

The Unintended Consequences of Informal Childcare Subsidies for Older Women's Retirement Security

Yulya Truskinovsky

March 2016

Abstract

Grandmothers provide a significant amount of childcare in the US, but little is known about how this informal, and often uncompensated, time transfer impacts their economic and health outcomes. This project addresses the impact of federally funded, state-level means-tested programs that compensate grandparent-provided childcare on the retirement security of older women, an economically vulnerable group of considerable policy interest. Childcare assistance can be used to compensate grandparent-provided childcare and/or to substitute market care for grandparent care. I use the variation in the availability and generosity of childcare subsidies to model the effect of government payments for grandchild care on grandmothers' time use, income, earnings, interfamily transfers, and health outcomes. After establishing that more generous government payments induce grandmothers to provide more hours of childcare, I find that grandmothers adjust their behavior by reducing their formal labor supply and earnings. Grandmothers make up for lost earnings by claiming Social Security earlier, increasing their reliance on Supplemental Security Income (SSI) and reducing financial transfers to their children. While the policy does not appear to negatively impact grandmothers' immediate economic well-being, there are significant costs to the state, in terms of both up-front costs for care payments and long-term costs as a result of grandmothers' increased reliance on social insurance.

1 Introduction

Grandparents, particularly grandmothers, provide a significant amount of childcare in the United States¹, but little is known about how this informal, and often uncompensated, time transfer impacts the economic and health outcomes of older American women². The implications of such transfers and the scope of the consequences are empirically important, as the number of Americans age 65 and over is expected to double by 2050 to nearly 89 million, while the projected costs of Medicare and Social Security are expected to reach 15 percent of GDP by the same year. This project uses a previously unexplored dimension of government-provided childcare subsidy policy to identify the causal impact of providing grandchild care on the economic and health outcomes of grandmothers.

Federally funded childcare assistance, provided by states to families with young children earning up to 85% of state median income, can be used to compensate grandparent-provided childcare or, alternatively, to substitute market care in the place of grandparent care (Ho, 2014). Childcare subsidies reduce or eliminate out of pocket costs for childcare, allowing low-income families with young children to participate in the labor market or in educational programs (Meyers et al., 2002; Tekin, 2005; Washbrook et al., 2011). However, by subsidizing informal care at or near market rates, state subsidies may incentivize families to shift the burden of childcare to grandparents via informal care arrangements. Policy discussions often ignore the potential effect of childcare subsidies on long-term economic and welfare outcomes of the

¹ Nearly a quarter of children under five were cared for by a grandparent in 2011 (Laughlin, 2013).

² There is a large literature exploring the impact of raising grandchildren on grandparent physical and mental health, and labor market outcomes that finds largely negative correlations. (Blustein, Chan, & Guanais, 2004; Wang & Marcotte, 2007). In this paper I address the case of grandmothers who provide childcare but are not the primary guardians of their grandchildren.

elderly.

The direction of the effect will depend on the individual grandmother's opportunity costs and formal labor force attachment, as well as the family's preferences for childcare mode. Subsidized grandchild care may generate new income-earning opportunities for grandmothers, which would likely improve well-being (Black et al., 2012) and might offset other government transfers to grandmothers, such as Supplemental Security Income (SSI). Alternatively, it could take altruistic grandmothers out of the (higher-paying) formal sector (Rupert & Zanella, 2014), weakening their long-term economic welfare and raising long-term government costs for their support. Caregiving could also directly affect a grandmother's physical or mental wellbeing by requiring constant physical strain while imposing social isolation, or conversely provide her with stimulating and meaningful activity (Blustein et al., 2004).

State funding for means-tested childcare assistance comes primarily via the Child Care and Development Fund (CCDF), an \$11 billion federal block grant that replaced a group of smaller federal grants during the welfare system overhaul of 1996. Within broadly defined parameters, states have great flexibility in administering these funds. As a result, there is significant heterogeneity in many dimensions of childcare subsidy policy, including eligibility requirements, co-pays and maximum reimbursement amounts. However, previous work has not exploited this state-year variation in potential payments to examine the effects of subsidy policy. In this paper, I use this heterogeneity to address two related empirical questions. First, how does the availability and generosity of subsidies shape the decision of older women to provide grandchild care? Second, what are the causal impacts of subsidizing grandchild care on the formal labor supply, living arrangements, retirement security, and health outcomes of grandmothers?

Ceteris paribus, grandmothers eligible for higher subsidies are more likely to commit a significant amount of time to taking care of their grandchildren (Doyle, 2007), even though reimbursement rates for legally unregulated informal care – the rates that apply to grandmothers and other relatives - are frequently far below minimum wage (Ho, 2014). Rates are as low as \$175 per month for full time care in Florida for a 4-year-old or \$0 in Massachusetts, which does not subsidize unregulated informal care. There are some notable exceptions, however, including Indiana, which reimburses legally unregulated informal care providers at the state minimum wage of \$1,276 per month, regardless of how many children are in their care (Giannarelli, Minton, & Durham, 2012), and California, where the monthly rate for three infants is over \$2,000.

Because labor market and caregiving decisions are interrelated (Blau & Robins, 1989; McGarry, 2006; Wakabayashi & Donato, 2006; Weber, 2011), the decision to provide grandchild care and the effects of such caregiving are not straightforward to establish. For example, grandparents who provide childcare may be altruistically forgoing paid work in the formal labor market, or they may be choosing to provide grandchild care because of unattractive outside options. Similarly, grandparents who care for their grandchildren may be in poor health, but poor health may be the cause, rather than the consequence, of substituting childcare for formal work. The direction of causality of relationships between health, formal labor market outcomes, and care provision is impossible to establish with cross sectional or even longitudinal data on family behavior (McGarry, 2006; Rupert & Zanella, 2014). By contrast, studying these relationships in the context of differing incentives provided by childcare subsidies represents an advance over previous work in that: 1) it focuses on a caregiving role driven in part by government policy, and 2) the policy provides a set of natural experiments, which allows for an examination of the causal

channels behind the relationships between caregiving, work, and well-being. However, this approach is not without its limitations. In particular, along with changes the tradeoffs in the budget constraint (leading grandmothers to substitute childcare for work) subsidizing childcare also shifts the budget constraint up, by increasing income at any given level of grandchild care. As a result, the policy has both an income and a substitution effect, which I am not be able to separately identify.

In addition to the social scientific value of determining relationships between care, income, and well-being, establishing the specific causal impact of *subsidized* grandparent-provided childcare on grandmothers is important for several reasons. State childcare subsidy policy, which targets lower-income working families, may have spillovers through the family to grandmothers - another vulnerable demographic. Women comprise the majority of caregivers, as well as the majority of the poor elderly in the US (GAO, 2008). Women 65 and older have on average less retirement income and have higher rates of poverty than men, and this disadvantage is due in part to the caregiving role they play over their lifetime (McGarry, 2006; Wakabayashi & Donato, 2006). Women are more likely to rely solely on Social Security as their primary source of income in retirement, and likewise make up the majority of elderly poor recipients of Supplemental Security Income (SSI) (GAO, 2008, 2012). Women nearing retirement age are also more likely to face age-based discrimination in hiring (Neumark, Burn, & Button 2015) and may have more difficulty entering the labor force after time out for caregiving.

If states direct federal block grant spending towards the use of grandparent care as a lower-cost alternative to formal care and thereby pull low-skilled women in their fifties and sixties out of the formal labor force (Wakabayashi & Donato, 2006), the federal government may end paying more money in the form of Supplemental Security Income (SSI) or Medicaid outlays

down the road. Additionally, state-determined childcare subsidy policy might be directly undermining federal initiatives to encourage older workers to postpone retirement. Quantifying these causal impacts is of policy importance, for understanding both how work and family policies impact older women's behavior and ability to finance their retirement, and how those behavioral changes translate to changes in costs at the state and federal level.

To address this topic, I use longitudinal survey data from the Health and Retirement Study (HRS) over the period 2006 to 2012 and match grandmothers to the childcare policy regime in their state. I calculate an expected value of the government payment that a grandmother would receive for grandchild care based on her family's characteristics using family information in the HRS. I model the government payment as a function of the characteristics of an HRS respondent's daughter - the working-age parent of the grandchildren who require care. Individual daughter income eligibility and grandmother outcomes may be correlated, so instead of using income, I assign subsidies based on daughter characteristics – age, education level, race, and marital status. To further abstract from state-level economic and demographic characteristics that may determine both program eligibility and grandmother outcomes, or that may be endogenous to state subsidy policy, I use a variation of a simulated instrument approach developed by Currie & Gruber (1996). Specifically, I draw a nationally representative random sample of working age mothers of each age, education level, race, and marital status and calculate average individual subsidies for this sample using each state's specific policy parameters while excluding from the sample those who reside in that specific state. Then I sum the average subsidy each daughter is eligible to give an informal provider to care for her children across all of a woman's daughters, to get the total predicted informal caregiver payment each HRS grandmother can receive if she cares for all her grandchildren under age 6.

Having assigned a predicted government payment for grandchild care for each grandmother in my sample, I exploit the wealth of information about respondents in the HRS to address in detail the relationship between caregiving, work and well-being. I model outcomes of interest as a function of the payment, and control for individual (grandmother level) characteristics as well as state fixed effects, year fixed effects, a fixed effect for daughter characteristics and number of grandchildren in care, and a state specific time trend. Because the object of interest is the overall impact of subsidized care on outcomes that are long-term and “sticky” in nature, I model cumulative level of subsidy over the length of the exposure period – i.e. as long as a grandmother has grandchildren under six.

Looking at mean effects, I find that a one standard deviation increase in annual payment (\$2,587, equivalent to an increased wage of \$1.29 per hour) results in an intent-to-treat (ITT) effect of 22 additional hours of care. Scaling this effect by the number of eligible families who actually receive subsidies (treatment-on-the-treated, or TOT effect), I find that a one standard deviation increase in annual payment increases caregiving by 79 hours, or 6.6 hours per week.

Given this finding, I next investigate the effects of this subsidized caregiving on grandmother economic and health outcomes. I find that a one standard deviation increase in predicted subsidy reduced individual earnings by \$333/year, with a TOT effect of \$1,189. This implies that the government transfer crowds out individual earnings at a rate of 2:1. In addition to earnings, I find that grandmothers reduce labor supply on both the intensive and the extensive margin. Grandmothers are 1.2 percentage points less likely to be working for pay, and reduce both weeks worked per year and the likelihood of working a 2nd job (TOT of 1.12 weeks and 1%, respectively). Consistent with the reduction in labor supply, a one standard deviation increase in annual payment induces grandmothers to start claiming Social Security over half a year earlier,

and to be 20% more likely to receive SSI (0.6 percentage point increase from a baseline of 3%). Additionally, as grandmothers substitute towards time transfers to their daughters by providing care, they substitute away from financial transfers within the family—a one-standard-deviation increase in payment leads to a \$307 decrease in annual transfers from grandmother to daughter, or approximately \$14 for each additional hour of care provided.

I find no effects of predicted payment on measures of household wealth or poverty status, implying that grandmothers are able to compensate for any loss of earnings due to changes in labor supply. In contrast to large literature documenting correlation between grandchild care and poor physical and mental outcomes for grandparents, I find that the increase in grandchild care has no impact on a wide range of health outcomes.

