Does Labor Force Participation Reduce Informal Caregiving?

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Abstract

This paper examines the causal impact of labor force participation on informal caregiving. To address the endogeneity of labor force participation, we exploit local business cycles and instrument for individual labor force participation with state unemployment rates. Using data from the Survey of Income and Program Participation (SIPP), we find that labor force participation significantly reduces informal caregiving. Among women, working an additional 10 hours per week reduces the probability of providing informal care by 12.5 percentage points and reduces the number of care hours by 32 percent. We also find that the effect of labor force participation is stronger among women with low income and wealth, who are the most important target of many welfare policies that promote labor force participation. Our results imply that demographic trends and work-promoting policies have the unintended consequence of reducing informal caregiving in an aging society that faces rising demand for informal care.

Keywords: informal care, elderly care, employment, labor force participation, local business cycle, state unemployment rate.

JEL codes: I1, J14, J22

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I. Introduction

Along with many other developed countries, the U.S. faces twin headwinds in its attempts to take care of the elderly. On the one hand, demand for elderly care is rapidly increasing as the baby boomers hit retirement with rising longevity and high chronic disease prevalence (National Center for Health Statistics, 2012). Informal care -- broadly defined as unpaid care usually provided by family members, friends, and charities -- has been the majority source of elderly long-term care,[1] since formal institutional care is expensive and unappealing to many elderly who prefer staying in their communities.[2] As the society continues to age, one can reasonably expect the demand for informal care to rise substantially. On the other hand, certain demographic trends and various work-incentive policies may imply a dwindling supply of elderly care -- in particular, of informal care -- if time in the labor market crowds out informal caregiving. For example, one of the most prominent demographic trends in the U.S. in the past several decades is the dramatic increase in female labor force participation.[3, 4] How does this trend affect the informal caregiving decisions of women, who provide the majority of informal care?[5,6] Meanwhile, the U.S. has implemented various policies that promote labor force participation.[7] What are the implications

[1] McGarry (1998) estimates that only a little over 13 percent of primary caregivers are paid helpers. Arno, Levine, and Memmott (1999) estimate that the value of informal care in 1997 totaled $196 billion, bigger than the combined cost of $115 billion for nursing homes and paid home health care. In an AARP Brief, Gibson and Houser (2007) estimate the monetary value of informal care in 2006 at $350 billion, larger than total Medicare expenditures or total Medicaid expenditures, state and federal funding combined

[2] The national average cost of a private nursing home room in 2011 was $87,235 annually (Metlife, 2011). Formal home health care will become more expensive in the U.S. when the Labor Department's new rules applying overtime and minimum wage laws to home health workers take effect in 2015.

[3] Women accounted for 46 percent of the U.S. labor force in 2007, up from 34 percent in 1960, an increase of almost 48 million women (Gruber et al., 2009).

[4] Other demographic trends that may negatively affect the supply of informal care include declining fertility and smaller family sizes.

[5] Johnson and Wiener (2006) estimate that about two thirds of informal caregivers are women. McGarry (1998) estimates that, among non-spousal caregivers, more than 70 percent are female.

[6] McGarry (2006) conjectures that "…the recent rise in women's labor force participation and the increase in the ratio of female to male wages would be expected to result in a decline in the fraction of caregivers who are female." (pg. 26)

[7] The U.S. increased the Social Security full eligibility age from 65 to 67 for those born after 1960 (Social Security, 2013) and some argue for raising the Medicare eligibility age (Butler and Aaron, 2012). A central feature of the 1996 welfare reforms is to impose work requirements and time limits for welfare recipients (Public Law 104-193, 1996). In particular, the Temporary Assistance for Needy Families program imposes a 60-month life time limit on federally funded assistance for most families and also requires recipients to start working no later than two years after receiving assistance. The Earned Income Tax Credit uses an even more direct work-incentive, granting

of those policies for our ability to care for the elderly? To answer those questions, it is important to quantify the causal impact of labor force participation on caregiving.

In this paper, we examine how labor force participation affects informal caregiving. The biggest empirical challenge is that labor force participation is probably endogenous to caregiving. Specifically, our concern for endogeneity is three-fold. First, a negative correlation between labor force participation and caregiving could just reflect reverse causality: caregiving hurts individuals' labor market prospects and thus reduces labor force participation (Ettner,1995). Second, some unobservable individual characteristics could influence both labor force participation and caregiving simultaneously and thereby induce a spurious correlation between the two. For example, employed individuals may on average have a higher unobservable "ability" and people with high ability may also be good at taking care of others. Third, individual labor force participation variables such as employment and work hours are often measured with error, which may further bias the relationship as most surveys use long recall periods such as one year or longer.[8]

We employ an instrumental variables strategy to address those endogeneity concerns. Using data from three panels of the Survey of Income and Program Participation (SIPP 1996, 2001, and 2004), we instrument for individual labor force participation using within-state variation in the state unemployment rate. Our estimation strategy deals with the reverse causality issue because individual behavior is unlikely to affect the state unemployment rate. State-level unemployment rates probably also contain less measurement error than individual labor force participation status, because the errors in individual responses could cancel each other in aggregation.

Perhaps more importantly, we argue that the state unemployment rate is a valid instrument that plausibly satisfies the exclusion restriction after we control for a set of factors that may affect the demand or supply of informal caregiving at the individual or state level. First, we flexibly control for a

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benefits only to working individuals. These policies have been found to increase employment significantly. For example, see Hotz and Scholz (2003) for a review of the literature on effects of the Earned Income Tax Credit.

[8] Griliches (1977) notes a similar measurement error issue when estimating the wage return to schooling.

comprehensive set of individual characteristics such as demographics, race, education, household wealth, and household income (excluding the individual's own labor earnings). Second, we control for any time-invariant state-level factors that may affect the supply or demand of informal care by including state fixed effects in all our specifications. Those state fixed effects also control for any unobservable individual-level factors as long as the *distributions* of those factors are time invariant. For example, we do not observe in the SIPP data the presence or number of siblings nor do we observe the care recipients' financial situations, both being potentially important determinants of informal caregiving. However, as long as the distributions of those factors are stable at the state level over our short sample period (10 years), state fixed effects account for those factors. Third, because our instrument varies at the state level over time, it is important to account for other time-varying factors that may affect the demand or supply of informal care at the state level. Two factors are of particular importance. The first is the availability of formal care at the state level; prior research has shown that formal care and informal care are substitutes (Van Hortven and Norton, 2004 and 2008; Bolin et al, 2008). We therefore account for the availability of formal care at the state level by controlling for the time-varying state Medicaid expenditure per enrollee or the state Medicaid long-term care expenditure per enrollee. The second is the possible recession-caused decline of seniors' health noted in a recent literature (McInerney and Mellor, 2012). We therefore also control for state-level time-varying Medicare expenditure per enrollee. Our results are robust to the inclusion of those state-level controls.

We have two main findings. First, labor force participation reduces caregiving on both the extensive and intensive margins. Among women, working an additional 10 hours per week reduces the probability of providing informal care by 12.5 percentage points and reduces the number of care hours by about 32 percent. Second, the effect of labor force participation on caregiving is heterogeneous. The effects are stronger for women with fewer financial resources than for women with more resources. The effects are also stronger among women than among men. Given rising female labor force participation in the past several decades and the various work-promoting welfare policies targeting individuals (especially women) with low socioeconomic status, our findings suggest a dwindling supply of informal care that is

unlikely to meet the growing demand for informal care in an aging society. In addition, because informal care and formal care are potential substitutes, our findings have important policy implications for public health care programs such as Medicare, Medicaid, and other state and local programs. In particular, the already-strained public sector will have to carry a bigger burden if we are to maintain the current level of elderly care.

The vast majority of the literature on the relationship between labor force participation and informal care assesses the effect of informal caregiving on caregivers' labor market outcomes, the opposite of our focus.[9] Among the small set of papers studying the effect of labor force participation on informal caregiving, only a few try to correct for endogeneity of labor force participation, and they yield mixed results. Stern (1995) uses previous employment status to instrument for current period employment and finds no effect of employment on informal caregiving; the empirical identification relies on the strong assumption that individuals' expectations about future caregiving activities do not influence their current employment decisions. Using a difference-in-differences approach comparing families with and without children (who were affected differently by welfare reform and Earned Income Tax Credit expansion in the 1990s), Golberstein (2008) finds that increased work incentives reduce the likelihood of a woman co-residing with a disabled parent, which is a key form of informal caregiving.[10] Another related study is Nizalova (2012), who examines the effect of the wage on informal caregiving using cross-sectional state unemployment rates and industry structures as instruments.[11]

[9] See, for example, Moen et al. (1994); Ettner (1995); Robison et al. (1995); Pavalko and Artis (1997); McGarry (2006); Coe et al. (2011); and Van Houtven et al. (2013).

