Essays on Informal Care, Labor Supply and Wages

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ABSTRACT

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This dissertation examines how caregiving for an elderly parent affects an adult child's labor supply and wages.

In the first chapter (co-authored with Courtney H. Van Houtven and Norma B. Coe) we identify the relationship between informal care and labor force participation in the United States, both on the intensive and extensive margins, and examine wage effects. We control for time-invariant individual heterogeneity; rule out or control for endogeneity; examine effects for men and women separately; and analyze heterogeneous effects by task and intensity. We find modest decreases—1.4-2.4 percentage points—in the likelihood of working for caregivers providing personal care. Male and female chore caregivers, meanwhile, are more likely to retire. For female care providers who remain working, we find evidence that they decrease work by 3-10 hours per week and face a 2.3-2.6 percent wage penalty. We find little effect of caregiving on working men's hours or wages except for a wage premium for male intensive caregivers.

In the second chapter I formulate and estimate a dynamic discrete choice model of elder parent care and work to analyze how caregiving affects a woman's current and future labor force participation and wages. Intertemporal tradeoffs, such as decreased future earning capacity due to a current reduction in labor market work, are central to the decision to provide care. The existing literature, however, overlooks such long-term considerations. I depart from the previous literature by modeling caregiving and work decisions in an explicitly intertemporal framework. The model incorporates dynamic elements such as the health of the elderly parent, human capital accumulation and job offer availability. I estimate the model on a sample of women from the *Health and Retirement Study* by efficient method of moments. The estimates indicate that intertemporal tradeoffs matter considerably. In particular, women face low probabilities of returning to work or increasing work hours after a caregiving spell. Using the estimates, I simulate several government sponsored elder care policy experiments: a longer unpaid leave than currently available under the Family and Medical Leave Act of 1993; a paid work leave; and a caregiver allowance. The leaves encourage more work among intensive care providers since they guarantee a woman can return to her job, while the caregiver allowance discourages work. A comparison of the welfare gains generated by the policies shows that half the value of the paid leave can be achieved with the unpaid leave, and the caregiver allowance generates gains comparable to the unpaid leave.

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Contents

Chapter 1

The Effect of Informal Care on Work and Wages

1.1 Introduction

The population of disabled elderly is large and growing fast, and the care they receive is often informal care from family and friends. For elderly parents, adult children are the most common type of care providers. Furthermore, adult children are predicted to be an increasingly important source of informal care as the Baby Boomer generation ages, the number of divorcees increases, and the differential life expectancy between men and women results in a larger number of widowed elderly women. Given that a typical adult child caregiver is in her late 50s or early 60s, and still in her working years, providing care for an elderly parent may involve considerable opportunity costs.

Caregiving could affect work behavior on the extensive and/or intensive margin. Changes in the extensive margin include quitting work temporarily or retiring early. Changes in the intensive margin include reducing work hours, taking on fewer responsibilities, or forgoing a promotion to fulfill caregiving obligations (Carmichael and Charles 2003). Both margins are important, with potential implications for current earnings and retirement income that could affect quality of life long after the caregiving episode ends.

The labor market consequences associated with informal care are important for understanding how the costs of long-term care are distributed among the government and the family. In the United States, long-term care is one of the largest uninsured risks facing the elderly; only about 15 percent of those 65 and older have private insurance which provides some, albeit capped, coverage;[1] Medicare finances only short-term nursing home stays and limited home health care; and, Medicaid provides catastrophic insurance once individuals spend down their assets. This piecemeal and incomplete insurance, combined with the high out-of-pocket costs of care, often leads individuals to rely on informal care from family and friends instead of paid market care. Feeling the pinch of these health costs, governments have devised and promoted policies, such as cash benefits and tax credits, that explicitly aim to reduce government long-term care expenditures by encouraging the elderly to remain in the community, presumably relying on informal care. Evaluating the labor market costs of informal care provision is especially relevant for the sustainability, design and implementation of policies that encourage informal care provision as well as understanding the total costs and benefits of such programs.

Although there is a substantial literature trying to estimate the causal relationship between caregiving and work, it suffers from three main concerns. The most significant methodological issue is whether there is an endogeneity problem that leads to biased estimates of the causal effect of informal care on work. Adult children who have poor labor market opportunities or less attachment to the labor force may be more likely to become caregivers, creating a selection bias in reduced-form estimates. Much of the older literature ignores the problem; newer work tries a variety of different estimation methods to address endogeneity and draws mixed conclusions about its existence. Second, much of the recent longitudinal literature has focused on Europe, leaving it an open question as to how informal care affects work in the United States when controlling for permanent unobserved heterogeneity. The United States has a relatively less generous welfare state than in Europe, less

[1] Authors' calculations from the 2010 survey wave of the *Health and Retirement Study*.

generous public pension coverage, health insurance that is often tied to work under age 65, and typically higher levels of female labor market participation. For all of these reasons, European findings may not be generalizable to the U.S. context, and may indeed be an upper-bound. Third, the literature has yet to reach a consensus. Much of the literature looks at either the extensive or intensive work margin, or measures the impact on wages, but does not measure all three margins of adjustment.[2] Given the lack of consensus about the impact caregiving has on work and wages, it is very difficult to pool estimates across papers to have a comprehensive and cohesive picture of the impact caregiving has on labor market outcomes.

This paper strives to fill this gap in the literature. Specifically, we identify the causal relationship between informal care and various labor market outcomes using a U.S. longitudinal sample of nationally representative prime age working individuals. We examine both the intensive and extensive margins of work and whether there are wage effects from informal care, separately for men and women. Furthermore, we control for time-invariant individual heterogeneity via fixed effects, allowing for individual characteristics such as taste for caregiving or attachment to the labor force that may impact both caregiving and work behavior, and we test for remaining endogeneity after including fixed effects. We also distinguish between the types of care being provided—chore assistance versus personal care, or intensive care, as measured by hours. Understanding the differential effects of care across these domains is important for structuring long-term care policies and for better targeting caregiver supports, such as respite care services. Lastly, we look beyond the traditional labor outcomes examined in this literature to consider whether informal care affects a person's (self-reported) retirement. Such analysis informs about the potential impact of informal care on retirement financial security and Social Security benefits. A comprehensive approach like ours has been lacking in U.S. studies, and is important for understanding the full costs of elder parent care. By considering the total costs of informal care against the government expenditures saved in paid home

[2]The one exception in Europe, Bolin et al. (2008), analyzes all three margins using one survey wave of data.

care and nursing home costs, policy-makers can better evaluate the cost-effectiveness and overall sustainability of policies aimed to keep the elderly in the community.

The rest of the paper is as follows: Section 1.2 describes the existing literature. Section 1.3 presents the empirical strategy and models. Section 1.4 provides details about the data, sample selection criteria, and outcome measures. Section 1.5 presents the main results: informal care's effect on labor force participation, retirement, and hours of work and wages conditional on working. Section 1.5 also presents the robustness and sensitivity analysis, and Section 1.6 concludes that there is interesting heterogeneity in the labor market response to informal care provision based on the type and intensity of care provided as well as the gender of the care provider. Our estimates suggest that personal care provision causes some care providers to stop working while chore care provision leads some care providers to partially or fully retire. Interestingly, female chore care providers that work significantly cut back their work hours and experience wage penalties, while we find much less of an impact on the hours or wages of male care providers who work.

1.2 Background

Ex ante, it is not clear what effect caregiving will have on work. Time being scarce, caregivers may reduce work hours or exit employment in response to the informal care needs of a parent. However, caregivers may instead decrease their leisure time and maintain their labor force attachment due to financial considerations, such as employer-sponsored health insurance, or because it provides a break from caregiving (Carmichael and Charles 2003, Wilson et al. 2007). In addition, the impact of informal care on labor market outcomes may vary with the type of care being provided. For example, providing help with personal activities such as eating, bathing, or dressing may require a larger time commitment than providing assistance with chores. Some care tasks such as assistance with chores are shiftable over the day or even in between days, while personal care seems to contain unshiftable activities that need to be provided at specific times in the day. There may be opportunity costs associated not only with a larger time commitment, but also from non-shiftable caregiving tasks (Hassink and Van den Berg 2011). Thus, we distinguish between types of care in our analysis, as well as the intensity of care provided.

The literature analyzing the relationship between caregiving and work is quite extensive, using a variety of datasets, country and institutional settings, and cross-section and longitudinal estimation methods. However, this long literature has not led to a consensus about the causal relationship between these two activities. Most studies have found a negative relationship between informal care provision and the extensive margin of work (Bolin et al. 2008, Crespo and Mira 2010, Ettner 1995, Heitmueller 2007, Pavalko and Artis 1997).[3] There is less consensus concerning whether caregivers who remain in the labor force reduce their work hours. Bolin et al. (2008), Casado-Marín et al. (2011), and Wolf and Soldo (1994) find little evidence of caregiving reducing work hours, while Ettner (1996) and Johnson and LoSasso (2000) find caregivers in the US do reduce their work hours. In addition, some studies have found evidence of wage penalties (Carmichael and Charles 2003, Heitmueller and Inglis 2007), foregone promotions, and losses in pension entitlements (Parker 1985) from providing informal care. The European literature finds substantial heterogeneity of the impact of caregiving on work, namely that the effect tends to be stronger for intensive caregivers (Carmichael and Charles 1998, 2003, Casado-Marín et al. 2011, Heitmueller 2007, Spiess and Schneider 2003).[4] Coresidential caregiving has stronger negative effects on work in Europe (Casado-Marín et al. 2011, Heitmueller 2007, Heitmueller et al. 2010), whereas Ettner (1996) found only non-coresidential female caregivers experience significant short-term negative

[3] Wolf and Soldo (1994) is a notable exception which finds no evidence of informal care reducing the propensity of married women to be employed in the U.S.

[4] These studies define intensive caregivers by the hours of care provided per week or month. However, the data we use only records the hours of care at two-year intervals, making it particularly difficult to identify intensive caregivers in a way that is directly comparable to previous work. We use the type of care given—personal care versus chore care—as a measure of the commitment provided by the child, and the number of hours of care over a two-year interval to create a threshold variable of intensity.

work effects in the United States.[5] Some studies find stronger work effects for women caregivers compared to men (Carmichael and Charles 2003, Do 2008) while others do not (Bolin et al. 2008, Johnson and LoSasso 2006).

To our knowledge, Dentinger and Clarkberg (2002) is the only study that examines how informal care affects the transition to retirement. They find that wives caring for husbands have retirement odds five times greater than non-caregiving women, but find little evidence that men or women caring for parents or parents-in-law experience faster transitions to retirement. However, their sample is of 763 pension-eligible pre-Baby Boom men and women. They caution against generalizing their findings to all women from these cohorts or the experiences of the Baby Boomers since their sample is not nationally or cohort representative, with a sample that is biased in favor of women who have the strongest attachment to the labor force. Our approach accounts for such attachment by controlling for permanent unobserved heterogeneity. Furthermore, we examine whether there are heterogeneous effects of care provision on retirement by the type and intensity of care provided.