This analysis is the first to address the direct impact of childcare subsidies on grandmothers, and highlights a broader economic tradeoff implicit in government policy that subsidizes grandparent provided childcare. In sum, my results reveal that while relative care appears on the surface to be a low cost alternative to center care from the perspective of the state, there are significant hidden costs for the federal government, both short and long term. While there is no change in immediate grandmothers' well-being, their increased reliance on social insurance and early claiming of Social Security may impact their economic welfare later on. These translate to higher federal outlays down the road, while in the short-term, state subsidies purchase little additional care. In particular, \$2578 in subsidy payment can purchase about 2 months of full-time center care in the average state, while inducing an increase of less than 2 weeks of full-time grandma care.

The remainder of the paper proceeds as follows: Section 2 reviews several strands of literature that address the impacts of childcare subsidies on various outcomes, as well as the the

consequences of caregiving, Section 3 describes the policy context, Section 4 the data, and Section 5 the empirical strategy. Section 6 presents results and Section 7 concludes.

2 Literature

Evidence on the direct impact of childcare subsidies on increasing the labor supply of mothers is mixed. Focusing on the pre-PRWORA³ period, Meyer and Rosenbaum (2001) look at the effect of a mix of government programs enacted in the late 1980's through the mid 1990's on the labor force participation of single mothers and find that, relative to the Earned Income Tax Credit (EITC), childcare subsidies had a positive, but small impact. In the post-PRWORA landscape, Washbrook et al. (2011) find little to no effect of similar subsidies on mother's work participation. A possible explanation for these mixed results is that childcare subsidies are primarily taken up by women who already work, and therefore already use some form of childcare⁴. The subsidy instead affects childcare *mode*, because subsidies allow, and in some cases require, low income families to shift from informal and relative-based towards more formal and center-based care (Blau & Currie, 2004; Currie & Hotz, 2004; Havnes & Mogstad, 2011; Ho, 2015; Washbrook et al., 2011). In contrast to these studies, Meyers et al. (2002) find that actual receipt of (rather than just eligibility for) subsidies may raise mother's labor force participation by as much as twenty percent.

Existing studies using variation in child care subsidy policy to examine labor market outcomes focus primarily on maternal labor supply, ignoring the joint labor supply decision of the multigenerational family (Bainbridge, Meyers, & Waldfogel, 2003; Black et al., 2012; Felfe, Nollenberger, & Rodríguez-Planas, 2013; Meyer & Rosenbaum, 2001). A notable exception in

³ Personal Responsibility and Work Opportunity Act (PRWORA) Act of 1996

⁴ Havnes and Mogstad (2011) report a similar finding in the Norwegian context

the pre-PRWORA period is Blau and Robbins (1998), who propose a model of family labor supply and childcare choice where a family member besides the mother can provide informal care, and estimate the model using the Employment Opportunity Pilot baseline household survey. They conclude that both mothers' and other family members' labor supply is responsive to the market price of childcare, as is the mode of childcare chosen.

Blau and Robbins do not specify the identity of the other family member in their model, but there is evidence that grandparents often provide daily or weekly babysitting for their grandchildren. A recent report from the Census Bureau finds that 24 percent of children under five were regularly cared for by a grandparent in 2011 (Laughlin, 2013). In a recent example, Compton and Pollak (2014) find that women who live within 10 miles of their mothers or mothers-in-law are more likely to work and attribute this to the availability of grandparent provided childcare. While they recognize that both labor supply and location may be endogenous, their work illustrates the large role played by grandparents, and specifically grandmothers, as a source of childcare⁵.

Despite the evidence that grandchildren are a significant input into grandparent decision making, particularly around labor force participation and retirement decisions (Ho, 2013; Lumsdaine & Vermeer, 2015; Rupert & Zanella, 2014), the majority of the literature on childcare subsidies does not address in a meaningful way the decision by grandmothers to care for their grandchildren and the resulting impacts.⁶ One exception is Ho (2014) who uses a

⁵ The emphasis on grandmothers (vs grandfathers) as caregivers is also echoed in Compton (2013), and Wang & Marcotte (2007).

⁶ A largely separate literature has identified negative correlations between grandchild care and well-being among grandparents who are primary caregivers, with a particular focus on grandparent mental and emotional health (Blustein et al., 2004; Deaton & Stone, 2013; Wang & Marcotte, 2007).

difference-in-differences framework to show that the 1996 welfare reform led to a decrease in childcare provision and an increase in financial transfers by single grandmothers to their welfare-eligible single daughters with young children. She also finds an increase in non-childcare hours worked by grandmothers. Ho suggests that the expansion of childcare subsidies under the 1996 reform overall incentivized a net shift towards formal childcare, thereby driving her findings, but she is not able to directly identify this proposed mechanism. Furthermore, this result do not take into account the significant heterogeneity in childcare policies across states—only some of which encourage formal over family care—that may increase or decrease the frequency of grandparent-provided care arrangements. Looking at national averages in the presence of such heterogeneity masks important state level effects that can be used to shed light on the question of the effects of policy on intergenerational family behavior (Blau & Currie, 2004; Currie & Hotz, 2004; Snyder, Bernstein, & Adams, 2008).

Research addressing the relationship between caregiving and grandparent outcomes has difficulty identifying causal effects, because these outcomes may themselves also drive the decision to provide grandchild care. To my knowledge, no study has identified and exploited exogenous variation in grandparent-provided care to study the causal impact of providing such care on grandparent outcomes in either the short- or long-term. Furthermore, few empirical studies have focused on grandchild care among low-skilled older women, a group that is most likely to assume the role of caregiver and is also particularly vulnerable to the challenges of aging (McGarry, 2006; GAO, 2012).

A parallel line of research that addresses the relationship between work and caregiving in this age group focuses on caregiving to elderly parents (McGarry, 2006; Wakabayashi & Donato, 2006). Generally, studies in this literature are hampered by the same concerns of endogeneity

that face existing studies of childcare. Broadly, this literature concludes that elder caregiving, provided primarily by women, has little relationship with work status and labor market participation, and instead crowds out leisure time. However, using the HRS, Wakabayashi & Donato (2006) find that female caregivers have more intermittent job histories, are more likely to incur job loss and subsequent earnings loss, and have poor long-term economic and health outcomes.

Using state level policy variation as an instrument.

In my approach, I take advantage of the significant variation in childcare subsidy policies across states to identify outcomes of interest. Previous studies have taken advantage of other aspects of state-level heterogeneity in U.S. childcare policy. Specifically, Currie and Hotz (2004) have measured the relationship between childcare regulations and incidence of childhood accidents by using state-level variation in the regulation of childcare centers between 1987-1998. They find that while educational requirements for day care center directors reduce the incidence of unintentional injuries, they also crowd some children out of formal care (Currie & Hotz, 2004). Washbrook et al. (2011) exploit variation in childcare subsidies' work exemptions and overall levels of generosity (as measured by state and federal expenditures), and look at maternal labor supply as an outcome. They find few effects of these policy variables on maternal labor supply, but note that neither of their measures of state-level variation is very precise.

In sum, significant gaps in the literature remain. Much of the existing work on subsidies and labor supply considers only maternal, and not other family members', labor supply. Studies that look at grandparent outcomes focus mostly on grandparents who are primary guardians, and do not address the endogeneity of grandparent-provided care. Finally, most of these studies focus on the mid 1990's and early 2000's. My approach will study a more recent time period and will

use state-level heterogeneity to identify the causal effects of a policy that subsidizes grandchild care on grandparent outcomes. I will address both the direct impact of such childcare on grandparents, as well as study the broader economic tradeoff implicit in government policy that subsidizes grandparent-provided childcare.

3 Policy Context

The current childcare subsidy regime was put into place as part of the Personal Responsibility and Work Opportunity Reconciliation Act (PRWORA) of 1996. The reform consolidated and expanded 4 separate smaller programs into a Child Care and Development Fund (CCDF) block grant. The CCDF allows states to serve families with incomes earning up to 85% of state median income (although many set the eligibility thresholds much lower), with children under 12 whose parents are working or in school. States may also put up to 30% of their Temporary Assistance for Needy Families (TANF) block grant towards childcare subsidies, and many states use additional funding to subsidize childcare through vouchers (Washbrook et al., 2011), although many states have also cut back such additional funding in recent years. There is therefore wide variation by state and year in the level of funding for subsidies. In addition, the block grant structure gives states near-total freedom to determine reimbursement rates, parent copayments, eligibility requirements, provider and facility certification requirements, and more, which results in significant variation in multiple dimensions across states (Currie, 2008). “Thus, while CCDF is a single program from the perspective of federal law, it is in practice a different program in every State and Territory” (Giannarelli et al., 2012).

These differences reflect a tradeoff between the somewhat conflicting goals of government subsidization of childcare – specifically, maternal employment versus child development (Fuller et al., 2002). For example, if the budget-constrained goal of a state is to

improve kindergarten readiness, that state will likely structure subsidies so as to shift parental choice towards formal care, particularly by accredited centers. By contrast, if the budget-constrained goal of a state is to maximize maternal employment, that state will likely structure subsidies so as to shift parental choice towards the lowest cost providers, e.g., grandmothers. One thing this calculation misses, however, is the potential hidden cost, both public and private, of this policy choice for grandmothers.

3.1 Specific Policy Parameters Used in the Analysis

Childcare subsidy policy is complex and multidimensional. States determine not only prices and eligibility cutoffs but also who can provide subsidized care, quality regulation, what information families must provide to obtain and maintain a subsidy, and how frequently they must update that information. Undoubtedly, all aspects of policy determine families' decision-making about childcare and their interaction with the subsidy system (Medeiros & Ananat 2015). Because subsidy receipt per se is endogenous to family characteristics,⁷ I focus instead on predicted eligibility and the predicted dollar value of the benefit. In this section, I provide more detail on the three policy components that enter directly into my analysis: eligibility rates, reimbursement rates, and family copays.

3.1.1 Eligibility

Subsidized childcare is a means-tested federal program. Federal law mandates that states set the maximum allowable family income limit at 85% of state median income.⁸ However, states are free to set eligibility thresholds below that limit, and in practice, income eligibility limits vary a

⁸ With the exceptions of Rhode Island and Nebraska, eligibility for childcare assistance does not depend on asset tests.

great deal by state. For example, in 2013, the income threshold for a family of three ranged from \$1,545 per month in Kentucky to \$4,915 per month in North Dakota (Minton, Durham, and Giannarelli 2014). Figure 1 presents maximum state eligibility cutoffs for a three-person family in 2012. Cutoffs can vary dramatically even between states with similar income distributions, such as Alabama and Mississippi, Wisconsin and Iowa, and Nebraska and Kansas.

3.1.2 Reimbursement rates

Reimbursement rates are determined at the state (or county) level and apply to all subsidy beneficiaries. While copayments are based on family characteristics, reimbursement rates depend only on the mode of childcare used and the age of children in care. As with eligibility rates, federal guidelines provide broad parameters within which states have significant leeway. In particular, states are required to set center reimbursement rates using a market rate survey, which establishes the range of the cost of childcare within a specific geographic area at a particular time. Center reimbursement rates can range from the 3rd to the 75th percentile of the market rate, depending on region (Schulman and Blank 2004).

