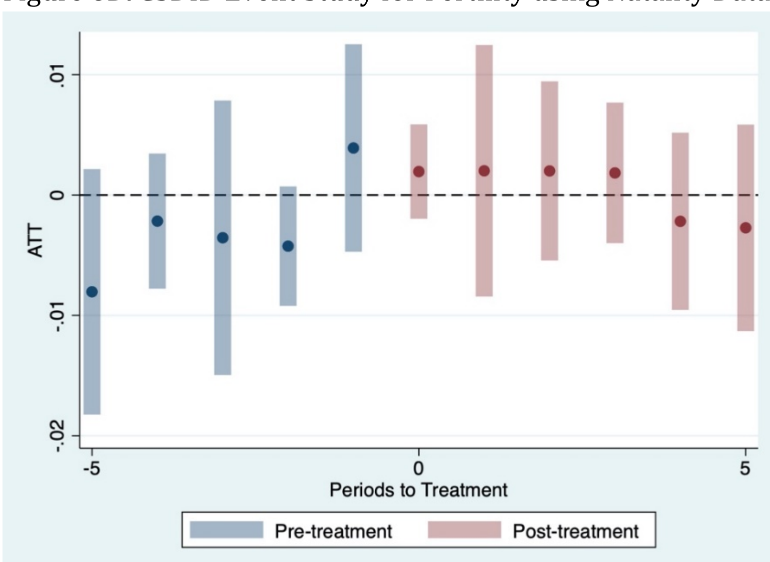


Figure 6D. CSDID Event Study for Fertility using Natality Data



Notes: These figures show the coefficients and the 95 percent confidence intervals from estimating Callaway and Sant'Anna (2020) dynamic treatment effects. The outcome equals 1 if a birth occurred in year t+2. Treatment is defined as living in a state with a CDCTC at time t and the comparison group is comprised of women who live in a state without a CDCTC at time t. The x-axis measures time relative to treatment. Models include the full set of controls as shown in Table 1.

Figure 6E. TWFE Event Study for Average Birth Weight using Natality Data

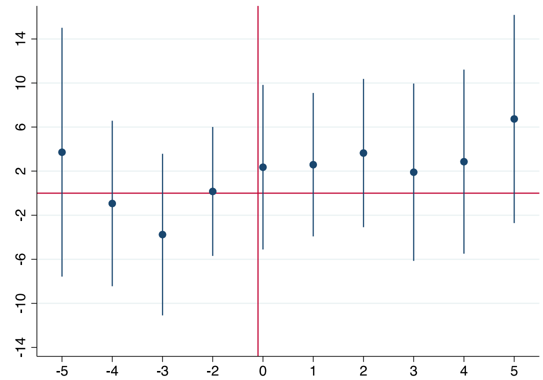


Figure 6F. TWFE Event Study for Average Gestational Age using Natality Data

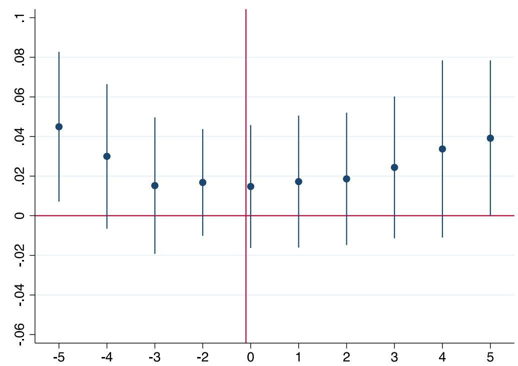
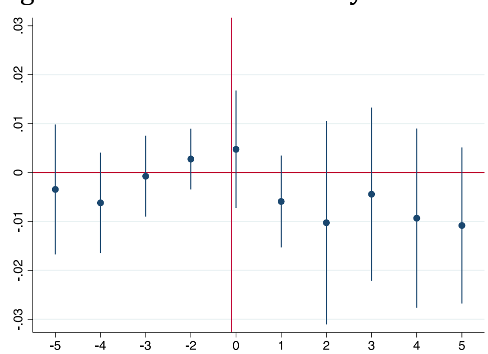


Figure 6G. TWFE Event Study for Maternal Smoking Rate using Natality Data



Notes: These figures show the coefficients and the 95 percent confidence intervals from a TWFE event study regression where the outcome equals 1 if a birth occurred in year t+2. Treatment is defined as living in a state with a CDCTC at time t and the comparison group is comprised of women who live in a state without a CDCTC at time t. The x-axis measures time relative to treatment. Models include the full set of controls as shown in Table 1.

