



DEPARTMENT OF SOCIAL POLICY AND INTERVENTION

State Child and Dependent Care Tax Credits and Their Effects on Child Care Supply

Maya Katherine Jasinska

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Abstract

This thesis considers a fundamental inadequacy in the American child care market-- the insufficient supply of care—and explores how well-suited state child and dependent care tax credits (CDCTCs) are to solving it. CDCTCs increase families' incomes and therefore also increase parents' power to purchase formal care. It follows that the credit may also impact the level of child care supply. This study explores this relationship. I construct a multilevel, random intercept model and use total slot data for 2,211 counties in the U.S., acquired directly from and approved by 36 state Child Care and Development Fund administrators. Although my results are not statistically significant, I find that every \$1000 increase in state CDCTC generosity is associated with an increase of four slots per 100 children in the county and that refundable credits are associated with a 9% increase in slots compared with nonrefundable credits. Lastly, I find some evidence that the relationship between state CDCTCs and supply may be nonlinear. Ultimately, this study contributes to the existing policy debate over whether demand-side interventions are effective in building child care supply.

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1. Introduction

“We have got to figure out how to make [child care] affordable, accessible, and safe for everybody in Pennsylvania,” Governor Tom Wolf urged during a July 2022 news conference announcing the state’s new child and dependent care tax credit (CDCTC), which went into effect in 2023 (Kilmer, 2022). While the Governor correctly summarized the three key components of the present early childhood education and care (ECEC) crisis—cost, quantity, and quality—in the United States (U.S.), the policy solution he offered, a nonrefundable state tax credit reimbursing families for a portion of their formal child care expenses, seems poised to tackle only one of these three issues: affordability. This thesis explores whether increases in generosity to state CDCTC policies have any bearing on accessibility, or the supply of child care in those states.

According to the Bipartisan Policy Center, the average child care supply gap—the difference between the number of slots and the potential need (estimated as the number of children 0-6 with all available parents in the labor force)—in the U.S. is 31.1% of potential need (Bagley, 2021).¹ In other words, on average, almost a third of parents who might want to use the formal child care system cannot find a place for their child. This is a problem for parents and the economy: about 70% of children under six in the U.S. have all available parents in the labor force (American Community Survey, 2021). There is a

¹ It should be noted that, because there will always be some number of parents who prefer to use informal child care (relative or parental) care, there will always be some degree of child care gap. Modeling actual child care demand is complicated, and Leslie et al. found that child care decision-making is a dynamic and complex process filled with trade-offs and influenced by family ideology, employment status, income, and race/ethnic background (2000). The other dimension that is difficult in quantifying actual demand is that the availability and cost of informal care are unobserved (Blau and Currie, 2006). However, without any other constraints, Rose and Elicker found that 52.7% of parents would prefer to use formal child care for their preschoolers, but that 87.6% of parents prefer parental care for their infants (Rose and Elicker, 2010). “Latent demand” is also difficult to precisely estimate, but the Bipartisan Center found in a survey of parents using informal care that 40% were doing so because they found formal care inaccessible (2022; Queralt and Witte, 1998).

lot of variation in the extent of the child care gap at both the county and state level, across urban and rural areas and it is larger in low-income neighborhoods than in higher income areas (Bagley, 2020; Malik & Hamm, 2018; Queralt and Witte, 1998).

Beyond losing the long-term child development benefits of high quality early childhood programs, insufficient child care supply has serious consequences for gender equality, family incomes, poverty alleviation efforts, and local economies. Child care availability and women's labor force participation are shown to be strongly correlated (Morrissey, 2017; Cascio, 2009; Cascio and Schanzenbach, 2013; Herbst, 2017). The gendered consequences of insufficient child care supply became especially visible during the Covid-19 pandemic, when mothers took on a disproportionate share of unpaid child care at home, even while working, during the lockdowns and provider closures (Zamarro and Prados, 2021). Working mothers of children under the age of five were especially affected: They worked the least number of hours per week in 2020 compared with parents of older children (Kochar, 2020; Collins et al., 2020). This has reverberations for the larger American economy. Following their effort to assess the scale of the child care supply gap in 35 states, Bagley and Jerrett estimated that the 10-year economic impact of one year of the supply gap was a total potential loss between \$142.5 billion and \$217 billion in economic output—measured as household income decreases, declines in business productivity, and losses in tax revenue (2021). Another study estimated that the U.S. economy loses \$122 billion per year from the infant and toddler (0-3) child care supply crisis alone—estimated in lost parental earnings, business revenues, and tax revenue (Belfield, 2023). The entire child care market in the U.S. was valued at approximately \$60 billion in 2019 (U.S. Treasury, 2021).

Estimates as to the exact losses in child care supply incurred during the pandemic vary. In 2022, the Bureau of Labor Statistics reported a loss of 100,000 child

care workers over the course of the pandemic (Goldstein, 2022). Child Care Aware reported that 16,000 child care providers shut down between December 2019 and March 2021 (2022). Lockdowns initially caused child care providers to shutter their doors and the average length of a provider’s waitlist for families increased 28% between February 2020 and February 2022 (Carrazana, 2023). At the same time, historic stimulus relief packages and temporary state-level policy innovations kept many businesses afloat. As the U.S. emerges from the health and economic crisis of the Covid-19 pandemic and reckons with the resulting child care supply crisis, it may use “path dependent” policy responses to this crisis; this study explores the efficacy of one of those paths (Pierson, 1996).

This thesis considers this fundamental inadequacy in the present child care market—the insufficient supply of care: affordable, quality, or otherwise—and explores how well suited the longest-running ECEC policy in the U.S. is to solving it. Child care tax credits, which increase families’ incomes, theoretically impact the level of demand for formal child care (Blau, 2001). By increasing parents’ power to purchase formal care, the credit may also impact the level of child care supply. I pose the question: are more generous state CDCTCs associated with higher levels of child care supply? To answer it, I construct a multilevel, random intercept model and use total slot data for 2,211 counties in the US, acquired directly from and approved by 36 state Child Care and Development Fund (CCDF) administrators.² Ultimately, I hope this study can contribute to the existing policy debate over whether demand-side interventions are effective in building child care supply.

² This data was acquired as part of the “Child Care Gap” report, funded by the Buffett Foundation (2021). My thanks to Linda Smith and Anubhav Bagley for sharing and permitting me to use this data.

This thesis is organized as follows: First, a literature review describes the existing ECEC policies in the US as well as the economic models on which they are based. Second, my data and methods chapter describes in detail the two unique datasets this study uses: both comprehensive slot data as well as an original dataset of state CDCTC policies. I also describe the suitability of multilevel modeling for this project. Third, my results describe the findings of the three hypotheses I test. Finally, my discussion considers what we can glean from those findings and the limitations of my study.

2. Theoretical Framework and Literature Review

2.1 Theories of Family and ECEC policy

Family life has changed dramatically since the Golden Age of welfare state expansion, and many of the new “social risks” the welfare state is asked to confront are results of changing demographics in family and care arrangements (Furstenberg, 2019). These include an aging population, women’s expansion into the public sphere and especially into the labor force, and higher incidences of divorce and single parenthood (Furstenberg, 2019; Bonoli, 2005). Care for young children, traditionally provided in the home by women/mothers, has shifted to nonparental contexts and become an issue of public responsibility.

One conceptualization of family policy frames welfare states’ approaches to care policy as either “familizing” or “defamilizing”—which is to say, they either promote care for young children that is provided by the parents/family (familizing) or care that is provided by the state through public child care services (defamilizing) (Daly, 2011). However, given the fact that in 2019, 59% of American children under the age of five were in a regular, weekly, nonparental care arrangement, it is not practical to discuss U.S. ECEC policy in those terms: Since ECEC services are not publicly provided, they are not defamilizing. At the same time, they are not familizing, because they do not reify the nuclear family either (Tekin, 2021). Instead, the U.S. has no federal parental leave policy, and all parental leave is employer-provided. Families use informal, relative care or seek formal care for their young children in not-for-profit or for-profit private child care centers, family child care homes, faith-based organizations, or community-based organizations. Formal public schooling begins with kindergarten, for children five or older.

A second conceptualization of family policy has used “regime” analysis to uncover different clusters of countries than traditional welfare scholarship finds based on the question of “who provides care” (Lewis, 1992; Sainsbury, 1999). Even in these new pairings, the U.S. has been grouped with other Anglo countries, in its traditional “liberal” policy regime for its heavy emphasis on market-based provision of care. However, as McLean notes, this fixation on provision obscures other important and influential types of state action in ECEC in liberal regimes: regulation and funding. While the U.S. is relatively inactive and scattered with regard to provision, its regulatory and funding policies shape the dynamics and operation of the child care market (McLean, 2014). As a result, McLean characterizes the U.S. as taking a “market moderator” approach that attempts to be relatively *laissez-faire* in all three of these dimensions (2014). However, though American ECEC policies attempt to be hands-off, policies such as the child care subsidy program and staff to child ratios do impact the child care market. Furthermore, as is typical of the federalist system, there is great diversity in approach to regulation, provision, and financing among different states, and this *laissez-faire* image paints an incomplete picture of state involvement in the private ECEC market. States regulate health and safety requirements, license providers, administer the child care subsidy program (CCDF), and, in some cases, sponsor and direct their own preschool programs.

A third conceptualization of ECEC and family policy is through the “social investment” lens. The social investment policy paradigm emerged from changes to the welfare state in the late 1990s, when welfare states faced budget deficits, rising poverty, and high structural unemployment and pivoted to “activating” social policies rather than passive social protection—including expansion of ECEC as part of the public education sector (Cantillon, 2011). The theoretical framework of ‘activation’ and social investment might suit the American case better—especially considering the recent expansion of

state-sponsored preschool programs. Even so, the focus of this framework is on provision of services, which leaves out the majority of U.S. state involvement in the ECEC system.

McLean characterizes U.S. ECEC policy as oriented toward ‘cost-easing’ rather than building a coherent system of child care provision, but more than this, it is oriented around alleviating poverty through encouraging parental employment. This focus on activating low-income and single mothers rather than children’s future human capital, has roots in the welfare reforms of the 1990s, and specifically the 1996 Personal Responsibility and Work Opportunity Reconciliation Act (PRWORA). Orloff explains that the politics of this act, which ended the Aid to Families with Dependent Children program and replaced it with two employment-oriented anti-poverty programs (Temporary Assistance for Needy Families and Earned Income Tax Credit), permanently shifted the discourse around child care policy in the United States by eliminating any support for caregiving that was not linked to participation in the labor market. In other words, the social institution that was reified after these family policy reforms was the labor market, rather than the family (Orloff, 2002).

McLean’s framework of state intervention in ECEC policy allows me to explore the dynamics of the child care market and how state intervention, whether through regulation or funding, shapes and affects the child care crisis trilemma of cost, quality, and quantity (Blau, 2001). It also allows me to see whether the market and the U.S.’s ECEC policy approach align with and influence any of the many possible goals of ECEC policy: be they labor market activation, ending poverty, promotion of gender equality, or support of child development. The impact of these policies—funding, regulation, and provision—on supply are described below.

2.2 Simple Economic Models and Child Care Utilization: Are child care supply and demand actually linked?

Where funding enters—on the supply or demand side of the market—is an especially important dimension of ECEC policy in the absence of state provision. As McLean explains, supply-side funding that goes directly to providers allows the state to influence the type of provision available (quality incentives, promotion of community-based organization or for-profit provision, etc.). Demand-side funding, targeted at purchasers of care, by contrast, “relies more heavily on market mechanisms by giving consumers more control over the type of provision they purchase.” (McLean, 2014: 125).

As my research question is fundamentally about the relationship between supply and demand-side funding in the child care market, I begin by accepting the existing economic modelling of the ECEC market that is the basis of the funding component of American ECEC policy. I will use strategically simplified economic models from the traditional ECEC economic literature to illustrate how and why supply and demand are (assumed to be) connected.