Because no market rate surveys exist for legally unregulated informal providers, which include relatives in all states that reimburse for relative care, there are no guidelines for how to set the rates for relative-provided care. These rates may be set as a percentage of the center rate, may follow state minimum wage laws as in Indiana, or may follow their own schedule. Figure 2 presents the reimbursement rate for center care and relative care between 2006 and 2012 for a family with two children in care in California, Illinois, Indiana, Louisiana, New Hampshire, and Ohio.

3.1.3 Family Copay

Families are usually required to cover a share of childcare costs in the form of a family

copayment. The structure of copayments varies by state, but is always a function of family income and family size. The copayment may be: per child or set at the family level regardless of the number of children in care; it may be a percentage of the childcare costs, a percentage of family income, or a flat dollar amount that rises stepwise with family income; it may have a minimum of \$0, or there might be an expected contribution even for families with no income. For example, the monthly copay for a three-person family with a monthly income of around \$1,250 would range between \$0 and \$414 in 2013, depending on state of residence (Minton, Durham, and Giannarelli 2014).

Figure 3 presents the family copay calculator in 2010 as it applies to a single woman with two children in care, along with the relative reimbursement rate, for a subset of states. The horizontal axis is annual family income, and the vertical axis is monthly income. The vertical dashed line is at \$20,000, which is about the federal poverty rate.

4 Data

Measuring the effects of childcare subsidies on grandmothers requires a dataset containing information about three generations of family members (grandmothers, daughters, and grandchildren), grandmother economic and health information, as well as daughter subsidy take-up and childcare outcomes. No existing nationally representative dataset contains this level of information for the US population. The Health and Retirement Study (HRS) is a nationally representative, biannual, longitudinal survey of Americans over 50 that collects a wealth of information about labor force participation, income and assets, family transfers, co-residence patterns, and various health metrics, and as such is well-suited to look at grandmother outcomes. The HRS also collects detailed information about respondents' family members, as well as interfamily transfers, including, crucially, the total hours of time transfers, including childcare,

between respondents and their children. This allows me to determine the payment a grandmother would receive for taking care of her grandchildren based on her daughters' characteristics. The longitudinal nature of the HRS allows me to focus on both short- and long-term outcomes, and to construct a more complete picture of grandmothers' outside options.

To conduct my analysis, I create a unique dataset that matches respondents from the HRS with the relevant childcare subsidy policy in their state of residence. Information about childcare subsidies comes from the Child Care and Development Fund (CCDF) Policies Database, a detailed and up-to-date database that captures the intricacies of individual state policy created and maintained by the Urban Institute. The database includes information about multiple dimensions of state policy, focusing on administration, rules and regulations. Information is organized topically into 32 separate data sets (Giannarelli et al., 2012). The CCDF database indexes and standardizes a large amount of information, making it possible to compare childcare regimes across states and time periods.

Additionally, I use the Administration for Children and Families' (ACF) CCDF Administrative Database, which compiles case-level data reported monthly to the ACF by states and territories, as required by the Personal Responsibility and Work Opportunity Act of 1996. This dataset reports the monthly counts of families who receive subsidy services in each state, which I use to calculate rates of subsidy receipt.

4.1 Sample Selection

My population of interest is women with grandchildren under the age of six from biological, adopted, or step-daughters. I focus only on grandchildren from daughters because subsidy eligibility and the level of payment is based on the circumstances of the mother of the grandchild, and I cannot observe the characteristics of the mothers of grandchildren from sons

unless the son is married to or living in the same household as the child's mother (a highly selected group). I focus on grandchildren under six because school-age children (six and over) will not, in most cases, require continuous full-time care. I leverage the longitudinal nature of the HRS and select an (unbalanced) panel of grandmothers who appear in the survey between 2006 and 2012.⁹ I use female respondents with daughters between the ages of 18 and 50 with at least one child under the age of six at the first wave interview.¹⁰ I drop any wave in which the respondent interview was conducted by proxy, and I drop grandmothers who ever reported being the primary guardian for a grandchild. I also drop observations for which I am missing any daughter demographic information necessary to match to subsidy parameters. My final sample consists of 4,658 grandmother-year observations. Table 1, Panel 1, Columns 1 and 2 report descriptive statistics for the full sample. Grandmothers in this sample are on average 64 years old, 70% white, and just over 52% have less than a high school education. They have an average household income of about \$60,000 and household wealth of just over \$386,000. Median household wealth is nearly \$180,000.

Not all grandmothers in this sample have daughters that will be eligible for childcare subsidies, and so this sample may not be representative of grandmothers who may be eligible for subsidies. Columns 3 and 4 of Table 1 report descriptive statistics for the sample of grandmothers with daughters who are eligible¹¹ for a positive level of subsidy. This subsample consists of 3,323 grandmother-year observations, or about 70% of the full sample. Grandmothers

⁹ The earliest CCDF information that I have is for 2002, but that includes subsidy data for only a few states. Most of the identifying variation in payments used in this paper comes from 2008-2012.

¹⁰ As the outcomes I am interested in are long-term and "sticky," I include grandmothers in the sample even after their grandchildren have aged out of the 0-6 age range.

¹¹ How the daughter subsidy level is determined is described in the next section.

in this subsample do not appear significantly different from the full sample. Notably, there is no difference in mean household income or wealth. Mean household wealth is 29% lower in the restricted sample.

4.2 Grandmother variables

4.2.1 Grandchildren

I focus my analysis on care for grandchildren under six, because school aged children are in school during the day and do not require continuous care. While the HRS contains a wealth of information about respondents' family members, it does not report the ages of individual grandchildren. Respondents are asked, at every survey wave, if they had any new grandchildren since the previous wave. To approximate the number of grandchildren under six, I calculate the number of new grandchildren reported for up to 6 years prior to the current interview (3 waves). For example, for respondents in 2008 I add up the number of new grandchildren they report in 2008, 2006 and 2004 to approximate the number of grandchildren under 6 they have. I assume that all new grandchildren arrive at age zero, rather than being adopted at an older age. Critically, I can also link grandchildren to their mothers. Because the subsidy is determined at the parent level, this allows me to precisely estimate the predicted payment a grandmother can receive for providing care to all of her grandchildren.

The HRS panel of respondents was updated with a new cohort in 2004 and again in 2010. For new respondents in those waves, I do not have previous waves with which to estimate the number of grandchildren under six. Thus, with the current approach, I undercount the number of grandchildren under six respondents have and the payment the grandmother can receive; this should lead to attenuation bias in my estimates. Table 1 reports sample statistics for number of grandchildren. Grandmothers in this sample have on average 6 grandchildren and 1.2

grandchildren under six from on average one daughter.

4.2.2 Quantity of grandchild care provided

My measure of caregiving is the answer to the question “*Did you ... spend 100 or more hours in total (in the last two years) taking care of grand or great grandchildren?*” and to the follow-up question about how many hours precisely, if over 100¹². The distribution of grandchild care is therefore left censored at 100 hours. For this reason, I can only measure changes in grandchild care at the intensive margin – i.e. whether higher subsidies result in more hours of care, rather than the extensive margin – i.e. whether subsidies encourage grandmothers to start providing care.

Although I cannot observe the extensive margin for the decision to provide any care - this is not likely to be a meaningful margin in the context of a subsidy targeted to supporting maternal employment. More relevant in the context of this policy is the margin at which a grandparent might provide a “substantial” amount of care. For example, the 100 hour per 2 years’ margin in the HRS questionnaire structure translates to about ½ of an hour per week. Similarly, 500, 1000 and 2000 hour cutoffs translate to 5, 10 and 20 hours per week over 2 years, respectively. Table 1 reports sample statistics for hours of childcare reported in the HRS. In the full sample, 44% providing grandchild care in excess of 100 hours over the last two years. Grandmothers who report providing more than 100 hours of care provided about 800 hours of care, or about 8 hours per week.

4.3 Policy variables

The wealth of information available in the CCDF datasets allows me to leverage several

¹² If respondents do not give the number of hours directly, they are prompted to give a range of hours. In these cases, I impute a direct value by drawing randomly from the distribution of directly reported hours that fall within the reported range.

dimensions of child care policy, and in particular to exploit within-state variation based on family characteristics. Unlike previous studies that use state and even national subsidy levels (Ho, 2013), I am able to predict a precise value of the potential government payment for providing childcare for every grandmother in the HRS sample.

The value of the payment is determined by the daughter's characteristics – i.e., the characteristics of the working parent who qualifies for the childcare subsidy. HRS contains extensive information on daughter characteristics, including income and family composition, all of which are reported by the grandmother. One concern is that grandmother-reported daughter's income may be imprecise and subject to significant measurement error. Furthermore, even without error, individual income may be endogenous to childcare subsidy program rules. Instead, I assign a predicted subsidy to each of a grandmother's daughters based on average subsidies for demographically similar women, and then sum them to determine the payment that a grandmother is predicted to be eligible to receive in each period if she cares for all her daughters' children under age 6. Demographically similar women in the same state, however, are subject to the same program rules and thus the same endogeneity concerns. I address this by employing a strategy derived from the simulated instrument approach developed by Currie and Gruber (1996) to study the impact of states' Medicaid expansion on children's health in the mid 1990's. In their approach, Currie and Gruber instrument for actual Medicaid eligibility with the fraction of children from a nationally representative sample of demographically similar children who would be eligible under each state's policy rules. The simulated instrument addresses bias that arises from the correlation between individual eligibility and outcomes that would be mirrored at the demographic group level within the same state.

Because I do not observe actual daughter eligibility, I cannot replicate the first stage of

their procedure. Instead, I conduct a simpler procedure. To predict each daughter's potential subsidy, I select a sample from the American Community Survey (ACS) of women age 18 to 50 who have at least one child under the age of 6. For each state, I calculated directly the level of subsidy for the sample using the state specific rules, based on their income and family size, omitting residents of that state. I then calculate the average subsidy for women in 144 different age, education, race, and household composition categories by state and year. This approach allows me to address any omitted variable bias arising from state specific factors that may be correlated with both a demographic group's eligibility for subsidy and the outcomes of the group's mothers.

Using the corresponding daughter information in the HRS (age, education level, race, marital status) I create the same 144 family profiles in the HRS sample and assign each HRS respondent's daughter the average subsidy in her state and year based on the grandmother's report of her characteristics¹³. The components of the family profile are also grandmother-reported in the HRS, but they are likely less prone to measurement error than family income. Below I describe more precisely how I calculate each component of the subsidy and grandmother payment.

4.3.1 Reimbursement rate

The reimbursement rate is reported per child and depends on age in months, as well as the type of provider and hours of care. In my analysis I use the lowest reimbursed legally unregulated informal in-home rate to capture what a state is likely to pay a grandmother for providing care. In some states, a rate is explicitly identified as applicable for care provided by

¹³ A note on dimensionality: policy information is at the quarterly level, ACS is at the yearly level and HRS is biannual. I create weighted average values of the predicted subsidy over each 2-year increment.

relatives or neighbors.