Figure 6H. CSDID Event Study for Average Birth Weight using Natality

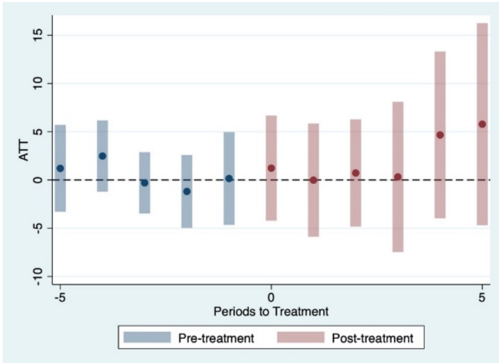


Figure 6I. CSDID Event Study for Average Gestational Age using Natality Data

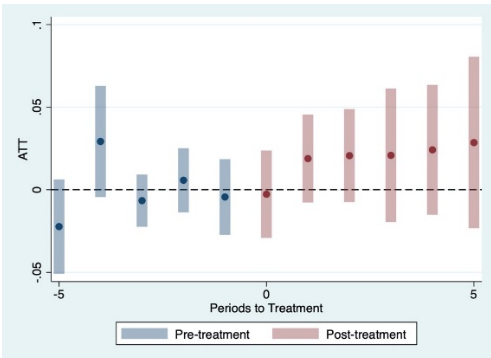
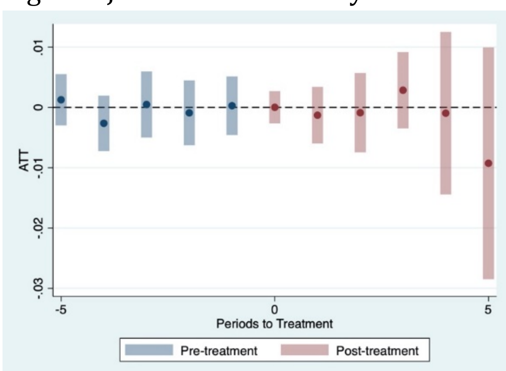


Figure 6J. CSDID Event Study for Maternal Smoking Rate using Natality Data



Notes: These figures show the coefficients and the 95 percent confidence intervals from estimating Callaway and Sant'Anna (2020) dynamic treatment effects. The outcome equals 1 if a birth occurred in year t+2. Treatment is defined as living in a state with a CDCTC at time t and the comparison group is comprised of women who live in a state without a CDCTC at time t. The x-axis measures time relative to treatment. Models include the full set of controls as shown in Table 1.

Table 1A: Weighted Sample Means, PSID years 1968-2019

Variable	Mean	Std. Dev.	Minimum	Maximum
Gave birth in either year t+1 or t+2	0.197	0.398	0	1
Number of kids	1.616	1.376	0	13
Age	30.603	5.318	20	39
Birth year of HHD head	1953.329	13.650	1903	1993
Mother’s education less than HS	0.189	0.391	0	1
Mother’s education Some College	0.635	0.481	0	1
Mother’s education College Degree	0.176	0.381	0	1
White	0.813	0.390	0	1
Black	0.154	0.361	0	1
Other races	0.034	0.180	0	1
Male head	0.722	0.448	0	1
Married	0.724	0.447	0	1
Maximum CDCTC benefit (1000, $2017)	2.279	1.236	0	7.315
CDCTC refundability	0.010	0.100	0	1
Maximum EITC benefit (1000, $2017)	2.467	2.210	0	9.695
EITC refundability	0.056	0.230	0	1
Maximum State Marginal Income Tax Rate	4.738	3.587	0	21.8
Maximum welfare benefit (1000, $2017)	0.764	0.376	0.162	2.045
Number of hospital beds (1000)	43.856	35.856	1.8	206.4
Per capita GDP, (1000 $2017)	39.550	8.771	19.891	124.090
Paid family leave	0.003	0.057	0	1
Live in a state with CDCTC benefit	0.100	0.300	0	1
Labor force participation for all women (N=41925)	0.741	0.438	0	1
Working hours for all women (N = 29441)	1577.305	675.871	1	3500
Highest grade for all women (N=49297)	12.511	2.260	1	17
Labor force participation for married women (N=30678)	0.734	0.442	0	1
Working hours for married women (N=21398)	1540.101	673.695	1	3500
Highest grade for married women (N=35564)	12.669	2.264	2	17
Labor force participation for unmarried women (N=11208)	0.759	0.428	0	1
Working hours for unmarried women (N=8072)	1676.470	670.612	4	3500
Highest grade for unmarried women (N=13683)	12.103	2.200	1	17
N=64540				