[10] Some other researchers deal with endogeneity of employment in its impact on informal caregiving. Boaz (1996) estimates a simultaneous equations model of employment and caregiving using implausible exclusion restrictions for employment (caregiver's schooling and age). Doty et al. (1998) also instrument for employment using variables that are likely endogenous, such as caregiver age, number of children, education, income, gender, race, activities of daily living disabilities, region, and whether caregiver received help from others. Mentzakis et al. (2009) control for lagged employment status in a panel data context to deal with the endogeneity of contemporary employment.

[11] Methodologically, our work is closest to Nizalova (2012). Our work differs from hers in several important ways. First, Nizalova studies the wage effect in the working population, rather than the effect of labor force participation in the entire population. Second, Nizalova's instruments identify only cross-state variation in wages, while we exploit within-state variation over time and therefore rule out the possibility that time-invariant state characteristics bias the estimates. Third, our instrument is strong with first-stage partial F-statistics above the commonly-used cutoff of 10 in our main specifications, while those in Nizalova (2012) are around 3 or 4.

II. A Simple Model of Informal Caregiving and Labor Market Participation

This section presents a simple economic model of informal caregiving and labor market participation. The purpose of the model is to illustrate the specific ways in which employment opportunities increase the opportunity cost of informal caregiving and thereby influence people's informal caregiving choices.

Let c denote the monthly hours of informal care a daughter gives to an elderly parent (or "care hours").[12] Let h denote her monthly hours of work in the formal labor market (or "work hours"), where she can earn wage rate w per hour. The rest of her time is spent in the residual category "leisure" (l). The daughter gets utility directly from leisure l, her own consumption x, and also the attained utility level of her parent U_p, which is a function of the amount of informal care the daughter gives. Therefore, the daughter's utility function U_d is:

$$U_d\big(l, x, U_p(c)\big). \tag{1}$$

Assume that utility is a concave increasing function of each argument. The daughter's total allotment of time is T, so the time constraint is:

$$T = c + h + l. \tag{2}$$

The daughter has I non-labor income, and her consumption is constrained to be equal to her total income:

$$x = I + wh. \tag{3}$$

To incorporate labor market opportunities for the daughter in a direct way, we add the following constraint:

$$h \leq \bar{h}. \tag{4}$$

The parameter $\bar{h}$ represents the maximum work hours that the formal labor market offers to the daughter. $\bar{h}$ characterizes employment opportunities that are exogenously determined by various factors such as

[12] These could be members of the same household or people outside the household. We write about a woman for simplicity, but the model could describe men's behavior just as well.

local economic conditions and social norms regarding women in the formal work force. For example, a booming local economy provides a higher $\bar{h}$ when it is easier for a woman to find formal employment or to work more hours.

The daughter maximizes her utility (Equation (1)) subject to the constraints in Equations (2)-(4). This is equivalent to maximizing the Lagrangian:

$$\mathcal{L} = U_d\big(l, x, U_p(c)\big) + \lambda_1(T - l - h - c) + \lambda_2(I + wh - x) + \mu(\bar{h} - h) \qquad (5)$$

where λ_1, λ_2, and μ are non-negative shadow values of their respective constraints. Consider the case where $h > 0$. Necessary first-order conditions (FOCs) for optimization are:

$$\frac{\partial U_d}{\partial l} - \lambda_1 \leq 0 \ , \ l \geq 0$$

$$\frac{\partial U_d}{\partial x} - \lambda_2 \leq 0 \ , \ x \geq 0$$

$$\frac{\partial U_d}{\partial U_p} \times \frac{\partial U_p}{\partial c} - \lambda_1 \leq 0 \ , \ c \geq 0$$

$$-\lambda_1 + \lambda_2 w - \mu \leq 0 \ , \ \mu \geq 0$$

where the conditions hold with complementary slackness (i.e., only one inequality in each line can be strict).

Assume that the daughter chooses strictly positive leisure *l* (e.g., sleep), consumption *x* (e.g., eating), and informal care *c*, so $\frac{\partial U_d}{\partial l} = \lambda_1 = \frac{\partial U_d}{\partial U_p} \times \frac{\partial U_p}{\partial c}$ and $\frac{\partial U_d}{\partial x} = \lambda_2$. Substituting into the final FOC and rearranging yields

$$\frac{\partial U_d}{\partial x} w - \mu \leq \frac{\partial U_d}{\partial l} \ , \ \mu \geq 0 \text{ and } \frac{\partial U_d}{\partial x} w - \mu \leq \frac{\partial U_d}{\partial U_p} \times \frac{\partial U_p}{\partial c} \ , \ \mu \geq 0.$$

Suppose the daughter's environment and preferences are such that she chooses to work all that she can ($h = \bar{h}$). This would be the case if *w* is high, *I* is low, and her marginal utility of consumption is high, so

the return to work is high at the margin.[13] Mathematically such a case implies that the shadow value on the maximum work constraint is strictly positive ($\mu > 0$), and thus the above conditions reduce to $\frac{\partial U_d}{\partial x} w - \mu = \frac{\partial U_d}{\partial l}$; that is, the return to work ($\frac{\partial U_d}{\partial x} w$ from increased consumption) is strictly larger than its marginal cost ($\frac{\partial U_d}{\partial l}$ from foregone leisure, or equivalently foregone informal care).[14]

Now suppose the local economy improves in this situation so $\bar{h}$ increases. Then, the daughter will work more hours to take advantage of the relatively high marginal benefit of work hours. In order to satisfy the time constraint (Equation (2)), she will have to reduce leisure, informal care, or both. Using the FOCs above, she will reduce leisure *l* and caregiving *c* so as to maintain $\frac{\partial U_d}{\partial l} = \frac{\partial U_d}{\partial U_p} \times \frac{\partial U_p}{\partial c}$ (from the first and third FOCs). If the marginal utility of leisure is high relative to that of informal caregiving, then the daughter will reduce caregiving more than leisure, and vice versa.

This is the particular mechanism we have in mind by which employment opportunities increase the opportunity cost of informal caregiving. As women experience greater employment opportunities over time, their costs of leisure and informal caregiving increase, which affects their leisure and caregiving decisions. They may choose to maintain constant caregiving activities, but only at the cost of giving up valuable leisure time. Our empirical strategy focuses on identifying how informal caregiving responds to individual labor force participation induced by exogenous changes in employment opportunities.[15]

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[13] A lower value of $\bar{h}$ also makes it more likely that the maximum-work constraint is binding. Note that the daughter is choosing her work hours *h*, rather than being forced into a particular level of work. We are focusing on the situation where the daughter chooses a corner solution.

[14] In addition, $\frac{\partial U_d}{\partial x} w - \mu = \frac{\partial U_d}{\partial U_p} \times \frac{\partial U_p}{\partial c}$.

[15] Changes in the offered wage rate w also influence work, leisure, and informal care choices. An increased market wage will probably reduce informal care hours (c). If the wage change's substitution effect on work hours h is relatively high, then the woman will work more and likely reduce informal care hours to compensate. This is especially the case for women who enter the work force in response to the offer wage increase. In addition, a higher market wage will increase household income, which might enable the family to hire formal caregiving services for the parent to substitute for informal caregiving (the formal caregiving option is not in the model above but is probably an important substitute for informal caregiving, as in Pezzin et al., 1996).

III. Estimation Strategy

To estimate the effect of labor force participation on informal caregiving, we begin with the following regression:

$$y_{ist} = \delta_0 + \delta_1 work\_hours_{ist} + \delta_2 X_{ist} + \delta_3 W_{st} + \nu_s + \eta_t + e_{ist} \quad (6)$$

where y_{ist} is a measure of informal caregiving by individual *i* living in state *s* at time *t*. y_{ist} can be an indicator for whether the individual provides any informal care ($care_{ist}$), or the amount of caregiving measured by the number of weekly informal care hours ($care\_hours_{ist}$). We set *care_hours* to zero for those who do not provide care.[16] $work\_hours_{ist}$ measures the number of weekly hours the individual works in the formal labor market, similarly set to zero for those who do not work. In an alternative specification, we replace $work\_hours_{ist}$ with a dummy variable $work_{ist}$ indicating whether the person works at all. X_{ist} is a vector of individual characteristics, W_{st} is a vector of residence state characteristics, ν_s is a residence state fixed effect, and η_t is a year fixed effect. Following the theoretical framework above, δ_1 measures the tradeoff between market work and informal care and is expected to be negative, because labor force participation raises the opportunity cost of caregiving.

