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ABSTRACT

Grandchildren and Their Grandparents' Labor Supply*

Working-age grandparents supply large amounts of child care, an observation that raises the question of how having grandchildren affects grandparents' own labor supply. Exploiting the unique genealogical design of the PSID and the random variation in the timing when the parents of first-born boys and girls become grandparents, we estimate a structural labor supply model and find a negative effect on employed grandmother's hours of work of about 30% that is concentrated near the bottom of the hours distribution, i.e., among women less attached to the labor market. Implications for the evaluation of child care and parental leave policies are discussed.

JEL Classification: D19, J13, J14, J22

Keywords: labor supply, grandparents, child care

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1 Introduction

According to the American Community Survey of the US Census Bureau there are about 70 million grandparents in the US (almost 1/3 of the adult American population), with an annual inflow of about 2 million. Most of these have grandchildren well before the end of working age and make large transfers to their offspring, both money and time transfers in the form of grandparent-provided child care. In the literature, much is known about the labor supply consequences of becoming a parent, something is known about the effect of grandparent-provided child care on parents' labor supply, but surprisingly little is known about the effect of grandparent-provided child care on grandparents' own labor supply. This paper addresses this issue and asks: How does becoming a grandparent affect the labor supply of older workers?

We structure this empirical question in a dynamic model of the allocation of time in which senior workers are altruistic towards their offspring and also directly value time spent with children. In the model, becoming a grandparent has an ambiguous effect on the labor supply of senior workers because grandparents can transfer child care time (thus working less, possibly) but also assets (thus working more, possibly). Such ambiguity is resolved empirically by combining structural labor supply methods and an IV design that exploits the different timing of becoming a grandparent for the parents of first-born girls and first-born boys. While the gender of one's first child is arguably random in the US, the parents of first-born girls have grandchildren earlier because girls marry and have children at a younger age than boys.

Results indicate that becoming a grandparent reduces female labor supply along the intensive margin by about 30% (a large effect reflecting the LATE nature of our estimate), with zero effect for men. This asymmetric effect by gender is consistent with the different responsiveness of men and women to changes in the opportunity cost of time, as has been documented repeatedly in the literature on labor supply elasticities, as well as with the fact that women provide more grandparenting time than men. No significant effect along the employment margin is found for either women or men, although this is due to large standard errors. Going beyond the baseline estimates, we find that these labor supply adjustments by employed grandmothers take place at the lower quantiles of the hours distribution, i.e., among women less attached to the labor market. We also find evidence that becoming a grandparent, which we label the "extensive margin" of grandparenting, is much more important in generating these effects than having additional grandchildren, i.e., the "intensive" margin of grandparenting, consistent with the presence of economies of scale in family-based child care. Moreover, our data suggest that the negative labor supply impact of grandchildren is stronger during the early years since becoming a grandmother.

These results have implications for the evaluation of child care and and parental leave policies. A common argument in support of subsidized child care is that this provision increases the labor force participation of young mothers, with possible positive spillovers on income tax revenues. This argument overlooks the presence of nonmaternal, nonpaid sources of child care different from subsidized child care centers and which mothers may be already using, such as grandparents. If these are providing for a substantial portion of child care needs (it is shown below that grandparent-provided child care is of first-order importance in the US), then expanding the public provision of child care may affect the labor supply of young women only marginally. Grandparents' involvement in child care explains why Havnes and Mogstad (2011) find that a 1975 reform expanding subsidized childcare in Norway for children aged 3–6 caused a little increase in maternal labor supply and a large decrease in informal child care arrangements. Similarly, simulating a quantitative model with free nonmaternal sources different from public child care centers, Bick (2016) finds that a policy subsidizing daycare universally in Germany would increase the participation rate of mothers with children aged 0–2 by relatively little. However, even if subsidizing child care affected mothers' labor supply marginally, our results suggest that such a policy would affect the labor supply of older female workers with grandchildren. Similarly, the involvement of grandparents in child rearing suggests that parental leave policies replace, in part, grandparental care with parental care. Based on our results, a side effect of a generous parental leave is to strengthen the labor market attachment of older women with grandchildren. Therefore, the correct evaluation of the benefits and costs of child care and parental leave policies requires bringing grandparents into the picture. These are little-explored questions.[1] Such broader family perspective also suggests new policies aimed at reconciling work and child care duties. For instance, if the rationale of parental leave is to reconcile work and child bearing, and if working-age grandparents also engage in child care, then the government should consider forms of "grandparental leave" to support the attachment of older workers to the labor market. In principle, every employed family member who is a potential source of child care (not just parents) would benefit from a temporary leave for child care duties. Thus, our analysis suggests that public child care, parental leave, and forms of "grandparental leave" are complementary in sustaining young mothers' labor supply while also increasing the earnings of older workers.

Survey data on informal child care arrangements and time-use data suggest that the labor supply effects we estimate are plausible. According to the Survey of Income and Program Participation, in 2011 as many as 23.4% of all children under 5 years old living with their mother benefitted from

[1] For Norway, Andresen and Havnes (2016) find no significant effect on grandparents' labor supply of an expansion of subsidized child care for toddlers enacted during the early 2000s.

grandparent-provided child care (between 5 and 14 years it is 13.4%), up from less than 15% in 1987. For 93% of these, grandparents were the primary child care arrangement. These statistics do not include children living with their grandparents, which according to the US Census Bureau amounted to about 7% of all children below 18 years old in 2010, up from 3.2% in 1970. The corresponding time transfer is large. In the Health and Retirement Study (HRS), individuals are asked how much time altogether they spent taking care of their grandchildren during the past 12 months. Grandmothers who were between 50 and 64 years old at the time of the first interview in 1992 and who had provided at least 1 hour of grandchild care reported spending, on average, 816.5 annual hours. The corresponding figure for grandfathers was 346.9 hours. These magnitudes agree, by and large, with those produced by more reliable time-use data. In the American Time Use Survey (ATUS), pooled 2003-2014 waves, 16% of women and 10.8% of men in the age range 50-64 report spending time in primary childcare.[2] Among those who do (i.e., conditional on a strictly positive time transfer), annual hours of childcare are 657.1 for women and 500.9 for men. Such large time transfers beg the question of how much grandparenting comes at the expense of other forms of "leisure" and how much comes at the expense of market labor supply? Providing an answer is the main contribution of the present paper.

This is a novel question. Abundant evidence has been produced about the causal effect of child bearing on parental labor supply, and the vast majority of studies find a negative effect.[3] More recently, researchers have begun investigating the effects of grandparent-provided child care on parental labor supply, the idea being that by providing free and flexible child care, grandparents may reduce the impact of child bearing on parents' labor supply. In an early paper, Cardia and Ng (2003) calibrate an OLG model and show that grandparent-provided childcare has a positive effect on the labor supply of parents. In an empirical counterpart of this calibration study, Dimova and Wolff (2011) use cross-country data from the Survey of Health, Aging, and Retirement in Europe (SHARE) and show that this is the case for young European mothers. Posadas and Vidal-

[2] These ATUS statistics refer to household and non-household children. The activities included are caring for and helping, activities related to children's education and health, and travel related to all of these.

[3] Studies providing indirect evidence of this connection via the evaluation of public child care programs on women's labor supply have a long tradition in modern labor economics, starting with Heckman (1974). More recent evidence has been produced using a variety of instruments—beginning with the seminal study of Rosenzweig and Wolpin (1980) using twin births as an exogenous shock to fertility—to address the endogeneity of children, such as twin births (Bronars and Grogger, 1994, for unmarried mothers in the US, and Jacobsen, Pearce, and Rosenbloom, 1999, for married mothers), sibling-sex composition (Angrist and Evans, 1998, for men and women in the US, and Cruces and Galiani, 2007, for women in Argentina and Mexico), gender of first-born child (Chun and Oh, 2002, for women in South Korea) early access to the pill (Bailey, 2006, for women in the US), abortion legislation (Bloom, Canning, Fink, and Finlay, 2009, in a large cross-country panel data set. However, when using self-reported measures of infertility as instruments, both Aguero and Marks (2008) in a sample of Latin American countries, and Rondinelli and Zizza (2010) in sample of older Italian women find no effect of child bearing on female labor force participation.

Fernandez (2013) instrument the availability of grandparent-provided child care with death of the maternal grandmother in the National Longitudinal Survey of Youth 1979 (NLSY79), and find that the availability of grandparents increases the labor force participation of mothers in the US. Compton and Pollak (2014) employ data from the US Census and from the National Survey of Families and Households (NSFH), and show that spatial proximity to grandmothers increases the labor supply of women with young children, presumably because of the availability of grandparent-provided child care. Aparicio-Fenoll and Vidal-Fernandez (2015) find that an increase of the legal female retirement age enacted in Italy in 2000 caused grandmothers to provide less child care and decreased the labor force participation of their daughters.[4] However, very little is known about the effects of grandparent-provided child care on grandparents' own labor supply. Existing studies are descriptive in nature, do not address causality, and report mixed correlations. Lei (2008) uses HRS data from 1996 to 2002, and finds a small positive correlation between the number of grandchildren and grandmother's labor supply along both the intensive and the extensive margin. However, when including fixed effects the correlation becomes negative and insignificant. Ho (2015) also uses HRS data and finds a positive correlation between the birth of a new grandchild and married grandparents' employment. She also finds a positive correlation between married grandmothers' hours of market work and the presence of a grandchild in the household. Zamarro (2011) estimates on SHARE data the effect of being an employed grandmother on the probability of providing child care. Instrumenting employment status with eligibility for social security benefits, she finds a negative effect. A recent paper by Frimmel, Halla, Schmidpeter, and Winter-Ebmer (2017) comes closest to what we do. These authors use data from Austria and find that women are more likely to leave the labor market after the birth of their first grandchild.

We take a systematic approach to this question using data from the Panel Study of Income Dynamics (PSID) to estimate the effect of becoming a grandparent on own labor supply in a simple structural labor supply model and addressing the endogeneity of the grandparent status. The PSID spans 50 years and is especially well-suited for this research question because it allows observing the same individuals when they become parents and, many years later, when they become grandparents; moreover, its unique genealogical design of offers us the opportunity to link grandparents, parents, and grandchildren over an extended period of time, observing the characteristics of all three generations. Although becoming a grandparent (unlike becoming a parent) results from the fertility choices of someone else, establishing a causal link between grandparenting and labor sup-

[4] Additional, possible effects of grandparenting not directly related to labor supply have also been explored. Reinkowski (2013) finds some positive correlation in SHARE data between taking care of the grandchildren and grandparents' physical and psychological health.

ply is tricky. There are two sources of endogeneity that our theoretical model highlights. First, preferences for fertility may be transmitted from parents to children. Second, the cost of having a child decreases with the time transfer a grandparent provides, which induces a simultaneity problem. Individual fixed effects may take care of the first problem, but this is not enough to take care of simultaneity. Our strategy in this respect is based on an instrumental variable for the probability of becoming a grandparent. The gender of one's first child (which is essentially random in the US) provides an exogenous source of variation in the age seniors become grandparents, with the parents of first-born girls having grandchildren two years earlier than the parents of first-born boys because females marry and have children at a younger age than males. We argue (with supporting evidence) that this variable does not otherwise affect the labor supply of older workers, although it is known to affect, possibly, the labor supply of young parents.[5]

The remainder of the paper is organized as follows. Section 2 presents the theoretical model, Section 3 describes the data set, Section 4 illustrates the econometrics and discusses identification, Section 5 reports the results, and Section 6 concludes.

2 Model

The model is intentionally simple, and its purpose is fourfold. First, to introduce organizing terminology and notation used in the rest of the paper. Second, to show how, even in a simple model, the effect of grandparenting on labor supply is theoretically ambiguous. Third, the model illustrates the fundamental sources of endogeneity of the grandparent status, even if (conditional on having children) it results from the fertility choices of someone else; this would bias naïve estimates of the effect of grandparenting on labor supply. Finally, the model allows us to construct counterfactuals and to structure the empirical analysis.