Table 1B: Weighted Sample Means, Natality
years 1970-2019

Birthrates within year [t-1, t] per 100 women	Mean	Std. Dev.	Minimum	Maximum
Panel A: birthrates				
All women	13.833	15.119	0	100
15- to 24-year-olds	17.086	18.575	0	100
25- to 29-year-olds	18.508	15.758	0	100
30- to 34-year-olds	13.664	13.322	0	100
35- to 39-year-olds	5.732	6.287	0	100
White	14.446	15.993	0	100
Nonwhite	11.642	11.193	0	100
First births	12.221	15.578	0	100
Second and higher order births	14.930	14.698	0	100
Less than high school	15.684	16.460	0	100
High school and some college	10.468	10.959	0	100
College or more	15.251	16.808	0	100
Unmarried	7.725	10.073	0	100
Married	18.836	16.648	0	100
Panel B: state-level controls				
Maximum CDCTC benefit (1000, $2017)	2.520	1.174	0	7.315
CDCTC refundability	0.059	0.236	0	1
Maximum EITC benefit (1000, $2017)	3.624	2.503	0	9.695
EITC refundability	0.103	0.304	0	1
Maximum welfare benefit (1000, $2017)	0.638	0.330	0.162	2.295
Maximum state marginal tax rate	4.392	3.254	0	21.8
Number of hospital beds	33.066	22.225	1.6	115
Per capita GDP, unit #1000	42.866	10.035	19.524	140.625
Paid family leave	0.004	0.063	0	1
Live in a state with CDCTC benefit	0.213	0.409	0	1
N=261,363				
Panel C: birth outcomes				
Average birth weight (N=183,860)	3327.428	131.542	2270.727	4056.5
Average gestational age (N=183,860)	38.966	0.517	33.94	41.909
Smoke rate (N=99,216)	0.112	0.119	0	1

Table 2. Main Estimation Results on Fertility.

	TWFE no covariates	TWFE covariates	CSDID no covariates	CSDID covariates
Panel A: PSID data. Y=1 if There is a Birth in the Household in Year t.				
Presence of state CDCTC in year t-2	-.016 (.015)	-.015 (.010)	-.032 (.029)	0.044 (.036)
Maximum state plus federal CDCTC $ in year t-2	-.015 (.020)	-.015 (.012)	N/A	N/A
N	64540			
Panel B: Natality Data. Y=birthrate.				
Presence of state CDCTC in year t-2	-0.009 (0.007)	-0.006 (0.006)	-0.012 (0.009)	-0.006 (0.012)
Maximum state plus federal CDCTC $ in year t-2	-0.005 (0.004)	-0.003 (0.003)	N/A	N/A
~~N~~	261363			

Notes: Each cell represents a separate regression. The outcome is fertility at time t and the presence of a state CDCTC is measured at time t-2. All models include the full set of covariates. Individual and year FE in TWFE models. Standard errors in parentheses are clustered by state for TWFE models for both Natality and PSID data. For the CSDID models, PSID standard errors are clustered by state and individual ID while Natality data standard errors are clustered by group and state. *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Quality at Birth using Natality Data