To obtain average monthly reimbursement rates for a family, I again use the ACS to calculate the typical age distribution in months of children in four family groups: families with one child under six, with two children under six, with three children under six, and with four children under six. Using these typical profiles, I calculate reimbursement rate for each of the family types, using the corresponding age distribution at the state-year level, by provider type. Rates are reported in hourly, daily, weekly or monthly, for full-time or part-time care, which varies by state. I standardize by coding the monthly rate for full-time care for each state. If the state does not report monthly reimbursement rates, I scale up the weekly, daily, or hourly full-time rate, assuming that full-time care is 40 hours per week.

4.3.2 Parent Copayments

In most cases, families who receive subsidies have to pay for some amount of the child care costs out of pocket. Parent copayment determination varies state by state, but is always a function of family income and family size. The copayment may be per child, or determined at the family level regardless of the number of children in care; it may be a percentage of the child care costs, a percentage of family income, or a flat dollar amount that increases stepwise with family income. Some states impose a minimum copayment, while others allow a copayment of zero for very low-income families. I calculate a monthly family copayment directly for each family in the ACS sample using reported income and family size. In states where the copay is calculated as a percentage of childcare costs, I approximate the cost of center provision by using the highest reimbursed center rate and the costs of informal care by the informal reimbursement rate.

5 Identification & Empirical Strategy

5.1 Parameterization of childcare subsidy policy

In this section, I describe how I parameterize the aspects of the policy described in the previous section into a single value for each HRS grandmother. Recall that the subsidy consists of two components: the reimbursement rate and the parent copay. As described above, a provider is responsible for collecting the parent copay directly from the family. When families have copay responsibilities, the state pays a provider the full reimbursement amount less the mandated family payment. When families choose center care, the cost of their childcare is the parent copayment they have to pay to the center. When families choose relative care they similarly are responsible for compensating the provider the copayment amount.

A key assumption I make is that when care is provided by a grandmother, she does not actually receive the portion of the childcare subsidy that is the parent copayment for which the family is responsible. The predicted payment for grandchild care is then the reimbursement rate less the statutory parent copayment, because that is what the state will actually pay the grandmother. While the reimbursement rate varies by state and year and number of children, the parent copayment also varies within state and year by family income and family size, generating a significant amount of within-state variation in copay amount in a given year, as well as between-state variation in copay amount for similarly situated families.

Modelling the net payment received by grandmothers in this way has both a theoretical and empirical basis. First, in the unitary household model (Becker, 2009) any financial transfers between family members do not change the pooled family budget constraint. Second, a case study of legally unregulated informal providers in the US provides qualitative evidence that

grandmothers who provide subsidized grandchild care do not collect the parent copayment from their daughters (Snyder et al., 2008).

I model the cost of market-based child care faced by the family as the parent copayment for center care based on the daughter's income and family size. For families who are above the state's eligibility cut off for receiving subsidies, the cost of market-based care is the state's highest reimbursement for center care. The subsidy for grandma care is the predicted payment which is the state reimbursement rate for relative care, less the mandated parent copayment.

To construct the predicted grandmother payment, I select a nationally representative sample from the ACS of women age 18-50 with at least 1 child under six. For each state, I calculated directly the level of subsidy for the sample using the state specific rules, based on their income and family size, omitting residents of that state. Specifically, I predict each mother i 's subsidy as a function of her family income, family size, and number of children under age 6, and year:

$$subsidy_i = f_{st}(income_i, family\ size_i, number\ of\ children\ under\ age\ 6_i)$$

The subsidy is calculated differently in every state, and also sometimes differently within a state in different years, which is captured by the subscript on f . I calculate a separate net subsidy for the number of kids under 6, so each mother has 4 values : $subsidy_{\{i,K=k\}}$, where $k \in \{1,2,3,4\}$. Note that $subsidy_i$ is usually nonlinear function of family size and income. Several states compute the family copay as a percent of income, in which case the relationship between income and copay is linear, but most use a step function or a more complex calculation. Furthermore, the copay is not a linear function of the number of children under six in care. In some states parent

copays are determined per child and so total net subsidy is the per-child net subsidy times the number of children in care, while in other states parent copays are determined per family and are either flat with number of children in care or rise less than one-for-one. Additionally, recall that reimbursement rates vary by the age distribution of children in care, and this variation differs by state and over time, which is an additional source of nonlinearity.

Using the ACS sample to predict subsidy value has several advantages over imputing subsidies directly for the daughters of grandmothers in HRS. First, I am able to abstract from family level omitted variables that may be correlated with both subsidy receipt and my outcomes of interest. However, there may still be omitted variables at the state level that jointly determine both eligibility and outcomes. To address this, I adopt a “simulated instrument” approach as in Currie and Gruber (1996) and generate the individual subsidy in each state and year using the sample of mothers in the remaining 49 states. This way, I am able to generate a variable based solely on the administrative aspects of state policy, rather than on the economic or demographic characteristics of the state that might be correlated with policy choices or based on endogenous behavioral responses by families toward their state’s policy.

Having simulated a range of individual subsidy values for every state, I calculate an average subsidy for 144 separate demographic cells within a state and year. These cells are determined by the following mother characteristics: age in 6 categories, education level in 4 categories, race in 3 categories, and marital status. As before, I calculate a separate subsidy amount by number of children under 6. An average cell subsidy is simply an unweighted average of individual subsidies of all the members of the cell:

$$\overline{CellSubsidy}_{f,k} = \frac{1}{N} \sum_{i \in cell} Subsidy_{i,k}, \quad i \in \{age = a; race = r; ed = e; marstat = m\}$$

The average cell subsidy is therefore a highly non-linear function of the cell characteristics.

Next, I match average cell subsidies to the HRS grandmother-daughter sample using cell characteristics. In the HRS, I am able to identify to which cell each daughter belongs, given her age, race, education level and marital status. For state, I use the state in which the grandmother resides when she first enters the study. I match each HRS daughter with her cell average subsidy and the number of kids under six she has:

$$Subsidy_{fk} = \overline{CellSubsidy}_{fk}$$

Finally, the predicted payment to an HRS grandmother depends on the number of daughters with children under six she has, as well as each daughter's individual characteristics. As the predicted subsidy is determined at each individual daughter level, the net potential payment to grandma is the sum of each of her individual daughters' predicted subsidy amounts (there is no legal limitation on the total subsidy an informal provider can receive, nor on the total number of related children who can be cared for by an informal provider.)

$$\widehat{Payment}_i = \sum_{d=1}^D Subsidy_{fk}$$

where D indexes the daughters. For example, a grandmother with two daughters who each have a child under six will have a predicted payment which is the sum of the two daughters' cell average subsidies.

The average predicted net payment for a grandmother in this sample, reported in Table 1 is about \$126 per month, or \$1,508 annually. This payment includes grandmothers who are predicted to be eligible for a zero payment, either because their daughters are predicted to be ineligible due to high income or because they live in a state that does not reimburse legally

unregulated informal childcare providers. The predicted payment conditional on receiving a positive subsidy is \$175 per month, or \$2,102 annually.

5.2 Pseudo first stage

Evaluating the strength of the simulated instrument in predicting the level of subsidy that a grandmother can receive for providing grandchild care would require a nationally representative dataset with information on all three generations, including precise hours of grandchild care provided and the dollar amount that grandmothers receive for the care. To my knowledge, no such dataset exists. The Annual Social and Economic (ASEC) Supplement to the Current Population Survey (CPS) included a question about receiving federal childcare assistance until 2009. Using this dataset, I draw a sample of mothers age 18-50 with at least one child under six, and I generate a predicted eligibility for childcare assistance based on CCDF rules using the same simulated approach that I describe in the previous section. I also create the corresponding 144 daughter demographic types.

This approach allows me to estimate how well my simulated instrument approach predicts *receipt* of childcare assistance. To do this, I estimate the following first stage specification:

$$Share\ Recieve_{fst} = D\widehat{Eligible}_{fst} + \lambda_t + \gamma_s + \varepsilon_{fst} \quad (1)$$

where the dependent variable is the share of mothers in the demographic cell who report receiving federal childcare assistance in the CPS, $\widehat{Eligible}_{fst}$ is the share of mothers in the demographic cell who I predict to be eligible for federal childcare assistance using the simulated instrument approach, λ_t is a year fixed effect, γ_s is a state fixed effects, and ε_{fst} is a demographic cell-level error term. Standard errors are clustered at the state level.

Table 2 reports results from this specification. Column 1 reports estimates from Equation

1 without state- and year-fixed effects, and Column 2 reports results from the complete specification. Predicted eligibility is a strong and robust predictor of subsidy receipt, which suggests that the simulated instrument approach is valid. A 1% increase in share eligible translates to a .054 percentage point increase in share who receive subsidies, over a base rate of 2%. This result remains virtually unchanged when I include state- and year-fixed effects.

5.3 Estimating Equation

The treatment variable $\widehat{Payment}_t$ is a continuous scalar that is the output of a multidimensional non-linear treatment function whose inputs are: characteristics and number of individual daughters, number of each daughter's children,¹⁴ state, and year. My estimation strategy exploits three sources of variation in subsidy: differences in payment across years, across states and across families within a state.

To measure the effect of this treatment on grandmothers, I estimate the following model:

$$y_{ifgst} = D\widehat{Payment}_t + \beta X_i + \gamma_s + \lambda_t + \gamma_s \times YEAR + \xi_{fi\ st\ i \in \{1..D\}} + \eta_g + \varepsilon_{ifgst} \quad (2)$$

Here y_{ifgst} denotes the outcome of interest for grandmother i with family type f with g grandchildren under six in state s and year t , while γ_s and λ_t are individual indicators for state and year which capture time-invariant state characteristics as well as annual shocks that affect all observations in a year. I also include $\gamma_s \times YEAR$, which is a state-specific linear time trend, to control for average trends at the state level. ξ_{fi} is an indicator for daughter cell for each of D daughters. This controls non-parametrically for family characteristics, which may be correlated

¹⁴ For example, in states where the copay rises less than one-for-one with each child, the net subsidy to a grandma from having 2 grandkids from 1 daughter and 1 grandkid from another daughter is smaller than the net subsidy from having 3 grandkids from 1 daughter, even if the daughters have the exact same characteristics.

with subsidy level and grandmother outcomes. X_i is a vector of grandmother-specific controls, and η_g is an indicator for the number of grandchildren under six. The key identifying assumption in the framework is that subsidy level is “as good as randomly assigned” conditional on covariates and fixed effects. If this identifying assumption is correct, the coefficient of interest, D , identifies the effect on a grandmother of a one standard deviation increase in the average payment for full time grandchild care over the last two years.

A potential concern with the specification in Equation 2 is that sharp deviations from state trends that may affect both childcare subsidy budgets and family-level outcomes may introduce bias into the estimates. Therefore, I also estimate a model that includes state-by-year fixed effects:

$$y_{ifgst} = D\widehat{Payment}_i + \beta X_i + \gamma_s + \lambda_t + \gamma_s \lambda_t + \xi_{fist i \in \{1..D\}} + \eta_g + \varepsilon_{ifgst} \quad (3)$$

This specification is identified off differences in year-by-year policy changes within states and across different family profiles.