The most basic economic model of the child care market assumes a uniform level of quality in a market wherein child care providers, nonprofit or for-profit, are firms that sell a service—care for young children—for a profit (in the case of nonprofit providers, these profits are reinvested in the business) (Blau, 2001). Demand constitutes the willingness of parents to pay for care at different price levels, given variation in their income and preferences for geographic location of care, hours during which the care is provided, etc. Supply constitutes the willingness of providers to offer care at different price levels, given values of teacher wages and other operating costs (Blau, 2001). This market reaches equilibrium when the “price of child care is such that all consumers who wish to purchase care at the market price are able to do so, and all providers that wish to

offer child care at the market price are able to find customers” (Blau, 2001, pg 60). Parents unable to find child care at the price they are willing to pay will exit the market and opt for informal care, whether parental or relative. Demand-side policies such as tax credits and subsidies, therefore, increase parents’ willingness/ability to pay (an upward shift of the demand curve) and, theoretically, given that child care supply is shown to be elastic, this allows more supply to be filled at higher prices (Blau, 2001).

A slightly more complex economic model allows for variation in quality, and therefore in price based on quality in this supply-demand relationship. In this market, we can expect both quality- and profit-maximizing providers to expand supply to meet their respective demand in the long run, as even in their pursuit of profit or quality, they face the budget constraint of needing to break even to stay in business (Blau, 2001).

From these models, we can derive two key drivers of the level of child care supply in a locality: income and women’s labor force participation. First, in a different economic model testing the income elasticity of demand, Blau found that as family income increases, families tend to increase their use of paid child care as well as switch to center care from other types of formal and informal care—this can be seen as shifts of the demand curve, with consequences for the quantity of care demanded (2001; Queralt and Witte, 1998). Relatedly, there is substantial evidence that lower-income families are more likely to use informal care than higher-income families: 62% of families at or above the federal poverty line (FPL) use formal child care, compared with 50% of families below the FPL (Tekin, 2021). Similarly, 44% parents below the FPL use informal care, compared with 37% of parents above the FPL (Tekin, 2021). Furthermore, Hotz and Wistwall found that the highest-income households (earning over \$75,000 per year) use twice as much nonparental care for the youngest children as the lowest income households (2019). One key challenge in modeling child care demand is the difference between potential and

actual demand (or utilization) for services. For example, a low-income community with many single working parents may have high potential demand for formal child care, but little financial capacity to acquire it (Queralt and Witte, 1998). This suggests that the equilibrium at which the child care market currently clears is not where it would clear for low-income families: We can anticipate seeing a higher quantity of care demanded if child care were offered at a lower price or if families had a greater ability to pay.

Second, research has shown that increased women's labor force participation drives demand for formal child care, with consequences for the level of supply. As Herbst and Barnow show in their study using census tract level data within Maryland, this relationship goes in both directions: Not only is increased child care supply associated with increased women's employment rates, but a 1% increase in a neighborhood's female labor force participation rate is associated with approximately three additional child care slots (2007). Queralt and Witte show in their study using neighborhood level data that the employment levels of a community were strongly correlated with the level of child care supply (1998). They especially found this to be true of family child care homes, which were most responsive to changes in local employment levels. Furthermore, Kahn and Kamerman showed that for-profit providers evaluate the level of labor force participation—i.e. the potential demand—in choosing where to open a center (1987). These results make sense: Maternal employment both increases demand for formal care (as mothers become unavailable to provide informal care, this constitutes a shift of the demand curve) as well as provide their family with additional income to purchase said care (another shift of the child care demand curve).

2.3 Problems with the Simple Economic Models: Empirical Nuances to the Current Child Care Market

In the last few years, the U.S. has begun to reckon with the success and failures of markets in and private provision of child care. Families across the U.S. paid an average of \$12,304 per year for infant center-care and \$10,001 for center-care for a 4-year-old child (Child Care Aware, 2020). Affordability remains a major concern for families: In general, working parents with children under the age of six spend about 10% of their income on center-based care (Child Care Aware, 2020). This portion of the family budget grows more drastic for low-income parents, who spend approximately 28% of their incomes on center-based care (Tekin, 2021). Despite these high expenses, however, the care most families purchase is not considered “quality”—or the kind that guarantees robust short- and long-term child development outcomes. According to the 2014 National Survey of Early Care and Education, only 60% of families using center-based care and 63% of families using family child care homes rated their child care arrangements as “excellent” or “nurturing” environments (Morrissey, 2017).

As a result of this imbalance between price and quality, in September of 2021, the U.S. Treasury called child care markets “unworkable” (Treasury, 2021). Why? The academic literature identifies three kinds of market failures which frustrate the success of the private child care market: insufficient supply of quality care, imperfect information, and child care workforce instability (low wages and high turnover). In the first failure, parents underinvest in quality care, which is shown to have many positive externalities on the rest of society. Financial constraints prevent parents from making these investments: Parents are expected to pay the high costs of child care when they are least financially capable of it—i.e., when they have the fewest assets, disposable income, or savings (as opposed to paying for higher education). In the second failure, parents make child care decisions with imperfect information about the benefits of quality care

to themselves and to the broader economy and do not prioritize quality when searching for care: When interviewing providers, parents tend to ask about convenience and cost before quality-related attributes such as licensing or turnover rates (Tekin, 2021).

The third failure, workforce instability, speaks to the challenges of the child care business model. Child care providers charge artificially low tuition that does not cover the true cost of quality care to keep care affordable for families; however, even with lowered prices and quality, tuition is still too high for most families to afford (CCAoA, 2020). This means that child care remains unaffordable for parents while child care workers themselves are poorly paid. Low pay makes recruiting and retaining the child care workforce especially difficult. Furthermore, workforce instability has important consequences for the level of child care supply in a locality. Labor costs make up the majority of expenses in a child care business—some estimate as much as 70% (Blau, 2001). Providers report that challenges recruiting workers have impeded their abilities to expand slots or remain open (Goldstein, 2022). Therefore, the supply of child care is in part dependent on whether child care businesses can find sufficient labor to operate classes and meet health and safety regulations.

It is worth noting that not everyone agrees that the present child care “problem” in the U.S. is best described as a market failure. In his core text on the economic models of child care, cited above, Blau argues that the child care supply gap does not indicate any market failure, but rather the correct allotment of parent preferences for quality (2001). Accordingly, the child care gap is a demand, rather than supply-side issue. What his modelling does not consider, however, is that child care market price is artificially low compared with the cost of delivering care.

Market failure or disequilibrium, ECEC faces a trilemma of cost, quality, and quantity. Up until now, most ECEC policy and research has focused on affordability and

quality, and used demand-side funding, as well as some supply-side work around quality regulation to realize these goals. However, all three of these issues are intimately interrelated and policy decisions aiming to fix one of these three prongs can have adverse consequences on the other two issues if the links between them are not fully considered.

2.4 ECEC Policy in the US and its impacts on supply

As is established above, there is no unified policy approach to ECEC in the U.S.: This is exaggerated by its federalism. These generous, ungenerous, streamlined, or decentralized systems all impact the supply of child care and the accessibility of care for families. This section applies McLean's framework to look at how different types of U.S. policies impact the level of child care supply.

Provision

Head Start is a free early intervention program that is federally funded and locally managed. It serves families below the FPL and in certain priority categories (such as homelessness, involvement with the foster care system, etc.). Head Start is the only instance of federally provided child care services, and thus makes up an essential piece of the supply puzzle. Due to underfunding, Head Start currently serves only 36% of all eligible families (First Five Years Fund, 2022).

In the last 20 years, there has been an extensive expansion of state-funded preschool programs for four-year-olds in the U.S. Forty-seven states now direct some funding toward preschool programs. Funding for preschool more than tripled between the years of 2002 and 2017 (Reid et. al, 2019). Beyond expanding publicly provided child care slots, expansions in state-sponsored pre-K programs have affected the supply of the private child care market. In her study of Florida's Universal Pre-Kindergarten (UPK) program for four-year-olds, Bassok found that UPK led to a 13% increase in capacity in

center-based care for four-year-olds (2016). Importantly, she also found a 6.4% drop in the percentage of three-year-olds enrolled in center-based care.

Regulation

The child care business is a difficult one to make profitable in part because regulatory constraints for health, safety, and quality make traditional “cost-cutting” strategies impossible to use. For example, labor costs make up the bulk of child care businesses’ costs because staff-to-child ratios are set by the state and cannot be changed. Providers also cannot simply accept more children—their license from the state establishes their maximum capacity per classroom. States set and monitor health and safety regulations and have begun to incentivize and promote quality improvement through the regulatory system. However, as part of the “moderator approach” they tend to regulate quality-related “inputs”—such as child-to-staff ratios or number of teachers with college degrees—rather than monitoring quality outcomes. Quality-related regulations, in particular, can produce negative externalities, including decreases in supply (Hotz and Xiao, 2011). Hotz and Xiao found that an increase in stringency of regulations on child care centers reduced the availability of child care centers—both in number of centers and in their capacity—especially in lower income areas because the regulations restrict the number of children that can be served by child care centers (2011). As a result, revenues in family child care homes increased because looser regulations enabled them to accept the children being crowded out of center-based care.

Funding

The predominant ECEC program in the United States is the Child Care Development Fund (CCDF), which administers child care subsidies. Families are eligible if they are working and earn less than 85% of their state’s median income. While the bulk of funding for ECEC comes from the federal government (\$11 billion of \$13 billion

appropriated for CCDF was provided by Congress in 2020), the administration of this funding occurs on the state level (Office of Child Care, 2022).

However, like Head Start, CCDF is underfunded. Only 14% of eligible children are currently served by the program (Rubinfeld, 2022; Adams, Luetmer, and Todd, 2022). As a result, the evidence on the actual impact of the subsidy program on the market is mixed: While some states report that the majority of their providers accept at least one child who receives the subsidy, Adams, Luetmer, and Todd found that “despite the central role that child care subsidy funds play in helping families afford child care, the funding that providers receive through the subsidy system is a fraction of the overall financing for providers in the child care market, which is dominated by parent payments and strongly affected by market forces” (2022: vi). Indeed, Greenberg et al. found that only a third of center-based providers and only a fifth of home-based providers received any revenue from the subsidy system (2018).

The second key problem in the policy design of the CCDF program is that subsidy rates are currently set based on the state’s calculation of the market rate—49 states set their reimbursement rates at 75% of the market price. However, due to the challenges with the child care business model described above, providers rarely charge families the true cost of delivering care, so these market-based reimbursement rates also undercompensate providers for the service they deliver (Aigner-Treworgy et al, 2022; Adams, Luetmer, and Todd, 2022). Though many have advocated raising these reimbursement rates to attempt to expand child care supply, raising rates alone cannot create new slots. This is especially true for “target” types of care which are more costly to provide and therefore have the most dramatic supply gaps. These include care for infant and toddlers, for children with special needs, and during nontraditional hours

(Adams, Luetmer, and Todd, 2022). The structure of the subsidy matters as well as reimbursement amount: as it is based on a child's attendance, it ends up being an extremely unstable source of income for providers and can dissuade providers from accepting children and families on subsidy (Adams, Luetmer, and Todd, 2022). This in turn decreases the impact of public funds in the market.

In other words, how the state intervenes in the private child care market, whether through direct provision of services or through subsidizing care, can directly impact the supply and availability of care.

2.5 Child and Dependent Care Tax Credits

As parents are the proxy consumers of ECEC services (where children themselves are the actual consumers), tax credits, like the CCDF subsidy vouchers, are a policy mechanism for supporting parental choice in the child care market (Lloyd, 2012). The federal CDCTC, first introduced in 1954, is a nonrefundable tax credit, credited to parents for care expenses related to working or looking for work. It was the largest U.S. child care program in the 1970s and 1980s and remains the third largest child care program today (after Head Start and CCDF) (Forry and Anderson, 2006). On top of the federal program, 30 states have instituted their own child care related tax credits, which families can claim on the state income taxes they owe (NWLC, 2022).