In order to estimate the causal effect of labor force participation on caregiving, however, one must be mindful that individuals make caregiving and labor force participation decisions jointly, and that there are other potentially confounding factors that influence both decisions. For example, as shown in the model in the previous section, caregiving needs (e.g., the presence of an ailing parent), the marginal utility of leisure relative to that of caregiving, and even the amount of non-labor income all directly affect the tradeoff between labor force participation and informal caregiving. Our empirical strategy is to focus on proxies for exogenously-determined employment opportunities ($\bar{h}$ in the model) as shifters of individual labor force participation decisions. Specifically, we instrument for individual labor force participation ($work\_hours_{ist}$) with the unemployment rate in individual *i*'s residence state *s* in year *t*. This

[16] Estimating the effect only on a subsample of individuals with *positive* care hours yields a quantity that does not have a causal interpretation, because the composition of the pool of individuals with a positive outcome has been changed by the causal variable, introducing a selection bias (Angrist and Pischke, 2009, pp.95-102). We therefore do not model the effect of labor force participation on the hours of informal care only among the caregivers.

strategy identifies the effect δ_1 using variation in individual labor force participation that is induced by variation over time in employment opportunities in the individual's residence state.

We therefore estimate Equation (6) by two stage least squares (2SLS). This estimation strategy allows us to isolate the causal effect of labor force participation on informal caregiving, rather than the effect of informal caregiving on labor force participation (reverse causality), because individual caregiving behavior, which may affect individual labor force participation decisions, is unlikely to affect the unemployment rate at the state level. In addition, instrumenting with state unemployment rates likely reduces bias caused by measurement errors if aggregation of individuals' unemployment statuses to the state level reduces the influence of recall bias and reporting errors (i.e., individual positive and negative errors cancel one another).

More importantly, our estimates of the effect of labor force participation on informal caregiving are unlikely to reflect the effects of other unobservable individual and family characteristics (omitted variables). Our identifying assumption is that unobservable individual and family characteristics that influence both labor force participation and informal caregiving are uncorrelated with the state's unemployment rate (after conditioning on a set of controls we explain below). We believe this assumption is reasonable. First, we flexibly control for a comprehensive set of individual characteristics including a full set of indicators for each age between 16 and 64, indicators for different educational levels, indicators for race and ethnicity, household income (excluding one's own labor earnings), and household wealth.

Second, we include a set of state fixed effects. State fixed effects control for any time-invariant factors at the state level that can affect individual caregiving. For example, state culture and norms may play an important role when one decides whether to care for her elderly parents. Perhaps more importantly, for certain unobservable individual characteristics (e.g., individual ability at work and care, availability of siblings, the presence of an ailing parent needing care), even if they are correlated with the local unemployment rate *in a given year,* they are unlikely to be correlated with *within-state* variation over time in the unemployment rate. This is because the distributions of such factors are plausibly *time*

invariant in the short span of our sample period (about 10 years) and thereby are unlikely to be correlated with *time variation* in state unemployment rates.[17]

Third, our specifications control for several time-varying state-level variables (W_{st} in Equation (6)) that may affect the supply of or demand for informal caregiving. One potential confounder is the availability of state Medicaid coverage that pays for formal long-term care services such as nursing home and home care for the eligible elderly. Prior studies have shown that formal care and informal care are substitutes (Van Hortven and Norton, 2004 and 2008; Bolin et al, 2008), so it is possible that a more generous state Medicaid program would lead to less demand for informal care. Meanwhile, the availability of Medicaid coverage likely is correlated with state economic conditions such as the unemployment rate, because Medicaid enrollment typically is counter-cyclical as reduced income in recessions makes more people eligible for the coverage. As a proxy for the generosity and availability of states' Medicaid coverage, we control for Medicaid spending per enrollee (or alternatively, Medicaid long-term care spending per enrollee) in the potential caregiver's residence state. In addition, because a recent literature shows that recessions may be associated with worsening health among seniors (McInerney and Mellor, 2012) and worsening health of potential care recipients may call for more caregiving, we control for state Medicare expenditure per enrollee as a proxy for seniors' health. Our coefficient estimates remain robust to the inclusion of those time-varying state-level controls.[18]

[17] By the same argument, unobservable time-invariant individual characteristics of potential care recipients are also unlikely to be correlated with the within-state variation in unemployment rates in a short period of time. For example, potential care recipients in states with high unemployment rates may be particularly poor and unable to afford formal care, so they have to rely on informal care as a substitute. Because we do not have any parent characteristics in the SIPP data to use as controls, this would be a problem if the potential care recipients' wealth and income correlates with the time variation in state unemployment rates. But because most care recipients are elderly or disabled, their income and wealth, even if possibly correlated with state unemployment rates at a given point of time, are unlikely to be substantively affected by local business cycles. We therefore believe this would introduce minimal bias, if any.

[18] Note we do not need to control for state-level time-varying variables such as income and wealth, education, racial composition, and age distribution even though those variables are likely correlated with the state unemployment rate, because we have already controlled for those variables at the *individual* level; for example, conditional on individual income, there is little reason to believe that the state average income level would affect an individual's care decision.

Conceptually, the state unemployment rate should be a significant predictor of individual labor force participation in a large enough representative sample, because the state unemployment rate is an aggregate of individual employment statuses. We confirm this significant correlation in our SIPP sample by presenting large first-stage partial *F*-statistics of the instrument in the Results section.[19,20]

Equation (6) controls for a set of demographic and socioeconomic statuses of individuals (X_{ist}). Because both labor force participation and caregiving may follow certain life-cycle patterns, we control flexibly for respondents' ages with an indicator for each age in years. Individuals with different human capital levels have different labor market opportunities and may also have different preferences for or opportunity costs of caregiving. We therefore control for respondents' schooling levels with indicators for high school completion, attainment of some college credit, bachelor's degree receipt, and attainment of post-bachelor's schooling, with less than high school education being the omitted base group. Recognizing that other demographic characteristics also influence both labor force participation and caregiving, we control for sex, race and ethnicity (indicators for white, black, and Hispanic, with other races as the base group), and marital status (an indicator for being married). It is also possible that labor force participation and caregiving are correlated because both are correlated with household financial resources. For example, wives in a rich family may work less (due to the standard positive income effect on leisure hours), and the elderly in rich families also may be more likely to purchase care in the formal market (i.e., formal caregiving is a normal good). This would generate a negative correlation between work and informal care unrelated to the causal channel of labor force participation on caregiving (i.e., higher opportunity costs of informal caregiving due to labor force participation). We therefore also

[19] SIPP is not representative at the state level (SIPP Users' Guide 2001, pp. 10-38). If it were representative, then the correlation between state unemployment rates and individual labor force participation may have been stronger than we observe.

[20] Other studies have used aggregate variables measured at local geographic areas to instrument for variables at the individual level. For example, Chetty and Szeidl (2012) use a state housing price index and state housing supply elasticities to instrument for individuals' housing property value and home equity. Currie and Gruber (1996) use state-year variation in the simulated proportion of children eligible for Medicaid to instrument for individual children's eligibility in that state.

control in the vector X_{ist} for two measures of household financial resources: 1) total household income net of respondents' labor earnings,[21] and 2) household net worth.

IV. Data

We use the Survey of Income and Program Participation (SIPP), a major ongoing survey conducted by the U.S. Census Bureau. The SIPP is a series of nationally representative longitudinal samples of non-institutionalized civilians aged 15 and older in the U.S. We restrict our sample to include only working-age respondents (between 15 and 64 years old), because our focus is on the labor force participation decision. We use three separate panels from the SIPP: those beginning in 1996, 2001, and 2004. Each panel was followed in a sequence of interview waves that were four months apart. The 1996 and 2004 panels have 12 waves each (about four years of information), and the 2001 panel has 9 waves (about three years of information). One advantage of the SIPP is its large sample sizes: 60,054 respondents in the 1996 panel, 53,317 respondents in the 2001 panel, and 72,844 respondents in the 2004 panel. Our main analysis uses only the female sample, so the sample size is roughly half of the full sample. In addition to increasing the sample size, using multiple panels allows us to control for time trends of informal caregiving behavior.