Overall, it is hard to discern from the literature the total impact of caregiving on work behavior of American caregivers. Almost all U.S. studies use cross-sectional data and cannot control for permanent unobserved heterogeneity.[6] In addition, international experience cannot readily be generalized to the United States.

1.3 Empirical Strategy

We analyze several labor market outcomes of the adult children, including the probability of working for pay, the probability of being retired, and weekly hours of work and logged hourly wages conditional on working. Generally, we write the

[5]We do not have a large enough sample of coresidential caregivers to test for heterogeneity of the effect for that subgroup of caregivers. Our results are not sensitive to whether we include coresidential caregivers or not.

[6]Johnson and LoSasso (2000) is an exception in the United States. They estimate a random effects model on two waves of *Health and Retirement Study* data and focus on the effect of informal care on work hours.

labor market outcomes as

$$y_{it} = f(CG_{it}, \mathbf{X}_{it}, \delta_i, \epsilon_{it}) \tag{1.1}$$

where y_{it} is the labor market outcome of interest for individual i at time t; CG_{it} is a measure of informal care, which we will define in several ways; $\mathbf{X}_{it}$, is a vector of demographic, socioeconomic, and work variables which varies depending on the outcome of interest; δ_i is a time-invariant, individual-specific error component; and ϵ_{it} is an individual- and time-varying error component. We model the time-invariant individual unobserved heterogeneity as a fixed effect; that is, we allow δ_i to be correlated with CG_{it} and $\mathbf{X}_{it}$. The fixed effect captures individual characteristics such as a taste for caregiving or labor market attachment that may impact both caregiving and work behavior.[7] There may be concern, however, that the individual- and time-varying error, ϵ_{it}, is correlated with our measure of caregiving, CG_{it}.[8] To address this potential endogeneity problem, we propose a vector of instruments, $\mathbf{Z}_{it}$, that are correlated with our measure of caregiving, $corr(CG_{it}, \mathbf{Z}_{it}) \neq 0$, and are uncorrelated with the individual and time-varying error component, $corr(\epsilon_{it}, \mathbf{Z}_{it}) = 0$. The instruments must be time-varying themselves or their effect will be captured in the fixed effect. We discuss the endogeneity concerns in more detail in Section 1.3.2.

1.3.1 Model Specification

For the labor force participation and self-reported retirement specifications, we model those outcomes as linear probability models with fixed effects.[9] The model

[7]For example, an adult child with strong family attachment may tend to work fewer hours and provide more informal care than adult children with relatively weak family attachments. Those who are especially diligent may devote more hours to work and care provision than adult children who are less industrious.

[8]Even after controlling for the "type" of person via the fixed effect, there may be remaining time-varying shocks that also could influence both caregiving and work, such as getting fired or experiencing a wage cut or increase.

[9]While the logit specification is a rare exception amongst non-linear models in that coefficients can be conditionally consistently estimated in the presence of fixed effects, it does not provide estimates of the individual fixed effects which are needed to compute statistics of interest such as (average) partial effects (Wooldridge 2002). We prefer the linear probability models since we can

is formalized as

$$LFP_{it} = \alpha_1 CG_{it} + \alpha_2 \mathbf{X}_{it} + \delta_i + \epsilon_{it} \tag{1.2}$$

where LFP_{it} is equal to one if person i is working (or retired in the retirement models) at time t. We estimate the model first treating informal care as exogenous, under the assumption that $E(\epsilon_{it}|CG_{it}, \mathbf{X}_{it}, \delta_i) = 0$, such that

$$E(LFP_{it}|CG_{it}, \mathbf{X}_{it}, \delta_i) = Pr(LFP_{it} = 1|CG_{it}, \mathbf{X}_{it}, \delta_i) = \alpha_1 CG_{it} + \alpha_2 \mathbf{X}_{it} + \delta_i \tag{1.3}$$

We then estimate the model treating informal care as endogenous using a two-stage least squares (2SLS) with fixed effects approach. We instrument informal care with our vector of time-varying instruments, $\mathbf{Z}_{it}$, under the assumptions that $corr(CG_{it}, \mathbf{Z}_{it}) \neq 0$ and $E(\epsilon_{it}|\mathbf{Z}_{it}) = 0$.

For the hours of work and log wage specifications, we model those outcomes as linear regressions with fixed effects conditional on working. The model is formalized as

$$y_{it} = \alpha_1 CG_{it} + \alpha_2 \mathbf{X}_{it} + \delta_i + \epsilon_{it} \quad \text{for } LFP_{it} = 1 \tag{1.4}$$

where y_{it} is either hours of work per week or the logged hourly wage. We estimate the model first treating informal care as exogenous, under the assumption that $E(\epsilon_{it}|LFP_{it} = 1, CG_{it}, \mathbf{X}_{it}, \delta_i) = 0$, such that

$$E(y_{it}|LFP_{it} = 1, CG_{it}, \mathbf{X}_{it}, \delta_i) = \alpha_1 CG_{it} + \alpha_2 \mathbf{X}_{it} + \delta_i \tag{1.5}$$

We then estimate the model treating informal care as endogenous using a 2SLS with fixed effects approach. We instrument informal care with our vector of time-varying instruments, $\mathbf{Z}_{it}$, under the assumptions described above. Since the hours of work and wage regressions are estimated only on those who work, we control for selection into work to the extent that selection is on individual time-invariant characteristics that will be captured in the fixed effect. If selection into work depends on individual

estimate partial effects, and we can straightforwardly perform the instrumental variables analysis with two-stage least squares.

and time-varying unobservables, then the impact of caregiving on hours of work or wages we find, $\hat{\alpha}_1$, also includes the impact via selection into work.

1.3.2 Endogeneity Concerns

Most studies using instrumental variables techniques with cross-sectional data are not able to reject exogeneity of informal care with respect to work (Bolin et al. 2008, Casado-Marín et al. 2011, Heitmueller 2007) or can reject exogeneity only at borderline significance levels (Johnson and LoSasso 2006). However, some of the instruments are weak (Bolin et al. 2008, Heitmueller 2007) or their own exogeneity has been called into question (for example, distance between parents and children or lagged work status). Some studies use other techniques to address the issue, including simultaneous equations methods (Crespo 2006, Wolf and Soldo 1994), lags and leads of caregiving (Heitmueller 2007), or dynamic panel data methods (Casado-Marín et al. 2011, Heitmueller et al. 2010).

The nature of the endogeneity concern in our analysis is different than in these past studies. The previous longitudinal studies address the potential endogeneity of informal care by allowing for time-invariant unobserved heterogeneity, usually via random effects estimation, which assumes that the individual-specific heterogeneity is independent of informal care and other explanatory variables. Our study allows for time-invariant unobserved heterogeneity via fixed effects, which allows for correlation between the individual-specific heterogeneity and informal care. However, endogeneity may still be a concern if the time-varying error is correlated with time-varying caregiving behavior even after controlling for permanent unobserved heterogeneity via fixed effects.

To address the potential endogeneity concern, we propose a set of time-varying instruments that are correlated with informal care provision but are assumed to be uncorrelated with the individual and time-varying error component of the labor market outcome equations. The identifying instruments we use measure parental health, broadly defined, such as having a parent or in-law who needs help performing activities of daily living (ADLs), who has a memory problem, or who cannot be left alone, and whether a parent or in-law has recently passed away or become widowed. The instruments are theoretically sound. Variation in the health of a parent or in-law should directly vary the demand for informal care, but not directly affect work behavior of an adult child other than through the informal care path. Concerns about intergenerational transmission of poor health should be alleviated by the fact that we control for the adult child's own health and by the inclusion of the fixed effect. Some argue that a parent's health may directly affect work if it provides new information about the child's ability to work later or if the mental health effects of watching a parent decline have a direct negative effect on health (Amirkhanyan and Wolf 2006), which may also affect work; however, we suspect these are relatively weak pathways (Coe and Van Houtven 2009). Having a parent or in-law who is widowed means their spouse is not available to assume the care-giving role, thereby increasing the demand for care provided by an adult child or child-in-law. The recent passing of a parent or in-law potentially explains much of the termination of care provision. The passing of a parent or in-law should only affect work behavior of an adult child via the termination of care provision for that parent or in-law or the provision of care for the widowed parent or in-law. Coe and Van Houtven (2009) find the death of a parent does not have a direct effect on one's health or depressive symptoms, which alleviates concerns that the death of a parent or in-law could influence work behavior via the bereavement effect. We discuss the empirical strength of the instruments in Section 1.4.4.

1.4 Data and Sample Selection

We use data from nine waves of the *Health and Retirement Study* (HRS) (1992-2008). The HRS is a panel survey which provides longitudinal information on labor supply, family structure, intergenerational transfers, health, income and assets. The baseline interviews were completed for 12,654 individuals in 7,702 households in 1992. At that time, respondents were approximately 51 to 61 years old or were married to individuals in that age range; thus, their parents were prime candidates to be care recipients. Follow-up interviews took place biennially.

1.4.1 Sample Selection Criteria

We examine men and women separately, given their different attachment to the labor force. Sample members include adult children between ages 45 and 70 who have at least one parent or parent in-law alive in the current survey wave or two previous waves, and who are observed in at least two waves. For our baseline specifications we eliminate observations from the 1992 wave because the survey did not ask about all types of care assistance in that wave. Table 1.1 shows details of the sample inclusion criteria for our baseline labor force participation and wage estimations where we define a caregiver as someone who provides either personal or chore assistance. The sample size changes slightly in each specification, depending on which measure of informal care we use and the labor market outcome of interest (the exact number of observations in each specification appears at the bottom of Tables 1.4-1.9).

1.4.2 Dependent Variables

We examine four separate self-reported labor market outcomes, taken from the RAND HRS data files. For labor force participation, our first work measure, we categorize anyone who reports that they are working for pay (either for someone else or self-employed) as working, and those out of work, looking for work, or retired as not working. For the second work measure, self-reported retirement status, we categorize anyone who states they are completely or partially retired as retired, with the remainder as not retired.[10] We also examine the usual number of hours worked per week among workers to address the intensive margin of the work decision. Lastly, we examine logged hourly wages among workers.[11]

[10]Housewives are categorized as not retired. In our robustness checks, we re-estimate the labor force participation and retirement specifications only on those who have worked at some point since age 45 and the results are qualitatively similar.

[11]If the respondent reports wages at a frequency other than hourly, the hourly wage rate is calculated using the usual hours worked per week, usual weeks worked per year, and pay rate, and adjusting for the periodicity of pay reported.