A tax credit directly reduces the taxes a family owes. The federal CDCTC reimburses families for 20% to 35% of their child care expenses, depending on the family's Adjusted Gross Income (AGI). The maximum expenses that can be claimed for the federal CDCTC is \$3,000 for one child/dependent and \$6,000 for two or more children/dependents (IRS). For example, the maximum credit a family with one child

earning \$15,000 could receive is \$1,050 ($\$3,000 * 0.35 = \$1,050$). If that same family had two or more children, the maximum credit they could receive is \$2,100 (IRS, 2022).

In tax year 2016, 6.2 million families claimed the federal CDCTC for \$3.4 billion dollars (Hotz and Wiswall, 2019). Studies of CDCTCs are limited, and the federal CDCTC's effects on the child care market have only been documented through the lens of its impacts on demand. Like other American ECEC policies, CDCTCs aim to incentivize parents to enter the labor force—the amount of credit claimed cannot exceed the income of the second spouse—and enable them to pay for care rather than have one parent stay at home. Using individual-level data from the 1985 Survey of Income and Program Participation, Ribar found that the federal CDCTC had a modest positive effect on married women's labor supply and a stronger positive effect on their paid care utilization (1995). This effect on paid care utilization was especially prevalent among part-time married women workers. In other words, the CDCTC instigates a positive shift of the demand curve by increasing both women's employment and income and enabling them to switch from informal to formal care (if only part-time)—filling some of the latent demand resulting from an inability to pay.

No study has looked at the impacts of state CDCTCs, which vary tremendously in generosity, design, and goals, on the child care market. This means that we know little about their effects on the child care market, on parental behavior, or child care utilization. To begin to understand these effects, I propose three hypotheses.

Hypothesis 1: Increased generosity in the state CDCTCs will have a positive relationship to the level of child care supply.

Ribar's study and Blau's economic modelling suggest that state CDCTCs, by further increasing families' purchasing power for formal care, stand to impact the level of child care supply. As shown in section 2.2, tax credits shift the demand curve, increasing families' willingness/ability to pay, and allowing supply to be filled in.

Hypothesis 2: Among states that have a state CDCTC, a refundable tax credit will have a larger effect on supply than a nonrefundable credit.

Importantly, the federal CDCTC is nonrefundable, a deviation from the anti-poverty goals of other American ECEC policies. This means that only moderate- and high-income families can obtain the full federal CDCTC because they are the only ones with a tax liability equal to or greater than the value of the credit (Forry and Anderson, 2008).³ In other words, the federal CDCTC fails to bring families who are excluded from the formal child care market due to low-income into it.

With a refundable credit, by contrast, if a family's tax credit exceeds their tax liability, they receive the difference as a refund check (making the credit function like a cash transfer to those families). In other words, a refundable tax credit constitutes a larger shift of the demand curve because it helps low-income families access the formal child care market.

Ribar's study also modeled the potential effects of a policy proposal to expand the federal CDCTC by raising the level of eligible expenses, making the benefit refundable, and introducing a sliding scale in which 80% of the expenses for those on the lowest end of the income scale are reimbursed. This proposal had substantial effects on married women's part-time paid care use, small effects on their full-time employment, and moderate effects on part-time employment –in other words, working families who had previously relied on informal care could now begin to purchase

³ The design of the federal CDCTC has other regressive components, such as its payout scheduling: child care expenses are ongoing and monthly, but the CDCTC is paid out only once a year (tax time) as a reimbursement (Cohen, 1996).

formal care (if only part-time) (1995). This illustrates that generosity in the tax credit shapes formal child care utilization which, in turn, is tied to the level of supply.

While some state CDCTCs merely replicate the federal CDCTC—where the state credit value is a percentage (i.e., 50%) of a family’s federal credit value—others experiment with compensating for the regressive components of the federal CDCTC. Some restrict eligibility to only low-income families, others expand the limit for claiming expenses, and 15 states have instituted a refundable credit. As a result, my second hypothesis explores the impact of refundable CDCTCs on supply.

Hypothesis 3: The relationship between state CDCTCs and supply is nonlinear.

Lastly, given the relatively small values of the state credits (mean CDCTC value in my dataset is \$246) compared with the high average cost of child care (approximately \$12,000/ year for infant/toddler care), it is possible that state CDCTCs are associated with different effect sizes on child care supply at different generosity values. It is worth noting that there might even be diminishing marginal returns associated with some threshold level of the CDCTC.

3. Data and Method

3.1 Dataset for the dependent variable – County level slot data

My dependent variable is the proportion of the number of child care slots per 100 children in a county. Given that parents generally seek child care close to their home or place of employment, it is reasonable to assume that child care markets are relatively small and dependent in part on features of local economies (Herbst and Barnow, 2007). Therefore, I make counties my unit of observation.

This project uses a unique dataset of facility-level data on child care capacity in terms of number of slots for children 0-5 in each county of 36 states⁴ for the years 2019-2022. I have received this data courtesy of Linda Smith, Executive Director of the Bipartisan Policy Center’s Early Childhood Initiative. This data was collected directly from and in collaboration with each state’s respective CCDF administrator and offices in charge of licensing and early learning, as part of the Child Care Supply Gap report, an ongoing project mapping the extent of the child care supply gap across the United States. Thirty-five states’ gaps have been mapped and published thus far, with plans to finish 47 states by the end of next year (2024). State administrators have opted in to this study and submitted their data to Bagley—who has standardized definitions of providers and mapped the supply gap down to the geographical unit of congressional districts. As this dataset was built directly in collaboration with state CCDF Administrators and licensing offices, it is the most comprehensive data on the number of slots—including public preschools, Head Starts, for-profit and nonprofit private providers, community-based organizations, and Department of Defense providers—to date.

⁴ 36 states in this study: Alabama, Arizona, California, Colorado, Connecticut, District of Columbia, Florida, Idaho, Illinois, Indiana, Iowa, Kansas, Kentucky, Maine, Maryland, Massachusetts, Michigan, Montana, Nebraska, New Hampshire, New Mexico, New York, North Carolina, North Dakota, Ohio, Pennsylvania, South Carolina, Texas, Utah, Vermont, Virginia, Washington, West Virginia, Wisconsin, Wyoming.

3.2 Dataset for the main explanatory variable – state CDCTC value

Combing through individual state tax codes and forms, I have constructed an original dataset of the maximum values of child and dependent care state tax credits available to families, per child. I include a total of 36 states in my analysis, 19 of which have a tax expenditure policy for child care expenses. Ten states in my model have a refundable tax credit.

The first challenge I faced in constructing this dataset was the variation in data vintage in the supply data which spanned the time immediately preceding, as well as the duration of, the Covid-19 pandemic. The pandemic was a period of immense social, economic, societal, and policy change, including in the ECEC context. Fortunately, the state CDCTCs were not policies that dramatically changed during Covid, and I matched each state CDCTC policy in my dataset with the supply data vintage. Some state benefits are tied to the federal tax credit policy, which did expand during Covid. However, without exception, my supply data is collected from before the federal CDCTC expansion went into effect (April 2022).

The second challenge came in working with the nuances in the tax credit policies between states. Many states institute a sliding scale for the benefit depending on a family's income and their actual care expenses. This means that there is great variation in the actual amount of credit a family can receive. For the sake of this study, which is attempting to establish whether there is any relationship in the first place between the credit and the level of child care supply, I decided to use the maximum credit value that a family could claim rather than an estimate of the median credit actually claimed by families. Given the fact that the maximum credit values are already only a fraction of what families pay for child care, I anticipate seeing the most effect of the credit on

families' purchasing power for care when the credit value is the maximum possible. For example, the state of Maine offers a tax credit which is 25% of the federal CDCTC value. However, if a family uses a quality designated provider, their CDCTC from their Maine income tax doubles in value and is refundable up to \$500. As the quality version of the policy is more generous, I include that version (a maximum CDCTC value of \$525, rather than \$212).

Four states (Idaho, Virginia, Massachusetts, and Montana) have tax deductions rather than tax credits. This means that the policy reduces the income that can be taxed rather than a family's tax liability. It is generally a less generous tax saving policy. I accounted for this by calculating the maximum tax savings value a family receives via the deduction (calculations in the appendix).

3.3 Additional explanatory variables

For the reasons described in the literature review above, I include women's labor force participation rate for women with children under the age of six, median income, and percent of the population below poverty level, as additional explanatory variables in my model, using data from the U.S. Census and Bureau of Economic Analysis (2020, 2021). I also include a couple control variables that fill in our understanding of child care utilization. First, additional research shows that there are disparities in child care utilization among different racial and ethnic groups. For example, Black children are the most likely to be in formal care and Hispanic children are the most likely to be in relative care (Urban Institute, 2006; Blau, 2001). Furthermore, the majority of child care workers in the U.S. are women of color (Mefferd and Dow, 2023). In other words, the racial and ethnic makeup of a community may influence both the level of demand in a county and the inputs into the level of supply.

Second, there is strong evidence in the U.S. and in European welfare states that as women's labor force participation has increased, grandparents have assumed significant child caring responsibilities; in 2001, Fuller-Thomson found that 7% of all grandparents in the US were providing at least 30 hours of child care per week to their grandchildren (extensive caregiving). Compton and Pollak found that the probability of employment and labor force participation was significantly higher for married women with young children living near their mothers or their mothers-in-law compared with those living further away (2013). According to a survey by the Bipartisan Policy Center, 80% of informal care is provided by grandparents (2021). At the same time, the number of three-generation households has risen, with one in four American children living in this type of household. Grandparental child care is more frequent as a result: According to the Pew Research Center, 14% of adults in multigenerational households say they provide care to children under the age of 18 who are not their own (Amorim et al, 2017). While grandparent care for young children is sometimes a family preference, it also may be a matter of necessity in response to the supply gap. Consequently, I include the number of multigenerational households per county as a proxy for availability of informal care.

I also include GDP per capita as another indicator of wealth in a county. Finally, as a proxy for quality regulations, I include the child to staff ratio for infants and preschoolers per state (HHS, 2011).

Unfortunately, I could not access child care workforce data for every county in my study. Consequently, I do not include this variable in my main model. Modeling with the available child care worker data is included in Appendix 2.2.

3.4 Method

To answer my research question, I need to use a method that will retain the hierarchical group structure of my data: counties nested in states with particular CDCTC

policies. This is important because I am estimating the relationship between two variables that are at two different “levels”, or units, of analysis. Multilevel modeling is a method that retains the nested structure of the data by allowing for residual components at each level of the hierarchy, thus enabling researchers to quantify individual level variability between groups versus within groups. (Rasbash, 2022). This multilevel model consists of two simultaneous components: a linear regression with 2,211 observations predicting the continuous outcome of slots per 100 children given county-level predictors and an intercept that can vary by county, and a linear regression with a 36 data points predicting the (variance of) state intercepts with state-level predictors (Gelman and Hill, 2007).

Multilevel models are desirable in this instance compared with traditional single level regression analyses because they produce more accurate estimates of standard errors, especially for higher level predictor variable coefficients such as the CDCTC, and by extension, more precise statements of statistical significance (Rasbash, 2022).

Hypothesis 1: Increased generosity of the state CDCTC will have a positive relationship to the level of child care supply.

I use a random intercept model to test this hypothesis. This model fixes the relationship between the state CDCTC and slots per 100 children, but accounts for the fact that counties have varying levels of supply.