	TWFE			CSDID		
	Birth weight	Gestational Age	Smoking	Birth weight	Gestational Age	Smoking
Presence of state CDCTC All women	2.582 (3.275)	0.002 (0.015)	-0.004 (0.004)	4.858 (6.392)	0.038* (0.021)	-0.003 (0.004)
Sample size	183,860	183,860	99,216	183,860	183,860	99,216
Presence of state CDCTC For women who already have children	4.684 (3.692)	0.010 (0.016)	-0.007 (0.005)	5.793 (7.138)	0.037* (0.022)	-0.004 (0.004)
Sample size	121,287	121,287	65,390	121,287	121,287	65,390
Presence of state CDCTC For women who have no children	-1.321 (3.145)	-0.012 (0.015)	0.001 (0.004)	3.100 (5.478)	0.040* (0.020)	-0.003 (0.004)
Sample size	62,573	62,573	33,826	62,573	62,573	33,826

Notes: Each cell represents a separate regression. All models include the full set of covariates. Individual and year FE in TWFE models. Standard errors in parentheses are clustered by state for TWFE models for both Natality and PSID data. For the CSDID models, PSID standard errors are clustered by state and individual ID while Natality data standard errors are clustered by group and state. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Mechanism Analysis using PSID

	TWFE			CSDID		
	Labor Force participation	Annual Hours of work (conditional on LFP=1)	Years of education	Labor Force participation	Annual Hours of work (conditional on LFP=1)	Years of education
Panel A. All women						
Presence of state CDCTC	0.038* (0.019)	30.371 (27.079)	-0.043 (0.031)	0.081 (0.058)	122.312 (226.082)	0.031 (0.078)
Sample size	41,925	29,441	49,297	41,925	29,441	49,297
Panel B. Married women						
Presence of state CDCTC	0.033 (0.021)	11.455 (30.562)	-0.042 (0.033)	0.145** (0.061)	177.312 (270.154)	0.037 (0.075)
Sample size	30,678	21,310	35,564	30,678	21,310	35,564
Panel C. Unmarried women						
Presence of state CDCTC	0.050* (0.030)	70.542 (43.541)	-0.028 (0.083)	-0.213 (0.156)	-95.408 (288.422)	-0.026 (0.490)
Sample size	11,208	8,072	13,683	11,208	8,072	13,683

Notes: Each cell represents a separate regression. All models include the full set of covariates. Individual and year FE in TWFE models. Standard errors in parentheses are clustered by state for TWFE models for both Natality and PSID data. For the CSDID models, PSID standard errors are clustered by state and individual ID while Natality data standard errors are clustered by group and state. ***p<0.01, ** p<0.05, * p<0.1.

Table 5. Subgroup Analysis

	Non-white	White	Unmarried	Married	Less than HS	HS or some college	College or more	Aged 20-29	Aged 30-39	Has no eligible kid	Has eligible kid
PSID Fertility	-.092 (0.139)	.043 (.038)	.021 (.089)	.062 (.041)	.085 (.142)	.139* (.072)	-.427 (.302)	.554 (.498)	-.002 (.081)	-0.282 (0.212)	0.041 (0.057)
N	28.875	35,611	18,841	45,617	15,172	40,297	8,616	29,526	31,233	15,496	46,054
Natality Birthrate	0.008 (0.014)	-0.008 (0.013)	0.004 (0.003)	-0.011 (0.017)	-0.002 (0.013)	-0.010 (0.010)	-0.012 (0.014)	-0.009 (0.017)	-0.001 (0.006)	-0.008 (0.012)	-0.005 (0.012)
N	127,427	133,936	129,567	131,796	89,352	88,424	83,587	129,553	131,810	88,265	173,098
Average birth weight	4.652 (11.018)	4.190 (6.436)	6.322 (10.136)	5.023 (6.142)	7.080 (7.374)	0.484 (5.814)	0.133 (5.344)	5.542 (6.582)	1.898 (5.928)	3.100 (5.478)	5.793 (7.138)
N	80,015	103,845	75,303	108,557	72,452	61,851	49,557	99,907	83,953	62,573	121,287
Average gestational age	0.071** (0.030)	0.031 (0.021)	0.063* (0.036)	0.036* (0.021)	0.030 (0.020)	0.043* (0.023)	0.044 (0.031)	0.033* (0.020)	0.052** (0.026)	0.040* (0.020)	0.037* (0.022)
N	80,015	103,845	75,303	108,557	72,452	61,851	49,557	99,907	83,953	62,573	121,287
Smoke rate	0.008 (0.012)	-0.003 (0.006)	-0.010** (0.005)	-0.001 (0.004)	-0.006 (0.006)	-0.003 (0.006)	-0.003 (0.003)	-0.005 (0.004)	-0.001 (0.004)	-0.003 (0.004)	-0.004 (0.004)
N	44,602	54,614	46,870	52,346	35,704	34,694	28,818	50,489	48,727	33,826	65,390