Consider a cohort of older individuals (Seniors) each with one adult child (Junior) whom in turn may or may not produce a grandchild (Baby). A family is composed of Senior, Junior, and, possibly, Baby. Time is discrete, and an individual in the cohort is a Junior at time $t = 0$, becomes a Senior at time $t = T$, and dies at time $t = D > T$. Producing Baby is Junior's choice. Therefore, from the viewpoint of Senior, being a grandparent at time t is an uncertain event, captured by a random variable denoted g_t. If Junior is a parent at t, then $g_t = 1$, otherwise, $g_t = 0$. Being a grandparent is an absorbing state, therefore $g_t = 1$ implies $g_\tau = 1$ for all $\tau > t$. Seniors are

[5] See, for instance, Dahl and Moretti (2008) and Ichino, Lindstrm, and Viviano (2014). The gender of one's first child has been used in the literature as an instrument for fertility (e.g., Chun and Oh, 2002). Its use, in an intergenerational setting, as an instrument for being a grandparent is new to this paper.

altruistic in that they care about Junior's welfare. However, Juniors do not value Senior's welfare.[6] Individuals derive utility from a composite consumption good, c, and from time spent with baby, b, but they derive disutility from work time, h, so that leisure, l, is valuable too. Both Junior (as a parent) and Senior (as a grandparent) enjoy spending time with Baby. In what follows we adopt the following three notational conventions: (i) a prime, " $\prime$ ", denotes objects that pertain to Junior; (ii) for derivatives, we adopt the subscript notation, so that f_y denotes the partial derivative of function f with respect to variable y; (iii) a 0 or 1 subscript denotes the value a variable or function takes at the optimum when $g = 0$ and $g = 1$, respectively, so that, for instance, y_0 is $y^*(g = 0)$ and f_1 is $f^*(g = 1)$, where a " $*$ " denotes a value at Senior's optimum.

Because we are interested in labor supply late in the working life, the initial period is when an individual turns into a Senior, i.e., $t = T$. Consistent with the empirical analysis, this is the first period when Junior can produce Baby. Therefore, time in both the theoretical setup and the empirical model corresponds to Senior's age. The period utility functions of Senior and Junior (Baby has no choices to make in this model) are denoted U_t and U_t', represent strictly increasing and strictly convex preferences, and are given by, respectively,

$$U_t = u(c_t, \mathbf{x}_t) - v(h_t, \mathbf{x}_t) + \upsilon(b_t, \mathbf{x}_t) + \rho[u(c_t', \mathbf{x}_t') - v(h_t', \mathbf{x}_t') + \upsilon(b_t', \mathbf{x}_t')], \tag{1}$$

$$U_t' = u(c_t', \mathbf{x}_t') - v(h_t', \mathbf{x}_t') + \upsilon(b_t', \mathbf{x}_t') + \xi(g_t), \tag{2}$$

where $\mathbf{x}_t$ and $\mathbf{x}_t'$ are individual taste shifters, ρ is the intergenerational altruism parameter, and $\xi(g_t)$ represents Junior's unobserved (to Senior) preference for having a Baby at time t. We assume that $u_c(0, \mathbf{x}_t)$ is large enough to ensure an interior solution for consumption. Notice that the deterministic components of preferences are perfectly transmitted from Senior to Junior. Also notice that $b_{0t} = b_{0t}' = 0$; that is, if Junior does not produce Baby, then everyone in the family is constrained to zero time spent with family children. Senior and Junior are endowed with 1 unit of time in each period, which they can supply to the labor market as work time at a given wage rate (w_t and w_t', respectively), enjoy as leisure, or spend with Baby (if present in the family). Hence the time constraints of Senior and Junior are given by $h_t + l_t + b_t = 1$ and $h_t' + l_t' + b_t' = 1$, respectively. Child rearing requires a single input, a fixed amount of time, $\bar{h}$, in each period until Baby becomes a Junior. Child care is also available on the market at a constant price p per unit of time. The market supply of child care is exogenous and perfectly elastic. Therefore, time spent with children is both an input to child rearing and home production of a valuable good (time spent with family children)

[6] This simplifying assumption rules out more sophisticated motives for grandparenting, such as implicit intergenerational contracts governing exchange of child care by grandparents and, later on, elderly care by one's children. The approach we take in this paper does not require us to consider this and other motives.

for which there is no market. Child care time cannot be sold outside the family, i.e., $b_t + b'_t \leq \bar{h}$. The crucial difference between the two generations is that Junior can produce Baby, while Senior can not. Therefore, the only way Senior can enjoy time with children is by supplying time to the child rearing process when Junior produces Baby. We label this time transfer "grandparenting". Because child rearing time can be purchased by Junior on the market, grandparenting at time t (b_t) is an intergenerational time transfer. The other form of intergenerational transfer Senior can make in each period is a monetary (consumption) transfer, denoted s_t. We assume there are no commitment problems when Senior chooses b_t and s_t. Denoting assets by a and the real interest rate by r, the budget constraints of Senior and Junior are given by, respectively,

$$c_t + s_t + a_{t+1} = w_t h_t + (1+r)a_t, \tag{3}$$

$$c'_t + (\bar{h} - b' - b)pg_t + a'_{t+1} = w'_t h'_t + s_t + (1+r)a'_t. \tag{4}$$

We first analyze Junior's decision to produce Baby in each period t, from the viewpoint of Senior. This decision can only be taken in periods $t \geq T$ when $g_{t-1} = 0$ (Junior can have at most one child). This is a standard dynamic binary choice problem for Junior, with choice variable $g_t \in \{0,1\}$, and the solution, from the viewpoint of Senior, is a conditional probability function expressing the probability that Senior is a grandparent at time t given the grandparent status at time $t-1$. Assuming for simplicity no time discounting, the Bellman equation is

$$V'(g_t) = \max_{g_t}\{U'_t + V'(g_{t+1})\}. \tag{5}$$

Because being a parent and a grandparent are absorbing states, the solution can be written as

$$\Pr(g_t = 1 | g_{t-1}) = \Pr_t(V'(1) \geq V'(0))(1 - g_{t-1}) + g_{t-1}. \tag{6}$$

The Bellman equation implies that, in particular,

$$\Pr_t(V'(1) \geq V'(0)) = G(\{b_\tau\}_{\tau=t}^D), \tag{7}$$

where G is a well-defined cumulative distribution function. That is, the probability that Senior becomes a grandparent at time t depends on her optimal sequence of time transfers from t to death in case Baby is born (the "grandparenting profile" $\{b_\tau\}_{\tau=t}^D$). It can be shown that this probability is nondecreasing in the grandparenting profile. Intuitively, the time transfer from Senior reduces Junior's cost of child bearing. The key point highlighted by equations (6) and (7) is that the grandparent status g_t and the grandparenting profile $b_t, b_{t+1}, b_{t+2}...$ are simultaneously determined.

Such simultaneity is the fundamental endogeneity problem one faces in empirical analyses of the effect of becoming a grandparent on labor supply: being a grandparent may reflect (rather than determine) one's prospective time transfer, and so one's prospective adjustment of labor supply. Another source of endogeneity is the intergenerational correlation of preferences: the probability that Senior becomes a grandparent depends on the shape of Senior's preferences that are common to Junior, i.e., u, v, and υ.

Next, we analyze the intergenerational transfers and labor supply choices of Senior. We first focus on the interior solution for labor supply, for both a Senior with a grandchild and one without, i.e., $h_{1t} > 0$ and $h_{0t} > 0$, respectively. Denoting by λ_t the multiplier on Senior's budget constraint at time t, the optimum for a Senior who is a grandparent at time t ($g_t = 1$) is characterized, in addition to the Euler equation and the time and budget constraints, by the following intratemporal conditions:

$$
\begin{aligned}
s_{1t} \quad &: \quad \lambda_{1t} \geq \rho \lambda'_{1t}, && (8)\\
b_{1t} \quad &\geq \quad 0 \\
b_{1t} \quad &: \quad w_t \lambda_{1t} \geq \upsilon_b(b_{1t}, \mathbf{x}_t) + \rho p \lambda'_{1t}, && (9)\\
h_{1t} \quad &: \quad v_h(h_{1t}, \mathbf{x}_t) = w_t \lambda_{1t}, && (10)
\end{aligned}
$$

where the inequality in condition (9) indicates that a grandparent may be unwilling to transfer grandparenting time. If (9) holds as a strict inequality at $b_{1t} = 0$, then a grandparent transfers no time: the value to Senior of the marginal unit of time in terms of either additional consumption via additional work or, equivalently in the light of condition (10), additional leisure exceeds the value of spending that unit of time with Baby, net of the benefit to Junior from the relaxation of Junior's budget constraint. The corresponding conditions for a Senior without a grandchild ($g = 0$) are:

$$
\begin{aligned}
s_{0t} \quad &: \quad \lambda_{0t} \geq \rho \lambda'_{0t}, && (11)\\
b_{0t} \quad &= \quad 0 \\
b_{0t} \quad &: \quad w_t \lambda_{0t} \lesseqgtr \upsilon_b(0, \mathbf{x}_t) + \rho p \lambda'_{0t}, && (12)\\
h_{0t} \quad &: \quad v_h(h_{0t}, \mathbf{x}_t) = w_t \lambda_{0t}. && (13)
\end{aligned}
$$

Inequality (12) may hold in either direction. If it holds with a $\geq$ then Senior would not transfer any time even if Baby appeared. However, when (12) holds with a $<$ then a Senior without Baby in the family is constrained into a suboptimal allocation of time. This Senior would like to spend time with the grandchild but cannot because Junior has not produced a Baby. When Baby appears, a reallocation of Senior's time takes place according to conditions (9) and (10). If we keep the monetary transfer s_t constant, then such reallocation necessarily takes the form of reduced reduced labor supply for a Senior who becomes a grandparent, because h_{0t} is at an interior. However, the monetary transfer is adjusted too when Baby appears, according to condition (8). If υ_b is sufficiently large and ρ is sufficiently small then work hours decrease. However, if υ_b is sufficiently small and ρ is sufficiently large then work hours increase; that is, if Senior cares sufficiently about Junior's welfare but not as much about spending time with Baby, then he or she may increase labor supply and the monetary transfer, but transfer little time or no time at all. Leisure decreases in either case if it is at an interior. The punchline of this theoretical analysis (for the purposes of the empirical analysis that follows) is that the labor supply response of becoming a grandparent for an employed Senior is ambiguous. The labor supply function of such a Senior is defined by condition (10) or (13), depending on whether $g_t = 1$ or $g_t = 0$, respectively:

$$h_{gt} = h(w_t, \mathbf{x}_t, \lambda_{gt} | e_{gt} = 1), \tag{14}$$

where the employment indicator e_{gt} is the outcome of the participation decision,

$$e_{gt} = \mathbb{I}[h_{gt} > 0] = \mathbb{I}[v_h(h_{gt}, \mathbf{x}_t) = w_t \lambda_{gt} \geq v_h(0, \mathbf{x}_t)], \tag{15}$$

$\mathbb{I}[.]$ is the indicator function and the second equality in equation (15) follows from a comparison of either condition (10) or (13) in the two couterfactual states of positive and zero work hours. Allowing, without loss of generality, $v_h(.)$ to contain an additive random term reflecting unobserved utility from the participation decision, equation (15) becomes a probability function,

$$\Pr(e_{gt} = 1) = F(w_t, \mathbf{x}_t, \lambda_{gt}). \tag{16}$$

Equations (14) and (16) form the system of structural labor supply functions we want to estimate. In particular, the treatment effect of interest for a Senior who is always at an interior (intensive margin effect) is the change in hours of work induced by having grandchildren, relative to the counterfactual state in which one is not a grandparent. That is, conditional on $h_{1t} > 0$ and $h_{0t} > 0$, the intensive margin effect is

$$h_{1t} - h_{0t}, \tag{17}$$

while the treatment effect for a Senior who may be ($h_{0t} = 0$) or end up ($h_{1t} = 0$) at a corner of the time constraint (extensive margin effect) can be expressed as

$$\Pr(h_{1t} > 0) - \Pr(h_{0t} > 0). \tag{18}$$

3 Data

We use data on household heads and their spouses from all of the available waves, to date, of the PSID (1968-2015). This longitudinal data set is especially suited for the research question addressed in this paper. Its key feature, besides a unique time span for survey data, is an endogenous intergenerational structure: when the offspring of sample members leaves the family to form her or his own household, the latter is added to the sample. These endogenous additions are known as "split-offs". This mechanism implies that all descendants of the original families are observed for many years if they were not yet born or if they were still living with their parents at the time of the first interview. Therefore, grandparents and parents of sufficiently young cohorts can be linked to their grandchildren and children, regardless of whether they live in the same household or not. Such linkage is possible thanks to the Family Identification Mapping System (FIMS), a supplementary data set specifically created for intergenerational analyses.[7] Because we observe the entire life cycle (or long portions of it) for several thousand individuals, we can observe the same individuals both when they become parents and when, many years later, they become grandparents.