This model can be represented by the equation:

$$y_{ij} = \beta_0 + \beta_1 X_{1ij} + \dots + \beta_n X_{nij} + u_j + e_{ij}$$

where:

- y_{ij} is the child care supply in county i in state tax policy j , per 100 children
- $u_j \sim N(0, \sigma^2 u) =$ level 2 variance, or the state CDCTC effects (level 2 residuals)⁵

⁵ Assumed to follow a normal distribution with mean zero and variance σ^2

- $e_{ij} \sim N(0, \sigma^2 e)$ = level 1 variance, or the county coefficient effects
- β_0 = intercept of mean slots per 100 children (intercept of overall regression line)
- $\beta_0 + u_j$ = intercept of group j
- β_1 is the coefficient of the main independent variable and B_n represents each of the control variables listed in the section above
- X_{1ij} = variable 1 from county i in state j

In this random intercept model, the fixed part of the equation (the relationship between state CDCTC value and slots per 100 children) is of substantive interest, and the random parameters (the variances) of the equation are a “nuisance.” This means that we can use hypothesis testing as in a single level model to determine the significance of the coefficients this model obtains.

Hypothesis 2: Among states that have a CDCTC, a refundable tax credit will have a larger effect on supply rather than a nonrefundable credit.

To test this hypothesis, I limit my study to just the states with CDCTCs and use the same random intercept model as above but remove the CDCTC variable. Instead, I code refundability as a binary variable and use that as my main explanatory variable.

Hypothesis 3: The relationship between state CDCTCs and supply is nonlinear.

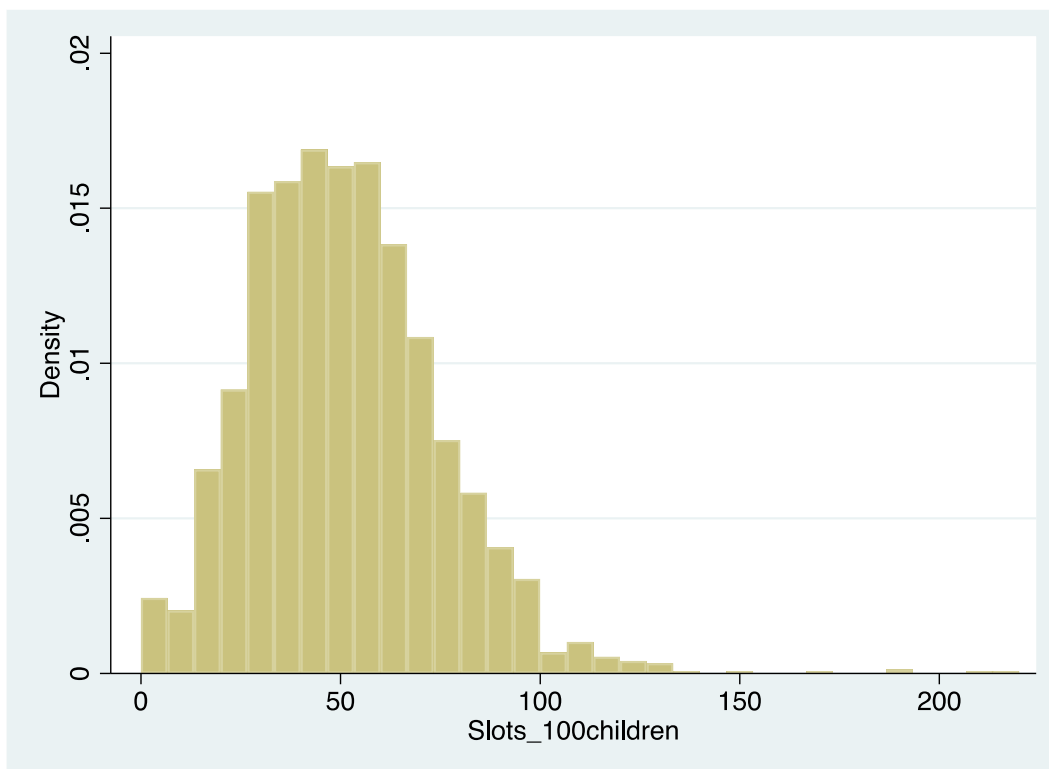
To test this hypothesis, I include a quadratic term (x_{ij}^2) into the random intercept model I used to test hypothesis 1.

4. Descriptive Statistics

4.1. The Outcome Variable: Slots per 100 children per county

My outcome variable is the number of slots per 100 children in a county. I have included 2,211 counties from 36 states in this study. The maximum number of slots per 100 children in a county is 220 slots, where the minimum is zero. The mean value is 51 slots per 100 children, and the median supply per county is 49 slots per 100 children under five.

Figure 1: Histogram of slots per 100 children



4.2 The Explanatory Variable: State CDCTC generosity

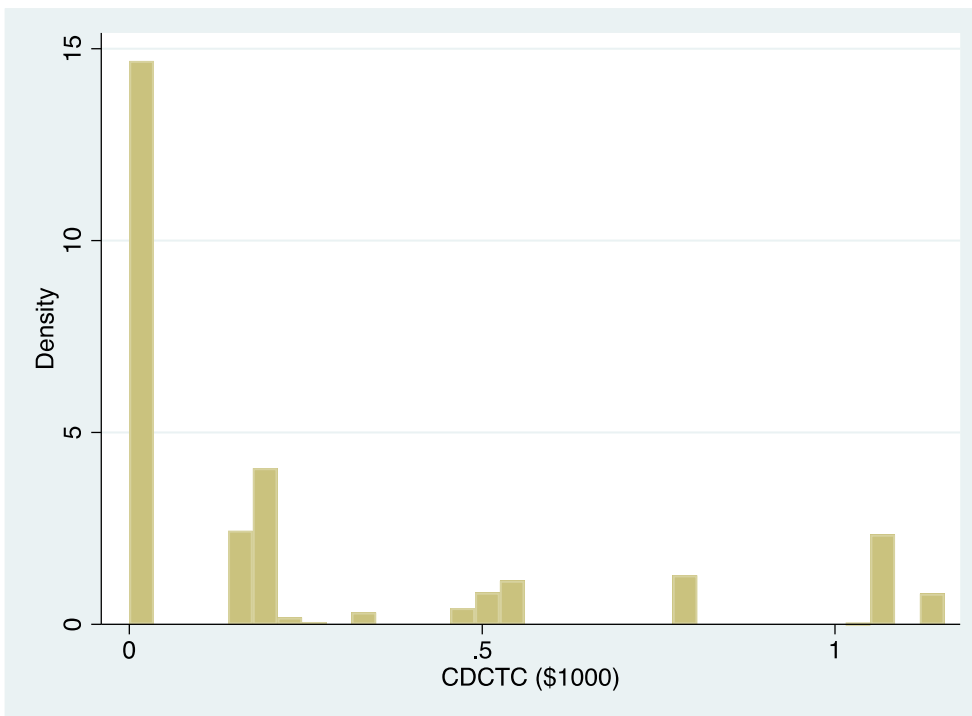
My key explanatory variable is the state CDCTC value (in \$1,000s). The minimum credit value is \$0, which applies to 1,136, or about half, of the counties in my study. The maximum credit value is \$1,155. The mean state CDCTC value is \$246. 181

counties have a tax credit value of \$1,050 per child, or the same credit value as the federal CDCTC.

Table 1: Frequency of state CDCTC values

CDCTC	Frequency (Counties)
\$ 0.00	1,136
\$ 166.00	56
\$ 173.00	133
\$ 196.00	105
\$ 210.00	210
\$ 242.00	14
\$ 263.00	5
\$ 336.00	24
\$ 480.00	33
\$ 500.00	64
\$ 525.00	88
\$ 788.00	99
\$ 1,035.00	1
\$ 1,050.00	181
\$ 1,155.00	62
Total	2,211

Figure 2: Histogram of state CDCTC values



5. Results

Before testing any of my hypotheses, I constructed an empty model to determine whether maintaining the group structure of the data is important. An empty model is one without any explanatory variables in it, in which one determines the Intra Class Correlation (ICC)—a proportion of variance between states. This tells us whether observations in the same state are closely correlated with each other. My ICC of 0.34 is a very strong indication that a multilevel model is important to use in this study. Lastly, there were five counties missing values for women’s labor force participation, so this decreased my total number of counties in the multivariate model to 2,206.

5.1. Hypothesis 1: Increased generosity of the state CDCTC will have a positive relationship to the level of child care supply.

Controlling for GDP/capita, women with children under six’s labor force participation rate, median income, racial demographics, poverty level, number of multigenerational households, and quality regulations per county, Table 2 shows that a \$1000 increase in state CDCTC generosity is associated with an increase of approximately four slots per 100 children. This result is not statistically significant, however, with a p-value of 0.49, and a confidence interval of (-8.6, 17.9)—meaning that we fail to reject the null hypothesis of “no effect” of CDCTC on child care supply. In other words, from this model, we cannot deduce a relationship between state tax credit generosity and the level of child care supply in a county. The variance of the constant is 156.9267, which speaks to the high degree of variation between states.

Table 2: Regression Results for Hypothesis 1

Variable	Coefficient	Std. Error	
CDCTC (\$1000)	4.6495	(6.7488)	
Women with children under age six, Labor Force Participation Rate (1%)	0.275155	(.033281)	***
GDP per capita	0.00003	(0.00002)	*
Before or During Covid	-0.3457	(4.6906)	
Median Income (\$10,000)	1.596	(0.348)	***
Population below poverty level (1%)	0.0835	(0.0985)	
Number of multigenerational households	-0.00003	(0.00005)	
Ratio of Child:Staff, Preschool	0.1448	(0.8635)	
Ratio of Child:Staff, Infants	-4.1918	(3.4411)	
Hispanic (1%)	-0.0670	(0.0393)	*
White (1%)	0.2141	(0.4337)	
Black (1%)	0.5120	(0.4288)	
American Indian/Alaska Native (1%)	0.4260	(0.4225)	
Asian (1%)	0.9164	(0.4031)	**
Constant	11.7765	(47.0681)	
Variance of the Intercept	156.9267	(39.9234)	

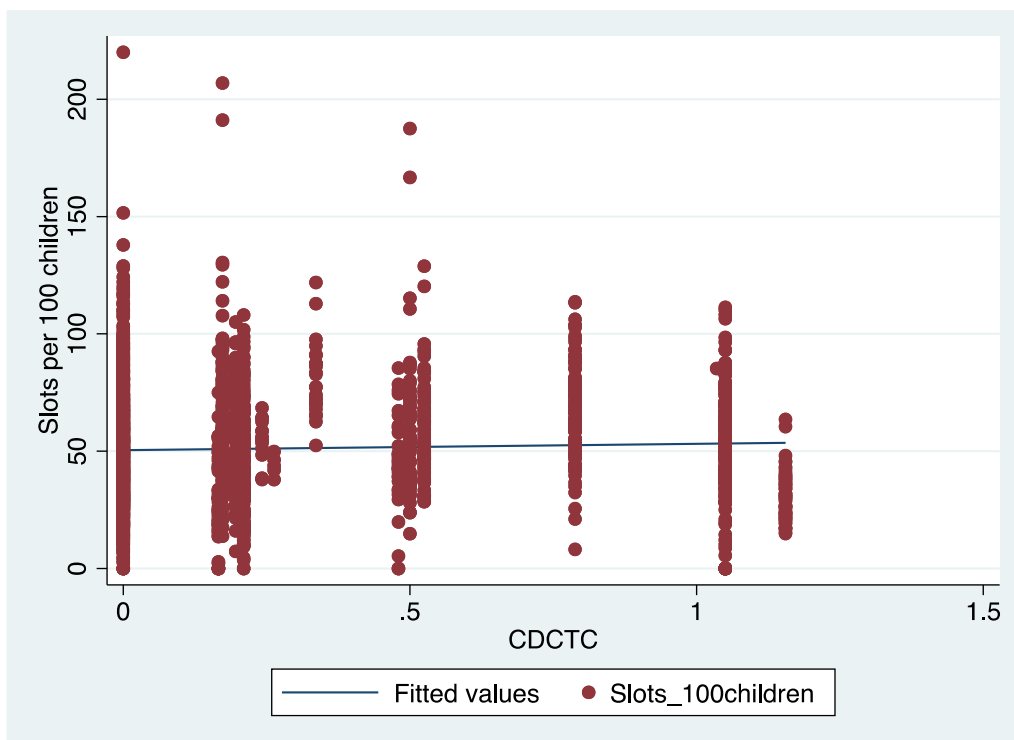
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

A couple of the control coefficients in Table 2 are worth commenting on as they confirm the findings of some of the literature describe above. The coefficient for women with children’s labor force participation rate (WLFP) is lower than expected (a one percent increase in WLFP is associated with an increase of 0.27 slots per 100 children) and statistically significant at the 99% confidence level. This confirms Herbst and Barnow’s findings that WLFP is a determinant of the level of supply in a locality, but not to the degree they found; this might speak to the complicated nature of child care decision-making (2007). Median income of the county also has a coefficient (1.6) that is statistically significant at the 99% level, confirming previous findings that higher income areas have more child care slots (Queralt and Witte, 1998).