The SIPP surveys contain core questionnaires that were administered in every wave on issues related to the main purpose of the survey, such as labor force participation and government program participation. In addition, wave 7 of each of the three SIPP panels includes a topical module about informal caregiving activities. This module contains a rich set of information about the respondent's informal caregiving behavior, including whether the respondent provided any informal care and the hours of care provided per week in the past month, whether providing care to household members or to non-household members and the respective care hours, and the relationship between the caregiver and care recipients. The main dependent variable $care_{ist}$ in our analysis is an indicator for informal caregiving,

[21] Income from the respondent herself would be largely from employment, which is the independent variable of interest, so we deduct own-earnings from the total household income.

equal to one if the respondent provided informal care to anyone in the past month and zero otherwise.[22] We also examine the average weekly hours of informal care provided in the past month (variable $care\_hours_{ist}$) with the variable set to zero for those who did not provide any informal care.

Respondents were asked in the core questionnaire to recall their labor force participation in each of the four months prior to the interview month, including employment status and work hours. We therefore can trace each respondent's employment and work hours closely and rather precisely throughout the panel period. Our main independent variable $work\_hours_{ist}$ is a measure of the extent of the individual's labor market participation around the time of wave 7 when the informal care module was administered. In our main specifications, $work\_hours_{ist}$ is the average hours worked per week in the 12 months prior to the informal care module; this variable is set to zero for those who were never employed during that time. We also define an alternative labor force participation measure as a dummy variable $work_{ist}$ taking the value of one if the individual worked positive hours in the formal market in any of the 12 months prior to wave 7, and taking the value of zero otherwise.

We obtain state unemployment rates from the Census Local Area Unemployment Statistics.[23] In particular, we use the state unemployment rates one year preceding the informal care module so that the instrument is consistent with the timing of the main explanatory variable -- average weekly hours worked in the previous 12 months.[24] We obtain the state-specific Medicare spending per enrollee ($medicare\_per_{st}$), Medicaid spending per enrollee ($medicaid\_per_{st}$), and Medicaid long-term care

[22] Variable $care_{ist}$ is called *EPVDCARE* in SIPP documentation. The precise language used in the 1996 survey was "*There are situations in which people provide regular unpaid care or assistance to a family member or friend who has a long-term illness or disability. During the past month, did* [the respondent] *provide any such care or assistance to a family member or friend living here or living elsewhere*?"

[23] The data set is available at http://www.bls.gov/lau/, accessed on September 30, 2012.

[24] That is, we use the 1997 unemployment rates for the 1996 SIPP panel for which our labor force participation variables are constructed using information from April-July 1997 to March-June 1998 (waves 5, 6, and 7) and informal caregiving variables are constructed using information from March-June 1998 (wave 7), 2002 unemployment rates for the 2001 SIPP panel for which our labor force participation variables are from February-May 2002 to January-April 2003 (waves 5, 6, and 7) and informal care variables are from January-April 2003 (wave 7), and 2005 unemployment rates for the 2004 SIPP panel for which our labor force participation variables are from February-May 2005 to January-April 2006 (waves 5, 6, and 7) and caregiving variables are from January-April 2006 (wave 7).

spending per enrollee (ltc_per_{st}) from the Center for Medicare & Medicaid Services.[25] We then convert those spending data to constant 2005 dollars.[26]

Topical modules in waves 3 and 6 of the SIPP panels include many questions about household assets and liabilities. Household net worth was generated by the SIPP as the sum of all household asset values minus the sum of all liability values. For each household, we average household net worth over the wave 3 and wave 6 values to reduce measurement errors (variable $household\_wealth_{ist}$).[27] In addition, the core surveys collect total household income from all sources and also each household member's total earned income. We subtract a respondent's own monthly earnings from her total monthly household income and average this "household income net of own earnings" across the 12 months in the year prior to the informal care module; this variable is called $household\_income_{ist}$. Both the household wealth and household income variables are measured in constant 2005 dollars.

Panel A of Table 1 displays summary statistics for our SIPP samples. Consistent with prior evidence, women are more likely to give informal care ($care_{ist}$=1 for 6 percent of women in our sample versus 3 percent among men). Among caregivers, the average weekly caregiving hours are 27 hours for women and 20 hours for men.[28] The employment rate in the 12 months prior to the informal care module

[25] The data set is available at http://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/NationalHealthExpendData/NationalHealthAccountsStateHealthAccountsResidence.html, accessed on July, 5, 2013.

[26] The 1996 and 2001 SIPP panels combine Maine and Vermont into one "state" identifier, and North Dakota, South Dakota, and Wyoming into another "state" identifier. To be consistent, we similarly group these states in the 2004 SIPP panel. We therefore have 45 "states" plus the District of Columbia in our final working sample, i.e., we have 46 state identifiers. To obtain the unemployment rates and the state spending data for the combined states, we calculate weighted averages with the weight being the state population.

[27] The specific SIPP created variable we use is called THHTNW. It is the total net worth recode. In the 1996 panel, THHTNW is the sum of equity in homes, vehicles, businesses, interest-earning assets at banks and other institutions, stocks and mutual fund shares, non-home real estate, other assets, IRA and Keogh accounts, and unsecured debt (THHTHEQ, THHVEHCL, THHBEQ, THHINTBK, THHINTOT, RHHSTK, THHORE, THHOTAST, THHIRA, and RHHUSCBT). In the 2001 and 2004 panels, the THHTNW definition adds equity in 401K and thrift savings accounts as well (the sum of THHTHEQ, THHVEHCL, THHBEQ, THHINTBK, THHINTOT, THHSTK, THHORE, THHOTAST, THHIRA, THHTHRIF, and THHUSCBT). The components of THHTNW were mostly top-coded and include imputations. Matthew Marlay at the U.S. Census Bureau kindly provided this information.

[28] The SIPP informal care hours may be measured with considerable errors. First, though SIPP 1996 reported care hours using a continuous measure, SIPP 2001 and 2004 reported the care hours in brackets with the highest bracket open (e.g., more than 116 hours) and the cutoffs of the brackets vary across panels. Second, some of the highest open brackets indicate incredibly high hours. For example, in SIPP 2001, the last open bracket has a low end point of 160+ hours for care provided to a household member, and 0.28 percent of respondents reported care hours more

is 67 percent for women and 73 percent for men, and the average hours worked per week among workers is 31 for women and 36 for men. Paired with the observation that women also give more informal care than men, this is consistent with greater employment opportunities reducing the optimal choice of informal caregiving by raising the opportunity cost of caregiving.

Table 1 also shows the year-by-year variation in the state-specific variables. There is considerable variation in state unemployment rates both within and across years. The mean across states is 4.77 in 1997, rises to 5.45 in 2002, and falls back to 5.02 in 2005, and the standard deviation in each year is about one percentage point. Across the states, Medicaid and Medicare spending per enrollee increased over the period, and Medicaid long-term care spending per enrollee decreased.

V. Main Results

V(i) Strength of the Instrument

We first document the strong correlation between our instrument and the endogenous explanatory variable. Using the sample of female respondents from the three SIPP panels, we regress $work\_hours_{ist}$, the average weekly hours worked in the previous 12 months (divided by 10), on the unemployment rate in the same period in the individual's residence state. The coefficient on the state unemployment rate measures the strength of the correlation between an individual's work hours and the state unemployment rate. Table 2 reports the results. Columns (1)-(5) differ only by the set of control variables included and all columns also control for a full set of age indicators, state fixed effects, and year fixed effects. Table 2 results show that higher unemployment rates at the state level predict fewer work hours at the individual

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than 120 hours per week. In the absence of a better imputation method, we impute the informal care hours in SIPP 2001 and SIPP 2004 by taking the midpoint of each closed bracket, or, if the respondents fall into the last open bracket, the midpoint of the lower end of this open bracket and 112 hours (7 days *(24 hours-8 hours for sleep) per day), the latter of which we take as the maximum hours of care one can possibly provide; for those last open brackets with a low end point higher than 112 hours, we combine them with the last closed bracket with high end point lower than 120 hours. We acknowledge the limitation of this imputation and caution that this imputation may introduce considerable measurement error into our measure of informal care hours. Nevertheless, our measures for average weekly caregiving hours are similar to published estimates from the American Time Use Survey (ATUS). In the 2011 ATUS, the average weekly hours of elder caregiving (among caregivers) are 24.5 hours for women and 18.2 hours for men (Bureau of Labor Statistics, 2012).

level; the coefficient of -0.04 in column (5) -- our preferred specification -- implies that a one percentage point increase in the state unemployment rate is associated with a statistically significant 0.4 hours reduction in weekly work hours (or about 22 hours in a year), or an about 2 percent drop from the baseline women's average work hours (20.9). The last row of the table presents the first-stage partial *F*-statistics of the instrument, which are well above the commonly-used cutoff of 10, indicating a strong instrument. Note that this relationship is robust to the inclusion of individual-level controls, suggesting that observable individual characteristics are uncorrelated with the state unemployment rate. This gives us more confidence that *unobservable* individual characteristics are also uncorrelated with the state unemployment rate (and thus are unlikely to cause omitted variables bias).