Notes: Each cell represents a separate CSDID regression. All models include the full set of covariates. Individual and year FE in TWFE models. Standard errors in parentheses are clustered by state for TWFE models for both Natality and PSID data. For the CSDID models, PSID standard errors are clustered by state and individual ID while Natality data standard errors are clustered by group and state. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Reverse Causality

	Presence of a state CDCTC	Maximum State CDCTC Conditional on having a state CDCTC
Proportion of births in state i in year t, PSID	-.047 (.056)	-.249 (.183)
Sample Size	1873	499
Birth rate in state i in year t, Natality	-1.961 (1.174)	-8.945 (6.906)
Sample Size	1976	622

Notes: Each column is a separate regression. Each contains the full set of covariates and is estimated with TWFE. Fertility is measured at year t and the CDCTC is at year t+1. Sample is aggregated to the state-year level. Standard errors in parentheses and clustered by state. PSID sample weights are used. All models include the full set of covariates. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: CSDID Estimation of Effect of State's Introduction of a CDCTC on State-Level Demographic and Economic Policies

	Introduction of State CDCTC
White	0.104 (0.129)
Married	0.093 (0.111)
Less than HS	-0.145 (0.104)
High School or some college	0.106 (0.123)
College or more	0.038 (0.050)
Number of kids	-0.174 (0.241)
Age	***-2.313 (0.854)
Husband's income	-5197.849 (11537.170)
State Max. EITC	**-0.976 (0.382)
State Max. Welfare Benefit	0.049 (0.072)
State Hospital beds	1.994 (10.215)
State per capita GDP	5.915* (3.301)
N	1650

Notes: Each row is a separate model with the full set of covariates using samples aggregated to the state-year level. All models are estimated with CSDID using the PSID data. Standard errors clustered by state are in parentheses. All models include the full set of covariates. *** p<0.01, ** p<0.05, * p<0.1.