The outcomes in which I am interested, including grandchild care, labor force participation, retirement security, and health, are cumulative and sticky in nature. Therefore, I measure the impact of subsidy levels over the entire period that a grandmother is “at risk” for qualifying for subsidies – i.e. as long as she has grandchildren under six¹⁵. To estimate this dose effect, my variable of interest is the running sum of the average subsidy for as long as she has grandchildren under six in the panel. Further, I want to examine her cumulative and current outcomes even after her grandchildren age out of subsidized care.

¹⁵ Additionally, I do not know precisely when the HRS survey was conducted with each individual, nor do I know at which point a new grandchild arrived. Thus, my preferred specification looks at the overall impact of the subsidy over the entire exposure period.

6 Results

6.1 Effects on child care provision

The first outcome I explore is how the generosity of childcare subsidies influence grandmother's likelihood of providing grandchild care.¹⁶ I am interested in both the effect of exposure to a childcare subsidy on the total amount of childcare provided while a grandmother is "at risk" for providing such care, i.e., when her grandchildren are aged 0- 6, as well as any effects on subsequent care. Thus, my outcome of interest is the natural log of the cumulative hours of care over the exposure period. The coefficient of interest, D , should be interpreted as the percent increase in childcare hours generated by a one standard deviation increase in the predicted annual payment.

Table 3 reports results from an ordinary least squares (OLS) regression (Equation 2) of cumulative subsidy on log cumulative childcare hours. Even columns report results for only for "at-risk" grandmothers – i.e., grandmothers who currently have grandchildren under six, while odd columns include all grandmothers. Columns 1 and 2 include all grandmothers, while columns 3-6 restrict the sample to grandmothers whose daughters collectively have a 25% and 50% likelihood of being eligible for childcare assistance. Each column includes the full set of controls indicated in the previous section. All coefficients are reported as the effect of one standard deviation increase in annual payment, which is \$2,537 annually or \$215 monthly.

For the unrestricted sample, I find that a one standard deviation increase in the predicted annual payment for full-time care increases total number of hours provided by 4.2 percentage points from a base rate of 515.2 hours, or about 21.7 hours per year. This effect is somewhat

¹⁶ For grandmothers who indicate that they provided less than 100 hours of childcare over the last 2 years, I assign a value of 50 hours. Results are not sensitive to other choices of minimum value. Results available upon request.

larger for grandmothers who currently have grandchildren under six (column 2), although this sample has a lower base rate. A one standard deviation increase in predicted payment increases total number of hours by 4.7 percentage points, or 23.3 hours per year.

There is substantial evidence that a majority of families eligible for subsidies do not receive them.¹⁷ An effect size of 4.2 percentage points should then be interpreted as an ITT effect – the average treatment effect for all families based on their eligibility, regardless of whether they actually receive a subsidy. To estimate a “treatment on the treated” (TOT) effect, this coefficient should be adjusted by the rate of eligible families who actually receive subsidies. I calculate the national average rate of subsidy receipt for eligible families with at least one child under six over the time period in question to be 28%,¹⁸ which is within the range calculated by others (Witte and Queralt 2002; Currie 2004). Using this average, the TOT effect of a one standard deviation increase in the predicted annual payment for grandchild care increases the annual hours of care provided by 77.5 hours. This translates to a monthly effect of 6.6 hours for just over \$200 additional dollars. For the “at risk” sample, the effect is just over 7% larger. Panel 2 of Table 3 reports the monthly TOT effects with a 95% confidence interval. Effect sizes are somewhat stronger for the subsamples restricted by eligibility; however, as average hours of care decreases as eligibility increases, average effects remain constant.

6.2 Effect Heterogeneity

Grandmothers’ responsiveness to financial incentives for providing grandchild care depends on many factors. The direction and magnitude of this heterogeneity is an empirical question. For example, younger grandmothers may be more responsive because they have greater physical

¹⁷ The primary reason for this is that states with more generous eligibility cutoffs have many more eligible families than funds to serve them, resulting in waiting lists.

¹⁸ Calculations available upon request.

capacity for caregiving but may also have more lucrative outside options. In this section, I consider how the caregiving response varies by grandmother characteristics.

Table 4 reports results from Equation 3 on subsamples split by grandmother characteristics. The treatment effect for white grandmothers is about twice as large as the effect for black or Hispanic grandmothers (Columns 1-3). While grandmothers increase their care by nearly 10 hours per month for a \$200 increase in subsidy. Hispanic grandmothers are less responsive, providing an additional four hours of care monthly. This effect is similar in magnitude for black grandmothers but not precisely estimated. This suggests that Hispanic grandmothers may already be providing the maximum hours of grandchild care without the subsidy. However, Hispanic grandmothers also have the lowest average cumulative hours of care. They provide about 30% less care than white grandmothers do.

The effect size does not vary by grandmother marital status (Table 4, Columns 4 and 5).¹⁹ However, married grandmothers provide more care on average than unmarried grandmothers do. Looking at grandmother age, grandmothers younger than 65 have a stronger response to financial incentives than grandmothers over 65 have. As reported in Column 6, Panel 2, of Table 4, grandmothers under 65 provide 8.22 additional hours of care per month in response to more generous payments, almost twice as much as grandmothers 65 and over. While average hours of caregiving does not vary by grandmother education, grandmothers with no college education are much more responsive to financial incentives for caregiving than grandmothers with at least some college education. Columns 8 and 9 of Table 4 report caregiving results by grandmother education status. Grandmothers with no college education provided nearly seven additional hours of care per month, while the effect for grandmothers with some college education is

¹⁹ Marital status is measure at the first wave that a grandmother is observed in the HRS.

smaller and not precisely estimated.

One significant factor in grandmothers' responsiveness to financial incentives for caregiving had to do with geographic proximity. Grandmothers cannot care for children who do not live within a reasonable distance. Daughter location is not available in the restricted HRS dataset. However, there is a variable in the constructed data that records whether a daughter lives within a 10-mile radius of her mother. Using this variable, in columns 10 and 11 of Table 4, I split the sample by distance to at least one grandchild. Grandmothers who live within 10 miles of a grandchild increase hours of care by over 5%, providing nearly 11 additional hours of care per month for a \$200 increase in subsidy payment.²⁰ While grandmother location is undoubtedly endogenous to caregiving and possibly to the subsidy generosity, the fact that this result moves in the expected direction serves as a robustness check to the empirical strategy.

6.2.1 Alternative specifications

In this section, I consider several alternative specifications of the empirical approach. Table 5 reports the main caregiving results using Equation 3, which includes a more restrictive state-by-year fixed effect. Column 1 reports results for the full sample, while column 2 reports results for the sample of "at-risk" grandmothers only. These results are nearly indistinguishable from the main results in Table 2, which suggests that the identifying variation does not come from sharp deviations within states that may be correlated with grandmother caregiving outcomes.

6.3 Earnings and labor supply

Given these findings on the effect of subsidies on caregiving, I explore the effect of more generous payment rates for childcare care on several determinants of grandmothers' retirement security. In this section, I look at the effects on earnings and labor supply. Current earnings and

²⁰ This does not include co-resident grandchildren, which will be addressed in the next chapter.

labor force participation are an important predictor of future economic security, including future Social Security payments, especially for older workers.

Results on earnings and labor supply are reported in Table 7. OLS results of the estimating equation on earnings are reported in column 1. More generous grandmother payments reduce grandmother earnings. A one standard deviation (\$2589) increase in predicted annual payment reduces grandmother earnings by \$334 per year. The TOT effect is about \$1,189 per year. This implies that every \$2 increase in government payment reduces individual earnings by \$1.

This reduction in earnings could reflect a labor supply reduction at either the extensive margin (dropping out of the labor force to take care of grandchildren) or the intensive margin (reducing working hours), and there is evidence of both effects in response to more generous subsidies. Table 7 reports OLS estimates of the effect of Equation 2 on the likelihood of working for pay, the likelihood of working a second job, and the number of weeks worked per year (columns 2-4). At the extensive margin, a one standard deviation increase in annual government payment for childcare reduces the likelihood that grandmothers are working for pay by .55 percentage points from a base rate of 40%. This translates to a TOT effect of 1.2 percentage points. At the intensive margin, grandmothers reduce the likelihood of working a second job (TOT effect of 1 percentage point over a baseline of 3.7 percent) and reduce weeks worked per year (TOT of 1.2 weeks per year).

6.4 Intergenerational Transfers

In this section, I present evidence on the impact of more generous payments for childcare on intergenerational transfers within the family. The results of the previous section suggest that the value of a government transfer will compensate a grandmother for about half of her forgone

earnings. Ho (2013) posits that expanding access to subsidized formal childcare post welfare reform led many families to move from informal to center care, and that as a result single grandmothers substituted transfer of time in the form of childcare with a financial transfer. I find that this substitution effect holds in the opposite direction as well: grandmothers substitute away from financial transfers when they increase their caregiving in response to more generous payments from the government.

Results from OLS regression of the estimating equation on net cumulative financial transfers are reported in reported in Table 8. To get a measure of net financial transfers between grandmothers and their children, I subtract financial transfer from children to parents from financial transfers in the other direction. The dependent variable in this model is net financial transfers over the exposure period. I find that for a one standard deviation increase in the annual level of government payment reduced financial transfers from from grandmothers to their daughters by \$307. The TOT estimate is \$1,096/ per year or \$91 per month. Given that they are providing an additional 6.3 hours of care monthly, this implies that grandmothers charge their daughters about \$14.4 / hour on top of the government payment they are receiving.

Overall, the results on transfers, coupled with those from the previous section on work outcomes, suggest that subsidized childcare crowds out intergenerational transfers, grandmother labor supply and earnings. However, the net effects on grandmother retirement security are not immediately clear, and may differ in the short- and long-term. If grandmothers are able to replace the lost earnings through a combination of the compensation for care, a reduction in financial transfers to her children and other means, the immediate impact on grandmother economic welfare may not be negative. In fact, if grandmothers are substituting grandchild care for unsatisfying jobs, they may well be better off in the short-term. However, if reducing formal

labor supply weakens their later security through reduced savings, Social Security, or pension benefits, the long term impacts of the policy may be unambiguously negative. In the next section, I provide evidence on grandmother's welfare in the short-term and behavior that may impact their welfare in the long-term.

6.5 Wealth and and Social Security

Columns 1&2 of 9 report the results of OLS regressions of payments for grandchild care on household wealth and the likelihood of being below the poverty line. There appear to be no effects on either outcome, suggesting that grandmothers' reduction in labor supply does not appreciably impact their immediate economic wellbeing. Columns 3&4 of Table 9 report the results on age at which respondents claim Social Security as well as the likelihood that they are receiving SSI. A one standard deviation increase in annual payment for childcare reduces the age at which grandmothers claim social security by .2 years, over a baseline of 60.6 years. The TOT estimate is .6 years, or more than 7 months. Additionally, a one standard deviation increase in annual subsidy raises the likelihood that grandmothers receive SSI by .6 percentage points (TOT), which is a 20% increase over a baseline of 3%.