1.4.3 Explanatory Variables

Informal care is self-reported by HRS respondents. Specifically, the HRS asks whether individuals spent time helping each parent and in-law with "basic personal activities such as dressing, eating, and bathing" or, in another question, "with other things, such as household chores, errands, transportation, etc." Our baseline specification uses a combined discrete measure of any caregiving (personal care or chore care), but we explore differential effects for those providing personal care and those providing chore assistance.[12] Further, we analyze the impact of intensive caregiving, defined as providing 1,000 or more hours of care (any type) during the previous two years.[13]

The labor force participation, retirement, and hours of work models include the same set of control variables. These models include individual fixed effects, which capture time-invariant observed and unobserved individual characteristics. Thus, many of the standard demographic variables shown to be important in other labor supply models are captured in the fixed effect, such as the respondent's race and education. However, time-varying characteristics remain: marital status, age and age squared, an indicator for achieving the Social Security Early Entitlement Age (EEA) (62) but younger than the Full Retirement Age (FRA), an indicator for being at or over the FRA (65-66 depending on birth year), and two discrete variables for self-reported health (poor/fair and good indicators with excellent/very good as the omitted category). Household characteristics include household size, whether there is a child under age 18 in the home, and household asset quartiles (lowest quartile omitted). Wave dummies control for time trends.

The logged hourly wage equation is an augmented Mincer wage equation. Controls include years of work experience, experience squared, tenure, tenure squared,

[12] The caregiving question regarding chores and errands was not asked in 1992. Thus, we omit the 1992 wave from our specifications that use the combined measure of caregiving. However, we include observations from the 1992 wave in the specifications that use the personal care measure.

[13] For the 1994 survey wave only, we modify our intensive caregiving definition to include those who report providing 500 or more hours of care since the question in that wave asks about the amount of care provided in the last 12 months (rather than the last two years as in all subsequent waves).

an indicator for whether a person is a salaried worker (versus an hourly wage worker), discrete variables for self-reported health and marital status, and an individual fixed effect.[14,15]

1.4.4 Instrumental Variables

The identifying instruments we use measure parental health, broadly defined. We experimented with the limited parental health information available in the HRS: needing assistance with activities of daily living, having a memory problem, and not being able to be left alone. Through extensive testing, we found "ill-health" of a parent, defined as having any of these three conditions, to be a better instrument than the three separate variables for parental health. We also use information about potential alternative sources of informal care provision, mainly through whether the parent or in-law was recently widowed. Our final sets of instruments include: separate indicators for the mother (in-law) being ill; separate indicators for the mother, father, mother-in-law, and/or father-in-law not being alive at any time in the last two years; and, separate indicators for the mother (in-law) becoming widowed since the last survey wave.[16] We estimate our specifications using various combinations of these instruments as described in the Appendix.

Our criteria for empirically strong instruments is that the joint F-statistic for the excluded instruments in the first stage equation is above the conventionally-accepted floor of 10 (Staiger and Stock 1997) and we fail to reject the null hypothesis of the over-identification test of the excluded instruments.[17] We also test whether we can

[14] Inclusion of fixed effects is why education and other time-invariant characteristics do not appear in the wage equation.

[15] In our robustness checks, we omit experience, experience squared, tenure, tenure squared, and the salaried indicator since they may be endogenous, and replace them with age and age squared instead, and our results are qualitatively similar.

[16] We do not include indicators for the father (in-law) being ill or becoming recently widowed since these instruments perform poorly and do not predict informal care provision well, which is consistent with studies that find fathers are less likely to receive care than mothers (Byrne et al. 2009, Hiedemann and Stern 1999). Women's greater longevity also explains the weak performance of the instruments since wives are more likely to provide care for their husbands, and adult children are then likely to be called upon to care for their widowed mothers (Szinovacz and Davey 2008).

[17] The Sargan-Hansen test is employed to test the over-identifying restrictions. The joint null hypothesis is that the instruments are valid instruments, i.e., uncorrelated with the error term, and that the excluded instruments are correctly excluded from the estimated equation. A rejection casts doubt on the validity of the instruments.

treat the suspect endogenous regressor as exogenous.[18] A summary of the results from these tests is provided in Table 1.2. An 'X' indicates that the instruments are strong as defined above and that we cannot reject exogeneity of informal care, after including individual fixed effects in our specifications. Note, for women we cannot reject exogeneity of any, personal, chore, or intensive caregiving with respect to three of the four work-related outcomes. However, we do find evidence of endogeneity of care provision with respect to women's work hours conditional on working. For men, we cannot reject exogeneity of any, personal, chore, or intensive caregiving with respect to all of the work-related outcomes, but we do face a weak instrument problem when instrumenting for men's intensive caregiving. Thus, we present the results for men and women treating all measures of care provision as exogenous, except for women's hours of work, where we additionally present the instrumental variables results.

1.5 Results

1.5.1 Descriptive Results

Table 1.3 presents the descriptive statistics of the sample, by gender, and by whether or not these individuals become caregivers during the observation period. Because we use an unbalanced panel with repeated observations, we report the descriptive statistics for the first time we observe the individual. Individuals who become caregivers are actually more likely to be working at the baseline than their non-caregiving counterparts (64 percent vs. 57 percent for women; 73 percent vs. 67 percent for men). However, among those working, their hours of work and wages are similar.[19]

The difference in labor force participation rates is likely driven by a combination of the demographic characteristics because the individuals who become caregivers

[18] We perform this test by analyzing the difference between two Sargan-Hansen statistics: one for the equation treating informal care as endogenous, and one for the equation treating informal care as exogenous. Under the null hypothesis that informal care can actually be treated as exogenous, the test statistic is distributed as chi-squared.

[19] All dollar amounts are reported in constant 2008 dollars.

are younger, more educated, have a longer attachment to the labor force, and are in better health, on average, in the baseline year. The differences in these observable characteristics could cause worry about the estimates because one would want comparable controls. First, we control for these observable differences. Second, if there is something unobservable and time-invariant about the individuals who do not become caregivers (i.e., a permanent disability) that makes them less likely to provide informal care and less likely to work, then the individual fixed effects model would address this issue. However, since the fixed effects model is identified off within-person changes, if the non-caregivers have little or no variation in their caregiving and labor market behavior, then we face an efficiency issue and are unlikely to find significant effects. To help address this concern—that the non-caregiver sample is unobservably less able to caregive or work, perhaps too sick or too old to do either—we test the robustness of our results using different estimation samples (Section 1.5.3).

1.5.2 Main Results

We discuss the results from the models of labor force participation, retirement, and hours and logged wages conditional on working, examining differential effects by the various caregiving definitions (any chore or personal care; personal care; chore care; intensive care). Again, since we were not able to reject exogeneity of our various measures of care provision with respect to almost all the labor market outcomes of interest, we discuss the results from the models treating informal care as exogenous. However, for women's work hours, we also discuss the instrumental variables results since we rejected exogeneity in those models.[20] Unless noted in parentheses in the text, the effects discussed below are significant at least at the 5 percent level.

[20]The instrumental variables results for the other work outcomes are discussed in the Appendix and presented in Appendix Tables 1.1-1.4.

Extensive Margin: Labor Force Participation

The linear probability model with individual fixed effects indicates that caregiving of any type has no significant effect on labor force participation for men or women (Table 1.4). Women who provide personal assistance with activities of daily living are 1.4 percentage points ($p < 0.10$) less likely to be working, whereas male personal caregivers are 2.4 percentage points less likely to be working. This represents a reduction in mean participation rates of 2.7 percent for women and 3.9 percent for men. We find no significant effect of providing chore or intensive care on the labor force participation of men or women.

Not surprisingly, some of the strongest negative effects on labor force participation are the Social Security EEA and FRA. Women (men) between 62 and the FRA are 6-7 (9-10) percentage points less likely to work than women (men) younger than 62. The effects are similar for being at or older than the FRA. Being married makes women significantly less likely to work. Being in poor or fair health makes one less likely to work than those in good health or better—women in poor or fair health are about 8 percentage points less likely to work compared to women in excellent/very good health, whereas men are 10 percentage points less likely to work. Many of these findings are consistent across all the definitions of informal care.

Our estimates of the effects of caregiving on labor force partcipation tend to be in the lower range of those found in the international literature. Heitmueller (2007) estimates any care provision reduces labor force participation in the U.K. by 6 percent, and providing 20 or more hours of care per week reduces labor force participation by up to 26 percent, while Casado-Marín et al. (2011) find providing 28 or more hours of care per week decreases the probability of working by 4.5 percentage points for women in Spain. Our finding that any type of care provision has no significant effect on the probability of working is consistent with that of Wolf and Soldo (1994) who find care provision has no effect for married women in the U.S. However, our results highlight the importance of analyzing differential effects by the type of care provided since we find personal care does significantly reduce women's labor force participation.

Extensive Margin: Retirement

We next turn to the relationship between caregiving and the self-reported retirement decision. Using this more subjective retirement status allows us to separate the disabled and the unemployed from retired individuals (Maestas 2010). We also suspect the subjective retirement definition to be more prevalent among older respondents, and thus might respond differently to caregiving than the traditional labor force participation outcome modeled above due to individual heterogeneity correlated with age. Interestingly, our estimates do suggest a different relationship between caregiving and retirement compared to labor force participation. The linear probability model with individual fixed effects indicates that caregiving of any type increases the probability of being retired by 1.7 percentage points for women and 1.6 percentage points for men ($p < 0.10$) (Table 1.5). This represents an increase in mean self-reported retirement of 5.3 percent for women and 3.4 percent for men. Unlike the labor force participation results, providing personal care has no significant effect on the probability of retiring for men or women. Instead, the impact of caregiving on retirement is driven by chore assistance, and not personal or intensive caregiving. The retirement response to chore assistance may reflect the adult child's anticipation of the parent's future caregiving needs and trajectory. Providing chore care to a parent may be a sign of slowly-deteriorating health, which may require informal care for many years, as opposed to a health shock in which personal care is needed immediately. Further, because of the specific time-demands that often accompany personal care provision, it may be less compatible with paid labor force participation, whereas chore care would not involve such time constraints. Our estimates suggest that chore caregiving changes one's overall attitude towards continued work as opposed to the labor force participation outcome itself.

Intensive Margin: Hours

We then turn our attention to hours of work. We estimate the hours regressions on those who are currently working for pay. The results when treating caregiving as exogenous suggest that providing informal care has no significant impact on hours worked among workers (Table 1.6). However, this was the one case where we found evidence of remaining endogeneity in the female sample after controlling for fixed effects. Table 1.7 presents the first and second-stage instrumental variables estimates for women using IV Set 1 (mother and mother-in-law illness), as discussed in the Appendix. When instrumenting for caregiving, we find that informal care has a negative and significant effect on hours worked for working women, decreasing work by 3.7 hours per week on average ($p < 0.10$), or 185 hours per year. This represents a 10.4 percent decrease in hours worked per week among working women. This effect is driven by women providing chore care assistance, who decrease their hours per week by almost 4.5 hours ($p < 0.10$). We also find intensive caregiving reduces women's work for those who are working by about 10 hours per week ($p < 0.10$), or 500 hours per year. Combined with the results from Tables 1.4 and 1.5, these estimates suggest that personal caregiving leads some women to leave the paid labor market, while chore care leads some women who work to decrease their hours, perhaps combined with partial retirement.