Although neither are statistically significant, the infant child-to-staff ratio coefficient (-4.2) is negative and has a much larger effect size than the pre-school child-to-staff ratio coefficient (0.14)—these effect sizes support Hotz and Xiao’s findings that stricter quality regulations depress the levels of child care supply (2011). Furthermore, counties with a higher percentage Hispanic population see a decline in child care supply (negative coefficient), compared with other ethnic and racial groups, though these effect sizes are unremarkable (NCES, 2019; Blau, 2001). Notably, counties with a higher percentage Asian population saw statistically significant, positive (if small) results. This group’s child care utilization is under-discussed in the literature.

Figure 3 also illustrates the lack of relationship between the tax credit and the supply of child care. Were there a compelling relationship between state CDCTC and the supply of child care, we would expect the data points to gather tightly around the trend line. Instead, at a state CDCTC of zero, we see both the minimum and maximum values for slots per 100 children.

Figure 3: Scatterplot of state CDCTC and Slots per 100 children



5.2. Hypothesis 2: Among states that have a tax credit, those with a refundable tax credit will have a larger effect on supply rather than those with a nonrefundable credit.

Due to collinearity, I was not able to include a variable regarding the refundability of a credit in my main model. With a Pearson Product Correlation Coefficient of 0.7, we can say that these two variables are highly correlated and violate the Gauss-Markov assumption of independence. Instead, I ran a separate model among only the 19 states with a CDCTC to explore the potential relationship between refundability of the tax credit policy and the level of supply. In this model, I included whether the state CDCTC policies were refundable or not as a binary variable.

Table 3: Regression Results for Hypothesis 2

Variable	Coefficient	Std. Error	
Refundable (Yes/No)	8.8660	(5.2324)	*
Women with children under age six, Labor Force Participation Rate (1%)	0.253274	(0.049232)	***
GDP per capita	0.0002	(0.0000)	***
Before or During Covid	-11.3710	(6.5585)	*
Median Income (\$10,000)	1.94	(0.525)	**
Population below poverty level (1%)	-0.2574	(0.1479)	
Number of multigenerational households	-0.0001	(0.0001)	
Ratio of Child:Staff, Preschool	1.4491	(1.2991)	
Ratio of Child:Staff, Infants	-2.7405	(3.2945)	
Hispanic (1%)	-0.1859	(0.0722)	**
White (1%)	1.2544	(0.9260)	
Black (1%)	1.6306	(0.9091)	*
American Indian/Alaska Native (1%)	1.5940	(0.9045)	*
Asian (1%)	1.6454	(0.8610)	**
Constant	-98.6312	(96.6911)	
Variance of the Intercept	91.8502	(35.0960)	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Again, I found the relationship between state CDCTC and slots per 100 children to be statistically insignificant with a p-value of 0.09 and a confidence interval of (-1.4, 19.1). The statistical insignificance in this model is unsurprising as I had to reduce my number of observations by almost half, thus significantly reducing the statistical power of the model. However, the practical significance of the coefficient is especially noteworthy: Refundability was associated with an increase of almost 9 slots per 100 children compared with states where the tax credit was nonrefundable. Refundable tax credits are significantly more generous policies as they make the benefit, and formal child care, accessible to low-income families. This larger effect size confirms my hypothesis and suggests that refundability change the effects of the CDCTC on the child care market.

5.3. Hypothesis 3: The State CDCTCs will have different effects on supply at different values, resulting in a nonlinear relationship.

The statistical significance of the coefficients in Table 4 suggests that, in fact, the relationship between state CDCTC values and child care supply is nonlinear. To interpret this, I have calculated the predicted values at different CDCTC amounts, reported in Table 5. Figure 4 shows the line fitted to these predicted values, accounting for the curved nature of the relationship between CDCTC and slots.

Table 4: Regression Results for Hypothesis 3

Variable	Coefficient	Std. Error	
CDCTC (\$1000)	50.1348	(20.0165)	**
Quadratic CDCTC	-45.4085	(18.9870)	**
Women with children under age six, Labor Force Participation Rate (%)	.275176	(0.033273)	***
GDP per capita	0.00003	(0.00002)	*
Before or During Covid	-2.5445	(4.4569)	
Median Income (\$10,000)	1.605	(0.348)	***
Population below poverty level (1%)	0.0824	(0.0985)	
Number of multigenerational households	-0.00003	(0.0001)	
Ratio of Child:Staff, Preschool	0.5466	(0.8137)	
Ratio of Child:Staff, Infants	-5.4518	(3.2262)	*
Hispanic (1%)	-0.0688	(0.0392)	
White (1%)	0.2023	(0.4336)	
Black (1%)	0.4992	(0.4287)	
American Indian/Alaska Native (1%)	0.4147	(0.4224)	
Asian (1%)	0.8957	(0.4030)	**
Constant	11.5475	(46.7006)	
Variance of the Intercept	132.305	(34.3830)	

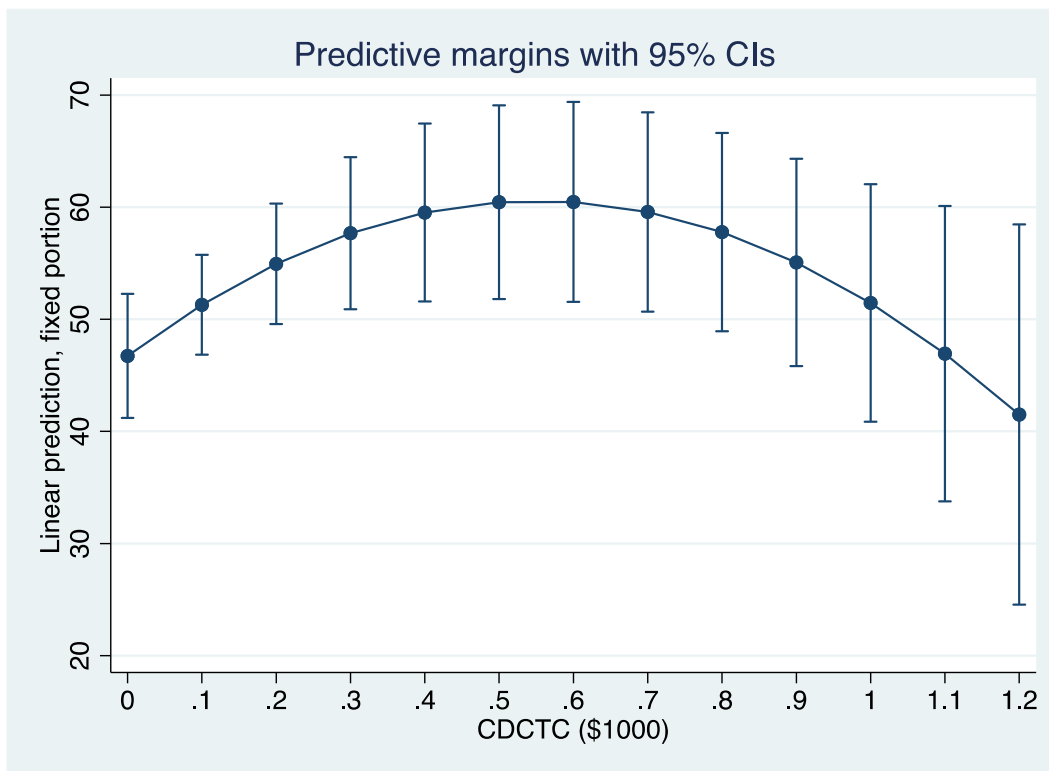
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Margins of Predicted Values

CDCTC Value	Margins	Std. Error
\$ 0	46.7301	2.8238
\$ 100	51.2895	2.2732
\$ 200	54.9408	2.7411
\$ 300	57.6838	3.4606
\$ 400	59.5187	4.0478
\$ 500	60.4454	4.4084
\$ 600	60.4640	4.5480
\$ 700	59.5743	4.5344
\$ 800	57.7765	4.5116
\$ 900	55.0706	4.7138
\$ 1,000	51.4564	5.4018
\$ 1,100	46.9341	6.7170
\$ 1,200	41.5036	8.6479

Table 5 shows that an increase from \$0 to \$100 in CDCTC is associated with an increase of 5 slots per 100 children, that an increase in CDCTC from \$100 to \$200 is associated with an increase of 3 slots per 100 children, and so on until a CDCTC value of \$500, at which point any further increases in CDCTC amount are associated with decreases in slots. This is likely due to the skew of my data: I have far more counties associated with the lower values of the CDCTC than data points (counties) for the higher values of the credit. This is reflected in the standard errors of the margins table: As the credit value increases, the standard errors for those plot points increase, reflecting a larger degree of uncertainty for the highest values of the CDCTC. The negative curve in Figure 4 illustrates that over time, the level of supply will decrease with increasing levels of the tax credit.

Figure 4: Margins plot of predicted values



Given the limited range of the actual tax credit values in my data, the predicted values that we can estimate from this model are equally limited.

5.4. Robustness checks

Using the available workforce supply data, I was able to explore the effect of adding the number of child care employees in a county to verify the robustness of my model (Appendix 2.2). This still did not yield statistically significant results for the CDCTC coefficient, but it also decreased my sample size to ~1500 observations. I also tested Hypothesis 1 with an interaction term to determine if the CDCTC effect on the number of slots changed during Covid and found that during Covid, the credit was associated with a decrease of 3 slots per 100 children compared with before Covid (Appendix 2.1). This interaction term was also statistically insignificant.

6. Discussion

This study is the first of its kind in investigating the role of state CDCTCs in the child care market and in beginning to draw links between CDCTCs and the level of supply. This is important given that between 2021 and 2023, two states (Pennsylvania and Wisconsin) introduced state CDCTCs and three (Massachusetts, Nebraska, and Vermont) expanded their existing credits by raising maximum credit levels and making the benefit refundable. In other words, policymakers continue to rely on CDCTCs even though we lack information about their effects.

The results of this study are inconclusive. Having controlled for GDP per capita, WLFP, median income, quality regulation stringency, racial demographics, poverty level and the number of multigenerational households, we cannot, based on this model, say that there is a relationship between an increase in state CDCTC generosity and the level of child care supply in a county. The CDCTC coefficient, which indicates that every \$1000 increase in state CDCTC generosity is associated with an increase of four slots per 100 children in the county, is not statistically significant with a p-value of 0.65, and a confidence interval of (-9.12, 18.07). However, a 4% increase in supply levels with every \$1000 increase to the credit is of practical significance as are the findings of hypothesis two, that refundable credits are associated with a 9% increase in capacity compared with nonrefundable credits. We can make sense of these inconclusive results two ways.