6.6 Health behaviors and outcomes

A sizeable body of literature reports negative correlations between living with grandchildren and grandparent physical and mental health, both in cases where grandparents are primary caregivers (Blustein et al., 2004) and when they are not (Deaton & Stone, 2013). In this section, I present evidence on the causal impact of providing subsidized childcare on grandmother's health. Table 10 presents results of OLS estimates of the estimating equation on a subset of grandmother physical and mental health outcomes. The dependent variable in column 1, "in poor health," is a binary outcome set to one if the grandmother responded that she was in fair or poor health to a

five category question on self-reported health. The dependent variable in column 2 is the count of Instrumental Activities of Daily Living (IADLs) the grandmother reports having trouble with, and the dependent variable in column 3 is the Center for Epidemiological Studies Depression (CESD) Scale. A higher value on the CESD scale corresponds to a higher rate of depression. The results in Table 6 suggest that despite the correlational evidence, providing grandchild care (when it is compensated) does not have causal effects on grandmothers' physical or mental health.

7 Conclusion

Older women are a policy-relevant population at risk for poverty in retirement (GAO 2008, 2011). In this paper, I consider previously unexplored dimensions of childcare subsidy policy to examine how subsidizing grandmothers to provide childcare impacts this population's economic outcomes. I use the multi-dimensional variation in the predicted grandmother payment for childcare to identify the impacts of providing subsidized care on a set of grandmother outcomes, including time use, labor market participation, earnings, use of social insurance and interfamily financial transfers. Previous studies looking at the relationship between providing childcare and outcomes rely on correlations (Wang & Marcotte, 2007) or use the birth of grandchildren as shocks to identify labor market outcomes (Ho, 2015; Lumsdaine & Vermeer, 2015). To my knowledge, no study has identified the causal impacts of providing additional care on labor supply, nor on a wider range of related outcomes.

I find that in response to more generous government payments for providing grandchild care, grandmothers increase the hours of childcare they provide. However, the effect sizes are economically small. For a one standard deviation increase in predicted payment (\$2456, or approximately \$200 per month) grandmothers provide an additional 79 hours of care per year, or

7 hours of care per month. These results are robust to a number of specifications. This suggests that grandmother care is largely inframarginal – i.e., that grandmothers provide care with or without the subsidy. The payment can be understood primarily as an income effect. As a result, the additional care ends up being heavily subsidized, at \$30 per hour, compared with an average center reimbursement rate of \$60 *per day* for two children in care.

Along with the increase in compensated childcare, Grandmothers reduce their labor earnings by reducing labor supply at both the intensive and extensive margin. Additionally, they reduce financial transfers to their children at a rate of about \$14 per each additional hour of care provided. I find no effects on short term well-being, including household wealth, poverty status, or health. However, I do find that grandmothers claim Social Security over half a year earlier, and 30% more likely to depend on monthly SSI payments. These results suggest that while subsidized grandchild care may not have immediate effects on grandmother outcomes, there may be permanent long-term consequences for their well-being, as well as increased long-term costs for the government.

8 References

- Bainbridge, J., Meyers, M. K., & Waldfogel, J. (2003). Child Care Policy Reform and the Employment of Single Mothers. *Social Science Quarterly*, 84(4), 771–791.
- Becker, G. S., (2009). *A Treatise on the Family*. Harvard university press.
- Bitler, M. P., Gelbach, J. B., & Hoynes, H. W. (2008). Distributional Impacts of the Self-Sufficiency Project. *Journal of Public Economics*, 92(3-4), 748–765.
- Bitler, M. P., Gelbach, J. B., & Hoynes, H. W. (2006). What Mean Impacts Miss: Distributional Effects of Welfare Reform Experiments. *The American Economic Review*, 96(4), 988.
- Black, S. E., Devereux, P. J., Løken, K. V., & Salvanes, K. G. (2012). Care or Cash? The Effect of Child Care Subsidies on Student Performance. *Review of Economics and Statistics*, 96(5), 824-837.
- Blau, D. M., & Robins, P. K. (1989). Fertility, Employment, and Child-Care Costs. *Demography*, 26(2), 287–299.
- Blau, D., & Currie, J. (2006). Pre-School, Day Care, and After-School Care: Who's Minding the Kids?. *Handbook of the Economics of Education*, 2, 1163-1278.
- Blustein, J., Chan, S., & Guanais, F. C. (2004). Elevated Depressive Symptoms among Caregiving Grandparents. *Health Services Research*, 39(6p1), 1671–1690.
- Compton, J. (2013). Family proximity and the Labor Force Status of Women in Canada. *Review of Economics of the Household*, 13(2), 323–358.
- Compton, J., & Pollak, R. A. (2014). Family Proximity, Childcare, and Women's Labor Force Attachment. *Journal of Urban Economics*, 79, 72–90.
- Currie, J. M. (2008). *The Invisible Safety Net: Protecting the Nation's Poor Children and Families*. Princeton University Press.
- Currie, J., & Gruber, J. (1996). Health Insurance Eligibility, Utilization of Medical Care, and Child Health. *The Quarterly Journal of Economics*, 111(2), 431–466.
- Currie, J., & Hotz, V. J. (2004). Accidents Will Happen?: Unintentional Childhood Injuries and the Effects of Child Care Regulations. *Journal of Health Economics*, 23(1), 25–59.
- Deaton, A., & Stone, A. A. (2013). *Grandpa and the Snapper: The Wellbeing of the Elderly who Live with Children* (No. w19100). National Bureau of Economic Research.
- Djebbari, H., & Smith, J. (2008). Heterogeneous Impacts in PROGRESA. *Journal of Econometrics*, 145(1-2), 64–80.
- Doyle, J. J. (2007). Can't Buy Me Love? Subsidizing the Care of Related Children. *Journal of Public Economics*, 91(1), 281–304.
- Felfe, C., Nollenberger, N., & Rodríguez-Planas, N. (2012). Can't Buy Mommy's Love? Universal Childcare and Children's Long-Term Cognitive Development. *Journal of population economics*, 28(2), 393-422.
- Fuller, B., Kagan, S. L., Casparly, G. L., & Gauthier, C. A. (2002). Welfare Reform and Child Care Options for Low-Income Families. *The Future of Children*, 97–119.
- GAO, *Retirement Security: Women Face Challenges in Ensuring Financial Security in*

- Retirement*, GAO-08-105 (Washington, D.C.: Oct. 11, 2007)
- GAO, *Retirement Security: Women Still Face Challenges*, GAO-12-699 (Washington, D.C.: Oct. 11, 2012)
- Giannarelli, L., Minton, S., & Durham, C. (2012). *Child Care and Development Fund Policies Database User Guide*. Urban Institute.
- Havnes, T., & Mogstad, M. (2011). Money for Nothing? Universal Child Care and Maternal Employment. *Journal of Public Economics*, 95(11-12), 1455–1465.
- Havnes, T., & Mogstad, M. (2015). Is Universal Child Care Leveling the Playing Field? *Journal of Public Economics*, 127, 100–114.
- Ho, C. (2013). Grandchild Care, Intergenerational Transfers, and Grandparents' Labor Supply. *Review of Economics of the Household*, 13(2), 359–384.
- Ho, C. (2015). Welfare-to-Work Reform and Intergenerational Support: Grandmothers' Response to the 1996 PRWORA. *Journal of Marriage and Family*, 77(2), 407–423.
- Laughlin, L. (2013). Who's Minding the Kids?: Child Care Arrangements, Spring 2011. *Journal of Marriage and Family* Vol. 77, pp. 407–423.
- Lumsdaine, R. L., & Vermeer, S. J. C. (2015). Retirement Timing of Women and the Role of Care Responsibilities for Grandchildren. *Demography*, 52(2), 433–454.
- McGarry, K. M. (2006). Does Caregiving Affect Work? In *Health Care Issues in the United States and Japan* (pp. 209–228). University of Chicago Press.
- Meyer, B. D., & Rosenbaum, D. T. (2001). Welfare, the Earned Income Tax Credit, and the Labor Supply of Single Mothers. *The Quarterly Journal of Economics*, 116(3), 1063–1114.
- Meyers, M. K., Heintze, T., & Wolf, D. A. (2002). Child Care Subsidies and the Employment of Welfare Recipients. *Demography*, 39(1).
- Minton, S., Durham, C., & Giannarelli, L. (2014). The CCDF Policies Database Book of Tables: Key Cross-State Variations in CCDF Policies as of October 1, 2013. OPRE Report 2014-72. Washington, DC.
- Neumark, D., Burn, I., & Button, P. Is It Hard for Older Workers to Find Jobs? New and Improved Evidence From a Field Experiment. *NBER Working Paper No. 21669*.
- Rupert, P., & Zanella, G. (2014). Grandchildren and Their Grandparents' Labor Supply. *SSRN Electronic Journal*.
- Snyder, K., Bernstein, S., & Adams, G. (2008). Child Care Vouchers and Unregulated Family, Friend, and Neighbor Care. The Urban Institute.
- Tekin, E. (2005). Child Care Subsidy Receipt, Employment, and Child Care Choices of Single Mothers. *Economics Letters*, 89(1), 1–6.
- Wakabayashi, C., & Donato, K. M. (2006). Does Caregiving Increase Poverty among Women in Later Life? Evidence from the Health and Retirement Survey. *Journal of Health and Social Behavior*, 47(3), 258–274.
- Wang, Y., & Marcotte, D. E. (2007). Golden Years? The Labor Market Effects of Caring for Grandchildren. *Journal of Marriage and Family*, 69(5), 1283–1296.
- Washbrook, E., Ruhm, C. J., Waldfogel, J., & Han, W.-J. (2011). Public Policies, Women's

Employment after Childbearing, and Child Well-being. *The BE Journal of Economic Analysis & Policy*, 11(1).

Weber, R. B. (2011). Understanding Parents' Child Care Decision-making: A Foundation for Child Care Policy Making. *Research-to-Policy, Research-to-Practice Brief OPRE*, 12.