Our analysis is restricted to PSID core sample individuals (as well as their split-offs descendants) who were at most 48 years old at the time of the first interview in 1967. These are individuals who, at that time, were no older than twice the median age (24 years) parents were having their first child in the PSID before 1967. By adding up, roughly, the age at first birth of two generations, this criterion maximizes the chances that at least some of the children (Junior) of these individuals (Senior) are still present in the household at the time of the first interview and eventually become part of the PSID as split-offs, so that grandchildren (Baby) are observed when they appear, while at the same time retaining a large sample size.[8] This leaves us with an unbalanced panel of about 31,000 individuals. We selected from this sample observations younger that 80 years of age who satisfy the following two criteria: (1) are biological or adoptive parents; (2) their oldest child is at least 14 years old. These two criteria ensure that we are making a proper comparison—only those who satisfy them may be or become grandparents. The final sample is composed of about 12,500 individuals, each observed on average for 25.3 years (minimum 1 year, maximum 48 years).

Table 1 reports summary statistics in the pooled sample, for all individuals and for grandparents, by gender. Grandparents are of course the oldest among all parents with children in fertile age, which explains differences such as those in the distribution of education. The lower inci-

[7] Attrition does not distort the mapping: it's enough that the household of one's descendant is observed once.

[8] Table A.2 in the Appendix reports a robustness test on this cohort restriction by replicating the main results in the sample of individuals who were at most 50, 45, 40, or 35 years old at the time of the first interview in 1967.

dence of men observed in the table reflects their shorter longevity relative to women. The table also shows that grandparents have higher fertility than the rest of the sample, and a total of 5.7 grandchildren, on average. The average age at which individuals in our sample first have grandchildren is remarkably low: about 46 for women, and 49 for men. Although these numbers are in line with the correspondingly young age they became parents (about 22 for women, and 25 for men), a more accurate estimate of the age Americans become grandparents can be obtained by restricting our sample to cohorts that have nearly completed their life cycle. For instance, if we consider the average age individuals in our sample born before 1940 became grandparents in the 1968-2015 period, this is 49.2 for women (the median is 48), and 51.9 for men (the median is 51). These estimates from the PSID are more in agreement with estimates from other sources, as well as national trends in women's age at first birth.[9] We conclude from these statistics that Americans, on average, become grandparents around age 50, well before reaching the end of their working life. The relatively high employment rate of grandparents in Table 1 is in line with this fact.

In addition, we employ consumption data so to keep marginal utility of wealth constant in our structural estimation, as explained in greater detail in the Section 4 below. Up to the 1997 wave, the PSID collected consumption data for food items only, which limited researchers' ability to estimate intertemporal labor supply functions. Beginning with the 1999 wave, detailed consumption data on a number of non-food items were included (such as utilities, transportation, child care, education, insurance, health care, etc.). Using these richer consumption data, as well as data on rents or house value to estimate housing consumption, Attanasio and Pistaferri (2014) devised a statistical procedure that allows them to impute pre-1999 consumption retrospectively to all PSID individuals in a way that is consistent with post-1999 information as well as with the NIPA. In order to obtain a homogeneous series, these authors exclude food consumption and categories such as clothing and entertainment. Using the estimates from Attanasio and Pistaferri (2014) and replicating their procedure to estimate individual consumption for years 2012 and 2014 (PSID waves 2013 and 2015 had not been released at the time their article was published), we obtain the full 1967-2014 consumption series to be merged into our data set. Summary statistics on these consumption data are reported at the end of Table 1. In order to ensure an invariant sample across the different econometric specifications, the estimation sample is balanced by dropping observations with missing covariates, missing consumption data, or missing wages (if employed).

[9] According to the OECD Family Database, the average age of American women at the birth of their first child was about 25 in 2006, up from about 22.5 in 1970.

Table 1: Summary statistics, pooled final sample

	All individuals	Grandparents	Grandmothers	Grandfathers
Age	52.4	58.2	57.5	59.4
	(10.9)	(9.7)	(10.0)	(9.1)
Male	0.427	0.400	0.000	1.000
	(0.495)	(0.490)	–	–
White	0.841	0.835	0.803	0.883
	(0.365)	(0.371)	(0.398)	(0.322)
Black	0.118	0.121	0.151	0.078
	(0.323)	(0.326)	(0.358)	(0.268)
Married	0.763	0.733	0.658	0.843
	(0.425)	(0.443)	(0.474)	(0.363)
Widowed	0.071	0.113	0.154	0.052
	(0.257)	(0.317)	(0.361)	(0.221)
Divorced or separated	0.152	0.146	0.176	0.100
	(0.359)	(0.353)	(0.381)	(0.300)
Less than high school	0.204	0.258	0.257	0.261
	(0.403)	(0.438)	(0.437)	(0.439)
High school degree	0.407	0.428	0.468	0.369
	(0.491)	(0.495)	(0.499)	(0.482)
College degree	0.203	0.152	0.116	0.206
	(0.402)	(0.359)	(0.320)	(0.405)
Children in household	0.76	0.33	0.34	0.30
	(1.24)	(0.84)	(0.87)	(0.80)
Total fertility	3.10	3.53	3.54	3.51
	(1.75)	(1.94)	(1.94)	(1.94)
Age became parent	23.8	23.0	22.1	24.5
	(4.6)	(4.2)	(4.0)	(3.9)
Ever grandparent	0.811	1.000	1.000	1.000
	(0.391)	–	–	–
Grandchildren in household	–	3.6	3.7	3.5
	–	(2.9)	(3.0)	(1.9)
Total number of grandchildren	–	5.7	5.8	5.7
	–	(4.2)	(4.3)	(4.0)
Age became grandparent	–	47.2	46.1	48.8
	–	(7.0)	(7.0)	(6.7)
Employment rate	0.710	0.598	0.543	0.681
	(0.454)	(0.490)	(0.498)	(0.466)
Total family income	83.3	69.5	63.7	78.2
	(97.4)	(78.6)	(74.9)	(83.2)
Total family non-food consumption	19.8	18.0	17.0	19.7
	(13.2)	(11.5)	(11.0)	(12.0)
Adult-equivalent non-food consumption	9.9	10.3	10.0	10.8
	(7.0)	(6.9)	(6.8)	(7.1)
Individuals	12,519	6,884	4,140	2,744
Observations	151,713	116,912	71,754	45,158

Notes: Summary statistics by grandparent status and by gender. Income and consumption are expressed in thousands of 2010 dollars. Sample: PSID core sample, waves 1968-2015, individuals younger than 80 who have at least one child who is 14 or older, and who were no older than 48 years of age in 1967. Individual sampling weights are applied.

4 Econometrics

To build our econometric model, we first impose parametric restriction to obtain versions of equations (14) and (16) that can be easily estimated with the data just described. Specifically, we assume that preferences over consumption and work are of the CRRA type:[10]

$$u(c_t,\mathbf{x}_t)=\frac{c_t^{1-\gamma}}{1-\gamma}\exp(\theta_c\mathbf{x}_t);\qquad v(h_t,\mathbf{x}_t)=\frac{h_t^{1+\frac{1}{\eta}}}{1+\frac{1}{\eta}}\exp(\theta_h\mathbf{x}_t).$$

Therefore, labor supply at an interior takes the log-linear form, and we can write (14) as

$$\ln h_{0t} = \eta\ln w_t+\delta\mathbf{x}_t+\mu\ln c_{0t}, \tag{19}$$

$$\ln h_{1t} = \eta\ln w_t+\delta\mathbf{x}_t+\mu\ln c_{1t}, \tag{20}$$

$$\ln h_t = g_t h_{1t}+(1-g_t)h_{0t}, \tag{21}$$

where $\delta\equiv\eta(\theta_c-\theta_h)$, $\mu\equiv-\eta\gamma$, and $\theta_c\mathbf{x}_t-\gamma\ln c_{gt}=\ln\lambda_{gt}$. Replacing equations (19) and (20) into (21) leads to the estimating equation for the intensive margin effect:

$$\ln h_{it}=\eta\ln w_{it}+\beta_i g_{it}+\delta\mathbf{x}_{it}+\mu\ln c_{i0t}+\varepsilon_{it}, \tag{22}$$

where i denotes an individual, $\beta_i\equiv c_{i0t}-c_{i1t}$, g_{it} is a dummy variable equal to 1 if individual i is a grandparent in year t, and 0 otherwise,[11] and ε_{it} represents unobservable (to the econometrician) determinants of individual hours for workers. Included in vector $\mathbf{x}_{it}$ are a constant, a smooth fourth-order polynomial in age, marital status, race and education indicators. Year dummies will also be employed to absorb common time trends otherwise implicitly included in ε_{it}. Finally, assume that the unobserved utility components leading to equation (16) are normally distributed so that F is the standard normal cumulative distribution and the participation equation follows a Probit model, where the explanatory variables are the same as in equation (22), except for the wage rate which is not observed for nonemployed individuals:

$$\Pr(e_{it}=1)=\Phi(\tilde{\beta}_i g_{it}+\tilde{\delta}\mathbf{x}_{it}+\tilde{\mu}\ln c_{i0t}). \tag{23}$$

The parameters of interest in this analysis are β_i and $\tilde{\beta}_i$, i.e., the labor supply intensive and extensive margin effects of having grandchildren. Under the parametric restrictions we have im-

[10] This is a common assumption in the labor supply literature, see for instance Keane and Rogerson (2012).

[11] Because being a grandparent is an absorbing state, g_{it} is equal to 0 at the baseline and switches permanently to 1 when a parent becomes a grandparent.

posed, these parameters tell us how becoming a grandparent (a permanent switch of g_{it} from 0 to 1) shifts the work profiles described by equations (14) and (16), respectively. Note that these effects are individual-specific, but here we focus on average effects, i.e., the average intensive margin effect conditional on being at an interior,

$$\beta = \mathbb{E}(\ln h_{i1t} | h_{i0t} > 0, h_{i1t} > 0) - \mathbb{E}(\ln h_{i0t} | h_{i0t} > 0, h_{i1t} > 0), \tag{24}$$

which corresponds approximately to $h_{1t} - h_{0t}$ in equation (17) when expressed in percentage terms, and the average extensive margin effect,

$$\tilde{\beta} = \mathbb{E}(\mathbb{I}[h_{i1t} > 0]) - \mathbb{E}(\mathbb{I}[h_{i0t} > 0]), \tag{25}$$

which corresponds to $\Pr(h_{1t} > 0) - \Pr(h_{0t} > 0)$ in equation (18).