The control variables are correlated with work hours largely as expected. More educated women work more hours. White women work more than women of any other race. Married women work significantly less than single women. Household income net of own earnings is negatively correlated with work hours, consistent with a positive income effect on non-work time such as leisure. The wealth coefficient is negative as well.

V(ii) Results on Whether Providing Informal Care

Table 3 reports our main results from estimating the effect of weekly work hours on the probability of providing informal care.[29] For ease of comparison, we present the OLS estimates in columns (1)-(5) and the 2SLS estimates in columns (6)-(10). As with Table 2, we gradually add individual- and state-level controls, and all columns control for a full set of age indicator variables, state fixed effects, and year fixed effects. Columns (1)-(5) consistently show a negative correlation between labor force participation and caregiving. The statistically significant coefficient estimate of -0.004 implies that working 10 more hours per week is associated with a reduced probability of a woman

[29] In the main specifications, we use the average work hours in the previous 12 months in order to allow some lag time for informal caregiving to respond to labor force participation. As discussed next in the robustness checks subsection, we vary the reference period for working to be the same month, previous four months, and previous eight months. The results are robust to those alternative definitions.

providing informal care by 0.4 percentage points. However, the OLS estimates -- even when controlling for various individual characteristics -- are potentially biased.

Columns (6)-(10) of Table 3 show results from our instrumental variable estimation where we use state unemployment rates to instrument for weekly work hours. The 2SLS estimates are substantially larger than the OLS estimates. The coefficient of -0.125 in column (10) -- our preferred specification -- implies that working 10 more hours per week on average reduces the likelihood of providing informal care by 12.5 percentage points. Equivalently, women working full-time (40 hours per week) are almost half as likely to provide care as otherwise-similar non-working women.

Recall that our concerns with the OLS specifications were three: reverse causality, omitted variables such as "ability" or whether a sibling is present, and measurement errors. These concerns may lead to bias of different directions. Reverse causality would induce a downward bias to OLS results, while omitted variables could lead to upward or downward bias.[30] Classical measurement errors would induce an attenuation bias, which is an upward bias in case of a negative coefficient, though the direction of bias is not clear with non-classical measurement errors. The much larger magnitude of our 2SLS estimates in Table 3 implies that the upward bias in the OLS estimation, perhaps due to omitted variable bias or measurement errors or a combination of both, dominates the downward bias of reverse causality.

The control variables behave reasonably in the 2SLS specifications. For example, higher education is correlated with more informal caregiving. This is consistent with higher "ability" individuals providing more care. White women are more likely to provide care than women of any other race or ethnicity. Household wealth and household income (net of own labor earnings) are negatively correlated with informal caregiving. This is consistent with wealthier families using more formal care as a substitute for informal care. The coefficients on state per-enrollee Medicaid and Medicare spending are small and

[30] Omitted variables that are either positively or negatively correlated with both informal caregiving and labor force participation would induce an upward bias, and omitted variables that are correlated with caregiving and labor force participation in opposite directions would induce a downward bias.

insignificant. Somewhat puzzling is the finding that married women are less likely to provide care than unmarried women.[31]

V(iii) Results on the Amount of Care

We next examine the effect of labor force participation on the intensive margin of caregiving. Instead of being an indicator for any informal caregiving, the dependent variable in Equation (6) is replaced with the amount of care provided, measured as the log of average weekly care hours in the past month.[32] Table 4 presents the results from this exercise. Again, columns (1)-(5) report the OLS results for comparison and columns (6)-(10) report the 2SLS results. The results are consistent with those in Table 3: increasing work hours reduces informal caregiving significantly in both the OLS and 2SLS specifications, but the 2SLS estimates are substantially larger in magnitude than the OLS estimates. The coefficient estimate of -0.39 in column (10) -- our preferred specification -- implies that informal care hours fall by about 32 percent (=100*(exp(-0.39)-1)) when a woman works 10 more hours per week.

V(iv) Robustness Checks

Our findings of a significant negative labor force participation effect on informal caregiving are robust to alternative definitions of labor force participation and informal caregiving. Table 5 presents the 2SLS results of estimating Equation (6) with alternative definitions of labor force participation. The same set of controls is included as in the main Tables 3 and 4. For reference, column (1) repeats the main coefficient estimate from column (10) of Table 3. Columns (2)-(4) show results from alternative labor force participation measures with different reference periods: instead of average weekly work hours in the previous 12 months, we use average weekly work hours in the previous month (*work_hours_samemnth*$_{ist}$), in the previous 4 months (*work_hours_4mnth*$_{ist}$), in the previous 8 months (*work_hours_8mnth*$_{ist}$), or in the year prior to the previous year (from 24 months ago to 12 months ago:

[31] Given that wives usually provide more care than husbands, we had expected that married women would provide more care because married women have both their own and their spouses' families who may need care.

[32] In practice, we use ln(care hours+1) instead of ln(care hours) so that those who do not provide care are included in the sample and still coded as providing zero hours.

work_hours_lag$_{ist}$). Columns (1)-(5) show that the coefficient estimates are robust to these alternative definitions.

In addition to these continuous measures of labor force participation, we also define a set of dichotomous measures: an indicator for any positive work hours in the previous 12 months (variable *work*$_{ist}$) and a parallel set of variants with different reference periods: an indicator for any work in the same month (*work_samemnth*$_{ist}$), an indicator for the previous 4 months (*work_4mnth*$_{ist}$), an indicator for the previous 8 months (*work_ 8mnth*$_{ist}$), or an indicator for any work between 24 months and 12 months prior to the informal care module (*work_lag*$_{ist}$). We present in columns (6)-(10) the results for specifications using these indicator explanatory variables. Again, the coefficients are robust across the various alternative definitions; working substantially reduces the probability of providing informal care by 0.52-0.77. The instrument, however, is less powerful in predicting the indicators for work as shown by the first-stage *F*-statistics, so we caution that some of the estimates in columns (6)-(10) may be biased.

Table 6 explores the robustness of our main findings to alternative measures of informal caregiving. We define two indicator dependent variables indicating whether one's weekly informal care hours total more than 20 hours or more than 40 hours, respectively. The purpose is to see whether labor force participation has a differential impact on those providing a lot of care and for those providing less care. It is possible that care provision has some fixed costs (e.g., time spent travelling to the recipient's house) so that there is a threshold of care effort past which additional informal caregiving is not very costly. In such a case, working would have a smaller effect on the high end of the care hours distribution. Again for reference, column (1) repeats the coefficient estimate from column (10) of Table 3. Columns (2)-(3) of Table 6 present the 2SLS results using the two indicator dependent variables. Both coefficients are negative. Labor force participation has a smaller effect on the probability that one provides a higher amount of care per week, consistent with a threshold effect.

In another robustness check, we replace state Medicaid spending per enrollee by state Medicaid long-term care spending per enrollee, because not all Medicaid spending is for care that is potentially a substitute for informal care. The coefficient estimates are robust to this change (results upon request). To

allow for possible nonlinear relationships even more flexibly, we include polynomials to the 5th power for household income, household wealth, state Medicaid per enrollee spending, and state Medicare per enrollee spending. The main coefficient estimates remain very similar (results upon request)

VI. Heterogeneous Effects

In this section, we examine whether the effect of labor force participation varies by income and wealth, as well as by gender. It is important to understand the possible heterogeneity in the effects in order to design public policies that target the right sub-populations. We are particularly interested in knowing whether the effect varies by income and wealth for two reasons. First, poor women are the target of many social welfare programs that set time limits and work requirements and that have been shown to increase labor force participation.[33] Second, such women are more likely to be the main source of elderly care for aging parents, because formal care could be prohibitively expensive for their families.[34]

We therefore stratify our female sample by whether a woman's household income net of her own earning is above the sample median, and by whether her household wealth is above the sample median. We then estimate Equation (6) on the subsamples for our main outcome variables: whether the woman provided informal care or not and the log of care hours she provided per week. All of the regressions control for the full set of control variables as in our main specifications in Tables 3 and 4 except for excluding the relevant sets of variables that are used to split the samples. That is, when we examine the subsample of women with household income (or household wealth) below or above the median, household income (or household wealth) is dropped from the set of control variables.

Table 7 reports the results. Again for comparison, we report both the OLS results (columns (1)-(4)) and the 2SLS results (columns (5)-(8)). Panel A presents heterogeneous effects by income. Similar

[33] For example, Dave et al. (2012) find that welfare reforms in the 1990s raised the employment rate among at-risk women by about 8 percentage points, a finding similar to those found in McKernan et al. (2000) and Schoeni and Blank (2000).