Figure 1: Monthly Income Cutoffs for 3-person family in 2012

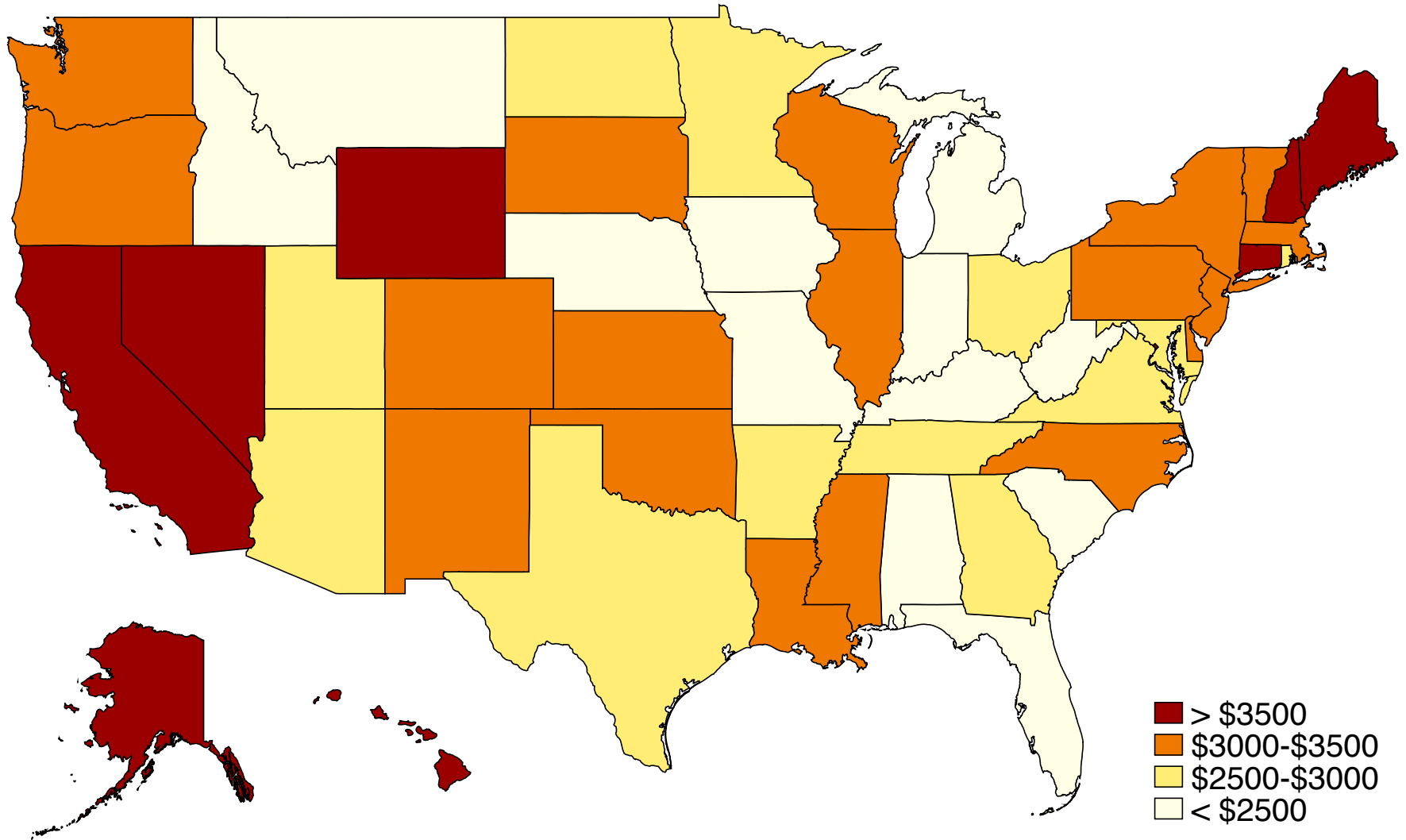


Figure 2 : Monthly Income Cutoffs for 3-person family in 2012

Max Reimbursement Rates, Grandmother & Center Care 2 Children in Care

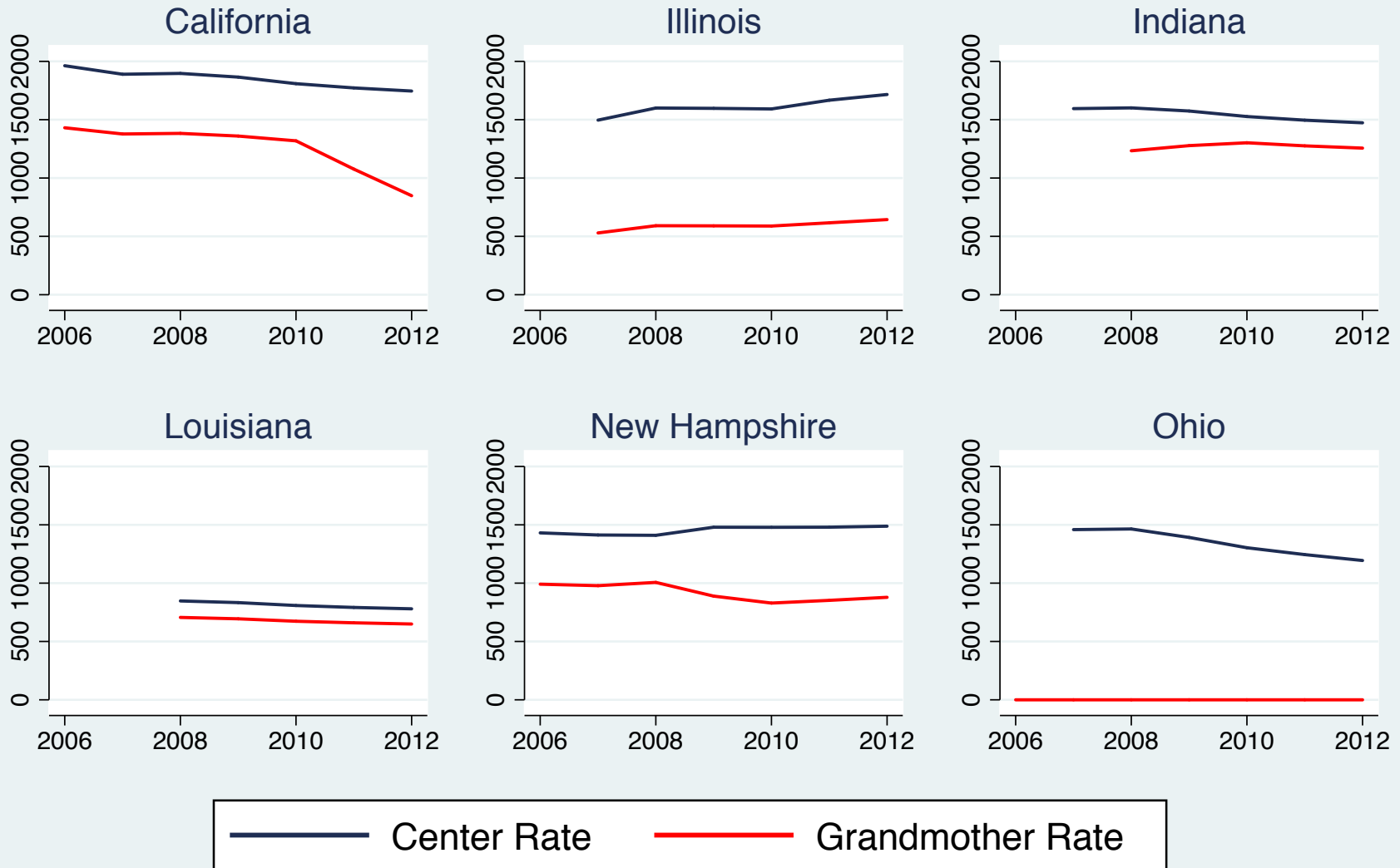


Figure 3: Copay Schedule as a Function of Family Income

Family Copay Schedule as Function of Annual Income, 2010

Single mother with 2 kids in care

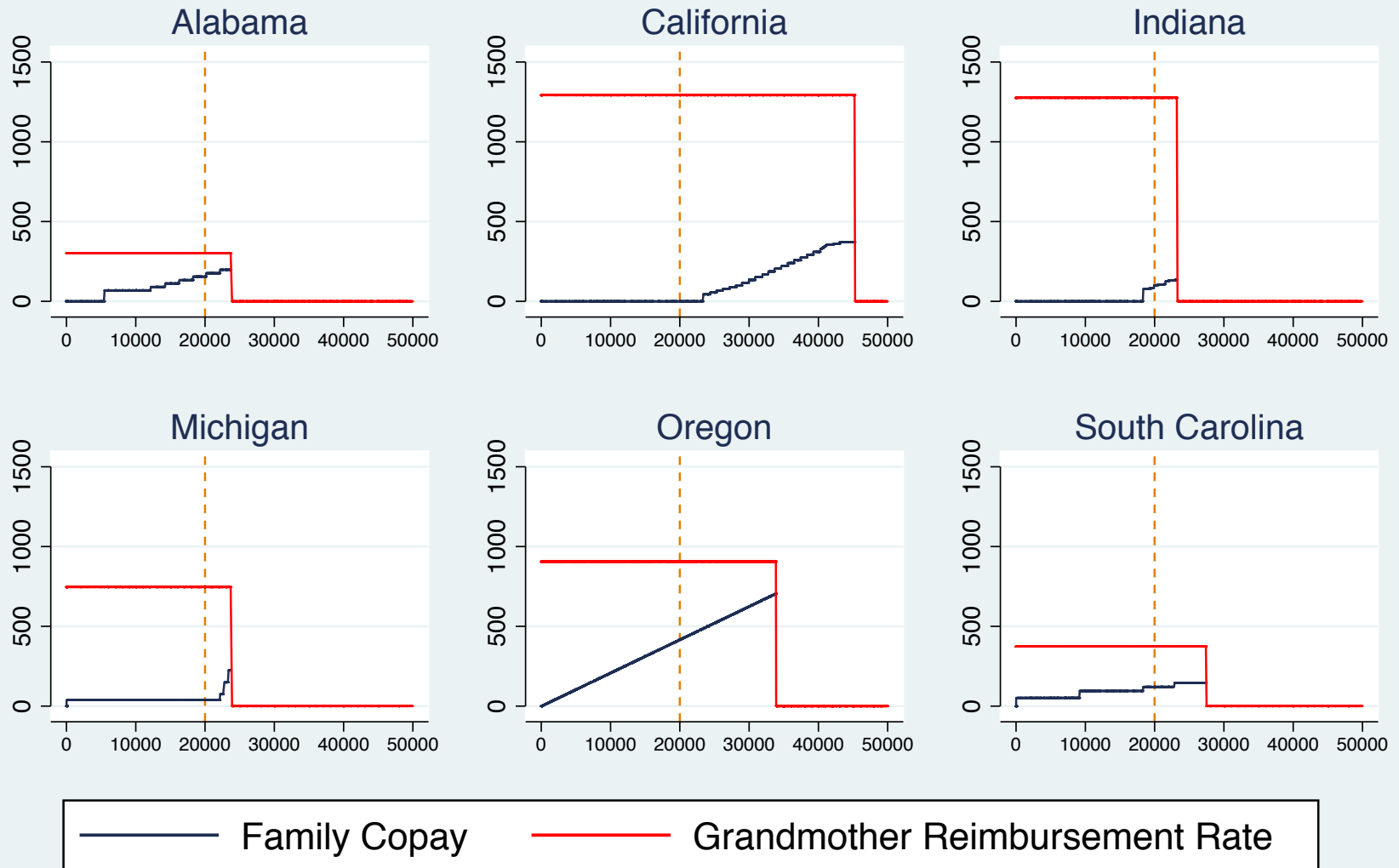


Table 1: Descriptive Statistics

<i>Variables</i>	<i>Full Sample</i>		<i>w/Eligible Daughters</i>	
	<i>mean</i>	<i>sd</i>	<i>mean</i>	<i>sd</i>
<i>Panel 1: Demographic Characteristics</i>				
Age (years)	64.14	(7.529)	63.22	(7.351)
White (%)	70.18		67.14	
Less Than High School (%)	52.43		51.10	
Total Grandchildren (N)	6.00	(3.120)	5.94	(3.135)
Grandchildren under six (N)	1.17	(0.846)	1.42	(0.735)
Daughters (N)	2.12	(1.178)	2.17	(1.220)
Daughters with children under six (N)	1.01	(0.626)	1.22	(0.478)
<i>Panel 2: Income and Wealth</i>				
Mean Household Income (\$)	\$60,976	(\$55,097)	\$61,613	(\$55,506)
Mean Household Wealth (\$)	\$386,292	(\$504,357)	\$364,647	(\$491,504)
Median Household Wealth (\$)	\$179,000		\$129,133	
<i>Panel 3: Grandmother Outcomes (Hours of Care)</i>				
Provide any Grandchild Care (%)	0.42	(0.49)	0.42	(0.49)
Total Hours of Care Provided (hours)	275.34	(635.30)	281.23	(643.31)
Cumulative Grandchild care (hours)	514.53	(1033.18)	475.40	(989.56)
<i>Panel 4: Grandchild Care and Payment</i>				
Predicted Monthly Payment for Grandchild Care (\$)	\$126	(\$211)	\$175	(\$232)
Predicted Annual Payment for Grandchild Care (\$)	\$1,508	(\$2,537)	\$2,102	(\$2,779)
Predicted Cumulative Payment (\$)	\$5,650	(\$10,045)	\$7,131	(\$11,234)
Cumulative Grandchild Care (hours)	514.53	(1033.18)	475.40	(989.56)
Years of Exposure (years)	3.62	(1.64)	3.26	(1.49)
Observations	4658		3323	

Notes: Descriptive statistics are from a pooled cross-section of the full sample of female HRS respondents with daughters age 18-50 and at least one grandchild under six in the panel. HRS waves 2008-2012 are used.