First, we could interpret these results to say that there is no relationship between the state CDCTCs and the level of child care supply. If that is true, these inconclusive results create cause for a study investigating the politics of these tax credit policies. If they have little to no impact on the present child care crisis, what explains their resilience and the continued interest shown in introducing new versions of them on the state level?

Whose interests do they serve? Tax expenditures have historically been described as having bipartisan appeal: Republicans like them because they keep government relatively small; Democrats because they serve social agendas (Prasad, 2016). However, Faricy found that the majority of tax expenditure legislation has been pursued by the Republican party (2011). It is important to note that there are political stakes to framing the child care problem as a supply versus demand side problem: demand individualizes the child care problem into a problem of parent preferences, whereas supply sees it as a structural market failure, something requiring community investment. This lack of relationship impugns demand-side policies as a solution for fixing child care supply (2022).

Alternatively, although this relationship is not statistically insignificant, it is of practical significance. This is especially true of the findings for refundable CDCTCs impact on supply compared with nonrefundable ones. At minimum, this practical significance suggests that further studies, with more statistical power, may be worthwhile. It is regrettable that I was not able to include the nine additional states that have CDCTC policies—this was due to insufficient supply data.⁶ This was especially unfortunate for testing Hypothesis three, which found statistical significance in a nonlinear relationship between CDCTC policies and the level of child care supply. Without any state in my dataset having a CDCTC value of more than \$1150 per child, and with limited numbers of counties associated with tax credits higher than \$500, we cannot predict whether or by how much behavior will change if the tax credit were to be worth substantially more (for example, half of a family’s child care expenses). The results of Hypothesis three suggests that further study could include using a nonlinear mixed

⁶ Arkansas, Delaware, Georgia, Hawaii, Louisiana, Minnesota, New Jersey, Oklahoma, Oregon

effects model to explore this relationship with the additional nine states, some of whom have substantially larger maximum credit values.⁷

The methods used in this study cannot interrogate or make claims about causality: only correlation. Further research, however, could investigate whether there is a causal relationship between state CDCTCs and the level of child care supply. A difference and difference study, for example, could use longitudinal supply data to look at the before and after effects of the implementation of the credit in a state and might be able to avoid the confounding circumstances of the pandemic: This would enable us to assess the direct effects of the policy. A difference-in-difference-in-difference design could even compare the effect of introducing a nonrefundable tax credit versus a refundable one and might explore whether the larger effect size I find can be explained by more families being able to access the CDCTC program through refundability. Another limitation of my study is that counties are quite large geographic areas: larger, in all likelihood, than the true size of local child care markets (Herbst and Barnow, 2007; Gordon and Chase-Lansdale, 2001). A study using individual-level data might be able to capture more nuances to the CDCTCs' effects on families' abilities to purchase care and would bring precision to modelling child care demand and parental decision-making around child care arrangements.

Lastly, we need context for the practical significance my results produce. A cost-effectiveness study could compare state CDCTC expenditures with more direct funding strategies to build the level of child care supply. A cost-effectiveness or cost-benefit analysis of the state CDCTCs will also help policymakers consider the other aims of ECEC policy: quality and affordability, as well as how effective the tax credit is in achieving those measures. In other words, even if the credit were shown to have a

⁷ Oregon has a maximum CDCTC value of \$9000 per eligible child.

statistically significant positive relationship on the level of child care supply in a county, using the credit to build supply may still be an inefficient strategy.

Despite what the traditional literature claims, there is a quite a lot of state activity in U.S. ECEC policy with regard to the ECEC market, even amidst scarce federal provision of early childhood services. As Howard shows, the tax code serves as a key vehicle for social policy provision and action in the US (1997). Building child care supply is no exception. For example, Louisiana and Colorado have both introduced supply-side tax credit measures on top of their CDCTCs: income tax credits for early childhood workers to incentivize teacher qualifications and assist with retention (NWLC, 2022). However, the efficacy of tax expenditure policies, and why they persist, are urgently deserving of further research, both to flesh out our understanding of the U.S. welfare state and how it structures family policy, and to ensure effective solutions to the present child care crisis. Although this study cannot definitively conclude whether state CDCTCs have an impact on the level of child care supply, it does lay the groundwork for further investigation.

Appendix

Word count: 700 words

1. Tax Deduction Calculations

Tax deductions function differently than tax credits: They reduce an individual's taxable income, rather than her direct tax liability. In this way, they are less generous policies than tax credits, especially as low-income people cannot benefit from them to the same extent and often at all.

To approximate the maximum "tax savings" a family could receive for one child's child care expenses from a tax deduction, and thus make them comparable to tax credits, I multiplied the maximum amount of expenses by the highest income tax rate in that state.

Idaho:

The maximum expenses you can claim in Idaho mimic the federal CDCTC policy of \$3,000 per eligible child. The top Idaho income tax rate is 7%. In this case, $(3,000 * 0.07)$ the maximum tax saving for one child is about \$210.

Massachusetts:

This policy is no longer in effect and beginning Tax Year 2022 was converted into a refundable tax credit. However, to match my Massachusetts data vintage, I use the old policy.

The maximum child care expenses a family can claim in Massachusetts for one family is \$4,800. The Massachusetts tax rate for all income levels is 5.05%. The maximum tax saving for one child is \$242 $(4,800 * .0505)$.

Montana:

The maximum amount of expenses you can claim in Montana for one child is \$2,400. The income tax rate for the top income bracket is 6.9%. Thus, the maximum tax saving for one child is \$166.

Virginia:

The maximum amount of child care expenses you can claim in Virginia for one child follow the federal CDCTC policy (\$3,000/eligible child). The top income tax rate in Virginia is 5.75%. The maximum tax saving for one child is \$173 $(\$3,000 * .0575)$.

2. Robustness Checks

2.1 Covid Interaction Term

Variable	Coefficient	Std. Error	
Women with children under age six, Labor Force Participation Rate (1 %)	0.275104	(3.3280)	***
GDP per capita	0.00003	(0.00002)	
Median Income (\$10,000)	2	(0.3)	***
Percent below poverty level	0.0843	(0.0985)	
Number of multigenerational households	-0.00003	(0.0001)	
Ratio of Child:Staff, Preschool	-0.1444	(0.8553)	
Ratio of Child:Staff, Infants	-3.9760	(3.3207)	
Hispanic (1%)	-0.0657	(0.0393)	
White (1%)	0.2085	(0.4337)	
Black (1%)	0.5098	(0.4288)	
American Indian/Alaska Native (1%)	0.4209	(0.4225)	
Asian (1%)	0.9091	(0.4031)	**
Before or During Covid	4.0883	(5.3881)	
CDCTC (\$1000)	16.8339	(10.4301)	
Interaction term between Covid and CDCTC	-19.7181	(13.1957)	
Constant	12.4259	(46.8947)	
Variance of the Intercept	144.8032	(37.1784)	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

In this model, I code Covid as a binary variable, where 0 represented supply data from before March 2020 and 1 represented supply data from March 2020 onward. Once again, the coefficient for the tax credit effect when Covid was equal to 0 (i.e. before Covid) was statistically insignificant. However, the practical significance of that

coefficient was similar: Before Covid, the tax credit was potentially associated with an increase of 4 slots per 100 children.

The interaction term tells us that the CDCTC effect on the number of slots did in fact change during Covid. During Covid, the credit was associated with a decrease of 3 slots per 100 children compared with before Covid ($16 + -19 = -3$).

2.2. Testing Hypothesis 1 with Workforce Supply Data

Variable	Coefficient	Std. Error	
CDCTC (\$1000)	5.4917	(6.8342)	
Women with children under age six, Labor Force Participation Rate (1%)	0.263493	(0.044384)	***
GDP per capita (in 2020 dollars)	0.0001	(0.00002)	***
Before or During Covid	0.8943	(4.9341)	
Median Income (\$10,000)	2	(0.3)	***
Population below poverty level (1%)	0.2226	(0.1030)	
Number of multigenerational households	-0.0003	(0.0001)	***
Ratio of Child:Staff, Preschool	0.3234	(0.8838)	
Ratio of Child:Staff, Infants	-3.5114	(3.4975)	
Hispanic (1%)	-0.0797	(0.0402)	**
White (1%)	0.9917	(0.5851)	
Black (1%)	1.2070	(0.5758)	**
American Indian/Alaska Native (1%)	0.9896	(0.5690)	
Asian (1%)	1.1993	(0.5443)	**
Number of Child Care Workers	0.0027	(0.0006)	***
Constant	-71.0945	(62.2893)	
Variance of the Intercept	164.4995	(41.2747)	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Including the number of child care workers per county bolsters the statistical power of the model, as seen by the increase in number of statistically significant coefficients. Although the number of child care workers coefficient is itself very significant, its effect size is tiny. CDCTC remains insignificant, though the effect size increases to 5.5 slots per 100 children.

References

- 2015 Nebraska Revised Statutes :: Chapter 77 - :: REVENUE AND TAXATION :: 77-2715.07 Income tax credits.* (no date) *Justia Law*. Available at: <https://law.justia.com/codes/nebraska/2015/chapter-77/statute-77-2715.07/> (Accessed: 20 August 2023).
- ‘2019 INSTRUCTIONS FOR FILING RI-1040’ (2019). Rhode Island Division of Taxation. Available at: https://tax.ri.gov/sites/g/files/xkgbur541/files/forms/2019/Income/2019-Resident-Instructions_12052019.pdf.
- 2019 New Mexico Statutes Chapter 7 - Taxation Article 2A - Corporate Income and Franchise Tax Section 7-2A-14 - Corporate-supported child care; credits allowed.* (2019) *NM Statutes*. Available at: <https://law.justia.com/codes/new-mexico/2019/chapter-7/article-2a/section-7-2a-14/>.
- Aassve, A., Arpino, B. and Goisis, A. (2012) ‘Grandparenting and mothers labour force participation: A comparative analysis using the Generations and Gender Survey’, *Demographic Research*, 27, pp. 53–84. Available at: <https://doi.org/10.4054/DemRes.2012.27.3>.
- Adams, G., Luetmer, G. and Todd, M. (2022) ‘Using Child Care Subsidy Payment Rates and Practices to Incentivize Expansions in Supply’, *The Urban Institute* [Preprint]. Available at: <https://www.urban.org/research/publication/using-child-care-subsidy-payment-rates-and-practices-incentivize-expansions-supply>.
- Aigner-Treworgy, S., Osborn, C. and Smith, L.K. (2022) *Charting the Path Forward for Child Care: USING COST MODELING TO DESIGN NEW SOLUTIONS*. Washington DC: The Bipartisan Policy Center. Available at: https://bipartisanpolicy.org/download/?file=/wp-content/uploads/2022/11/BPC_ECI_Cost-Model-Explainer_RV7.pdf.
- Aizer, A., Hoynes, H. and Lleras-Muney, A. (2022) ‘Children and the US Social Safety Net: Balancing Disincentives for Adults and Benefits for Children’, *Journal of Economic Perspectives*, 36(2), pp. 149–174. Available at: <https://doi.org/10.1257/jep.36.2.149>.
- ‘All Sectors: County Business Patterns, including ZIP Code Business Patterns, by Legal Form of Organization and Employment Size Class for the U.S., States, and Selected Geographies: 2020’ (2020). U.S. Census Bureau, County Business Patterns. Available at: <https://www2.census.gov/programs-surveys/cbp/data/2020>.
- Amorim, M. (2019) ‘Are grandparents a blessing or a burden? Multigenerational coresidence and child-related spending’, *Social Science Research*, 80, pp. 132–144. Available at: <https://doi.org/10.1016/j.ssresearch.2019.02.002>.
- An act relating to tax reductions and other aid for Vermonters* (2022) *Sec. 1. 32 V.S.A.* Available at:

<https://legislature.vermont.gov/Documents/2022/Docs/ACTS/ACT138/ACT138%20As%20Enacted.pdf>.