[34] Studies have found that adult children with more education and higher wages are less likely to provide care to elderly parents (Henretta et al., 1997; Laditka and Laditka, 2001).

to our main Tables 3 and 4, the 2SLS estimates are much larger in magnitude than the OLS estimates, though we lose some precision due to smaller sample sizes. This is the case for both subsamples. Note that the magnitudes of the coefficient estimates are larger for women with less income than for women with more income. Column (5) of Panel A shows that an extra 10 hours per week in the labor market decreases the probability of informal caregiving by 9.5 percentage points for women with less income and column (7) shows a much larger 14.9 percentage points reduction for richer women. Comparing columns (6) and (8) also suggests a larger effect of work hours on care hours for poorer women. One caveat in those results is that the first-stage *F*-statistics for instrument are considerably lower than the usual cutoff of 10 in those subsamples, and the 2SLS coefficient estimates thus may be biased towards the OLS estimates. We therefore interpret those results as suggestive evidence.

Panel B of Table 7 report results on subsamples stratified by household wealth. A similar pattern emerges. The effects of labor force participation are much stronger for women from households with fewer financial resources than for women from richer households, although we lack precision due to smaller sample sizes. . The first-stage *F*-statistics are even smaller in the subsample of the lower-wealth women, implying biased estimates for those women, but the direction of the bias (toward OLS estimates) works against the finding of larger impacts on women in less-wealthy households.

In Panel C of Table 7, we examine whether the effects differ between women and men. For comparison, columns (1)-(2) and (5)-(6) repeat results from Tables 3 and 4 that describe our baseline sample of women. We estimate the same models for the male SIPP sample and present the results in columns (3)-(4) and (7)-(8). Our estimates show that the effect of labor force participation is much weaker for men than for women. This smaller effect is consistent with men on average playing a secondary role in providing informal care relative to women. For example, recently-unemployed women

may be more likely than men to use their surplus time for informal care activities, while unemployed men may spend more time searching for another job.[35]

Finally, we examine another type of heterogeneous effect: whether the effect of labor force participation differs depending on characteristics of the *care recipients*, rather than of the caregivers. We perform two exercises here. First, we examine whether the effect is different when the care recipient is a household member versus a non-household member.[36] We separately estimate Equation (6) for caregiving to household members and to non-household members. Table 8 reports the results. Again, each regression is a 2SLS specification using state unemployment rates to instrument for an individual's weekly work hours with a full set of controls. Compared with the small and insignificant coefficient in column (2), the larger and statistically significant negative coefficient in column (1) implies that more work hours reduce women's probability of informal caregiving mainly by reducing care to household members, rather than reducing care to non-household members. Columns (4) and (5) show results from corresponding specifications with the log of informal care hours as the dependent variable. The results are similar: more work hours reduce informal caregiving to household members but not so much to non-household members. A caveat of this exercise, however, is that cohabitation with care recipients is itself a decision that may depend on one's labor force participation status and is thus endogenous.

Second, we examine whether the effect of labor force participation on caregiving to *parents* differs from the effect on caregiving to anybody. Column (3) of Table 8 presents coefficient estimates from regressing on $work\_hours_{ist}$ an indicator for providing informal care to a parent, again with a full set of controls.[37] The statistically significant coefficient estimate of -0.06 is smaller in magnitude than our coefficient estimate of -0.125 in Table 3. This is reasonable because potential caregivers probably place

[35] Men in the 2011 American Time Use Survey (ATUS) spent more time than women searching for work (the activity category is "Job search and interviewing"). The gender gap was wider among unemployed than employed respondents (author's own calculations from the ATUS, accessed through IPUMS). See Abraham et al. (2011) for information about IPUMS.

[36] If a SIPP respondent indicated that she provided any informal care, then she was asked next whether she provided care to household members and whether she provided care to non-household members.

[37] SIPP does not ask about the number of care hours provided to parents.

more weight on their parents' wellbeing than on other people's, so working more hours affects caregiving to parents less than it affects caregiving to other people.

VI. Conclusion

We use a large nationally representative data set covering multiple years to estimate the effect of labor force participation on informal caregiving behavior in the U.S. To address the endogeneity issue, we instrument for individual labor force participation using state-level unemployment rates. We find that among women, working an additional 10 hours per week reduces the probability of providing any informal care by 12.5 percentage points and reduces the number of care hours by about 32 percent. Also, the effect of labor force participation on caregiving is heterogeneous. In particular, the effect is stronger for women from poorer households than for women from richer households. The effect is also stronger among women than among men. In addition, potential caregivers' responses seem to depend on their relationships with the care recipients. For example, labor force participation of women has a larger effect on care to household members than to non-household members, and a larger effect on care to non-parent care recipients than to parents.

As with all instrumental variable estimators, our 2SLS estimation strategy estimates a local average treatment effect, in this case for those individuals whose labor force participation is affected by local labor market fluctuations. Those individuals could be different from an average person in the population. Our estimates therefore do not necessarily generalize to the entire population. Also note that the effect we estimate is a partial equilibrium effect, since we investigate changes in individuals' labor force participation induced by relatively high-frequency changes in state unemployment rates. This partial equilibrium effect could potentially be different from the general equilibrium effect of large-scale and permanent movements towards employment, such as the long-term increase in women's labor force participation occurring over the past several decades.

Nevertheless, our results are consistent with increased employment opportunities putting downward pressure on informal caregiving supply, especially by women. This implies that there will be

continuing strains on the long-term care infrastructure in the U.S. Increasing demand for elderly care brought on by demographic trends only adds to the strains. Unfortunately, the formal caregiving sector provides no panacea. Nursing home care is often prohibitively expensive to families, the private insurance market is very small, and the government insurance program Medicaid offers incomplete coverage with copays and coinsurance almost equal to one's wealth and income (Norton, 2000). A government-run compulsory long-term care insurance program -- such as the one enacted in Germany in 1995 -- could directly increase the provision of elderly care (Mellor, 2000), but the likelihood of increased social spending for a new entitlement program in the U.S. is minimal.[38] As a result, many elderly still largely rely on informal care, the majority of which is provided by women.

Policymakers should consider the tradeoff between informal care needs and labor force participation when regulating health care and labor markets. Some labor policies may help, such as mandatory flexible work schedules, the ability to work remotely, and other "family-friendly" policies. U.S. federal policy, primarily through the Family and Medical Leave Act of 1993 (FMLA), however, mandates less coverage for paid leave and work flexibility than most other countries (Heymann et al., 2007). On the other hand, companies acting in their own best interests have been increasingly adopting more-flexible work environments.[39] Such changes will relieve some of the tension between informal care needs and labor force participation, even without explicit public policy changes. A silver lining in the employment losses in the recent recession may have been an increased supply of informal care to the elderly. Ultimately, the nation needs to strike a balance between encouraging more people to work and satisfying the growing needs of elderly care in an aging society.

[38] Even a *voluntary* long-term care insurance program (the CLASS ACT) was repealed from the Affordable Care Act in 2013 (Gleckman, 2013).

[39] Even though a widely circulated internal memo revealed that Yahoo! recently reduced its employees' freedom to work at home (Swisher, 2013), a U.S. Census Bureau report demonstrates a broader trend toward more flexibility: significantly more Americans worked at home in 2010 than in 2000 (Shah, 2013).