Identification faces three challenges. First and most important, the endogeneity of the grandparent status g_{it} in equations (22) and (23). If this status, conditional on observables, were random or dependent on Senior's time-invariant preferences, then identification in panel data would be trivial. However, our theoretical model shows that such status reflects one's own grandparenting profile, i.e., time allocated to grandchildren care in every period: the probability of being a grandparent increases in such time transfer because it reduces the cost of child bearing for Junior. In this case, causation runs the other way and it is Senior's labor supply adjustment that causes Senior to become a grandparent. The ensuing simultaneity is a form of endogeneity which cannot be solved by individual fixed effects. A shock to the probability of being a grandparent at any point in time and that is otherwise unrelated to labor supply late in the life cycle may solve the problem. A candidate instrument generating such a shock is the gender of one's first child, formally defined as

$$z_i = \begin{cases} 1 & \text{if the first child of Senior } i \text{ is female,} \\ 0 & \text{if the first child of Senior } i \text{ is male.} \end{cases} \tag{26}$$

This instrument has been widely used in the fertility literature, but here the rationale is different as it operates through a timing channel: because girls marry and have children at a younger age than boys, a Senior whose first child was a girl has a higher probability of being a grandparent at any point in time relative to a parent whose first child was a boy. These facts are shown in Tables 2 and 3. Table 2 reports the age at which girls and boys belonging to different cohorts became parents, if they did. These statistics are produced using the entire PSID core sample, and the cohort span (1950-1979) is chosen so to capture the generation of Juniors. The table shows that girls generally have children between 2 and 3 years earlier than boys of the same age. The average difference when pooling all the cohorts is 2.5 years. Table 3 shows that this difference translates into a comparable difference at which the parents of first-born girls and boys become grandparents.

Table 2: Age at which girls and boys first have children

	Year of birth					
	1950-1954	1955-1959	1960-1964	1965-1969	1970-1974	1975-1979
Girls	23.8	23.9	24.3	24.6	24.5	25.1
	($N = 523$)	($N = 751$)	($N = 569$)	($N = 474$)	($N = 374$)	($N = 469$)
Boys	26.1	26.8	27.0	27.6	27.8	26.4
	($N = 385$)	($N = 507$)	($N = 371$)	($N = 332$)	($N = 259$)	($N = 322$)
Difference	–2.3	–2.9	–2.7	–3.0	–3.3	–1.3

Notes: The table reports the age at which girls and boys belonging to different cohorts became parents. Sample: PSID core sample, waves 1968-2015, all individuals born between 1950 and 1979. Sampling weights are applied.

Table 3: Effect of instrument on age one becomes a grandparent, fertility, and marital instability.

	Age becomes grandparent		Total fertility		Ever divorced or separated	
	Women	**Men**	**Women**	**Men**	**Women**	**Men**
First child is female (z_i)	–2.43**	–1.51**	0.011	0.113*	0.019	0.015
	(0.23)	(0.29)	(0.042)	(0.051)	(0.010)	(0.010)
Observations	3,819	2,613	7,214	5,027	7,214	5,027

Notes: The table reports the coefficients from regressions of age of a grandparent at birth of the first grandchild (columns 1-2), own total fertility (columns 3-4), or whether one was ever divorced or separated (columns 5-6) on the z_i dummy. A constant and family income in 1967 are included in the regression. Because the dependent variables are constant within individuals, only one observation per individual is used. Sample: PSID core sample, waves 1968-2015, individuals younger than 80 years of age who have at least one child who is 14 years of age or older. Robust standard errors in parentheses. Significance level: * 5%; ** 1%.

Specifically, the first two columns of Table 3 report the effect of z_i on the age women and men in our sample become grandparents. This effect is large and significant: women whose first child was a girl become grandmothers 2.5 years earlier than their counterparts with a first-born boy. For men, the effect is 1.5 years. As a consequence, the instrument has a strong first stage in the expected direction. This is shown in Table 4: having had a girl as a first child increases the probability of being a grandparent at any point in time by, on average, about 9 percentage points for women and by between 7 and 8 percentage points for men with small standard errors and a corresponding large F-stat ruling out weak instrument concerns.

Table 4: First stage estimates.

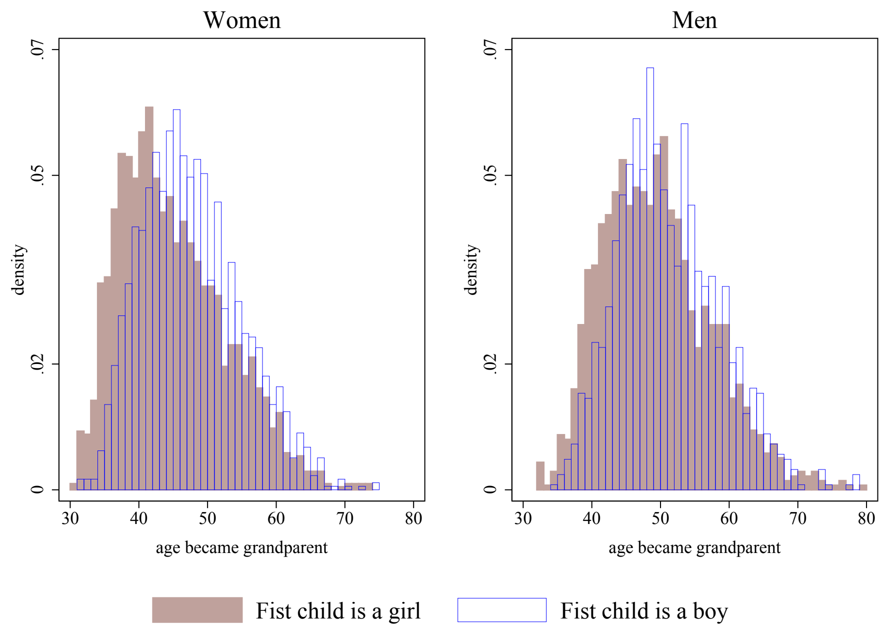
	Individual is a grandparent (g_{it})			
	Women		**Men**	
First child is female (z_i)	0.090**	0.087**	0.076**	0.072**
	(0.009)	(0.009)	(0.011)	(0.011)
F-stat, excluded instrument	90.0	87.5	47.1	44.3
Observations	84,951	88,497	55,898	55,898
Covariates ($\mathbf{x}_{it}$)	No	Yes	No	Yes

Notes: The table reports first-stage estimates, i.e., the coefficient from a regressions of the grandparent indicator g_{it} on the z_i dummy. A constant, year dummies, a fourth-order polynomial in age, and family income in 1967 are included in all of the regressions. Covariates include marital status, race and education indicators. Sample: PSID core sample, waves 1968-2015, individuals younger than 80 years of age who have at least one child who is 14 years of age or older. Robust standard errors in parentheses, clustered at the individual level. Significance level: * 5%; ** 1%.

Because the parameters of interest, β_i and $\tilde{\beta}_i$, are heterogeneous, identification via z_i makes our estimates local average treatment effects (LATE), i.e., average treatment effects for the compliers, provided that the monotonicity assumption holds. In this case the compliers are the parents of adult first-born daughters who have already become grandparents and the parents of adult first-born boys who are not yet grandparents, which makes our LATE a quite particular parameter. We will return on this point in the next Section when interpreting the IV estimates.

As for monotonicity, in this case it means that having a first-born daughter induces everyone (regardless of their observable or unobservable characteristics) to become a grandparent earlier relative to the counterfactual case in which one has a first-born son. Given that the main channel documented in Tables 2 and 3 is a mechanical one stemming from the earlier age at which girls first have children relative to same-age boys, there is a strong presumption that the monotonicity assumption holds. We further corroborate this assumption with two pieces of evidence. First, Figure 1 shows the probability mass function of the age at which Seniors become grandparents, by gender of Senior and by gender of Senior's first child. Clearly, having a first-born daughter shifts the entire distribution to the left (this is particularly evident for women, but the same pattern characterizes men), suggesting that in fact all Seniors whose first child was a girl become grandparents earlier, regardless of the age they first have grandchildren. Second, Figure 2 shows the fraction of Seniors who are grandparents at a given age, again by gender of Senior and by gender of Senior's first child. The figure indicates that at every age the proportion of Seniors who are grandparents is larger among those with a first-born daughter, both among women and among men. We report in the Appendix (Figure A.1) similar figures by dimensions of individual heterogeneity other than gender, namely ethnicity, education, total family income, and employment status. All of these additional figures exhibit the same pattern. Although far from conclusive, these two pieces of evidence support the monotonicity assumption and so the LATE interpretation of our estimand.

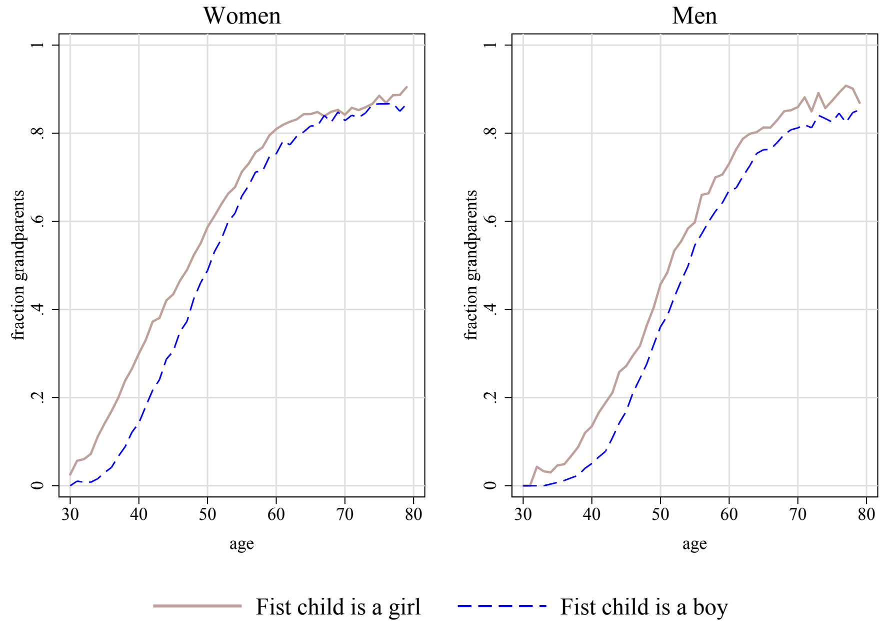
Figure 1: Distribution of the age Seniors become grandparents



Notes: The figure shows the probability mass function of the age at which Seniors become grandparents, by gender of Senior and by gender of Senior's first child. Sample: PSID core sample, waves 1968-2015, individuals younger than 80 years of age who have at least one child who is 14 years of age or older. Age one becomes a grandparent is constant for individuals, so only one observation per individual is used ($N = 3,819$ for women; $N = 2,613$ for men).

Supporting the validity of the exclusion restriction is more challenging. While the gender of one's first child is arguably as good as randomly assigned in the US (where there is no evidence of selective abortion over the period under investigation), there is well-established evidence that a first-born girl affects parents' behavior in ways that may be reflected in the allocation of time at different points of the life cycle. Lundberg (2005) offers a comprehensive survey of such evidence, and concludes that "one problem with child gender as an instrument is that the evidence

Figure 2: Fraction of Seniors who are grandparents at a given age



Notes: The figure shows the fraction of Seniors who are grandparents at a given age, by gender of Senior and by gender of Senior's first child. Sample: PSID core sample, waves 1968-2015, individuals younger than 80 years of age who have at least one child who is 14 years of age or older. ($N = 88,497$ for women; $N = 58,264$ for men)

[...] indicates that sons and daughters may have pervasive effects, not just on marital stability, but also on parental time and resource allocation." (p. 352). Dahl and Moretti (2008) and Ichino *et al.* (2014) produce additional evidence about the lifetime consequences of a first-born girl vs. a first-born boy. We address these concerns from two different angles. First, we employ a formal test of necessary conditions for instrument validity in a LATE model recently devised by Kitagawa (2015).[12] For the continuous measure of labor supply that we employ (i.e., h_{it}) the test does not reject the validity of the gender of one's eldest child as an instrument for being a grandparent, for

[12]The idea behind this test is the following. Let $L(g,z)$ be a labor supply measure as a function (in a counterfactual sense) of whether one is a grandparent (g) and whether one's eldest child is female (z), and let $g(z)$ be the grandparent status as a function of z, again in a counterfactual sense. It is well known that the three conditions from the LATE theorem (Imbens and Angrist, 1994) that ensure the validity of our binary instrument z_i (exclusion restriction: $L(g,1) = L(g,0)$ almost surely; random assignment: $z \perp L(g,z), g(z)$; monotonicity: $g(1) \geq g(0)$ almost surely) imply the following nesting relationships between the conditional densities of L and g, denoted below by f:

$$f(L, g=1|z=1) - f(L, g=1|z=0) \geq 0,$$
$$f(L, g=0|z=0) - f(L, g=0|z=1) \geq 0.$$

Kitagawa (2015) suggests testing these necessary conditions formally by means of a variance-weighted Kolmogorov-Smirnov test statistics. A key parameter determining the weight is a trimming constant which we set to 0.07 following Kitagawa's criterion to maximize the power of the test and his own empirical applications.

either men or women. The p-values are essentially equal to 1.