‘Annual County Resident Population Estimates by Age, Sex, Race, and Hispanic Origin: April 1, 2020 to July 1, 2022 (CC-EST2022-ALLDATA)’ (2020). Available at: <https://www.census.gov/data/tables/time-series/demo/popest/2020s-counties-detail.html>.

Bagley, A., Jerrett, D. and Smith, L.K. (2021) *The Economic Impact of America’s Child Care Gap*. The Bipartisan Policy Center.

Bagley, A., Smith, L.K. and Wolters, B. (2021) *Child Care in 35 States: What we know and don’t know*. The Bipartisan Policy Center. Available at: childcaregap.org.

Bassok, D. (2012) ‘Competition or Collaboration?: Head Start Enrollment During the Rapid Expansion of State Pre-kindergarten’, *Educational Policy*, 26(1), pp. 96–116. Available at: <https://doi.org/10.1177/0895904811428973>.

Bassok, D., Fitzpatrick, M. and Loeb, S. (2014) ‘Does state preschool crowd-out private provision? The impact of universal preschool on the childcare sector in Oklahoma and Georgia’, *Journal of Urban Economics*, 83, pp. 18–33. Available at: <https://doi.org/10.1016/j.jue.2014.07.001>.

Bassok, D., Miller, L.C. and Galdo, E. (2016) ‘The effects of universal state pre-kindergarten on the child care sector: The case of Florida’s voluntary pre-kindergarten program’, *Economics of Education Review*, 53, pp. 87–98. Available at: <https://doi.org/10.1016/j.econedurev.2016.05.004>.

Baum, C.L. (2002) ‘A dynamic analysis of the effect of child care costs on the work decisions of low-income mothers with infants’, *Demography*, 39(1), pp. 139–164. Available at: <https://doi.org/10.1353/dem.2002.0002>.

Belfield, C.R. (2023) *Child Care and Working Families: A Post-Pandemic Economic Analysis for the U.S.* Council for a Strong America. Available at: <https://strongnation.s3.amazonaws.com/documents/1596/4db2b14c-a85b-4b49-9390-c6b90935e3de.pdf?1674854543&inline;%20filename=%22Child%20Care%20and%20Working%20Families:%20A%20Post-Pandemic%20Economic%20Analysis%20for%20the%20U.S..pdf%22>.

Blau, D. (2001) *The child care problem: an economic analysis*. New York: Russell Sage Foundation.

Bonoli, G. (2005) ‘The politics of the new social policies: providing coverage against new social risks in mature welfare states’, *Policy & Politics*, 33(3), pp. 431–449. Available at: <https://doi.org/10.1332/0305573054325765>.

Brewer, M. and Hoynes, H. (2019) ‘In-Work Credits in the UK and the US: In-work credits in the UK and the US’, *Fiscal Studies*, 40(4), pp. 519–560. Available at: <https://doi.org/10.1111/1475-5890.12207>.

Cantillon, B. (2011) ‘The paradox of the social investment state: growth, employment and poverty in the Lisbon era’, *Journal of European Social Policy*, 21(5), pp. 432–449. Available at: <https://doi.org/10.1177/0958928711418856>.

Carrazanna, C. (2023) ‘Day care waitlists are so long, moms are quitting their jobs or choosing to stop having kids’, *The 19th*. Online, 30 March. Available at: <https://19thnews.org/2023/03/day-care-waitlists-child-care-strain-parenting/>.

Cascio, E.U. (2009) ‘Maternal Labor Supply and the Introduction of Kindergartens into American Public Schools’, *Journal of Human Resources*, 44(1), pp. 140–170. Available at: <https://doi.org/10.1353/jhr.2009.0034>.

Cascio, E.U. and Schanzenbach, D.W. (2013) *The impacts of expanding access to high-quality preschool*. Brookings Institution, pp. 127–178. Available at: <https://www.brookings.edu/articles/the-impacts-of-expanding-access-to-high-quality-preschool-education/>.

Child & Dependent Care Expenses Refundable Credit/ 50 percent Credit if Adjusted Gross Income not over \$100,000 (California) (2018). Available at: <https://www.ftb.ca.gov/tax-pros/law/legislation/2017-2018/sb1213-021518.pdf>.

‘Child and Dependent Care Tax Credit (Maryland)’ (no date) *Tax Credits, Deductions and Subtractions for Individual Taxpayers*. Available at: <https://www.marylandtaxes.gov/tax-credits.php>.

Child care expenses tax credit - legislative declaration - definitions (Colorado) (no date). Available at: <https://casetext.com/statute/colorado-revised-statutes/title-39-taxation/specific-taxes/income-tax/article-22-income-tax/part-1-general/section-39-22-1195-child-care-expenses-tax-credit-legislative-declaration-definitions>.

‘Children Under 6 with All Available Parents in the Labor Force in United States’ (no date). KIDSCOUNT. Available at: <https://datacenter.aecf.org/data/tables/5057-children-under-age-6-with-all-available-parents-in-the-labor-force#detailed/1/any/false/2048,1729,37,871,870,573,869,36,868,867/any/11472,11473>

.

‘Child-Staff Ratios and Maximum Group Size Requirements in 2011’ (2011). U.S. Department of Health and Human Services, Administration for Children and Families, Office of Child Care. Available at: https://childcareta.acf.hhs.gov/sites/default/files/547_1305_ratiosgroupsize_2011.pdf.

Cohen, A.J. (1996) ‘A Brief History of Federal Financing for Child Care in the United States’, *The Future of Children*, 6(2), p. 26. Available at: <https://doi.org/10.2307/1602417>.

Collins, C. *et al.* (2021a) ‘COVID-19 and the gender gap in work hours’, *Gender, Work & Organization*, 28(S1), pp. 101–112. Available at: <https://doi.org/10.1111/gwao.12506>.

Collins, C. *et al.* (2021b) ‘COVID-19 and the gender gap in work hours’, *Gender, Work & Organization*, 28(S1), pp. 101–112. Available at: <https://doi.org/10.1111/gwao.12506>.

Compton, J. and Pollak, R.A. (2014) ‘Family proximity, childcare, and women’s labor force attachment’, *Journal of Urban Economics*, 79, pp. 72–90. Available at: <https://doi.org/10.1016/j.jue.2013.03.007>.

Couch, K.A., Fairlie, R.W. and Xu, H. (2022) ‘The evolving impacts of the COVID-19 pandemic on gender inequality in the US labor market: The COVID motherhood penalty’, *Economic Inquiry*, 60(2), pp. 485–507. Available at: <https://doi.org/10.1111/ecin.13054>.

CREDIT FOR CHILD AND DEPENDENT CARE (2017). Available at: <https://www.ksrevenue.gov/taxnotices/notice17-07.pdf>.

Daly, M. (2011) ‘What Adult Worker Model? A Critical Look at Recent Social Policy Reform in Europe from a Gender and Family Perspective’, *Social Politics: International Studies in Gender, State & Society*, 18(1), pp. 1–23. Available at: <https://doi.org/10.1093/sp/jxr002>.

DeAngelis, C.A., Holmes Erickson, H. and Ritter, G.W. (2020) ‘What’s the state of the evidence on pre-K programmes in the United States? A systematic review’, *Educational Review*, 72(4), pp. 495–519. Available at: <https://doi.org/10.1080/00131911.2018.1520688>.

Demanding Change: Repairing our Child Care System (2022). Child Care Aware of America. Available at: [https://info.childcareaware.org/hubfs/2022-03-FallReport-FINAL%20\(1\).pdf?utm_campaign=Budget%20Reconciliation%20Fall%202021&utm_source=website&utm_content=22_demandingchange_pdf_update332022](https://info.childcareaware.org/hubfs/2022-03-FallReport-FINAL%20(1).pdf?utm_campaign=Budget%20Reconciliation%20Fall%202021&utm_source=website&utm_content=22_demandingchange_pdf_update332022).

Eissa, N., Kleven, H.J. and Kreiner, C.T. (2008) ‘Evaluation of four tax reforms in the United States: Labor supply and welfare effects for single mothers’, *Journal of Public Economics*, 92(3–4), pp. 795–816. Available at: <https://doi.org/10.1016/j.jpubeco.2007.08.005>.

Esping-Andersen, G. (2013) *The Three Worlds of Welfare Capitalism*. Place of publication not identified: John Wiley and Sons, Inc.

First Five Nebraska (2023) *Historic Nebraska Child Care Tax Credit package signed into law*. Available at: <https://www.firstfivenebraska.org/blog/governor-signs-lb754-into-law/#:~:text=Households%20with%20annual%20income%20between,strengthen%20local%20child%20care%20options>.

Folbre, N. (2022) *Valuing Children: Rethinking the Economics of the Family*. Cambridge, MA: Harvard University Press.

Forry, N.D. and Anderson, E.A. (2006) ‘The Child and Dependent Care Tax Credit: A Policy Analysis’, *Marriage & Family Review*, 39(1–2), pp. 159–176. Available at: https://doi.org/10.1300/J002v39n01_09.

Fuller-Thomson, E. and Minkler, M. (2001) ‘American Grandparents Providing Extensive Child Care to Their Grandchildren’, *The Gerontologist*, 41(2), pp. 201–209. Available at: <https://doi.org/10.1093/geront/41.2.201>.

Furstenberg, F.F. (2019) ‘Family Change in Global Perspective: How and Why Family Systems Change’, *Family Relations*, 68(3), pp. 326–341. Available at: <https://doi.org/10.1111/fare.12361>.

‘GDP and Median Income by County, 2020’ (2020). Bureau of Economic Analysis, US Department of Commerce. Available at: <https://apps.bea.gov/regional/downloadzip.cfm>.

Gelman, A. and Hill, J. (2006) *Data Analysis Using Regression and Multilevel/Hierarchical Models*. 1st edn. Cambridge University Press. Available at: <https://doi.org/10.1017/CBO9780511790942>.

Goldstein, D. (2022) ‘Why You Can’t Find Child Care: 100,000 Workers Are Missing’, *The New York Times*. online, 13 October. Available at: <https://www.nytimes.com/2022/10/13/us/child-care-worker-shortage.html#:~:text=The%20shortage%20is%20contributing%20to,the%20Bureau%20of%20Labor%20Statistics>.

Gordon, R.A. and Chase-Lansdale, P.L. (2001) ‘Availability of child care in the United States: A description and analysis of data sources’, *Demography*, 38(2), pp. 299–316. Available at: <https://doi.org/10.1353/dem.2001.0016>.

Greenberg, E. *et al.* (no date) *Are Higher Subsidy Payment Rates and Provider-Friendly Payment Policies Associated with Child Care Quality?* Washington DC: The Urban Institute. Available at: https://www.urban.org/sites/default/files/publication/96681/are_higher_subsidy_payment_rates_and_provider_friendly_payment_policies_associated_with_child_care_quality_2.pdf.

‘GY 2022 CCDF Allocations (Based on Appropriations)’ (2022). Office of Child Care, Administration for Children and Families. Available at: <https://www.acf.hhs.gov/occ/data/gy-2022-ccdf-allocations-based-appropriations>.

Hartley, R.P. *et al.* (2022) ‘Paying for Childcare to Work? Evaluating the Role of Policy in Affordable Care and Child Poverty’, *Social Service Review*, 96(1), pp. 34–72. Available at: <https://doi.org/10.1086/718635>.

Hassmer, S. and Matsui, A. (2018) *Making Care Less Taxing: State Child and Dependent Care Tax Provisions*. Washington DC: National Women’s Law Center.
Herbst, C.M. (2017) ‘Universal Child Care, Maternal Employment, and Children’s Long-Run Outcomes: Evidence from the US Lanham Act of 1940’, *Journal of Labor Economics*, 35(2), pp. 519–564. Available at: <https://doi.org/10.1086/689478>.