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Table 1 Sample Statistics

	(1) Female Sample	(2) Male Sample	(3) Pooled Sample
	(standard deviations in parentheses)		
Individual Level Variables			
care	0.06	0.03	0.04
	(0.23)	(0.17)	(0.20)
care to household members	0.03	0.02	0.02
	(0.16)	(0.12)	(0.14)
care to non-household members	0.03	0.02	0.03
	(0.18)	(0.13)	(0.16)
care to parents	0.02	0.01	0.01
	(0.13)	(0.09)	(0.11)
care to parents (among caregivers)	0.30	0.29	0.29
	(0.46)	(0.45)	(0.46)
care hours (in 10 hours)	1.48	0.61	1.06
	(9.40)	(5.71)	(7.86)
care hours to household members (in 10 hours)	1.04	0.46	0.77
	(8.58)	(5.36)	(7.24)
care hours to non-household members(in 10 hours)	0.55	0.20	0.38
	(4.65)	(2.61)	(3.82)
care hours (among caregivers)	26.84	20.42	24.71
	(30.33)	(26.24)	(29.19)
care hours to household members (among caregivers)	40.30	29.87	36.64
	(35.52)	(31.21)	(34.42)
care hours to non-household members (among caregivers)	16.25	11.73	14.82
	(19.71)	(16.36)	(18.83)
care hours more than 20 hours	0.02	0.01	0.02
	(0.15)	(0.09)	(0.12)
care houses more than 40 hours	0.01	0.00	0.01
	(0.11)	(0.09)	(0.09)
care hours more than 20 hours (among caregivers)	0.40	0.29	0.36
	(0.49)	(0.46)	(0.48)
care hours more than 40 hours (among caregivers)	0.23	0.16	0.21
	(0.42)	(0.36)	(0.41)
work hours (in 10 hours)	2.09	2.65	2.36
	(1.86)	(2.05)	(1.97)
work hours among workers (in 10 hours)	3.10	3.64	3.37

	(1.42)	(1.47)	(1.47)
work	0.67	0.73	0.70
	(0.47)	(0.44)	(0.46)
age	38.53	37.96	38.26
	(13.71)	(13.83)	(13.77)
male	-	-	0.48
			(0.50)
married	0.52	0.54	0.53
	(0.50)	(0.50)	(0.50)
high school	0.28	0.28	0.28
	(0.45)	(0.45)	(0.45)
some college	0.32	0.29	0.30
	(0.46)	(0.46)	(0.46)
college degree	0.15	0.15	0.15
	(0.36)	(0.35)	(0.36)
graduate degrees	0.07	0.08	0.07
	(0.25)	(0.27)	(0.26)
white	0.70	0.72	0.71
	(0.46)	(0.45)	(0.45)
black	0.13	0.11	0.11
	(0.34)	(0.31)	(0.32)
Hispanic	0.11	0.11	0.11
	(0.31)	(0.32)	(0.32)
household net assets (household_wealth, $1000s)	176.41	181.30	178.74
	(959.48)	(728.78)	(856.89)
household income net of self earning (household_income,	3.97	3.13	3.57
$1000s)	(4.32)	(3.54)	(3.99)
State Level Variables			
	1997	2002	2005
State unemployment rate	4.77	5.45	5.02
	(1.18)	(0.96)	(1.04)
State Medicaid spending per enrollee (medicaid_per, $1000)	6.10	6.66	6.82
	(1.84)	(1.86)	(1.87)
State Medicaid long-term care spending per enrollee (ltc_per,	1.10	1.02	0.99
$1000)	(0.62)	(0.62)	(0.55)
State Medicare spending per enrollee (medicare_per, $1000)	6.06	6.60	7.46
	(0.99)	(0.89)	(0.96)

Note: Sample statistics are taken across SIPP 1996, 2001, and 2004 panels.. All dollar amount variables, i.e., *household_wealth, household_Income, medicaid_per, ltc_per, medicare_per*, are in constant 2005 dollars.

Table 2: 2SLS First Stage Results

dependent variable=work hours (in 10 hours)

VARIABLES	(1)	(2)	(3)	(4)	(5)
	First Stage				
rateunemp	**-0.048*** **	**-0.044*** **	**-0.043*** **	**-0.044*** **	**-0.040*** **
	(0.011)	**(0.012)**	**(0.012)**	**(0.012)**	**(0.010)**
highsch		0.684***	0.709***	0.731***	0.731***
		(0.025)	(0.027)	(0.028)	(0.028)
somecol		0.881***	0.899***	0.947***	0.947***
		(0.022)	(0.023)	(0.025)	(0.025)
college		1.150***	1.192***	1.279***	1.279***
		(0.034)	(0.033)	(0.037)	(0.037)
gradsch		1.485***	1.520***	1.625***	1.625***
		(0.043)	(0.044)	(0.046)	(0.045)
white		0.190***	0.186***	0.184***	0.184***
		(0.031)	(0.033)	(0.038)	(0.038)
black		0.274***	0.169***	0.106**	0.106**
		(0.039)	(0.042)	(0.044)	(0.044)
hispanic		0.088***	0.087***	0.042	0.041
		(0.028)	(0.028)	(0.028)	(0.029)
married			-0.408***	-0.310***	-0.309***
			(0.023)	(0.024)	(0.024)
household_wealth				-0.000**	-0.000**
				(0.000)	(0.000)
household_income				-0.046***	-0.046***
				(0.003)	(0.003)
medicaid_per					0.024*
					(0.014)
medicare_per					-0.041
					(0.031)
Observations	80887	80887	80887	78725	78725
F-statistics for IV strength	**18.74**	**13.49**	**13.22**	**13.48**	**14.87**

Note: Less than high school education is the omitted category for the education variables while other races is the omitted category for the race/ethnicity variables. All regressions control for a full set of age dummies indicating each age from 15-64, state fixed effects, and year fixed effects. Robust standard errors clustered at the state level in parentheses. ***p<0.001, ** p<0.05, *p<0.1.

Table 3: 2SLS Results on Whether Providing Informal Care

dependent variable=care, endogenous variable =work hours (in 10 hours), instrument variable=state unemployment rate

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
			OLS					2SLS		
work_hours	**-0.004*** **	**-0.004*** **	**-0.004*** **	**-0.004*** **	**-0.004*** **	**-0.111*** **	**-0.122** **	**-0.125** **	**-0.121** **	**-0.125** **
	(0.001)	**(0.001)**	**(0.001)**	**(0.001)**	**(0.001)**	**(0.042)**	**(0.050)**	**(0.051)**	**(0.052)**	**(0.051)**
highsch		0.004	0.005*	0.006**	0.006**		0.085**	0.091**	0.092**	0.094**
		(0.003)	(0.003)	(0.003)	(0.003)		(0.034)	(0.037)	(0.039)	(0.038)
somecol		0.014***	0.014***	0.015***	0.015***		0.118***	0.123***	0.126**	0.129***
		(0.003)	(0.003)	(0.003)	(0.003)		(0.044)	(0.046)	(0.049)	(0.049)
college		0.001	0.002	0.004	0.004		0.137**	0.146**	0.153**	0.158**
		(0.003)	(0.003)	(0.003)	(0.003)		(0.058)	(0.062)	(0.066)	(0.066)
gradsch		0.004	0.005	0.008**	0.008**		0.180**	0.189**	0.198**	0.203**
		(0.003)	(0.003)	(0.003)	(0.003)		(0.074)	(0.078)	(0.084)	(0.083)
white		0.005*	0.005*	0.006**	0.007**		0.028**	0.028**	0.028**	0.029**
		(0.003)	(0.003)	(0.003)	(0.003)		(0.011)	(0.011)	(0.012)	(0.012)
black		0.006*	0.005	0.005	0.005		0.039**	0.025**	0.017*	0.017*
		(0.004)	(0.004)	(0.004)	(0.004)		(0.015)	(0.011)	(0.009)	(0.010)
hispanic		0.001	0.001	0.001	0.001		0.011	0.011*	0.006	0.006
		(0.003)	(0.003)	(0.003)	(0.003)		(0.007)	(0.007)	(0.005)	(0.005)
married			-0.006***	-0.005**	-0.005**			-0.056***	-0.041***	-0.042***
			(0.002)	(0.002)	(0.002)			(0.021)	(0.016)	(0.016)
household_wealth				-0.000**	-0.000**				-0.000*	-0.000*
				(0.000)	(0.000)				(0.000)	(0.000)
household_income				-0.001***	-0.001***				-0.006***	-0.006***
				(0.000)	(0.000)				(0.002)	(0.002)
medicaid_per					-0.000					0.003
					(0.002)					(0.003)
medicare_per					0.008					0.000
					(0.007)					(0.007)
Observations	80887	80887	80887	78725	78725	80887	80887	80887	78725	78725
Mean of Dep. Var.	0.0558	0.0558	0.0558	0.0558	0.0558	0.0558	0.0558	0.0558	0.0558	0.0558
First Stage F-stat						**18.74**	**13.49**	**13.22**	**13.48**	**14.87**

Note: Less than high school education is the omitted category for the education variables while other races is the omitted category for the race/ethnicity variables. All regressions control for a full set of age dummies indicating each age from 15-64, state fixed effects, and year fixed effects. Robust standard errors clustered at the state level in parentheses. ***p<0.001, ** p<0.05, *p<0.1.