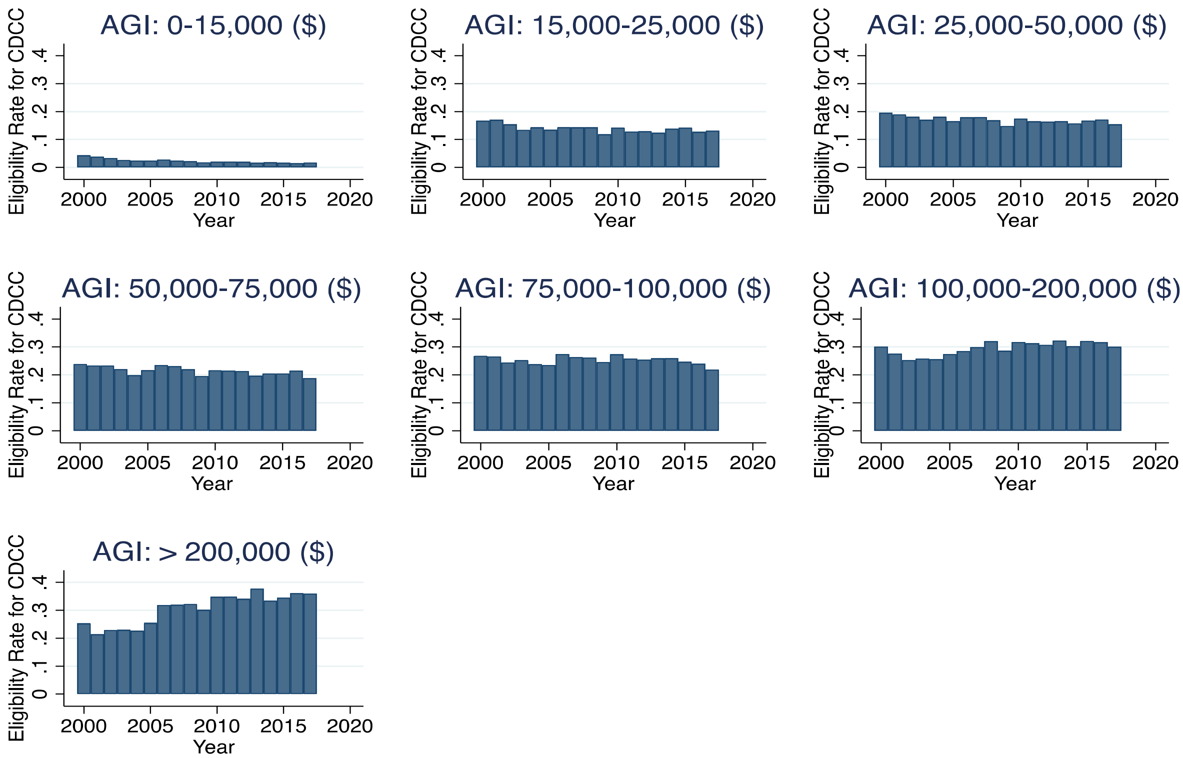
Appendix

Table A1: TWFE Estimation Full Set of Results for Fertility

Variable	PSID	Natality
Presence of CDCTC	-0.015	-0.006
	(0.010)	(0.006)
White	-0.015	
	(0.051)	
Married	-0.172*	
	(0.092)	
Educ: Less than high school	-0.038	
	(0.034)	
Educ: High school or some college	-0.037	
	(0.022)	
# Kids	-0.148***	
	(0.006)	
Age	-0.067	
	(0.044)	
Age square	0.003*	
	(0.001)	
Age cubic	-0.000*	
	(0.000)	
Husband's income, 1000000, 2017$	-0.000**	
	(0.000)	
Refundability of CDCTC	-0.024	-0.011*
	(0.059)	(0.006)
Maximum EITC benefit, 1000, 2017$	0.003	-0.001
	(0.010)	(0.003)
Refundability of EITC	-0.035*	-0.007
	(0.018)	(0.006)
Maximum welfare benefit, 1000, 2017$	-0.003	-0.006
	(0.029)	(0.015)
Maximum income MTR	0.003	-0.000
	(0.003)	(0.001)
Number of hospital beds	-0.000	0.000
	(0.001)	(0.000)
Per capita GDP,1000, 2017$	0.001	0.001**
	(0.001)	(0.000)
Paid family leave	0.022*	-0.016***
	(0.012)	(0.006)
N	64540	261,363
R-squared	0.355	0.842

*** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standard errors in parentheses are clustered by state.

Figure A1. CDCTC Eligibility rates by Adjusted Gross Income (AGI)