We have various sets of instrumental variables we could use to estimate the impact of caregiving on work hours for those who work. If there is heterogeneity in the response of work hours to care provision, the estimated coefficient we find should be interpreted as the Local Average Treatment Effect (LATE). It is interesting to see how our estimates of the LATE of caregiving on work hours change with the instruments used. In Table 1.8, we present the results using four combinations of the instruments described in Section 1.4.4: (1) Mother or mother-in-law ill; (2) Mother or mother-in-law ill and indicators for recent death of each of the four parents/in-laws; (3) Mother or mother-in-law ill and mother or mother-in-law recently widowed; and (4) All of these instruments. We presented the results using IV Set 1 in Table

1.7, where we find that working women who are induced to caregive due to having an ill mother or mother-in-law decrease their work effort by 3.7 hours per week. Adding indicators for recent death of the four parents/in-laws (IV Set 2) decreases the magnitude of the estimated hours effect. This suggests that work hours are less sensitive to caregiving changes for the group of working women who terminate care provision after the passing of a parent (or who could also be induced to provide care to a parent after the passing of another parent) than caregivers induced due solely to an ill mother or mother-in-law. When we consider ill health of a mother or mother-in-law and recent widowhood of a mother or mother-in-law (IV Set 3), we find a larger hours effect. This makes sense intuitively. Recent widowhood is likely correlated with a loss of an informal spousal care provider, so those working women induced to provide informal care under those circumstances may be spending more time, effort, or energy than those who provide care when their parent or in-law has a spouse to provide informal care as well. Finally, when we include all of our instruments, we estimate the hours effect of caregiving to be roughly the average of the effects found using the previous three sets of instruments. Using the full set we estimate slighly smaller hours effects than in our baseline specification. Working women providing any type of care decrease their work effort by 2.6 hours per week; personal care provision leads to a 2.9 hour per week decrease; chore care provision leads to a 3.3 hour per week decrease, and intensive caregiving leads to a 9.0 hour per week decrease.

Our estimates of the effect of caregiving on worker's hours fall interestingly within those of the prior literature. Several U.S. and European studies find care provision has no significant effect on work hours (Bolin et al. 2008, Casado-Marín et al. 2011, Wolf and Soldo 1994), which we also find when treating informal care as exogenous. However, like Ettner (1996), we find there is an endogeneity bias on the effect of caregiving on work hours towards zero for women, and the effect of care provision is significantly larger and negative when this endogeneity bias is accounted for. Ettner (1996) estimates that non-coresidential caregiving leads to a 11-13 hour decrease in women's work per week, and Johnson and LoSasso (2000) find care provision reduces both men and women's work by about 460 hours per year (or 9.2 hours per week assuming 50 weeks of work per year). We find any type of care provision reduces women's work hours by only 3.7 hours per week, but the effect of intensive caregiving on women's work hours is comparable to the effects in Ettner (1996) and Johnson and LoSasso (2000). These results underscore the importance of analyzing the effects of caregiving by the intensity of care provided.

Intensive Margin: Wages

Finally we turn our attention to estimating the effect of caregiving on wages among workers. Providing any informal care has a negative effect on female workers' wages. Caregiving of any type leads to a 2.3 percent reduction in a woman's hourly wage, on average, compared to not caregiving ($p < 0.10$) (Table 1.9). Using a Duan smearing factor to account for retransformation bias (Duan 1983), female caregivers are predicted to have a wage of \$15.91 compared to \$16.28 for non-caregivers, or a loss of \$0.37 per hour in absolute terms. Extrapolating to a year's worth of work given mean hours worked per week among female workers observed in our sample was 35 and, assuming 50 weeks of paid work a year, the wage penalty accumulates to \$647 in lost earnings for one year on average. Providing personal care does not have a significant effect on women's wages, but providing chore assistance decreases a woman's hourly wage by 2.6 percent ($p < 0.10$), a loss of \$0.42 per hour on average (\$15.86 compared to \$16.28). Chore care provision also led to fewer work hours among female workers, so this wage effect is compounded by the hours effect reported in Table 1.7. We find with a simple back-of-the-envelope calculation that female chore care providers who work forgo up to \$5,400 per year on average from the combined effect of chore care provision on hours and wages.[21]

Since identification of the wage effect is coming off within-person variation, the wage penalty we find may suggest that female caregivers are moving to lower paying

[21] Working chore care providers decrease their work by 4.5 hours per week. On average, working women in our sample work 35 hours per week at \$21 per hour, for 50 weeks per year. Thus, the combined effect of chore care provision on earnings through hours and wages is approximately \$5,400 per year.

jobs (perhaps with more flexible work arrangements) or experiencing a decrease in productivity due to caregiving that is reflected in the wage. According to a 2009 survey, 12 percent of caregivers reported ever reducing work hours or taking a less demanding job as a result of care provision, while 66 percent reported often arriving late to work or leaving early due to caregiving needs (National Alliance for Caregiving and AARP 2009). Such work accommodations could result in a lower wage for caregivers.

We find evidence of a wage premium among male workers who are providing intensive care. Men providing intensive care earn almost 16 percent more than their non-caregiving counterparts, on average, ($p < 0.10$) (\$30.53 compared to \$26.03). To the extent that selection into work is driven by time-varying unobservables, this estimated wage effect includes the impact of selection into work, which may account for the surprising sign. However, given the insignificant and small effect of intensive caregiving on male labor force participation, this wage premium does not seem likely to be driven by selection into work, but instead is a true wage effect. Given that over half of the intensively caregiving men are married to intensively caregiving women, it is possible that these men are moving to higher wage jobs to insure their wife's potential decrease in labor income. These men may also be moving to higher wage jobs in order to contribute to future formal care expenses, especially if the parent's health is deteriorating severely.

Our estimates of the effect of caregiving on wages for those who work tend to fall in the range found in the international literature. While Bolin et al. (2008) find care provision does not significantly affect the wages of men or women in Europe, much of the U.K. literature finds evidence of wage penalties. Carmichael and Charles (2003) find caregiving more than 10 hours per week reduces wages by 9 percent for women and 18 percent for men, while Heitmueller and Inglis (2007) find caregivers in the U.K. earn 3 percent less than non-caregivers with similar characteristics. Importantly, we find the wage penalty for women is concentrated among those providing chore assistance, and while caregiving for the most part does not affect the wages of working men, there is evidence of a wage premium for intensively caregiving men.

1.5.3 Robustness and Sensitivity Checks

Thus far we have estimated our specifications on the sample of men and women between ages 45 and 70 who have a parent or in-law alive in the current survey wave or the last two waves. We assess how sensitive the results are to these sample restrictions. First, we re-estimate our specifications on those who have had a parent or in-law alive at any point during the survey. This implies we observe each individual for more waves, but have potentially less variation in caregiving behavior. To address the opposite concern, that we may be including too many people with parents who do not need any care, we re-estimate on the subsample of individuals who have parents or in-laws who are ever ill during the sample frame, where our measure of being ill includes having ADL needs, having a memory problem, or not being able to be left alone. The results with any of these samples are qualitatively similar to our baseline results for all our labor market outcomes of interest. The largest quantitative difference is found when we restrict the sample to those who have worked since age 45. We present both the baseline results and the results from restricting the sample to those who have worked since age 45 in Table 1.10. We find the effects are largely the same, but the impact of caregiving on women's retirement is slightly stronger among the sample that has worked since age 45. These results suggest that the retirement effect is larger among recent workers, with any caregiving and chore caregiving increasing the probability of retirement by 2.2 percentage points (compared to 1.7 and 1.8 percentage points respectively in the baseline model).

We also analyze whether caregiving has heterogeneous impacts by marital status in the labor force participation and retirement specifications, and find that none of the interaction terms are significant. We do, however, find heterogeneous impacts by age, particularly for women at the FRA or older in the labor force participation equations, and for men above the EEA in the retirement specifications. For example, personal caregiving decreases the probability of work for women at the FRA or older by an additional 5.3 percentage points compared to female personal caregivers younger than 62, while caregiving of any type and chore caregiving decreases the probability of labor force participation for women at the FRA or older by an additional 3.9 percentage points compared to those younger than 62. Caregiving of any type increases the probability of retirement for men between the EEA (62) and the FRA by an additional 3.5 percentage points and for men at the FRA or older by 3.9 percentage points compared to male caregivers younger than 62. Personal care provision increases the probability of retirement for men between the EEA and FRA by an additional 5.4 percentage points compared to those younger than 62.

We also examine the sensitivity of our estimates to different wage equation specifications. Our baseline specification is motivated theoretically by Mincer's work. However, since we are estimating labor force particpation equations and finding some significant effects of caregiving on working, there may be concern that the tenure and experience variables are endogenous in the wage equation. We estimate alternative specifications (see Table 1.11). In column 1, we present our baseline estimates for comparison purposes. Specification 2 removes the tenure and experience-related variables as well as the salaried indicator from the equations. The third specification adds age and age squared to Specification 2, to capture the age-profile of wages without relying on the tenure and experience information to do so. We find quantitatively similar estimates across the specifications. Our baseline specification, if anything, give us lower estimates of the wage effect for women, while the effect for men remains virtually identical.

Last, we compare the results of our fixed effects models to those from random effects models.[22] The random effects models tend to overstate the effects of care provision compared to the fixed effects results, especially for female intensive caregivers. For example, we find no significant effect of intensive caregiving on female labor force participation or retirement probabilities in the fixed effects models, but intensive caregiving reduces the probability of working by 3.0-3.5 percentage points,

[22]For the labor force participation and retirement models, we compare our fixed effects linear probability model results to random effects linear probability model and random effects probit results, and for the work hours for men and log wage models, we compare our fixed effects linear regression results to random effects linear regression results. For the women's work hours models, we compare the results of fixed effects and random effects 2SLS using Instrument Set 1. We test whether a fixed or random effects model is appropriate for each of our regressions, and in every case we soundly reject consistency of the random effects estimator, suggesting fixed effects is appropriate.

and increases the probability of being retired by 2.8-3.1 percentage points in the random effects models (Table 1.12). In addition, we did not find evidence of significant wage effects for female intensive caregivers in the fixed effects model, but find intensive caregiving reduces a working intensive caregiver's wage by 5.3 percent in the random effects model. For men, the random effects models overstate the effects of any caregiving and personal caregiving on labor force participation as well as the effects of any, personal, and chore care provision on the probability of being retired compared to the fixed effects results (Table 1.13). Importantly, the overall qualitative pattern we find in our fixed effects results does not change in the random effects results—personal care impacts labor force participation, while chore care impacts retirement. These findings suggest that prior studies which account for permanent unobserved heterogeneity via random effects may overstate or provide an upper bound on the effects of caregiving on labor market outcomes by assuming the permanent heterogeneity is uncorrelated with care provision and other explanatory variables.