Second, because this formal test of necessary conditions cannot of course validate the instrument, we consider the main possible violations of the exclusion restriction that have been pointed out in the literature. One such violation is via own fertility. If a first-born girl induces higher fertility (Dahl and Moretti, 2008) and if fertility has a persistent effect on labor supply, then the instrument affects the outcome via a channel other than the probability of becoming a grandparent. However, the evidence does not support this scenario. Although young children do have a negative effect on the labor supply of young mothers, Bronars and Grogger (1994), Angrist and Evans (1998) Jacobsen *et al.* (1999), and Rondinelli and Zizza (2010) all consistently find that this effect is non-persistent, vanishing by age 40. That is, higher fertility seems to be unrelated to women's labor supply after age 40, when grandparenting may kick in. Furthermore, the third and fourth columns of Table 3 show that the instrument has no significant effect on total fertility in our sample for women, although it has some effect for men.[13]

Another well-documented effect of a first-born girl vs. first-born boy is reduced marital stability, a fact first noted by Morgan, Lye, and Condran (1988).[14] The last two columns of Table 3 show that in our sample the instrument has no significant effect on the probability of having ever been divorced or separated in our sample.[15] To further document the irrelevance of this channel (as well as other possible channels violating the exclusion restriction), we test whether a first-born

[13]This lack of a significant effect on total fertility agrees with the findings of Ichino *et al.* (2014), who point out that the significant fertility effects of z_i in Dahl and Moretti (2008) are driven by the selection of a sample of married women. Our sample includes women across the marital status categories, like the samples used by Ichino *et al.* (2014).

[14]Using data from the June 1980 CPS, they find that "For couples with one child, [...] the risk of disruption is 9% higher for those with a daughter than for those with a son" (p. 115).

[15]The point estimates indicate some increase in the probability of marital disruption for individuals with $z_{it} = 1$. Even if the gender of one's first child affected labor supply late in the working life via marital history, we can establish the sign of the ensuing bias which, if present, makes our estimates a lower bound for the effect of interest. To see this, consider the univariate version of the empirical model in equation (22), with marital stability as an omitted variable:

$$\ln h_{it} = \alpha + \beta g_{it} + \varepsilon_{it}; \quad (27)$$
$$\varepsilon_{it} = \psi \cdot D_{it} + \xi_{it}, \quad (28)$$

where D_{it} takes value 1 if individual i is divorced or separated at time t, and 0 otherwise. Johnson and Skinner (1986) and Bedard and Deschenes (2005) show that D_{it} is associated with higher female labor supply. Therefore, for these women $\psi > 0$. Suppose we use z_i as an instrument for g_{it} and that $cov(z_i, \xi_{it}) = 0$. The evidence on the effect of a first-born girl on marital stability implies $cov(z_i, divorce_{it}) = \sigma > 0$, which in turn implies that $cov(z_i, \varepsilon_{it}) = \psi\sigma > 0$ so that the exclusion restriction is violated. The probability limit of the IV estimator in this case is:

$$\text{plim } \widehat{\beta}_{IV} = \beta + \frac{\psi\sigma}{cov(z_i, g_{it})}.$$

Given that $\psi\sigma > 0$, the bias term is positive because our first-stage implies $cov(z_i, g_{it}) > 0$. Therefore, for women in our final sample $\widehat{\beta}_{IV}$ is a lower bound (in absolute value, given that this estimate is negative) of the true effect of interest, β. This line of reasoning, of course, extends to the multivariate model we employ.

daughter has a direct effect on the allocation of time *before* this daughter reaches fertility age, i.e., before one becomes a Senior. Specifically, we regress hours and participation on the instrument in the sample of parents whose eldest child is *younger* than 14 years of age, for different age ranges of the parent, in the same cohorts of Seniors used in the main estimation below, so these Juniors are referred to as the "potential Seniors". To perform this check, we estimate the following equations,

$$\begin{aligned} \Pr(e_{it}=1) &= \Phi(\tilde{\pi} z_i + \tilde{\delta}\mathbf{x}_{it} + \tilde{\mu}\ln c_{i0t}) + \tilde{\zeta}_{it}, \\ \ln h_{it} &= \pi z_i + \delta \mathbf{x}_{it} + \mu \ln c_{i0t} + \varepsilon_{it}, \end{aligned}$$

deferring the illustration of how we measure c_{i0t} and how we deal with wages and selection into employment. The results from these regressions are reported in Table 5, which shows that the gender of one's first child does not affect labor supply early in the working life for those individuals whose children have not yet reached fertility age and so are not yet eligible to become grandparents.

Table 5: Effect of a first-born girl on the labor supply of a potential Senior, by gender and age.

	Women				**Men**			
Age range:	25-29	30-34	35-39	25-39	25-29	30-34	35-39	25-39
	employment indicator (e_{it})							
z_i	0.003	-0.008	-0.024	-0.008	0.002	-0.007	-0.004	-0.002
	(0.009)	(0.011)	(0.014)	(0.008)	(0.003)	(0.026)	(0.005)	(0.003)
Obs.	20,921	18,131	8,259	47,311	13,401	16,141	11,008	41,512
	log conditional hours ($\ln h_{it}$)							
z_i	-0.018	0.007	-0.014	-0.009	0.002	-0.012	-0.002	-0.004
	(0.021)	(0.022)	(0.032)	(0.017)	(0.010)	(0.009)	(0.011)	(0.007)
Obs.	14,752	13,169	6,357	34,278	13,365	16,230	10,699	40,294

Notes: The table reports the coefficients from Probit regressions of an employment dummy (e_{it}) or linear regressions of log annual work hours conditional employment (h_{it}) on whether one's first child is a girl (z_i). For the employment equation, we report the effect of z_i on $\Pr(e_{it}=1)$ and s.e. computed via the delta method. A constant, a fourth-order polynomial in age, marital status, race and education indicators, year dummies, family income in 1967, and c_{i0t} are included in all of the regressions. Sample: PSID core sample, waves 1968-2015, Junior individuals in Senior cohorts (potential Seniors, see text) whose eldest child is younger than 14 years of age. Robust standard errors in parentheses, clustered at the individual level.

A residual concern is that the exclusion restriction may be violated for reasons underlying the different residential patterns of maternal and paternal grandparents.[16] Compton and Pollak (2013) have documented that married women in the US live closer to their mothers than married men. Consistent with this finding, in our final sample, 44.1% of grandparents whose first child was a girl live in the same Metropolitan Statistical Area of at least one grandchild. For grandparents whose first child was a boy this figure is 37.5%. To check against the possibility that this pattern correlates with labor supply later in the working life for reasons unrelated to grandparenting, we estimated the effect of the instrument z_i on the labor supply of Seniors who are at least 45 years of age and who are *not* grandparents. As it turns out, the gender of one's first child does not affect labor supply when excluding grandparents from the sample.[17] As we show below in Section 5, it does instead affect labor supply when grandparents are included, which corroborates the assumption that the instrument has an effect via grandparenting only. In sum, we are confident that the instrument defined in (26) provides an exogenous shock to the probability of being a grandparent late in the life cycle while not affecting the labor supply of a Senior via other channels.

A second challenge to identification is how to condition on c_{i0t} in equations (22) and (23), the counterfactual (for grandparents) consumption level in the no-grandchildren state. Such conditioning is necessary to the structural interpretation of our estimates, which requires keeping marginal utility of wealth constant.[18] To solve this problem, we write consumption as $c_t = c_{0t}\exp(\beta_c g_t)$, where β_c is (approximately) the percentage change in consumption following the birth of grandchildren since $\ln c_{it} = \ln c_{i0t} + \beta_c g_t$. Then one can run the following regression exploiting the consumption data described in Section 3,

$$\ln c_{it} = \beta_c g_{it} + \delta_c \mathbf{x}_{it} + \nu_{it}, \tag{29}$$

instrumenting g_{it} with z_i, and then take $\ln c_{it} - \widehat{\beta}_c g_{it}$ as an estimate of $\ln c_{i0t}$. This procedure imputes nongrandparents ($g_t = 0$) their actual consumption and grandparents ($g_t = 1$) the estimated counterfactual consumption in the $g_t = 0$ state.

The third and last challenge to identification is how to eliminate the possible bias stemming from selection into employment when estimating the intensive margin effect β in equation (22).

[16] We are grateful to an anonymous referee for raising this point.

[17] Detailed results are reported in Table A.1 of the Appendix, and derive from the same specification used to estimate the Intention-To-Treat effect reported in Section 5.

[18] When consumption is not directly observable, this problem is solved indirectly, under additional assumptions, by employing individual fixed effects (MaCurdy, 1981; Blundell and Macurdy, 1999). The consumption data described in Section 3 allows implementing a direct solution. Besides, even if the PSID is a panel, because the gender of one's first child is a constant at the individual level, two-stage within estimation would be infeasible and our IV estimates must be from pooled two-stage least squares in any case.

This problem can be solved by exploiting the model structure, which naturally suggests a Heckman-type selection correction procedure (Heckman, 1979). We implement this procedure parametrically in the standard two-stage way (the "Heckit" estimator), as follows. Note first that equation (23) is obtained from (15) by writing $e_{gt} = \mathbb{I}[\tilde{\beta}_i g_{it} + \tilde{\delta}\mathbf{x}_{it} + \tilde{\mu}\ln c_{i0t} + \zeta_{it} > 0]$ and by assuming that ζ_{it} is (standard) normally distributed. Further assuming that ε_{it} in equation (22) and ζ_{it} are joint normally distributed with mean zero and covariance ω implies that $\mathbb{E}(\varepsilon_{it}|e_{it} = 1, g_{it}, \mathbf{x}_{it}, \ln c_{i0t}) = \omega M(\tilde{\beta}_i g_{it} + \tilde{\delta}\mathbf{x}_{it} + \tilde{\mu}\ln c_{i0t})$, where $M(.)$ is the inverse Mills ratio. It is well known that this procedure requires including in $\mathbf{x}_{it}$ a variable affecting the participation decision but not hours conditional on being employed, i.e., an instrument for selection into work. As is common when dealing with this type of selection late in the working life in the US, a candidate instrument is whether an individual has reached age 62 or not, i.e., the early Social Security retirement age. Reaching that age threshold generates incentives to drop out of the labor force. As shown below, this instrument has in fact a strong first stage, reducing the probability of employment by about 3% for women and 4% for men. At the same time, there is no compelling reason why reaching age 62 (vs., say, 60 or 61) should induce a reduction in hours if one chooses to remain employed. We then estimate model (23) via IV Probit (which provides the extensive margin estimates reported in the next Section) and we use the predicted values $\widehat{\tilde{\beta}} g_{it} + \widehat{\tilde{\delta}}\mathbf{x}_{it} + \widehat{\tilde{\mu}}\ln c_{i0t}$ to construct the inverse Mills ratio. Including the latter into (22) as an additional regressor eliminates the possible selection bias in the estimated intensive margin effect β. In order to show in a transparent way how the solution to each of the problems discussed above affects the estimates, we will report results from cumulative specifications that add one set of variables at the time.