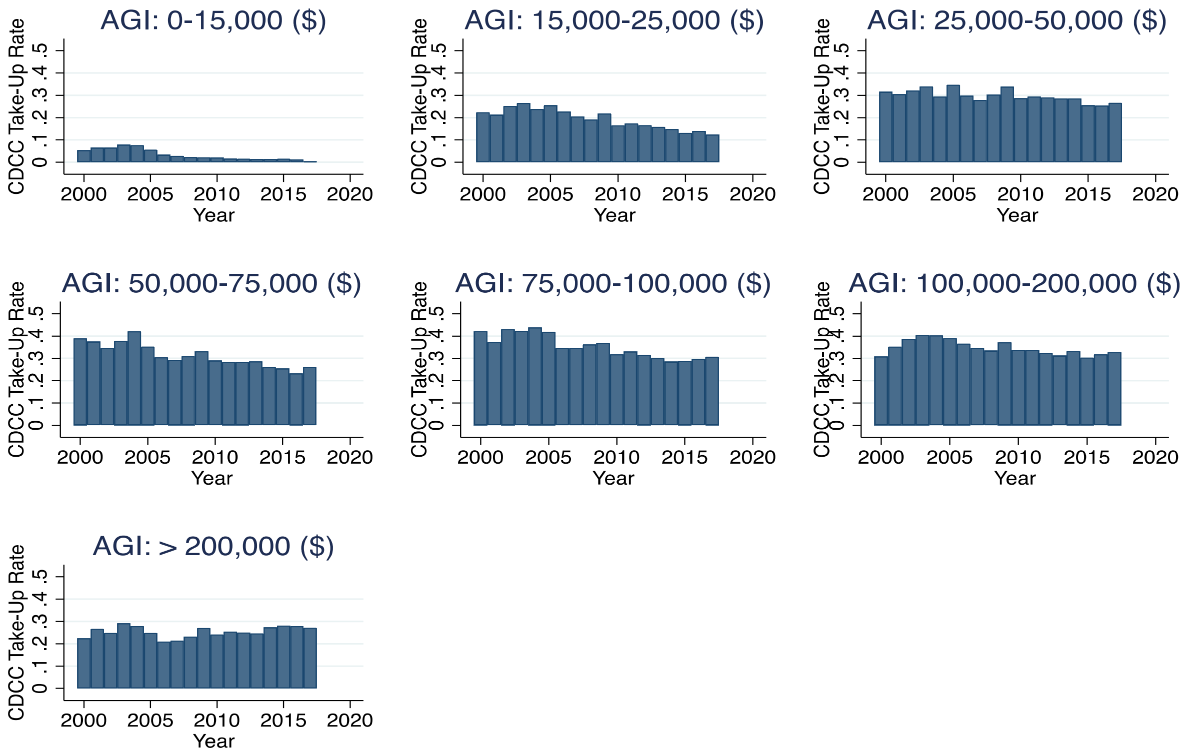


Source: Author’s calculations. Data source 1: IRS SOI tax stats, individual income tax returns complete report (publication 1304), table 3.3 (# of CDCTC filing) and table 1.4 (# total filing). https://www.irs.gov/statistics/soi-tax-stats-individual-income-tax-returns-complete-report-publication-1304#Basic%20Tables.

Data source 2: March CPS data 2001 - 2018. https://ceprdata.org/cps-uniform-data-extracts/march-cps-supplement/march-cps-data/

Note: Because there is no AGI data in CPS 2012, we impute data for that year.

Figure A2. CDCTC Take-up rates by Adjusted Gross Income (AGI)

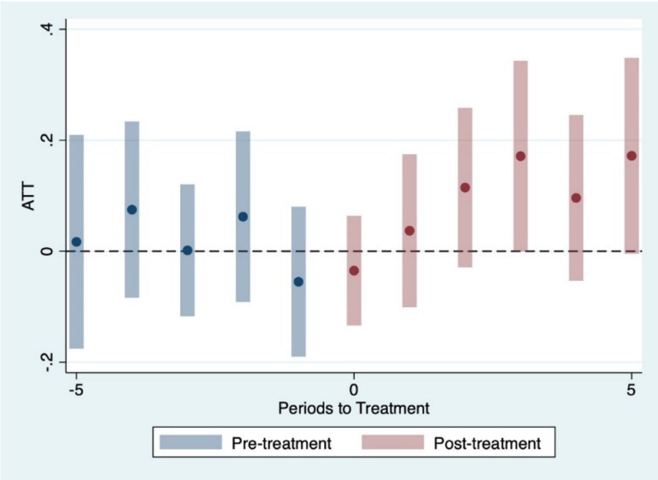


Source: Author's calculations. Data source 1: IRS SOI tax stats, individual income tax returns complete report (publication 1304), table 3.3 (# of CDCTC filing) and table 1.4 (# total filing). https://www.irs.gov/statistics/soi-tax-stats-individual-income-tax-returns-complete-report-publication-1304#Basic%20Tables.

Data source 2: March CPS data 2001 - 2018. https://ceprdata.org/cps-uniform-data-extracts/march-cps-supplement/march-cps-data/

Note: Because there is no AGI data in CPS 2012, we impute data for that year.

Figure A3: CSDID Event Study for Labor Force Participation using PSID Data



Notes: This figure shows the coefficients and the 95 percent confidence intervals from estimating Callaway and Sant'Anna (2020) dynamic treatment effects. The outcome equals 1 if a birth occurred in year t+2. Treatment is defined as living in a state with a CDCTC at time t and the comparison group is comprised of women who live in a state without a CDCTC at time t. The x-axis measures time relative to treatment. Models include the full set of controls as shown in Table 1.

Figure A4. Histogram of Working Hours Conditional on Labor Force Participation using PSID Data