1.6 Conclusion

In general, we find that only personal care assistance reduces the labor force participation of men and women. Our findings, of a 1.4 percentage point drop in labor force participation for women and a 2.4 percentage point drop for men lie in the lower end of the range found in the international literature. We also find evidence of caregiving women making adjustments on the intensive work margin, with heterogeneity in the response based on the type and intensity of care provided. While the U.S. literature has generally found substantial decreases in work hours for female caregivers, we find such large decreases are concentrated mostly among intensive caregivers.

We find that caregiving increases the likelihood of retirement for men and women by 1.6 to 1.8 percentage points, and that this increase seems to be driven by those providing chore assistance. The different relationship between caregiving and retirement compared to labor force participation underscores the importance of considering heterogeneous effects by the type of care provided. It may be that personal caregivers are leaving the labor force involuntarily because of an unexpected health shock to a parent or in-law that makes it difficult to juggle the personal caregiving with their paid job. These personal caregivers may expect to return to work, and are not calling themselves retired per se, especially if they view their provision of personal care as temporary (for example, for a year or two after a parent has had a stroke). The retirement response to chore care may reflect the adult child anticipating the future long-term care needs of the parent, as providing chore care may be a sign of slowly-deteriorating parental health. Thus, chore assistance may change one's expectations toward continued work and leads some to decrease their work hours in combination with partial retirement.

We also find modest wage penalties among female caregivers, around $0.40 per hour in wages, that is driven by chore assistance. This finding suggests female caregivers may be moving to lower paying jobs, perhaps with more workplace flexibility. If providing chore care is a sign of a parent's declining health and a possible lengthy caregiving episode, these caregiving women may anticipate future informal care needs and move to less demanding jobs. The wage penalty may also be a result of decreased productivity or reliability due to caregiving responsibilities. Surprisingly, we find a wage premium among male intensive caregivers. The wage benefits to these male caregivers are not insubstantial—a $4.50 per hour gain in predicted wages. This finding is hard to interpret, but may be the result of men moving to higher paying jobs, perhaps because their wife is also engaged in intensive caregiving (as is the case for most men providing large amounts of care) and he is insuring her foregone earnings. These men may also be moving to higher paying jobs in anticipation of future health care expenses that may arise if the parent's health deteriorates and formal care becomes necessary.

Our approach has allowed us to learn about three important features that should be considered in future work: (1) We do not find evidence of endogeneity after including fixed effects across many of the specifications explored in this paper. The instruments are strong; thus, we conclude that selection bias may not be a major concern for extensive margins of labor force participation after controlling for permanent unobserved heterogeneity with fixed effects. (2) It is important to distinguish between the types and intensity of care being provided. For both male and female caregivers, only personal care has a negative effect on labor force participation. On the other hand, personal care does not seem to impact self-reported retirement for men or women, but providing chore assistance does. Female chore caregivers also experience wage penalties. (3) It is important to model separately the effects of caregiving on men and women. Men experience a wage premium from intensive caregiving whereas women experience a wage penalty in several cases. In addition, working women who provide care reduce their work effort by 3-10 hours per week, while caregiving has no effect on working men's hours.

Most concerns raised about long-term care in the U.S. have focused on government expenditures on formal care, and in particular nursing home costs and state Medicaid budgets as well as home health care payments and the Medicare program. Our results show that adult children who provide care informally to their parents or in-laws face substantial opportunity costs. If policy-makers aim to enable more people to combine both caregiving and work, more flexible work arrangements or generous leave policies may be needed. In particular, if the wage penalty for female caregivers is due to women moving to less demanding or more flexible jobs, then mandated flexible work schedules may ameliorate this effect. Given caregivers are more likely to retire and female working caregivers are more likely to reduce their work hours, work programs for individuals near retirement age that detail the long-term financial penalties of retiring early or decreasing work effort, telecommuting options, or employer- or publicly-financed offers of respite care to older workers providing care to an elderly parent may be particularly well-targeted. Encouraging caregivers to remain in the labor force could help minimize welfare losses to the caregivers by maximizing their Social Security benefits in old age. Such efforts, however, would need to be balanced against the potential costs to care recipients and public insurance programs if adult children, by remaining in the labor force, are unable to provide informal care.

1.7 Chapter 1 Appendix

1.7.1 Instrumental Variables Estimation

We consider four sets of instruments:

1. An indicator for the mother being ill; an indicator for the mother-in-law being ill.

2. An indicator for the mother being ill; an indicator for the mother-in-law being ill; an indicator for mother died; an indicator for father died; an indicator for mother-in-law died; an indicator for father-in-law died.

3. An indicator for the mother being ill; an indicator for the mother-in-law being ill; an indicator for mother widowed; an indicator for mother-in-law widowed.

4. An indicator for the mother being ill; an indicator for the mother-in-law being ill; an indicator for mother died; an indicator for father died; an indicator for mother-in-law died; an indicator for father-in-law died; an indicator for mother widowed; an indicator for mother-in-law widowed.

Table 1.2 summarizes the empirical strength of the various sets of instruments in the different specifications. Generally, our instruments perform very well and are empirically strong. Except for men's intensive caregiving, the F-statistic of the excluded instruments in the first stage is above the conventionally accepted floor of 10 across our specifications, and we strongly reject the hypothesis that the excluded instruments are jointly equal to zero in the first-stage regression. We also generally find that our overidentifying restrictions are valid. With the exception of women's work hours, we cannot reject exogeneity of informal care regardless of how caregiving is defined. For this reason, our preferred specifications are those in which we treat informal care as exogenous (except for women's work hours).

Appendix Tables 1.1-1.4 compare the estimates from the models treating caregiving as exogenous to those treating caregiving as endogenous with 2SLS using Instrument Set 1 as described above. We find the effect of caregiving on men and women's labor force participation, self-reported retirement and log wages conditional on working as well as men's work hours conditional on working to be insignificant when using 2SLS, which is not surprising given the inherent loss in precision in instrumental variables estimation. In fact, in some specifications, the standard errors from the 2SLS models increase by a factor of 10 compared to those from the OLS models. The sign of the coefficients does switch in some of the 2SLS specifications, such as the effect of personal care on women's labor force participation, the effect of all the measures of care on men's labor force participation, and the effect of all the measures of care on men and women's self-reported retirement. However, the confidence intervals of the instrumental variables estimates overlap with the original estimates (under the exogeneity assumption) in all but the women's work hours specifications. This finding holds across the four different instrument sets. Thus, the only case where the 2SLS confidence intervals do not contain the OLS point estimates is also the only case in which we can soundly reject exogeneity of informal care (women's work hours).

Appendix Table 1.1: Comparison of 2SLS with Fixed Effects Linear Probability Models of Labor Force Participation

	Women		Men	
	OLS with FE	2SLS with FE	OLS with FE	2SLS with FE
Caregiver (any type)	-0.004	-0.008	-0.010	0.071
	(0.007)	(0.048)	(0.008)	(0.065)
F-test of first-stage instruments[a]		149.79 ($p < 0.01$)		88.86 ($p < 0.01$)
Over-identication test[b]		0.311 ($p = 0.577$)		0.475 ($p = 0.491$)
Exogeneity test[c]		0.006 ($p = 0.937$)		1.571 ($p = 0.210$)
Personal caregiver	-0.014*	0.030	-0.024**	0.101
	(0.008)	(0.043)	(0.011)	(0.078)
F-test of first-stage instruments[a]		236.53 ($p < 0.01$)		110.33 ($p < 0.01$)
Over-identication test[b]		0.002 ($p = 0.965$)		1.192 ($p = 0.275$)
Exogeneity test[c]		1.126 ($p = 0.289$)		2.651 ($p = 0.103$)
Chore caregiver	-0.008	-0.010	-0.006	0.085
	(0.007)	(0.060)	(0.009)	(0.080)
F-test of first-stage instruments[a]		98.67 ($p < 0.01$)		62.33 ($p < 0.01$)
Over-identication test[b]		0.312 ($p = 0.576$)		0.517 ($p = 0.472$)
Exogeneity test[c]		0.001 ($p = 0.982$)		1.331 ($p = 0.249$)
Intensive caregiver	-0.019	-0.031	-0.007	0.257
	(0.012)	(0.109)	(0.021)	(0.367)
F-test of first-stage instruments[a]		60.87 ($p < 0.01$)		13.46 ($p < 0.01$)
Over-identication test[b]		0.259 ($p = 0.611$)		1.142 ($p = 0.285$)
Exogeneity test[c]		0.011 ($p = 0.916$)		0.535 ($p = 0.465$)

Robust standard errors in parentheses. We used Instrument Set 1 which includes an indicator for the mother being ill and an indicator for the mother-in-law being ill.

Significance Levels: *** 1% level, ** 5% level, * 10% level

[a] Null of excluded instruments are jointly zero.

[b] Null of valid exclusion restrictions.

[c] Null of exogeneity.

Appendix Table 1.2: Comparison of 2SLS with Fixed Effects Linear Probability Models of Retirement

	Women		Men	
	OLS with FE	2SLS with FE	OLS with FE	2SLS with FE
Caregiver (any type)	0.017**	-0.034	0.016*	-0.058
	(0.008)	(0.050)	(0.009)	(0.075)
F-test of first-stage instruments[a]		148.14 ($p < 0.01$)		72.59 ($p < 0.01$)
Over-identication test[b]		1.379 ($p = 0.240$)		0.140 ($p = 0.709$)
Exogeneity test[c]		1.129 ($p = 0.288$)		1.033 ($p = 0.309$)
Personal caregiver	0.002	-0.045	0.015	-0.085
	(0.009)	(0.043)	(0.012)	(0.085)
F-test of first-stage instruments[a]		234.22 ($p < 0.01$)		94.58 ($p < 0.01$)
Over-identication test[b]		0.550 ($p = 0.458$)		0.596 ($p = 0.440$)
Exogeneity test[c]		1.270 ($p = 0.260$)		1.509 ($p = 0.219$)
Chore caregiver	0.018**	-0.043	0.016*	-0.069
	(0.008)	(0.063)	(0.009)	(0.090)
F-test of first-stage instruments[a]		98.15 ($p < 0.01$)		51.94 ($p < 0.01$)
Over-identication test[b]		1.365 ($p = 0.243$)		0.159 ($p = 0.690$)
Exogeneity test[c]		1.018 ($p = 0.313$)		0.928 ($p = 0.335$)
Intensive caregiver	0.021	-0.042	0.021	-0.205
	(0.014)	(0.116)	(0.024)	(0.412)
F-test of first-stage instruments[a]		58.84 ($p < 0.01$)		11.55 ($p < 0.01$)
Over-identication test[b]		1.720 ($p = 0.190$)		0.470 ($p = 0.493$)
Exogeneity test[c]		0.355 ($p = 0.551$)		0.344 ($p = 0.558$)

Robust standard errors in parentheses. We used Instrument Set 1 which includes an indicator for the mother being ill and an indicator for the mother-in-law being ill.