Table 4: 2SLS Results on Care Hours

dependent variable=log(care hours), endogenous variable=work hours, instrument variable=state unemployment rate

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
			OLS					2SLS		
work_hours	**-0.017*** **	**-0.017*** **	**-0.018*** **	**-0.018*** **	**-0.018*** **	**-0.335*** **	**-0.367** **	**-0.376** **	**-0.363** **	**-0.390** **
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.127)	(0.151)	(0.155)	(0.157)	(0.157)
highsch		0.007	0.008	0.011	0.011		0.246**	0.262**	0.263**	0.283**
		(0.008)	(0.008)	(0.008)	(0.008)		(0.105)	(0.112)	(0.118)	(0.119)
somecol		0.027***	0.029***	0.031***	0.031***		0.335**	0.350**	0.357**	0.383**
		(0.009)	(0.009)	(0.009)	(0.009)		(0.133)	(0.140)	(0.149)	(0.150)
college		-0.012	-0.009	-0.004	-0.004		0.391**	0.418**	0.437**	0.472**
		(0.009)	(0.009)	(0.008)	(0.008)		(0.176)	(0.188)	(0.203)	(0.204)
gradsch		-0.017	-0.014	-0.008	-0.007		0.502**	0.530**	0.552**	0.597**
		(0.010)	(0.010)	(0.010)	(0.010)		(0.223)	(0.235)	(0.254)	(0.256)
white		0.011	0.011	0.013	0.013		0.077**	0.077**	0.076**	0.081**
		(0.010)	(0.010)	(0.010)	(0.010)		(0.035)	(0.035)	(0.036)	(0.036)
black		0.021*	0.016	0.014	0.014		0.117**	0.076**	0.051*	0.053*
		(0.011)	(0.012)	(0.012)	(0.012)		(0.046)	(0.033)	(0.028)	(0.029)
hispanic		0.008	0.008	0.007	0.007		0.038*	0.039*	0.021	0.022
		(0.010)	(0.010)	(0.010)	(0.010)		(0.021)	(0.020)	(0.015)	(0.016)
married			-0.022***	-0.017**	-0.017**			-0.168***	-0.124**	-0.132***
			(0.007)	(0.007)	(0.007)			(0.064)	(0.049)	(0.050)
household_wealth				-0.000***	-0.000***				-0.000*	-0.000*
				(0.000)	(0.000)				(0.000)	(0.000)
household_income				-0.003***	-0.003***				-0.018***	-0.020***
				(0.000)	(0.000)				(0.007)	(0.007)
medicaid_per					0.001					0.011
					(0.006)					(0.009)
medicare_per					0.015					-0.009
					(0.021)					(0.021)
Observations	80841	80841	80841	78688	78688	80841	80841	80841	78688	78688
Mean of Dep. Var.	0.152	0.152	0.152	0.152	0.152	0.152	0.152	0.152	0.152	0.152
First Stage F-stat						**18.31**	**13.19**	**12.98**	**13.29**	**14.61**

Note: Less than high school education is the omitted category for the education variables while other races is the omitted category for the race/ethnicity variables. All regressions control for a full set of age dummies indicating each age from 15-64, state fixed effects, and year fixed effects. Robust standard errors clustered at the state level in parentheses. ***p<0.001, ** p<0.05, *p<0.1.

Table 5: Robustness Checks: Varying the Definition of Labor Force Participation

dependent variable=care, endogenous variable= 10 different variants of labor force participation, instrument variable=state unemployment rate

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	2SLS									
work hours	-0.125**									
	(0.051)									
work hours_samemnth		-0.184**								
		(0.094)								
work hours_4mnth			-0.158**							
			(0.071)							
work hours_8mnth				-0.142**						
				(0.061)						
work hours_lag					-0.124**					
					(0.056)					
work						-0.769*				
						(0.450)				
work_samemnth							-0.620**			
							(0.296)			
work_4mnth								-0.523**		
								(0.225)		
work_8mnth									-0.771*	
									(0.439)	
work_lag										-0.595**
										(0.287)
Observations	78725	78441	78520	78695	74283	78725	78441	78520	78695	74283
Mean of Dep. Var.	0.0558	0.0557	0.0557	0.0557	0.0568	0.0558	0.0557	0.0557	0.0557	0.0568
First Stage F-stat for work_lag	14.87	6.642	9.213	10.91	11.39	4.463	7.652	10.45	4.460	7.117

Note: All regressions control for a full set of age dummies indicating each age from 15-64, state fixed effects, and year fixed effects, as well as the full set of controls in Tables 3 and 4. Robust standard errors clustered at the state level in parentheses. ***p<0.001, ** p<0.05, *p<0.1.

Table 6: 2SLS Results Using Other Measures of Care Provision as Dependent Variables

dependent variable=see the column heading, endogenous variable=work hours, instrument variable=state unemployment rate

VARIABLES	(1)	(2)	(3)
	log (care hours)	whether care hours>20	whether care hours>40
work hours	-0.390**	-0.053**	-0.040
	(0.157)	(0.026)	(0.026)
Observations	78688	78688	78688
Mean of Dep. Var.	0.152	0.0218	0.0127
First Stage F-stat	14.61	14.61	14.61

Note: All regressions control for a full set of age dummies indicating each age from 15-64, state fixed effects, and year fixed effects, as well as the full set of controls in Tables 3 and 4 . Robust standard errors clustered at the state level in parentheses. ***p<0.001, ** p<0.05, *p<0.1.

Table 7: Heterogeneous Effects by Socioeconomic Status and by Gender

dependent variable=see the column heading, endogenous variable =work hours, instrument variable = state unemployment rate

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS				2SLS			
Panel A by household Income (female sample)								
	high income		low income		high income		low income	
	care	log(care hours)	care	log(care hours)	care	log(care hours)	care	log(care hours)
work hours	-0.005***	-0.020***	-0.003***	-0.017***	-0.095	-0.350	-0.149	-0.398*
	(0.001)	(0.002)	(0.001)	(0.003)	(0.071)	(0.215)	(0.099)	(0.225)
Observations	44300	44287	34425	34401	44300	44287	34425	34401
Mean of Dep. Var.	0.0514	0.138	0.0614	0.170	0.0514	0.138	0.0614	0.170
First Stage F-stat					5.122	5.058	3.591	3.560
Panel B: by household wealth (female sample)								
	high wealth		low wealth		high wealth		low wealth	
	care	log(care hours)	care	log(care hours)	care	log(care hours)	care	log(care hours)
work hours	-0.006***	-0.021***	-0.003***	-0.017***	-0.086*	-0.221	-0.316	-1.200
	(0.001)	(0.002)	(0.001)	(0.003)	(0.050)	(0.143)	(0.443)	(1.651)
Observations	35636	35631	43089	43057	35636	35631	43089	43057
Mean of Dep. Var.	0.0615	0.164	0.0510	0.142	0.0615	0.164	0.0510	0.142
First Stage F-stat					11.05	11.04	0.639	0.592

Panel C: by gender

	female		male		female		male	
	care	log(care hours)	care	log(care hours)	care	log(care hours)	care	log(care hours)
work hours	-0.004***	-0.018***	-0.001**	-0.005***	-0.125**	-0.390**	-0.042*	-0.080
	(0.001)	(0.002)	(0.000)	(0.001)	(0.051)	(0.157)	(0.025)	(0.068)
Observations	78725	78688	72210	72188	78725	78688	72210	72188
Mean of Dep. Var.	0.0558	0.152	0.0300	0.0730	0.0558	0.152	0.0300	0.0730
First Stage F-stat					14.87	14.61	18.48	18.64

Note: All regressions control for a full set of age dummies indicating each age from 15-64, state fixed effects, and year fixed effects, as well as the full set of controls in Tables 3 and 4 . Household income excludes the respondent's own labor earnings. High income and high wealth are defined as levels above the sample median, while low income and low wealth are levels below the sample median. Robust standard errors clustered at the state level in parentheses. ***p<0.001, ** p<0.05, *p<0.1.

Table 8: Heterogeneous Effects by Care Recipients.

dependent variable=see the column heading, endogenous variable=work hours, instrument variable=state unemployment rate

VARIABLES	(1)	(2)	(3)	(4)	(5)
				2SLS	
	whether care to household members	whether care to non-household members	whether care to parents	log (care hours to household members)	log (care hours to non-household members)
work hours	-0.101**	-0.046	-0.062**	-0.359**	-0.092
	(0.044)	(0.034)	(0.025)	(0.154)	(0.071)
Observations	71593	78725	76915	71591	78725
Mean of Dep. Var.	0.0257	0.0339	0.0171	0.0836	0.0798
First Stage F-stat	13.11	14.87	14.26	13.11	14.87

Note: All regressions control for a full set of age dummies indicating each age from 15-64, state fixed effects, and year fixed effects, as well as the full set of controls in Tables 3 and 4. Robust standard errors clustered at the state level in parentheses. ***p<0.001, ** p<0.05, *p<0.1.