Table 2 – Pseudo First Stage Results

	Share Receive Childcare Assistance (%)	
	(1)	(2)
Share Eligible for Childcare Assistance (%)	0.0540*** (0.007)	0.0543*** (0.008)
N	2445	2445
F-statistic	54.76	2.333
State & Year Fixed Effects		X
Dependent Variable Mean	0.019	

* p<0.05, ** p<0.01, *** p<0.001

Notes: Unit of observation is daughter demographic cell. Data come from the Annual Social and Economic Supplement of the Current Population Survey 2007-2009. Results are from OLS estimates of share of a demographic cell predicted to be eligible for childcare assistance on share of a demographic cell reporting receiving childcare assistance in the last year. The dependent variable the share of mothers in the demographic cell who report receiving childcare assistance. The independent variable is measures as the share of mothers who are predicted to be eligible for childcare assistance in that state and year using the CCDF database policy rules. Robust Standard Errors are clustered at the state level in parentheses

Table 3: Effect of a Standard Deviation Increase in Predicted Annual Payment for Grandchild Care

	Log of Cumulative Hours of Care					
	Full Sample		Daughter elig> 25%		Daughter elig> 50%	
	w/Any GK	w/Gk<6	w/Any GK	w/Gk<6	w/Any GK	w/Gk<6
	(1)	(2)	(3)	(4)	(5)	(6)
Panel 1						
Predicted annual government payment for childcare (SD)	0.0421*** (0.007)	0.0471*** (0.008)	0.0461*** (0.007)	0.0505*** (0.008)	0.0475*** (0.006)	0.0484*** (0.009)
<i>Observations</i>	4532	3775	3772	3171	2044	1720
<i>Dep var mean (hours)</i>	515.2	494.9	504.0	481.6	484.3	437.9
Panel 2						
<i>Effect of \$200/month increase in subsidy</i>	6.46	6.94	7.07	6.75	6.85	6.31
<i>95% Confidence Interval</i>	[4.3, 8.6]	[4.6, 9.3]	[4.8, 9.0]	[4.9, 9.5]	[5.1, 8.6]	[3.9, 8.7]

* p<0.05, ** p<0.01, *** p<0.001

Notes: Results are from OLS estimates of predicted cumulative subsidy on the log of reported cumulative hours of care. All columns control for grandmother characteristics including: age, age squared, foreign born, education, race, number of living children, number of children ever born, total number of grandchildren, number of living parents. All columns also include state, year and daughter-group fixed effects, a state specific linear trend, and control non-parametrically for the number of grandchildren under six. Odd columns include all grandmother and even columns restrict the sample to grandmothers with grandchildren under six. Column 3&4 restrict the sample to grandmothers whose daughters have a 25% likelihood of being eligible for childcare assistance. Columns 5&6 restrict the sample to grandmothers whose daughters have a 50% likelihood of being eligible for childcare assistance. Standard errors clustered at the state level are in parentheses.

Table 4: Effect of a Standard Deviation Increase in Predicted Annual Payment for Grandchild Care: Heterogeneity

	Log of Cumulative Hours of Care				
	white	black	hispanic	married	not married
	(1)	(2)	(3)	(4)	(5)
<i>Panel 1</i>					
Predicted annual government payment for childcare (SD)	0.059*** (0.012)	0.0277 (0.027)	0.0317*** (0.005)	0.0411*** (0.008)	0.0419** (0.019)
<i>Observations</i>	3194	732	606	3156	1376
<i>Dep var mean (hours)</i>	555.5	440.6	396.3	541.1	457.2
<i>Panel 2</i>					
<i>Effect of \$200/month increase in subsidy</i>	9.75	3.63	3.74	6.62	5.70
<i>95% Confidence Interval</i>	[5.79, 13.72]	[-3.49, 10.71]	[2.56, 4.91]	[4.04, 9.20]	[-.53, 10.87]

* p<0.05, ** p<0.01, *** p<0.001

Notes: Results are from OLS estimates of predicted cumulative subsidy on the log of reported cumulative hours of care. All columns control for grandmother characteristics including: age, age squared, foreign born, education, race, number of living children, number of children ever born, total number of grandchildren, number of living parents. All columns also include state, year and daughter-group fixed effects, a state specific linear trend, and control non-parametrically for the number of grandchildren under six. Standard errors clustered at the state level are in parentheses.

Table 5: Effect of a Standard Deviation Increase in Predicted Annual Payment for Grandchild Care: Heterogeneity, cont.

	Log of Cumulative Hours of Care					
	< 65	>=65	no college	at least some college	grandkids w/in 10 miles	no grandkids w/in 10 miles
	(6)	(7)	(8)	(9)	(10)	(11)
Panel 1						
Predicted annual government payment for childcare (SD)	0.0514*** (0.012)	0.0321** (0.014)	0.044*** (0.007)	0.0369 (0.022)	0.0527** (0.016)	0.0345*** (0.009)
<i>Observations</i>	2574	1958	3339	1193	1637	2895
<i>Dep var mean (hours)</i>	537.5	486.0	514.1	518.2	688.3	418.9
Panel 2						
<i>Effect of \$200/month increase in subsidy</i>	8.22	4.64	6.78	5.69	10.80	4.30
<i>95% Confidence Interval</i>	[4.38, 12.06]	[.059, 8.69]	[4.63, 8.92]	[-1.09, 12.47]	[4.24, 17.35]	[2.06, 6.54]

* p<0.05, ** p<0.01, *** p<0.001

Notes: Results are from OLS estimates of predicted cumulative subsidy on the log of reported cumulative hours of care. All columns control for grandmother characteristics including: age, age squared, foreign born, education, race, number of living children, number of children ever born, total number of grandchildren, number of living parents. All columns also include state, year and daughter-group fixed effects, a state specific linear trend, and control non-parametrically for the number of grandchildren under six. Standard errors clustered at the state level are in parentheses.

Table 6: Effect of a Standard Deviation Increase in Predicted Annual Payment for Grandchild Care- State by year fixed effects

	Log of Cumulative Hours of Care	
	w/Any GK	w/Gk<6
	(1)	(2)
Predicted annual government payment for childcare (SD)	0.0399*** (0.007)	0.0445*** (0.008)
<i>Observations</i>	4542	3785
<i>Dep var mean (hours)</i>	515.2	494.9

Notes: Results are from OLS estimates of predicted cumulative subsidy on the log of reported cumulative hours of care. All columns control for grandmother characteristics including: age, age squared, foreign born, education, race, number of living children, number of children ever born, total number of grandchildren, number of living parents. All columns also include state, year, state by year, and daughter-group fixed effects, and control non-parametrically for the number of grandchildren under six. Standard errors clustered at the state level are in parentheses.

Table 7 – OLS results of subsidy level on labor supply and earnings

	Earnings	Working for Pay	Working for Pay - 2nd Job	Weeks worked
	(1)	(2)	(3)	(4)
Predicted annual government payment for childcare (SD)	-333.84** (163.603)	-0.0055* (0.003)	-0.0027** (0.001)	-0.315** (0.132)
<i>Observations</i>	4539	4531	4492	1725
<i>Dep var mean</i>	13714.7	0.394	0.0378	47.54

Notes: Results are from OLS estimates of predicted cumulative subsidy on each outcome of interest. All columns control for grandmother characteristics including: age, age squared, foreign born, education, race, number of living children, number of children ever born, total number of grandchildren, number of living parents. All columns also include state, year and daughter-group fixed effects, a state specific linear trend, and control non-parametrically for the number of grandchildren under six. Standard errors clustered at the state level are in parentheses. All models report results for the full sample of grandmothers.

Table 8 - OLS Results of Subsidy Level on Family Financial Transfers

	Net Financial Transfers to Daughter
	(1)
Predicted annual government payment for childcare (SD)	-307.20* (152.690)
<i>Observations</i>	4539
<i>Dep var mean</i>	8830.5

Notes: Results are from OLS estimates of predicted cumulative subsidy on net family transfers. The dependent variable is measured as the difference between the value of reported transfers from parents to children and the value of reported transfers from children to parents over the exposure period. All columns control for grandmother characteristics including: age, age squared, foreign born, education, race, number of living children, number of children ever born, total number of grandchildren, number of living parents. All columns also include state, year and daughter-group fixed effects, a state specific linear trend, and control non-parametrically for the number of grandchildren under six. Standard errors clustered at the state level are in parentheses. All models report results for the full sample of grandmothers.

Table 9– OLS Results of Subsidy Level on Economic Well-being and Social Insurance

	Household Wealth	Household in Poverty	Age get Social Security (years)	Likelihood receiving SSI
	(1)	(2)	(3)	(4)
Predicted annual government payment for childcare (SD)	6519 (8674.38)	0.0014 (0.002)	-0.168* (0.089)	0.0017* (0.001)
<i>Observations</i>	4539	4507	2517	4539
<i>Dep var mean</i>	521739.7	0.118	60.66	0.0289

Notes: Results are from OLS estimates of predicted cumulative subsidy on each outcome of interest. All columns control for grandmother characteristics including: age, age squared, foreign born, education, race, number of living children, number of children ever born, total number of grandchildren, number of living parents. All columns also include state, year and daughter-group fixed effects, a state specific linear trend, and control non-parametrically for the number of grandchildren under six. Standard errors clustered at the state level are in parentheses. All models report results for the full sample of grandmothers.

Table 10– OLS Result of Subsidy Level on Health Outcomes

	In Poor Health	AIDL Summary	Depression Scale
	(1)	(2)	(3)
Predicted annual government payment for childcare (SD)	0.0012 (0.002)	-0.0028 (0.003)	0.0022 (0.009)
<i>Observations</i>	4539	4536	4432
<i>Dep var mean</i>	0.246	0.112	1.463

Notes: Results are from OLS estimates of predicted cumulative subsidy on each outcome of interest. All columns control for grandmother characteristics including: age, age squared, foreign born, education, race, number of living children, number of children ever born, total number of grandchildren, number of living parents. All columns also include state, year and daughter-group fixed effects, a state specific linear trend, and control non-parametrically for the number of grandchildren under six. Standard errors clustered at the state level are in parentheses. All models report results for the full sample of grandmothers.