Significance Levels: *** 1% level, ** 5% level, * 10% level

[a] Null of excluded instruments are jointly zero.

[b] Null of valid exclusion restrictions.

[c] Null of exogeneity.

Appendix Table 1.3: Comparison of 2SLS with Fixed Effects Work Hours Regressions

	Women		Men	
	OLS with FE	2SLS with FE	OLS with FE	2SLS with FE
Caregiver (any type)	0.014	-3.665*	0.174	0.961
	(0.287)	(2.074)	(0.362)	(2.921)
F-test of first-stage instruments[a]		51.27 ($p < 0.01$)		47.49 ($p < 0.01$)
Over-identication test[b]		0.131 ($p = 0.717$)		0.211 ($p = 0.646$)
Exogeneity test[c]		3.295 ($p = 0.069$)		0.062 ($p = 0.803$)
Personal caregiver	-0.202	-2.544	-0.028	4.026
	(0.364)	(1.821)	(0.509)	(3.625)
F-test of first-stage instruments[a]		95.50 ($p < 0.01$)		52.87 ($p < 0.01$)
Over-identication test[b]		0.243 ($p = 0.622$)		0.000 ($p = 0.997$)
Exogeneity test[c]		1.748 ($p = 0.186$)		1.316 ($p = 0.251$)
Chore caregiver	0.13	-4.461*	0.161	1.259
	(0.301)	(2.527)	(0.372)	(3.614)
F-test of first-stage instruments[a]		37.99 ($p < 0.01$)		33.53 ($p < 0.01$)
Over-identication test[b]		0.097 ($p = 0.755$)		0.199 ($p = 0.656$)
Exogeneity test[c]		3.464 ($p = 0.063$)		0.080 ($p = 0.778$)
Intensive caregiver	-0.601	-9.871*	-0.630	17.992
	(0.602)	(5.571)	(1.089)	(39.731)
F-test of first-stage instruments[a]		20.66 ($p < 0.01$)		1.59 ($p = 0.203$)
Over-identication test[b]		0.003 ($p = 0.957$)		0.093 ($p = 0.760$)
Exogeneity test[c]		2.987 ($p = 0.084$)		0.217 ($p = 0.642$)

Robust standard errors in parentheses. We used Instrument Set 1 which includes an indicator for the mother being ill and an indicator for the mother-in-law being ill.

Significance Levels: *** 1% level, ** 5% level, * 10% level

[a] Null of excluded instruments are jointly zero.

[b] Null of valid exclusion restrictions.

[c] Null of exogeneity.

Appendix Table 1.4: Comparison of 2SLS with Fixed Effects Log Wage Regressions

	Women		Men	
	OLS with FE	2SLS with FE	OLS with FE	2SLS with FE
Caregiver (any type)	-0.023*	-0.005	0.032	0.026
	(0.014)	(0.104)	(0.021)	(0.163)
F-test of first-stage instruments[a]		47.72 ($p < 0.01$)		33.54 ($p < 0.01$)
Over-identication test[b]		2.552 ($p = 0.110$)		0.523 ($p = 0.469$)
Exogeneity test[c]		0.118 ($p = 0.731$)		0.004 ($p = 0.949$)
Personal caregiver	-0.019	0.023	0.014	0.061
	(0.017)	(0.090)	(0.028)	(0.175)
F-test of first-stage instruments[a]		85.93 ($p < 0.01$)		43.95 ($p < 0.01$)
Over-identication test[b]		1.310 ($p = 0.252$)		0.251 ($p = 0.616$)
Exogeneity test[c]		0.084 ($p = 0.772$)		0.101 ($p = 0.751$)
Chore caregiver	-0.026*	0.000	0.033	0.026
	(0.015)	(0.128)	(0.022)	(0.218)
F-test of first-stage instruments[a]		35.43 ($p < 0.01$)		19.81 ($p < 0.01$)
Over-identication test[b]		2.629 ($p = 0.105$)		0.540 ($p = 0.462$)
Exogeneity test[c]		0.092 ($p = 0.762$)		0.006 ($p = 0.936$)
Intensive caregiver	-0.037	0.037	0.159*	0.081
	(0.028)	(0.307)	(0.087)	(2.441)
F-test of first-stage instruments[a]		16.27 ($p < 0.01$)		1.00 ($p = 0.366$)
Over-identication test[b]		2.808 ($p = 0.094$)		0.575 ($p = 0.448$)
Exogeneity test[c]		0.033 ($p = 0.856$)		0.008 ($p = 0.927$)

Robust standard errors in parentheses. We used Instrument Set 1 which includes an indicator for the mother being ill and an indicator for the mother-in-law being ill.

Significance Levels: *** 1% level, ** 5% level, * 10% level

[a] Null of excluded instruments are jointly zero.

[b] Null of valid exclusion restrictions.

[c] Null of exogeneity.

1.8 Chapter 1 Tables and Figures

Table 1.1: Sample Selection Criteria

	LFP Estimation		Wage Estimation	
	Women	Men	Women	Men
Person-wave observations	50,883	40,765	50,883	40,765
Between 45 and 70 years old	43,693	32,439	43,693	32,439
At least one parent or in-law alive in current or previous two waves	25,323	20,966	25,323	20,966
Eliminate 1992 wave (no chore question)	21,236	17,093	21,236	17,093
Working in current wave			11,096	10,409
Non-missing wage			9,681	8,860
Person-wave observations in estimation	21,057	17,006	9,547	8,716
Unique individuals in estimation	4,521	3,993	2,942	2,774

These sample sizes are for the labor force participation and wage models using any type of care as the informal care measure. When we use the personal care measure we gain observations since we can also estimate on the 1992 wave.

Table 1.2: Summary of the Empirical Strength of the Instruments

		Women				Men			
Care Measure	IV Set	LFP	Retirement	Hours	Wages	LFP	Retirement	Hours	Wages
Any	1	X	X	Reject exog (10%)	X	X	X	X	X
	2	X	X	Reject exog (10%)	X	X	X	X	X
	3	Reject over-ID (10%)	X	Reject exog (10%)	X	X	X	X	X
	4	X	X	Reject exog (5%)	X	X	X	X	X
Personal	1	X	X	X	X	X	X	X	X
	2	Reject over-ID (10%)	X	X	X	X	X	X	X
	3	X	X	X	X	X	X	X	X
	4	X	X	Reject exog (10%)	X	X	X	X	X
Chore	1	X	X	Reject exog (10%)	X	X	X	X	X
	2	Reject over-ID (10%)	X	Reject exog (10%)	X	X	X	X	X
	3	X	X	Reject exog (5%)	X	X	X	X	X
	4	X	X	Reject exog (5%)	X	X	X	X	X
Intensive	1	X	X	Reject exog (10%)	Reject over-ID (10%)	X	X	Weak	Weak
	2	Reject over-ID (10%)	X	Reject exog (10%)	X	Weak	Weak	Weak	Weak
	3	X	X	Reject exog (5%)	Weak	Weak	Weak	Weak	Weak
	4	X	X	Reject exog (5%)	X	Weak	Weak	Weak	Weak

'X' indicates the joint F-statistic for the excluded instruments in the first stage equation is greater than 10, we do not reject the over-identification test (null of valid exclusion restrictions), and we do not reject exogeneity at conventional significance levels.

First stage models also controlled for: Age, age squared, achieving the Social Security EEA (62) but younger than FRA, achieving FRA, discrete variables for self-reported health, household size, indicator for having a child under the age of 18 in the home, household asset quartiles, and wave dummies.

Instrument Sets:

1: Indicators for mother ill, mother-in-law ill.

2: Indicators for mother ill, mother-in-law ill, indicators for mother died, father died, mother-in-law died, father-in-law died.

3: Indicators for mother ill, mother-in-law ill, indicators for mother widowed, mother-in-law widowed.

4: Indicators for mother ill, mother-in-law ill, indicators for mother died, father died, mother-in-law died, father-in-law died, indicators for mother widowed, mother-in-law widowed.

Table 1.3: Characteristics of Adult Children

	Women			Men		
	Ever Caregivers	Never Caregivers		Ever Caregivers	Never Caregivers	
Working for pay	0.644	0.574	***	0.730	0.669	***
Retired	0.201	0.202		0.317	0.346	*
Hours of work/week[a]	36.99	36.84		43.75	43.88	
Hourly wage[a]	19.21	16.84		29.66	29.03	
Age						
Average age	54.80	55.67	***	57.69	58.78	***
Percent age EEA-FRA	0.066	0.095	***	0.114	0.162	***
Percent FRA and older	0.011	0.018	*	0.063	0.103	***
Married	0.761	0.762		0.858	0.837	*
Non-white	0.181	0.207	**	0.143	0.195	***
Education						
Less than high school	0.196	0.308	***	0.210	0.341	***
High school	0.398	0.354	***	0.325	0.298	*
Some college	0.218	0.197	*	0.221	0.154	***
College graduate	0.188	0.141	***	0.244	0.207	***
Has a child under 18	0.128	0.143		0.149	0.158	
Household size	2.584	2.662	**	2.640	2.703	
Self-reported health						
Excellent or very good	0.546	0.481	***	0.532	0.450	***
Good	0.282	0.279		0.300	0.299	
Fair or poor	0.172	0.240	***	0.168	0.251	***
Average years of work experience	24.03	21.19	***	36.23	34.98	***
Unique individuals	2,552	1,969		1,962	2,031	

The descriptive statistics are reported for the first survey wave in which the individual is observed in the fixed effects linear probability model of labor force participation using any type of care as the informal care measure.

Significant difference in a two-sided t-test as compared to non-caregivers at *** 1% level, ** 5% level, * 10% level.

[a]Conditional on working.