One final remarks is in order. Different from what we did in Section 3 to obtain representative means, we do not apply sampling weights in any of the regressions. This choice follows Solon, Haider, and Wooldridge (2015), who suggest that in a regression context it may be preferable to just condition on variables, if available, that account for the unequal sampling probabilities relative to the population of interest. Because the imbalance of the PSID core sample relative to the American population is chiefly due to differences in income at the time the sample was constructed in 1967[19], conditioning on family income in that year is a parsimonious way of retaining a large sample size while taking into account the different sampling probabilities.[20]

[19]The "core sample" of the PSID was constructed by merging two subsamples: the SRC subsample, which was extracted from the Census and was representative of the US population at the time, and the SEO subsample, which was a sample of low-income households.

[20]Weighting would cause the loss of about 1/3 of the sample because these observations are assigned a zero weight.

5 Results

Table 6 reports results from regressions (Probit for participation; OLS for hours) of labor supply on the gender of one's first child, i.e., the Intention-to-Treat (ITT) effect. Such an effect is present for employed women only, i.e., along the intensive margin of female labor supply, and it is negative: having had a girl as a first child reduces these women's hours by about 3%. Note that having reached age 62 reduces participation (as expected) by 3-4 percentage points, a precisely estimated effect that provides a relevant exclusion restriction for the selection-correction procedure illustrated in Section 4. These ITT estimates should be contrasted with the analogous estimates for these same Seniors when they were Juniors reported in Table 5, where no effect emerges.

The effect of being a grandparent is reported in Table 7. The first specification does not instrument for the grandparent status (it is a plain Probit for employment, and plain OLS for hours), and indicates negative labor supply effects along both margins for both grandmothers and grandfathers. The intensive margin effect is modest (0.7% for women; 3% for men) and statistically significant for men only. The extensive margin effect is more sizable and significant for both genders (about 5 percentage points for women; 3 for men). These estimates are inconsistent if the grandparent status and the time transfer to grandchildren are simultaneously determined like in the model of Section 2. The other specifications in Table 7 are based on the IV design (IV Probit for employment, and 2SLS for hours) and so correct the ensuing simultaneity bias. The point estimates for the extensive margin effect are unchanged but standard errors become very large and do not allow drawing reliable conclusions. As for the intensive margin estimates, these show a zero effect for employed men but a negative and sizable effect for employed women of about 30%, increasing to more than 35% when conditioning on covariates.[21] Given the baseline hours for these women, this means a reduction of about 480 hours per year. The magnitude of this intensive margin effect stands in sharp contrast with the OLS estimates, which are much smaller and much closer to zero than the IV ones. As for the magnitude, the estimated effect in Table 7 reflects the local nature of our IV estimand. As explained in Section 4, our instrument identifies a LATE which applies to the compliers only. Among grandmothers, the compliers are those women whose first-born child is a girl, i.e., women who are most likely maternal grandmothers. It is a well-documented fact that maternal grandmothers provide more child care than paternal ones (e.g., Compton and Pollak, 2014), and so the effect on the compliers should be larger than for the entire population of grandmothers.

[21] Although not reported in these tables in the interest of space, the coefficient on $\ln c_{i0t}$ is always highly significant and the coefficient on the inverse Mills ratio is generally significant. This indicates that the dynamics and selection into employment are relevant.

Table 6: Effect of having a first-born girl on the labor supply of a Senior, by gender.

	employment (e_{it})			conditional hours (h_{it})				
Women								
First child is female (z_i)	0.000	0.002	0.001	-0.032*	-0.031*	-0.033*	-0.034*	-0.034*
	(0.009)	(0.009)	(0.009)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Age $\geq$ 62	-0.029**	-0.030**	-0.032**					
	(0.009)	(0.09)	(0.009)					
Observations	84,951	84,951	84,951	54,886	54,886	54,886	54,886	54,886
Men								
First child is female (z_i)	0.007	0.010	0.010	-0.004	-0.000	-0.005	-0.004	-0.005
	(0.007)	(0.006)	(0.006)	(0.010)	(0.009)	(0.009)	(0.009)	(0.009)
Age $\geq$ 62	-0.033**	-0.039**	-0.039**					
	(0.007)	(0.006)	(0.006)					
Observations	55,898	55,898	55,898	15,469	15,469	15,469	15,469	15,469
$\ln c_{i0t}$	No	Yes	Yes	No	Yes	Yes	Yes	Yes
Inverse Mills ratio	No	No	No	No	No	Yes	Yes	Yes
$\ln w_{it}$	No	No	No	No	No	No	Yes	Yes
Covariates ($\mathbf{x}_{it}$)	No	No	Yes	No	No	No	No	Yes

Notes: The table reports the coefficients from Probit regressions of an employment dummy (e_{it}) or linear regressions of log annual work hours conditional employment (h_{it}) on whether one's first child is a girl (z_i), i.e., the Intention-To-Treat (ITT) effect. For the employment equation, we report the effect of z_i on $\Pr(e_{it} = 1)$ and s.e. computed via the delta method. A constant, year dummies, a fourth-order polynomial in age, and family income in 1967 are included in all of the regressions. Covariates include marital status, race and education indicators. Sample: PSID core sample, waves 1968-2015, individuals younger than 80 years of age who have at least one child who is 14 years of age or older. Robust standard errors in parentheses, clustered at the individual level. Significance level: * 5%; ** 1%.

Table 7: Effect of being a grandparent on the labor supply of a Senior, by gender.

	employment (e_{it})				log conditional hours ($\ln h_{it}$)					
Women	Employment rate: 0.628				Mean annual hours: 1,608.6					
Grandparent (g_{it})	-0.049**	-0.050	-0.043	-0.045	-0.007	-0.331*	-0.322*	-0.369*	-0.369*	-0.372*
	(0.009)	(0.103)	(0.099)	(0.100)	(0.015)	(0.153)	(0.154)	(0.166)	(0.158)	(0.160)
Age $\geq$ 62	-0.030**	-0.030**	-0.030**	-0.031**						
	(0.009)	(0.010)	(0.009)	(0.009)						
Observations	84,951	84,951	84,951	84,951	54,886	54,886	54,886	54,886	54,886	54,886
Men	Employment rate: 0.800				Mean annual hours: 2,126.2					
Grandparent (g_{it})	-0.026**	-0.027	-0.037	-0.036	-0.030**	-0.047	-0.000	-0.015	-0.000	-0.019
	(0.007)	(0.087)	(0.072)	(0.074)	(0.011)	(0.125)	(0.122)	(0.204)	(0.217)	(0.219)
Age $\geq$ 62	-0.033**	-0.033**	-0.039**	-0.038**						
	(0.007)	(0.007)	(0.006)	(0.006)						
Observations	55,898	55,898	55,898	55,898	46,029	46,029	46,029	46,029	46,029	46,029
g_{it} instrumented	No	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes
$\ln c_{i0t}$	No	No	Yes	Yes	No	No	Yes	Yes	Yes	Yes
Inverse Mills ratio	No	No	No	No	No	No	No	Yes	Yes	Yes
$\ln w_{it}$	No	No	No	No	No	No	No	No	Yes	Yes
Covariates ($\mathbf{x}_{it}$)	No	No	No	Yes	No	No	No	No	No	Yes

Notes: The table reports the coefficients from Probit regressions of an employment dummy (e_{it}) or linear regressions of log annual work hours conditional employment (h_{it}) on whether one is a grandparent (g_{it}). When the latter is instrumented, the instrument is a dummy equal to 1 if one's first child is a female and 0 otherwise (z_i). For the employment equation, we report the effect of g_i on $\Pr(e_{it} = 1)$ and s.e. computed via the delta method. A constant, year dummies, a fourth-order polynomial in age, and family income in 1967 are included in all of the regressions. Covariates include marital status, race and education indicators. Sample: PSID core sample, waves 1968-2015, individuals younger than 80 years of age who have at least one child who is 14 years of age or older. Sampling weights are applied to produce sample means of outcome variables. Robust s.e. in parentheses, clustered at the individual level. Significance level: * 5%; ** 1%.

As for the fact that OLS estimate of the intensive margin effect is positively biased, recall that our instrument is supposed to take care of the possible bias arising from simultaneity, such as the possibility that a future, anticipated reduction in Senior's labor supply reduces Junior's expected cost of child bearing and so increases the probability that Senior becomes a grandparent. If this is the case, under the hypothesis that the instrument identifies the true labor supply effect of becoming a grandparent, then not only there is no a priori reason to expect this bias to be small, but the OLS estimates may well be biased in the direction that we find.[22]

The remainder of this section deepens the IV analysis to gain a better understanding of the underlying mechanisms. The first question we address is whether there are different effects at different quantiles of the distribution of hours worked by employed grandmothers. This is a convenient way of checking how, in practice, these women adjust labor supply in response to the birth of grandchildren. To answer this question we employ the instrumental variable quantile regression method developed by Chernozhukov and Hansen (2006),[23] and we consider the 25$^{\text{th}}$ and 75$^{\text{th}}$ percentiles, where hours of employed women in our sample are 1144 and 2020, respectively, roughly corresponding to the part- and full-time levels. For men, hours at these same percentiles are 1880 and 2500, respectively. Results are reported in Table 8 using the baseline specifications. This table shows an interesting pattern: the bulk of the adjustment for employed women takes place at the bottom of the hours distribution, where part-time and more discontinuous jobs prevail. This suggests that it is working women less attached to the labor market who reduce labor supply in response to becoming a grandmother. At the 25$^{\text{th}}$ percentile level of hours in the sample, the drop

[22] An elementary example illustrates this point. Consider hours conditional on employment in a univariate two-equation model with perfect forecast about Senior's labor supply. The first equation determines hours as a function of the grandparent status, and the second equation is a linear probability model for the likelihood of becoming a grandparent as a function of the perfectly forecast variation in hours between period t and period $t+1$,

$$\ln h_{it} = \beta g_{it} + \varepsilon_{it} \tag{30}$$

$$g_{it} = b \Delta \ln h_{it} + \vartheta_{it}, \tag{31}$$

where $\Delta \ln h_{it} \equiv \ln h_{it+1} - \ln h_{it}$, the constant is omitted for simplicity, and $b < 0$ (i.e., the higher the expected reduction in hours, the higher the probability of becoming a grandparent). Solving the system, assuming for simplicity that ε_{it}, ϑ_{it}, and h_{it+1} are pairwise uncorrelated, assuming that ε_{it} and ϑ_{it} are zero-mean, and normalizing the variance of ε_{it} to 1, then if one runs a regression of h_{it} over g_{it}, one obtains the linear projection coefficient:

$$\frac{\mathbb{E}(h_{it} g_{it})}{\mathbb{E}(g_{it}^2)} = \frac{\beta b^2 \mathbb{E}(h_{it+1}^2) + \beta \operatorname{var}(\vartheta_{it}) - b}{b^2 \mathbb{E}(h_{it+1}^2) + \operatorname{var}(\vartheta_{it}) + b^2}, \tag{32}$$

which of course reduces to the true causal effect β if $b = 0$, i.e., if there is no simultaneity bias. Suppose $\beta < 0$ like our IV estimates indicate. It is easy to verify that if $b < 0$ then the linear projection coefficient in equation (32) is above β, like our OLS intensive margin coefficients are above the IV ones. The intution is the following. Grandparenthood is an absorbing state. If one ignores equation (31), then the OLS estimator associates a higher value of current labor supply h_t when g_{it} switches to 1 (relative to the lower value h_{t+1} in the subsequent period) to the switch itself rather than to the subsequent fall in labor supply which is one of the causes of the switch.