Herbst, C.M. (2018) ‘The impact of quality rating and improvement systems on families’ child care choices and the supply of child care labor’, *Labour Economics*, 54, pp. 172–190. Available at: <https://doi.org/10.1016/j.labeco.2018.08.007>.

Herbst, C.M. (2023) ‘CHILD CARE IN THE UNITED STATES: MARKETS, POLICY, AND EVIDENCE’, *Journal of Policy Analysis and Management*, 42(1), pp. 255–304. Available at: <https://doi.org/10.1002/pam.22436>.

Herbst, C.M. and Barnow, B.S. (2008) ‘Close to Home: A Simultaneous Equations Model of the Relationship Between Child Care Accessibility and Female Labor Force Participation’, *Journal of Family and Economic Issues*, 29(1), pp. 128–151. Available at: <https://doi.org/10.1007/s10834-007-9092-5>.

Hotz, V.J. and Wiswall, M. (2019) ‘Child Care and Child Care Policy: Existing Policies, Their Effects, and Reforms’, *The ANNALS of the American Academy of Political and Social Science*, 686(1), pp. 310–338. Available at: <https://doi.org/10.1177/0002716219884078>.

Hotz, V.J. and Xiao, M. (2011) ‘The Impact of Regulations on the Supply and Quality of Care in Child Care Markets’, *American Economic Review*, 101(5), pp. 1775–1805. Available at: <https://doi.org/10.1257/aer.101.5.1775>.

Household and dependent care service credit. (1990). Available at: <https://apps.legislature.ky.gov/law/statutes/statute.aspx?id=29058>.

Hustedt, J.T. and Barnett, W.S. (2011) ‘Financing Early Childhood Education Programs: State, Federal, and Local Issues’, *Educational Policy*, 25(1), pp. 167–192. Available at: <https://doi.org/10.1177/0895904810386605>.

Income tax credit for child care expenses (Maine) (2005) Title 36: TAXATION Part 8: INCOME TAXES Chapter 822: TAX CREDITS. Available at: <http://www.mainelegislature.org/legis/statutes/36/title36sec5218.html>.

‘Indicator 5: Early Childcare and Education Arrangements’ (2019), February. Available at: https://nces.ed.gov/programs/raceindicators/indicator_rba.asp.

‘Instructions for Form IT-216 Claim for Child and Dependent Care Credit’ (2022). New York State Department of Taxation and Finance. Available at: https://www.tax.ny.gov/pdf/current_forms/it/it216i.pdf.

Internal Revenue Service (2022) ‘Publication 503 (2022), Child and Dependent Care Expenses’. Available at: <https://www.irs.gov/publications/p503#:~:text=For%202022%2C%20the%20credit%20for,of%20your%20employment%2Drelated%20expenses>.

Iowa Department of Revenue (2022) ‘Child and Dependent Care Credit or Early Childhood Development Credit’. Available at: <https://tax.iowa.gov/expanded-instructions/child-dependent-care-credit-early-childhood-development-credit-2022>.

Kahn, A.J. and Kamerman, S.B. (1987) *Child care: facing the hard choices*. Dover, Mass: Auburn House Pub. Co.

Keep child care affordable tax credit. (no date) *District of Columbia*. Available at: <https://code.dccouncil.gov/us/dc/council/code/sections/47-1806.15>.

Kilmer, L. (2022) ‘Governor Wolf announces new state child care tax credit’, *WPXI Channel 11 Pittsburgh*, 26 July. Available at: <https://www.wpxi.com/news/local/governor-wolf-announces-new-state-child-care-tax-credit/WWTIQ27TY5AYJCT6FSVYLIUTYY/>.

Kochhar, Rakesh (2020) ‘Fewer Mothers and Fathers in U.S. Are Working Due to COVID-19 Downturn; Those at Work Have Cut Hours.’, 22 October. Available at: <https://www.pewresearch.org/short-reads/2020/10/22/fewer-mothers-and-fathers-in-u-s-are-working-due-to-covid-19-downturn-those-at-work-have-cut-hours/>.

Lee, E.K. and Parolin, Z. (2021) ‘The Care Burden during COVID-19: A National Database of Child Care Closures in the United States’, *Socius: Sociological Research for a Dynamic World*, 7, p. 237802312110320. Available at: <https://doi.org/10.1177/23780231211032028>.

Leslie, L.A., Ettenson, R. & Cumsille, P. Selecting a Child Care Center: What Really Matters to Parents?. *Child & Youth Care Forum* 29, 299–322 (2000). <https://doi.org/10.1023/A:1016609927849>

Lewis, J. (1992) ‘Gender and the Development of Welfare Regimes’, *Journal of European Social Policy*, 2(3), pp. 159–173. Available at: <https://doi.org/10.1177/095892879200200301>.

Lloyd, E. and Penn, H. (2012) *Childcare markets: can they deliver an equitable service ?* Bristol (GB) Chicago: Policy Press.

Malik, R. *et al.* (2018) ‘America’s Child Care Deserts in 2018’, *Center for American Progress* [Preprint]. Available at: <https://childcaredeserts.org/2018/>.

Mccabe, J. and Orr, R. (2022) ‘Strengthening Family Tax Benefits in Massachusetts’, 14 April. Available at: <https://www.niskanencenter.org/strengthening-family-tax-benefits-in-massachusetts/>.

McLean, C. (2014) ‘Market managers and market moderators: Early childhood education and care provision, finance and regulation in the United Kingdom and United States’, *Journal of European Social Policy*, 24(2), pp. 122–134. Available at: <https://doi.org/10.1177/0958928713517916>.

Mefferd, E. and Dow, D. (2023) ‘The US Child Care System Relies on Women of Color, but Structural Barriers Systematically Disadvantage Them’, 14 June. Available at: <https://www.urban.org/urban-wire/us-child-care-system-relies-women-color-structural-barriers-systematically-disadvantage#:~:text=In%20listed%20child%20care%20homes,those%20numbers%20are%20even%20higher>.

Morrissey, T.W. (2017) ‘Child care and parent labor force participation: a review of the research literature’, *Review of Economics of the Household*, 15(1), pp. 1–24. Available at: <https://doi.org/10.1007/s11150-016-9331-3>.

Order for claiming credits (2020) *Ohio Rev. Code*. Available at: <https://casetext.com/statute/ohio-revised-code/title-57-taxation/chapter-5747-income-tax/section-574798-effective3232022order-for-claiming-credits>.

Orloff, A.S. (2002) ‘Explaining US welfare reform: power, gender, race and the US policy legacy’, *Critical Social Policy*, 22(1), pp. 96–118. Available at: <https://doi.org/10.1177/02610183020220010801>.

Pierson, P. (ed.) (2001) *The New Politics of the Welfare State*. 1st edn. Oxford University Press Oxford. Available at: <https://doi.org/10.1093/0198297564.001.0001>.

‘Poverty Status in the Past 12 months’ (no date). American Community Survey, 5 Year Estimates, S1701. Available at: <https://data.census.gov/table?q=poverty+rate+by+county&g=010XX00US&tid=ACSS T5Y2021.S1701&tp=true>.

Prasad, M. (2016) ‘American Exceptionalism and the Welfare State: The Revisionist Literature’, *Annual Review of Political Science*, 19(1), pp. 187–203. Available at: <https://doi.org/10.1146/annurev-polisci-042214-044323>.

‘Presence of Multigenerational Households’ (2020). Decennial Census, Demographic and Housing Characteristics. Available at: <https://data.census.gov/table?q=PCT14&d=DEC+Demographic+and+Housing+Characteristics>.

Queralt, M. and Witte, A.D. (1998) ‘Influences on Neighborhood Supply of Child Care in Massachusetts’, *Social Service Review*, 72(1), pp. 17–46. Available at: <https://doi.org/10.1086/515744>.

Rasbash, J. (2022) ‘What are multilevel models and why should I use them?’ Available at: <https://www.bristol.ac.uk/cmm/learning/multilevel-models/what-why.html>.

Reid, J.L. *et al.* (2019) ‘Building a unified system for universal Pre-K: The case of New York City’, *Children and Youth Services Review*, 100, pp. 191–205. Available at: <https://doi.org/10.1016/j.childyouth.2019.02.030>.

Ribar, D.C. (1995) ‘A Structural Model of Child Care and the Labor Supply of Married Women’, *Journal of Labor Economics*, 13(3), pp. 558–597. Available at: <https://doi.org/10.1086/298385>.

Rose, K.K. and Elicker, J. (2010) ‘Maternal child care preferences for infants, toddlers, and preschoolers: the disconnect between policy and preference in the USA’, *Community, Work & Family*, 13(2), pp. 205–229. Available at: <https://doi.org/10.1080/13668800903314366>.

Rubinfield, S. (2022) *The FFYF Federal Guide to Early Learning*. First Five Years Fund. Available at: https://www.ffyf.org/wp-content/uploads/2023/01/FFYF_FederalECEReferenceBook_Digital_Final3.pdf.

Sainsbury, D. (ed.) (1999) 'Gender, Policy Regimes, and Politics', in *Gender and Welfare State Regimes*. 1st edn. Oxford University Press Oxford, pp. 245–276. Available at: <https://doi.org/10.1093/0198294166.003.0009>.

South Carolina Income Tax Act (2014) *South Carolina Code of Laws*. Available at: <https://law.justia.com/codes/south-carolina/2014/title-12/chapter-6/section-12-6-3380/>.

'STATES CAN MAKE CARE LESS TAXING' (2023), February. Available at: <https://nwlc.org/resource/making-care-less-taxing-state-and-dependent-care-tax-provisions-tax-year-2021/>.

Sullivan, E. (2021) *FEDERAL TAX CREDITS FOR INDIVIDUALS AND FAMILIES (Montana)*.

Montana State Legislature: Economic Affairs Interim Committee. Available at: <https://leg.mt.gov/content/Committees/Interim/2021-2022/Economic%20Affairs/Meetings/November%202021/Federal-Tax-Credits.pdf>.

Tekin, E. (2021) 'An Overview of the Child care Market in the United States', *NBER White Paper* [Preprint]. Available at: https://www.nber.org/sites/default/files/2021-10/White%20Paper-Tekin-101.06.21_revised.pdf.

THE ECONOMICS OF CHILD CARE SUPPLY IN THE UNITED STATES (2021).

U.S. Department of the Treasury. Available at: <https://home.treasury.gov/system/files/136/The-Economics-of-Childcare-Supply-09-14-final.pdf>.

Ünver, Ö., Bircan, T. and Nicaise, I. (2021) 'A multilevel approach to ECEC policies and intensity of formal childcare participation of young children in Europe', *Children and Youth Services Review*, 122, p. 105798. Available at: <https://doi.org/10.1016/j.childyouth.2020.105798>.

Virginia Child and Dependent Care Expenses Deduction (no date) Virginia Department of Taxation. Available at: <https://www.tax.virginia.gov/deductions#:~:text=The%20amount%20of%20the%20deduction,for%20two%20or%20more%20dependents>.

Webster, C.J. and White, S. (1997) 'Child-Care Services and the Urban Labour Market. Part 2: Modelling the Relationships between Child-Care Service Accessibility and Labour-Market Participation', *Environment and Planning A: Economy and Space*, 29(9), pp. 1675–1695. Available at: <https://doi.org/10.1068/a291675>.

'Wisconsin Income Tax Form 1 Instructions' (2022). Available at: <https://www.revenue.wi.gov/TaxForms2022/2022-Form1-Inst.pdf>.

'Women's Labor Force Participation Rate by Presence and Age of Children, State and County' (2013). Available at: <https://www.dol.gov/agencies/wb/data/womens-labor-force-participation-rate-presence-age-of-children>.

Zamarro, G. and Prados, M.J. (2021) 'Gender differences in couples' division of childcare, work and mental health during COVID-19', *Review of Economics of the Household*, 19(1), pp. 11–40. Available at: <https://doi.org/10.1007/s11150-020-09534-7>.