Table 1.4: Fixed Effects Linear Probability Models of Labor Force Participation

	Women				Men			
Caregiver (any type)	-0.004 (0.007)				-0.010 (0.008)			
Personal caregiver		-0.014* (0.008)				-0.024** (0.011)		
Chore caregiver			-0.008 (0.007)				-0.006 (0.009)	
Intensive caregiver				-0.019 (0.012)				-0.007 (0.021)
Age	0.02 (0.022)	0.04** (0.02)	0.02 (0.022)	0.02 (0.022)	0.048* (0.028)	0.054** (0.024)	0.048* (0.028)	0.048* (0.028)
Age squared	-0.0003*** (0.0001)	-0.0004*** (0.0001)	-0.0003*** (0.0001)	-0.0003*** (0.0001)	-0.0004** (0.0002)	-0.0005*** (0.0002)	-0.0004** (0.0002)	-0.0004** (0.0002)
Between EEA and FRA	-0.064*** (0.011)	-0.068*** (0.01)	-0.064*** (0.011)	-0.063*** (0.011)	-0.090*** (0.011)	-0.097*** (0.011)	-0.090*** (0.011)	-0.090*** (0.011)
FRA	-0.072*** (0.018)	-0.076*** (0.018)	-0.072*** (0.018)	-0.071*** (0.018)	-0.107*** (0.018)	-0.113*** (0.017)	-0.107*** (0.018)	-0.107*** (0.018)
Married	-0.064*** (0.017)	-0.064*** (0.016)	-0.064*** (0.017)	-0.064*** (0.017)	-0.029 (0.02)	-0.015 (0.017)	-0.029 (0.02)	-0.029 (0.02)
Child under 18	-0.040** (0.018)	-0.049*** (0.015)	-0.040** (0.018)	-0.040** (0.018)	-0.033* (0.018)	-0.028* (0.015)	-0.033* (0.018)	-0.033* (0.018)
Household size	-0.012*** (0.004)	-0.010*** (0.003)	-0.012*** (0.004)	-0.012*** (0.004)	0.014*** (0.005)	0.012*** (0.004)	0.014*** (0.005)	0.014*** (0.005)
Good health	-0.007 (0.008)	-0.0006 (0.008)	-0.007 (0.008)	-0.007 (0.008)	-0.019** (0.009)	-0.014* (0.008)	-0.019** (0.009)	-0.019** (0.009)
Fair/poor health	-0.080*** (0.013)	-0.081*** (0.011)	-0.080*** (0.013)	-0.080*** (0.013)	-0.099*** (0.013)	-0.103*** (0.012)	-0.099*** (0.013)	-0.099*** (0.013)
Observations	21,057	25,103	21,057	21,057	17,006	20,878	17,006	17,006
Unique individuals	4,521	4,697	4,521	4,521	3,993	4,258	3,993	3,993
Within R^2	0.124	0.13	0.124	0.124	0.182	0.199	0.182	0.182

Robust standard errors in parentheses. All regressions also include survey wave and asset quartile dummy variables.
Significance Levels: *** 1% level, ** 5% level, * 10% level

Table 1.5: Fixed Effects Linear Probability Models of Retirement

	Women				Men			
Caregiver (any type)	0.017**				0.016*			
	(0.008)				(0.009)			
Personal caregiver		0.002				0.015		
		(0.009)				(0.012)		
Chore caregiver			0.018**				0.016*	
			(0.008)				(0.009)	
Intensive caregiver				0.021				0.021
				(0.014)				(0.024)
Age	-0.121***	-0.123***	-0.121***	-0.120***	-0.088***	-0.109***	-0.089***	-0.089***
	(0.023)	(0.02)	(0.023)	(0.023)	(0.032)	(0.026)	(0.032)	(0.032)
Age squared	0.0003**	0.0004***	0.0003**	0.0003**	0.0002	0.0005***	0.0002	0.0002
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Between EEA and FRA	0.102***	0.112***	0.102***	0.102***	0.146***	0.154***	0.146***	0.146***
	(0.013)	(0.012)	(0.013)	(0.013)	(0.013)	(0.012)	(0.013)	(0.013)
FRA	0.117***	0.125***	0.118***	0.117***	0.164***	0.171***	0.163***	0.164***
	(0.022)	(0.02)	(0.022)	(0.022)	(0.021)	(0.019)	(0.021)	(0.021)
Married	0.021	0.027*	0.021	0.022	-0.021	-0.016	-0.021	-0.021
	(0.017)	(0.015)	(0.017)	(0.017)	(0.023)	(0.019)	(0.023)	(0.023)
Child under 18	0.029*	0.028**	0.029*	0.029*	0.006	0.016	0.006	0.006
	(0.016)	(0.013)	(0.016)	(0.016)	(0.02)	(0.016)	(0.02)	(0.02)
Household size	0.001	0.003	0.0009	0.0009	-0.006	-0.002	-0.006	-0.006
	(0.004)	(0.003)	(0.004)	(0.004)	(0.006)	(0.005)	(0.006)	(0.006)
Good health	0.006	0.006	0.006	0.006	0.015	0.012	0.015	0.015
	(0.009)	(0.008)	(0.009)	(0.009)	(0.01)	(0.008)	(0.01)	(0.01)
Fair/poor health	0.028**	0.036***	0.028**	0.027**	0.056***	0.051***	0.056***	0.056***
	(0.013)	(0.011)	(0.013)	(0.013)	(0.014)	(0.012)	(0.014)	(0.014)
Observations	20,622	24,578	20,622	20,622	15,281	18,817	15,281	15,281
Unique individuals	4,489	4,656	4,489	4,489	3,796	4,078	3,796	3,796
Within R^2	0.169	0.188	0.169	0.169	0.256	0.281	0.256	0.255

Robust standard errors in parentheses. All regressions also include survey wave and asset quartile dummy variables.
Significance Levels: *** 1% level, ** 5% level, * 10% level

Table 1.6: Fixed Effects Regressions of Weekly Work Hours Conditional on Working

	Women				Men			
Caregiver (any type)	0.014 (0.287)				0.174 (0.362)			
Personal caregiver		-0.202 (0.364)				-0.028 (0.509)		
Chore caregiver			0.13 (0.301)				0.161 (0.372)	
Intensive caregiver				-0.601 (0.602)				-0.630 (1.089)
Age	3.361*** (0.951)	3.557*** (0.832)	3.355*** (0.951)	3.361*** (0.952)	6.127*** (1.265)	5.259*** (1.073)	6.125*** (1.265)	6.147*** (1.263)
Age squared	-0.017*** (0.006)	-0.016*** (0.006)	-0.017*** (0.006)	-0.017*** (0.006)	-0.045*** (0.008)	-0.046*** (0.007)	-0.045*** (0.008)	-0.045*** (0.008)
Between EEA and FRA	-1.773*** (0.493)	-1.792*** (0.458)	-1.777*** (0.493)	-1.761*** (0.493)	-1.838*** (0.492)	-2.009*** (0.464)	-1.839*** (0.492)	-1.837*** (0.492)
FRA	-3.289*** (0.944)	-3.572*** (0.889)	-3.285*** (0.944)	-3.287*** (0.943)	-2.177** (0.89)	-2.704*** (0.84)	-2.177** (0.89)	-2.173** (0.89)
Married	-1.404** (0.688)	-1.225** (0.621)	-1.410** (0.688)	-1.407** (0.688)	0.805 (0.953)	0.888 (0.796)	0.809 (0.953)	0.808 (0.955)
Child under 18	-1.583** (0.634)	-1.305** (0.538)	-1.584** (0.634)	-1.588** (0.635)	-0.773 (0.724)	-1.003* (0.571)	-0.772 (0.724)	-0.785 (0.725)
Household size	-0.210 (0.169)	-0.179 (0.145)	-0.210 (0.169)	-0.211 (0.169)	0.11 (0.196)	0.048 (0.175)	0.11 (0.196)	0.106 (0.196)
Good health	-0.088 (0.313)	0.089 (0.285)	-0.089 (0.313)	-0.090 (0.314)	-0.694* (0.363)	-0.544* (0.318)	-0.695* (0.363)	-0.696* (0.363)
Fair/poor health	0.178 (0.528)	-0.0008 (0.472)	0.177 (0.528)	0.183 (0.529)	-0.994* (0.576)	-1.078** (0.503)	-0.995* (0.576)	-0.988* (0.576)
Observations	10,852	13,409	10,852	10,852	10,181	13,116	10,181	10,181
Unique individuals	3,122	3,449	3,122	3,122	2,984	3,417	2,984	2,984
Within R^2	0.075	0.07	0.075	0.075	0.131	0.134	0.131	0.131

Robust standard errors in parentheses. All regressions also include survey wave and asset quartile dummy variables.
Significance Levels: *** 1% level, ** 5% level, * 10% level

Table 1.7: 2SLS with Fixed Effects Regressions of Weekly Work Hours Conditional on Working for Women

	First Stage	Second Stage	First Stage	Second Stage	First Stage	Second Stage	First Stage	Second Stage
Caregiver (any type)		-3.665*						
		(2.074)						
Personal caregiver				-2.544				
				(1.821)				
Chore caregiver						-4.461*		
						(2.527)		
Intensive caregiver								-9.871*
								(5.571)
Age	0.029	3.502***	0.005	3.572***	0.043	3.587***	-0.004	3.361***
	(0.04)	(0.968)	(0.023)	(0.832)	(0.04)	(0.98)	(0.02)	(0.968)
Age squared	-0.0003	-0.018***	0.00004	-0.016***	-0.0004*	-0.019***	-0.00007	-0.018***
	(0.0002)	(0.006)	(0.0001)	(0.006)	(0.0002)	(0.006)	(0.0001)	(0.006)
Between EEA and FRA	0.026	-1.673***	0.015	-1.757***	0.028	-1.643***	0.019*	-1.577***
	(0.02)	(0.5)	(0.014)	(0.459)	(0.02)	(0.504)	(0.011)	(0.506)
FRA	-0.027	-3.409***	-0.005	-3.605***	-0.023	-3.411***	0.005	-3.259***
	(0.037)	(0.957)	(0.025)	(0.892)	(0.035)	(0.958)	(0.02)	(0.959)
Married	0.054**	-1.192*	0.037**	-1.124*	0.049**	-1.173	-0.007	-1.469**
	(0.026)	(0.715)	(0.015)	(0.63)	(0.025)	(0.723)	(0.014)	(0.71)
Child under 18	-0.003	-1.583**	-0.002	-1.308**	0.008	-1.537**	-0.010	-1.669**
	(0.024)	(0.646)	(0.013)	(0.538)	(0.024)	(0.653)	(0.012)	(0.66)
Household size	-0.0003	-0.212	0.005	-0.167	0.001	-0.206	-0.002	-0.228
	(0.006)	(0.17)	(0.004)	(0.145)	(0.006)	(0.17)	(0.003)	(0.171)
Good health	0.007	-0.062	0.005	0.099	0.006	-0.064	-0.002	-0.115
	(0.013)	(0.319)	(0.008)	(0.286)	(0.012)	(0.321)	(0.006)	(0.32)
Fair/poor health	0.03	0.279	0.036***	0.078	0.013	0.226	0.008	0.243
	(0.02)	(0.543)	(0.014)	(0.479)	(0.02)	(0.539)	(0.011)	(0.549)
Mother ill	0.165***		0.167***		0.138***		0.066***	
	(0.018)		(0.013)		(0.017)		(0.011)	
Mother-in-law ill	0.076***		0.076***		0.058***		0.015	
	(0.02)		(0.014)		(0.019)		(0.009)	
Observations	10,852		13,409		10,852		10,852	
Unique individuals	3,122		3,449		3,122		3,122	