[23] We implement this regression with the `ivqreg` Stata code written by Kwak (2010).

in hours is about 40%.[24] Instead, those women who hold full time, continuous jobs do not seem to adjust their labor supply much: At the 75th percentile, the decline is only about 4%. For men, no significant effect is found at either of these two percentiles.

Table 8: Effect of being a grandparent on hours worked at the 25th and 75th quantiles.

	log conditional hours ($\ln h_{it}$)			
Percentile:	25th	25th	75th	75th
Women				
Grandparent (g_{it})	-0.410**	-0.391**	-0.044**	-0.047**
	(0.095)	(0.097)	(0.011)	(0.014)
Observations	54,886	54,886	54,886	54,886
Sample mean of hours	1,144		2,020	
Men				
Grandparent (g_{it})	-0.013	-0.003	-0.032	-0.021
	(0.095)	(0.033)	(0.038)	(0.043)
Observations	46,029	46,029	46,029	46,029
Sample mean of hours	1,880		2,500	
$\ln c_{i0t}$	No	Yes	No	Yes

Notes: The table reports instrumental variable quantile regression (IVQR) at the 25th and 75th quantiles of the distribution of hours conditional on employment. The dependent variable is the log of annual hours of work for pay conditional on being employed (i.e., excluding zero hours, $\ln h_{it}$). The instrument is a dummy taking value 1 if one's first child is a female and 0 otherwise (z_i). A constant, year dummies, a fourth-order polynomial in age, and family income in 1967 are included in all of the regressions. Sample: PSID core sample, waves 1968-2015, individuals younger than 80 years of age who have at least one child who is 14 years of age or older. Sampling weights are applied to produce sample means of hours. Robust standard errors in parentheses, clustered at the individual level. Significance level: * 5%; ** 1%.

Next, we ask whether the number of grandchildren matters. So far we have considered the effect of being a grandparent vs. not being one, an "extensive margin" of grandparenting. Conditional on being a grandparent, does the number of grandchildren matter? This is labeled the "intensive margin" of grandparenting. The answer is not obvious a priori, because there are economies

[24]Notice that there is no contradiction between the large negative effect at the 25th percentile and the insignificant extensive margin effect reported in Table 7: given an average of 1144 hours at this percentile, even a drop of 500 hours leaves one in the range of a feasible annual work schedule.

of scale in child care: one can take care of two or three grandchildren employing roughly the same amount of time it takes to take care of one. On the other hand, the intensive margin may matter if one has several grandchildren living in different households. To answer this question, we interact the grandparent indicator g_{it} with the number of grandchildren that grandparent i has in year t, denoted n_{it}, using $z_i \times n_{it}$ as an additional instrument. Therefore, the sum of the coefficient on g_i and $g_i \times n_{it}$ is the grandparenting extensive margin effect, while the coefficient on $g_i \times n_{it}$ alone measures the grandparenting intensive margin effect, under the assumption that it is linear.[25] Table 9 reports the results, again for the baseline specifications. The grandparenting intensive margin is small and positive, an insignificant -4% for each additional grandchild. All of the labor supply adjustment of working grandmothers occurs when they first have grandchildren.

Table 9: Grandparenting "intensive" and "extensive" margins

	conditional hours (h_{it})	
Women		
g_{it}	-0.437	-0.439
	(0.229)	(0.229)
$g_{it} \times n_{it}$	0.042	0.046
	(0.30)	(0.229)
Grandparenting extensive margin	-0.395*	-0.393*
	(0.199)	(0.199)
Observations	54,886	54,886
$\ln c_{i0t}$	No	Yes

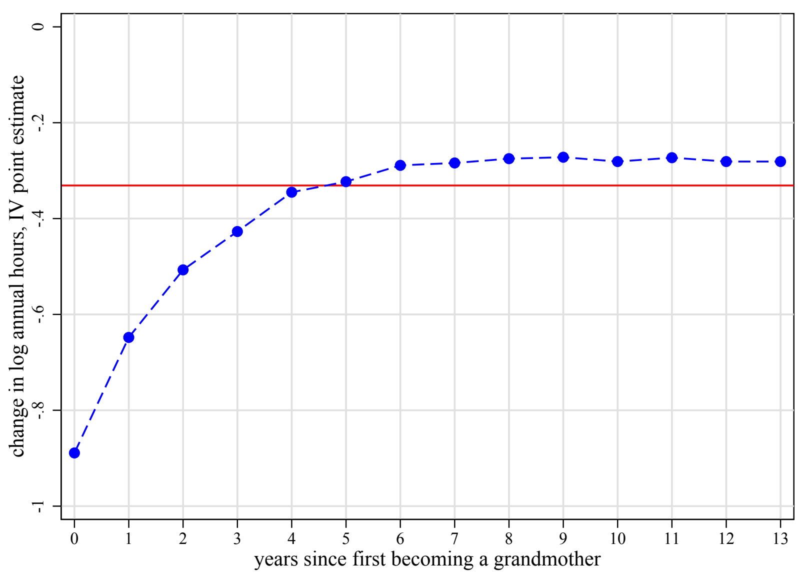
Notes: The table reports the coefficients from linear regressions of log annual work hours conditional employment (h_{it}) on whether one is a grandparent (g_{it}) and the latter interacted with n_{it}, the number of grandchildren individual i has in year t. The instruments are a dummy taking value 1 if one's first child is a female and 0 otherwise (z_i), and its interaction with n_{it}. A constant, year dummies, a fourth-order polynomial in age, and family income in 1967 are included in all of the regressions. The "Grandparenting extensive margin" is estimated as the sum of the coefficients on g_{it} and $g_{it} \times n_{it}$, and its standard error is computed using the delta method. Sample: PSID core sample, waves 1968-2015, individuals younger than 80 years of age who have at least one child who is 14 years of age or older. Robust s.e. in parentheses, clustered at the individual level. Significance level: * 5%; ** 1%.

Finally, the predominance of the grandparenting extensive margin suggests the importance of looking at how the labor supply effect we identify unfolds over time. We ask the following question: how does such effect varies with the number of years since one first became a grandpar-

[25]Notice that, by construction, $n_{it} = g_{it} \times n_{it}$, therefore only one of these two variables can be included in the regression. This is so because the intensive margin of grandparenting is defined for grandparents only, i.e., only if $n_{it} > 0$.

ent? This is also a convenient way of checking a potentially important margin of heterogeneity, namely having young vs. older grandchildren—presumably, the incidence of young grandchildren is higher during the first years since one first became a grandparent. To perform this exercise, we modify the grandparent indicator g_{it} to reflect "grandparenting lags". That is, we define indicators $g_{it\ell}$ for lags $\ell = 1, \ldots, 13$, where the lag is the number of years since one first became a grandparent. Indicator $g_{it\ell}$ takes value 0 until (if ever) one becomes a grandparent, then takes value 1 if in year t one has grandchildren but no more than ℓ years elapsed since one became a grandparent, and then takes value 0 again. Results are summarized in Figure 3, which plots the IV point estimates of the effect of $g_{it\ell}$ on the log of hours of employed grandmothers, as a function of the lag. These point estimates are produced by distinct 2SLS regressions, one per lag, using the baseline specification without controls. Treatment is given by $g_{it\ell}$, and only Seniors who are not yet grandparents or have been grandparents for no more than ℓ years are used as controls. The thick horizontal line is the average effect of -0.331 from the corresponding baseline specification reported in Table 7. The picture shows that hours drop substantially during the first years since becoming grandmothers, and then are readjusted upward as the grandchildren grow up. To be clear, the point estimates in Figure 3 are not statistically different from each other. However, they suggest a pattern that is worth investigating in future research.

Figure 3: IV point estimates by number of years since becoming a grandparent, women



Notes: The figure illustrates the IV point estimates of the effect of $g_{it\ell}$ on hours of working women. Only Seniors who are not yet grandmothers or have been grandmothers for no more than ℓ years are included in the regression. The thick horizontal line represents the baseline point estimate of -0.331 reported in Table 7.

6 Conclusions

This research provides causal evidence on the labor supply effects of becoming a grandparent, a relevant question in the light of time use data showing that many older workers make large time transfers in the form of grandparent-provided child care. The evidence from the PSID is that working grandmothers in the US reduce their labor supply by about 30%, on average, relative to their counterparts who are not (yet) grandmothers. This labor supply adjustment occurs towards the bottom of the hours distribution, is largely independent of the appearance of grandchildren beyond the first, and is progressively mitigated as the grandchild ages. How large is the effect we have identified? We have reported in Section 1 that conditional on strictly positive primary childcare in the ATUS, working-age women spend on average about 657 hours, after age 50, taking care of household and non-household children who are presumably their grandchildren. Our estimates account for about 70% of this, a large effect that reflects the LATE nature of our estimates. The instrument we used implies that maternal grandmothers (who provide much more child care than paternal grandmothers) are over-represented among the compliers. If all grandparents spent at least a few minutes with their grandchildren in primary care during a typical year, then this would be, for the compliers, the answer to the question we ask in the Introduction, namely how much grandparenting comes at the expense of other forms of "leisure" and how much comes at the expense of market labor supply? For men, instead, the answer is: a negligible amount. Increasing life expectancy in advanced countries offers parents an inexpensive, flexible, and reliable source of child care—grandparents. However, a prolonged and healthy mature age also requires a longer attachment to the labor market during the late stages of the life cycle. Our findings suggest that for women there is an important trade-off between these two desiderata that is relevant for retirement, taxation, child care policies, and family policies more broadly. In particular, the theoretical model and empirical findings highlight the generational linkages showing that policies designed toward subsidized child care affect not only the mother but older generations as well. If grandparents are providing for a substantial portion of child care needs, then a policy expanding the public provision of child care may affect the labor supply of young women only marginally, due to the substitution between informal and formal child care. Similarly, a parental leave policy may affect the labor supply of older women, due to the substitution between grandparental and parental child care. Forms of "grandparental leave" may offer a novel public policy to foster labor supply during the preretirement years.

References

Aguero, J. M., Marks, M. S., 2008, Motherhood and female labor force participation: Evidence from infertility shocks, American Economic Review 98, 500–504.

Andresen, M., Havnes, T., 2016, Child care and parental labor supply: A new look, Working paper, University of Oslo.

Angrist, J. D., Evans, W. N., 1998, Children and their parents' labor supply: Evidence from exogenous variation in family size, American Economic Review 88, 450–77.

Aparicio-Fenoll, A., Vidal-Fernandez, M., 2015, Working women and fertility: the role of grandmothers labor force participation, CESifo Economic Studies 61, 123–147.

Attanasio, O., Pistaferri, L., 2014, Consumption inequality over the last half century: Some evidence using the new PSID consumption measure, American Economic Review 104, 122–26.

Bailey, M. J., 2006, More power to the pill: The impact of contraceptive freedom on women's life cycle labor supply, The Quarterly Journal of Economics 121, 289–320.

Bedard, K., Deschenes, O., 2005, Sex preferences, marital dissolution, and the economic status of women, Journal of Human Resources 40, 411–434.

Bick, A., 2016, The quantitative role of child care for female labor force participation and fertility, Journal of the European Economic Association 14, 639–668.

Bloom, D., Canning, D., Fink, G., Finlay, J., 2009, Fertility, female labor force participation, and the demographic dividend, Journal of Economic Growth 14, 79–101.

Blundell, R., Macurdy, T., 1999, Labor supply: A review of alternative approaches, in: Ashenfelter, O., Card, D. (eds.), *Handbook of Labor Economics*, volume 3 of *Handbook of Labor Economics*, chapter 27, 1559–1695, Elsevier.

Bronars, S. G., Grogger, J., 1994, The economic consequences of unwed motherhood: Using twin births as a natural experiment, American Economic Review 84, 1141–56.

Cardia, E., Ng, S., 2003, Intergenerational time transfers and childcare, Review of Economic Dynamics 6, 431–454.

Chernozhukov, V., Hansen, C., 2006, Instrumental quantile regression inference for structural and treatment effect models, Journal of Econometrics 132, 491–525.

Chun, H., Oh, J., 2002, An instrumental variable estimate of the effect of fertility on the labour force participation of married women, Applied Economics Letters 9, 631–634.

Compton, J., Pollak, R., 2013, Proximity and Coresidence of Adult Children and their Parents in the United States: Description and Correlates, IZA Discussion Papers 7431, Institute for the Study of Labor (IZA).

Compton, J., Pollak, R. A., 2014, Family proximity, childcare, and women's labor force attachment, Journal of Urban Economics 79, 72 – 90.

Cruces, G., Galiani, S., 2007, Fertility and Female Labor Supply in Latin America: New Causal Evidence, Labour Economics 14, 565–573.

Dahl, G. B., Moretti, E., 2008, The demand for sons, Review of Economic Studies 75, 1085–1120.

Dimova, R., Wolff, F.-C., 2011, Do Downward Private Transfers Enhance Maternal Labor Supply? Evidence from Around Europe, Journal of Population Economics 24, 911–933.

Frimmel, W., Halla, M., Schmidpeter, B., Winter-Ebmer, R., 2017, Grandmothers' labor supply, Iser working paper 2017-11, University Essex.

Havnes, T., Mogstad, M., 2011, Money for nothing? Universal child care and maternal employment, Journal of Public Economics 95, 1455 – 1465.

Heckman, J. J., 1974, Effects of child-care programs on women's work effort, Journal of Political Economy 82, S136–S163.

Heckman, J. J., 1979, Sample selection bias as a specification error, Econometrica 47, 153–161.

Ho, C., 2015, Grandchild care, intergenerational transfers, and grandparents' labor supply, Review of Economics of the Household 13, 359–384.

Ichino, A., Lindstrm, E.-A., Viviano, E., 2014, Hidden consequences of a first-born boy for mothers, Economics Letters 123, 274 – 278.

Imbens, G. W., Angrist, J. D., 1994, Identification and estimation of local average treatment effects, Econometrica 62, 467–75.

Jacobsen, J. P., Pearce, J. W., Rosenbloom, J. L., 1999, The effects of childbearing on married women's labor supply and earnings: Using twin births as a natural experiment, Journal of Human Resources 34, 449–474.

Johnson, W. R., Skinner, J., 1986, Labor supply and marital separation, American Economic Review 76, 455–69.

Keane, M., Rogerson, R., 2012, Micro and macro labor supply elasticities: A reassessment of conventional wisdom, Journal of Economic Literature 50, 464–76.

Kitagawa, T., 2015, A test for instrument validity, Econometrica 83, 2043–2063.

Kwak, D. W., 2010, Implementation of instrumental variable quantile regression (ivqr) methods, Mimeo .

Lei, X. S., 2008, Grandchild care, financial transfers, and grandma's labor market decisions, Mimeo .

Lundberg, S., 2005, Sons, daughters, and parental behaviour, Oxford Review of Economic Policy 21, 340–356.

MaCurdy, T. E., 1981, An empirical model of labor supply in a life-cycle setting, Journal of Political Economy 89, 1059–85.

Morgan, S. P., Lye, D. N., Condran, G. A., 1988, Sons, daughters, and the risk of marital disruption, American Journal of Sociology 94, 110–129.

Posadas, J., Vidal-Fernandez, M., 2013, Grandparents' childcare and female labor force participation, IZA Journal of Labor Policy 2, 1–20.

Reinkowski, J., 2013, Should we care that they care? grandchild care and its impact on grandparent health, Ifo Working Paper Series Ifo Working Paper No. 165.

Rondinelli, C., Zizza, R., 2010, (non)persistent effects of fertility on female labour supply, Economic Working Papers 783, Bank of Italy, Economic Research and International Relations Area.

Rosenzweig, M. R., Wolpin, K. I., 1980, Testing the quantity-quality fertility model: The use of twins as a natural experiment, Econometrica 48, 227–40.

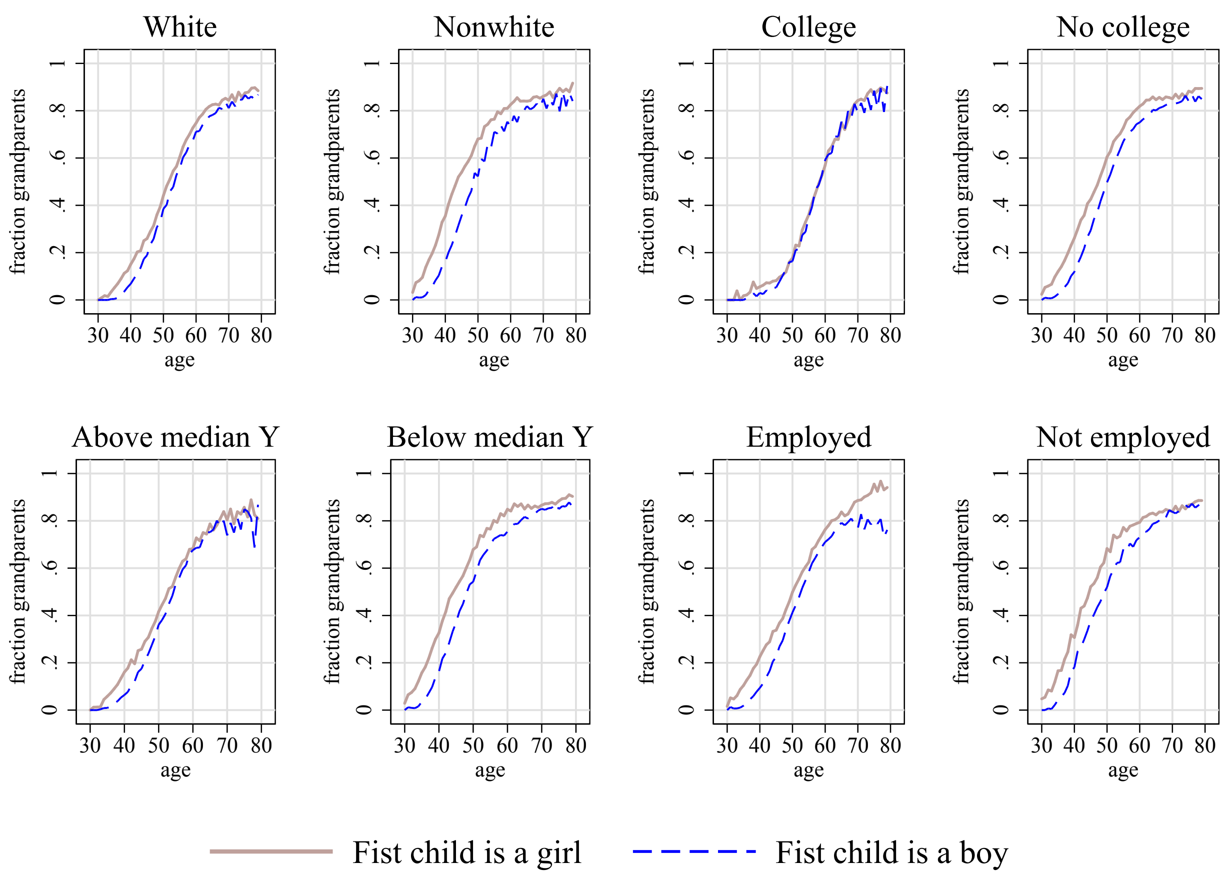
Solon, G., Haider, S. J., Wooldridge, J. M., 2015, What are we weighting for?, Journal of Human Resources 50, 301–316.

Zamarro, G., 2011, Family labor participation and child care decisions: The role of grannies, Working Papers 833, RAND Corporation Publications Department.

Appendix

A Additional figures and tables

Figure A.1: Fraction of Seniors who are grandparents at a given age



Notes: The figure shows the fraction of Seniors who are grandparents at a given age, by gender of Senior's first child and by whether Senior reports "White" as ethnicity (White vs. Nonwhite panels), by whether Senior has college degree or not (College vs. No college panels), by whether Senior's total family income in a given year is above the median total family income in that year (Above median Y vs. Below median Y panels), and by whether Senior is employed or not (Employed vs. Not employed panels). Sample: PSID core sample, waves 1968-2015, individuals younger than 80 years of age who have at least one child who is 14 years of age or older.

Table A.1: Effect of having a first-born girl on the labor supply of Seniors 45 years of age and older *without grandchildren*, by gender.

	employment (e_{it})			conditional hours (h_{it})				
Women								
z_i	0.012	0.004	0.001	-0.016	-0.019	-0.020	-0.018	-0.018
	(0.016)	(0.016)	(0.015)	(0.026)	(0.026)	(0.026)	(0.026)	(0.025)
age $\geq$ 62	-0.033	-0.037^{+}	-0.032^{+}					
	(0.019)	(0.019)	(0.019)					
Obs.	18,457	18,457	18,457	12,752	12,752	12,752	12,752	12,752
Men								
z_i	0.019	0.014	0.011	0.008	0.002	-0.004	-0.002	-0.001
	(0.010)	(0.009)	(0.008)	(0.014)	(0.013)	(0.014)	(0.013)	(0.013)
age $\geq$ 62	-0.011	-0.023*	-0.024*					
	(0.012)	(0.011)	(0.011)					
Obs.	17,836	17,836	17,836	15,469	15,469	15,469	15,469	15,469
$\ln c_{i0t}$	No	Yes	Yes	No	Yes	Yes	Yes	Yes
Inv. Mills ratio	No	No	No	No	No	Yes	Yes	Yes
$\ln w_{it}$	No	No	No	No	No	No	Yes	Yes
Covariates ($\mathbf{x}_{it}$)	No	No	Yes	No	No	No	No	Yes

Notes: The table reports the coefficients from Probit regressions of an employment dummy (e_{it}) or linear regressions of log annual work hours conditional employment (h_{it}) on whether one's first child is a girl (z_i), i.e., the Intention-To-Treat (ITT) effect. For the employment equation, we report the effect of z_i on $\Pr(e_{it} = 1)$ and s.e. computed via the delta method. A constant, year dummies, a fourth-order polynomial in age, and family income in 1967 are included in all of the regressions. Covariates include marital status, race and education indicators. Sample: PSID core sample, waves 1968-2015, individuals who are between 45 and 79 years of age, who have at least one child who is 14 years of age or older and who have *no grandchildren*. Robust standard errors in parentheses, clustered at the individual level. Significance level: + 10%; * 5%; ** 1%.

Table A.2: IV estimates of the effect of being a grandmother on hours, for different cohorts.

	conditional hours (h_{it})							
Women								
Grandparent (g_{it})	-0.332*	-0.325*	-0.302*	-0.296*	-0.275	-0.278	-0.186	-0.188
	(0.148)	(0.168)	(0.149)	(0.150)	(0.143)	(0.144)	(0.130)	(0.131)
Observations	55,579	55,579	53,436	53,436	50,480	50,480	47,181	47,181
Sample mean of h	1,604.1		1,615.4		1,628.8		1,662.7	
Max age in 1967	50		45		40		35	
$\ln c_{i0t}$	No	Yes	No	Yes	No	Yes	No	Yes

Notes: The table reports the coefficients from linear regressions of log annual work hours conditional employment (h_{it}) on whether one is a grandparent (g_{it}). The latter is instrumented with a dummy equal to 1 if one's first child is a female and 0 otherwise (z_i). A constant, year dummies, a fourth-order polynomial in age, and family income in 1967 are included in all of the regressions. Sample: PSID core sample, waves 1968-2015, individuals younger than 80 years of age who have at least one child who is 14 years of age or older belonging to different cohorts (maximum age in 1967). Sampling weights are applied to produce sample means of hours. Robust s.e. in parentheses, clustered at the individual level. Significance level: * 5%; ** 1%.