Robust standard errors in parentheses. All regressions also include survey wave and asset quartile dummy variables.
Significance Levels: *** 1% level, ** 5% level, * 10% level

Table 1.8: Comparison of 2SLS with Fixed Effects Work Hours Regressions for Women

	OLS with FE	IV Set 1	IV Set 2	IV Set 3	IV Set 4
Caregiver (any type)	0.014	-3.665*	-2.194	-4.868**	-2.620**
	(0.287)	(2.074)	(1.343)	(2.020)	(1.328)
F-test of first-stage instruments[a]		51.27 ($p < 0.01$)	54.11 ($p < 0.01$)	28.44 ($p < 0.01$)	41.36 ($p < 0.01$)
Over-identication test[b]		0.131 ($p = 0.717$)	2.232 ($p = 0.816$)	4.684 ($p = 0.196$)	8.185 ($p = 0.317$)
Exogeneity test[c]		3.295 ($p = 0.069$)	2.954 ($p = 0.086$)	5.844 ($p = 0.016$)	4.773 ($p = 0.029$)
Personal caregiver	-0.202	-2.544	-2.645*	-3.092*	-2.928*
	(0.364)	(1.821)	(1.570)	(1.810)	(1.561)
F-test of first-stage instruments[a]		95.50 ($p < 0.01$)	56.41 ($p < 0.01$)	49.64 ($p < 0.01$)	42.64 ($p < 0.01$)
Over-identication test[b]		0.243 ($p = 0.622$)	1.907 ($p = 0.862$)	6.198 ($p = 0.102$)	8.263 ($p = 0.310$)
Exogeneity test[c]		1.748 ($p = 0.186$)	2.675 ($p = 0.102$)	2.619 ($p = 0.106$)	3.660 ($p = 0.056$)
Chore caregiver	0.13	-4.461*	-2.834*	-5.665**	-3.284**
	(0.301)	(2.527)	(1.713)	(2.479)	(1.697)
F-test of first-stage instruments[a]		37.99 ($p < 0.01$)	36.10 ($p < 0.01$)	20.45 ($p < 0.01$)	27.50 ($p < 0.01$)
Over-identication test[b]		0.097 ($p = 0.755$)	2.121 ($p = 0.832$)	5.107 ($p = 0.164$)	8.332 ($p = 0.304$)
Exogeneity test[c]		3.464 ($p = 0.063$)	3.237 ($p = 0.072$)	5.348 (p=0.021)	4.635 ($p = 0.031$)
Intensive caregiver	-0.601	-9.871*	-7.885*	-12.284**	-8.961**
	(0.602)	(5.571)	(4.363)	(5.592)	(4.346)
F-test of first-stage instruments[a]		20.66 ($p < 0.01$)	18.25 ($p < 0.01$)	10.97 ($p < 0.01$)	13.70 ($p < 0.01$)
Over-identication test[b]		0.003 ($p = 0.957$)	1.455 ($p = 0.918$)	5.325 ($p = 0.149$)	7.475 ($p = 0.381$)
Exogeneity test[c]		2.987 ($p = 0.084$)	3.190 ($p = 0.074$)	4.273 ($p = 0.039$)	4.394 ($p = 0.036$)

Robust standard errors in parentheses.

Significance Levels: *** 1% level, ** 5% level, * 10% level

[a] Null of excluded instruments are jointly zero.

[b] Null of valid exclusion restrictions.

[c] Null of exogeneity.

Table 1.9: Fixed Effects Regressions of Logged Hourly Wages Conditional on Working

	Women				Men			
Caregiver (any type)	-0.023*				0.032			
	(0.014)				(0.021)			
Personal caregiver		-0.019				0.014		
		(0.017)				(0.028)		
Chore caregiver			-0.026*				0.033	
			(0.015)				(0.022)	
Intensive caregiver				-0.037				0.159*
				(0.028)				(0.087)
Experience	0.017	0.025	0.017	0.017	0.059**	0.074***	0.059**	0.058**
	(0.02)	(0.017)	(0.02)	(0.02)	(0.025)	(0.019)	(0.025)	(0.025)
Experience squared	-0.0001	-0.0002***	-0.0001	-0.0001	-0.0002	-0.0002	-0.0002	-0.0001
	(0.00009)	(0.00008)	(0.00009)	(0.00009)	(0.0002)	(0.0001)	(0.0002)	(0.0002)
Tenure	0.021***	0.022***	0.021***	0.021***	0.023***	0.024***	0.023***	0.023***
	(0.004)	(0.003)	(0.004)	(0.004)	(0.005)	(0.004)	(0.005)	(0.005)
Tenure squared	-0.0002*	-0.0003***	-0.0002*	-0.0002*	-0.0003**	-0.0003***	-0.0003**	-0.0003**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Married	-0.016	-0.043*	-0.016	-0.017	0.035	0.003	0.036	0.036
	(0.029)	(0.025)	(0.029)	(0.029)	(0.036)	(0.03)	(0.036)	(0.036)
Good health	0.016	0.01	0.016	0.016	0.009	0.011	0.008	0.008
	(0.016)	(0.014)	(0.016)	(0.016)	(0.019)	(0.016)	(0.019)	(0.019)
Fair/poor health	0.063**	0.047*	0.063**	0.063**	0.022	0.023	0.022	0.022
	(0.03)	(0.025)	(0.03)	(0.03)	(0.027)	(0.024)	(0.027)	(0.027)
Salaried	0.057**	0.058***	0.057**	0.057**	0.035	0.063*	0.034	0.035
	(0.024)	(0.021)	(0.024)	(0.024)	(0.039)	(0.034)	(0.039)	(0.039)
Observations	9,547	11,882	9,547	9,547	8,716	11,257	8,716	8,716
Unique individuals	2,942	3,295	2,942	2,942	2,774	3,206	2,774	2,774
Within R^2	0.04	0.041	0.04	0.04	0.036	0.042	0.036	0.037

Robust standard errors in parentheses. All regressions also include survey wave dummy variables.

Significance Levels: *** 1% level, ** 5% level, * 10% level

Table 1.10: Sensitivity of Labor Force Participation and Retirement Results to Sample Restrictions

	Women				Men			
Care Measure	LFP		Retirement		LFP		Retirement	
	I	II	I	II	I	II	I	II
Any type	-0.004	-0.004	0.017**	0.022***	-0.010	-0.009	0.016*	0.015*
	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)
Personal	-0.014*	-0.015*	0.002	0.006	-0.024**	-0.024**	0.015	0.013
	(0.008)	(0.009)	(0.009)	(0.009)	(0.011)	(0.011)	(0.012)	(0.012)
Chore	-0.008	-0.008	0.018**	0.022***	-0.006	-0.006	0.016*	0.015
	(0.007)	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)
Intensive	-0.019	-0.017	0.021	0.022	-0.007	-0.007	0.021	0.016
	(0.012)	(0.013)	(0.014)	(0.014)	(0.021)	(0.021)	(0.024)	(0.024)

Robust standard errors in parentheses.

Significance Levels: *** 1% level, ** 5% level, * 10% level

I: Baseline sample; II: Sample restricted to those who work at some point since age 45.

Table 1.11: Fixed Effects Log Wage Specification Comparison

	Women			Men		
Care Measure	I	II	III	I	II	III
Any type	-0.023*	-0.024*	-0.026*	0.032	0.026	0.026
	(0.014)	(0.014)	(0.014)	(0.021)	(0.022)	(0.022)
Personal	-0.019	-0.024	-0.024	0.014	0.008	0.008
	(0.017)	(0.017)	(0.017)	(0.028)	(0.029)	(0.029)
Chore	-0.026*	-0.027*	-0.030**	0.033	0.027	0.028
	(0.015)	(0.015)	(0.015)	(0.022)	(0.023)	(0.023)
Intensive	-0.037	-0.043	-0.044	0.159*	0.145*	0.146*
	(0.028)	(0.029)	(0.029)	(0.087)	(0.087)	(0.087)

Robust standard errors in parentheses.

Significance Levels: *** 1% level, ** 5% level, * 10% level

I: Baseline specification; II: Baseline specification removing experience, experience squared, tenure, tenure squared, and salaried indicator; III: Baseline specification removing experience, experience squared, tenure, tenure squared, and salaried indicator, and including age and age squared.

Table 1.12: Fixed Effects and Random Effects Results Comparison for Women

	LFP			Retirement			Work Hours		Log Wages	
Care Measure	FE LPM	RE LPM	RE Probit[a]	FE LPM	RE LPM	RE Probit[a]	FE 2SLS	RE 2SLS	FE	RE
Any type	-0.004	-0.004	-0.003	0.017**	0.024***	0.026***	-3.665*	-1.827	-0.023*	-0.022*
	(0.007)	(0.006)	(0.009)	(0.008)	(0.007)	(0.007)	(2.074)	(1.691)	(0.014)	(0.012)
Personal	-0.014*	-0.017**	-0.019*	0.002	0.010	0.009	-2.544	-1.209	-0.019	-0.030*
	(0.008)	(0.008)	(0.011)	(0.009)	(0.008)	(0.009)	(1.821)	(1.481)	(0.017)	(0.016)
Chore	-0.008	-0.007	-0.008	0.018**	0.024***	0.026***	-4.461*	-2.346	-0.026*	-0.027**
	(0.007)	(0.007)	(0.010)	(0.008)	(0.007)	(0.008)	(2.527)	(2.148)	(0.015)	(0.013)
Intensive	-0.019	-0.030***	-0.035**	0.021	0.031***	0.028**	-9.871*	-5.102	-0.037	-0.053**
	(0.012)	(0.012)	(0.017)	(0.014)	(0.012)	(0.013)	(5.571)	(4.430)	(0.028)	(0.025)

Robust standard errors in parentheses.

Significance Levels: *** 1% level, ** 5% level, * 10% level

[a] Marginal effects shown.

Table 1.13: Fixed Effects and Random Effects Results Comparison for Men

	LFP			Retirement			Work Hours		Log Wages	
Care Measure	FE LPM	RE LPM	RE Probit[a]	FE LPM	RE LPM	RE Probit[a]	FE	RE	FE	RE
Any type	-0.010	-0.015*	-0.019**	0.016*	0.027***	0.034***	0.174	-0.437	0.032	0.028
	(0.008)	(0.008)	(0.010)	(0.009)	(0.008)	(0.010)	(0.362)	(0.362)	(0.021)	(0.019)
Personal	-0.024**	-0.032***	-0.030**	0.015	0.028***	0.026**	-0.028	-0.387	0.014	0.013
	(0.011)	(0.010)	(0.013)	(0.012)	(0.011)	(0.012)	(0.509)	(0.477)	(0.028)	(0.026)
Chore	-0.006	-0.009	-0.014	0.016*	0.025***	0.032***	0.161	-0.382	0.033	0.028
	(0.009)	(0.008)	(0.010)	(0.009)	(0.009)	(0.010)	(0.372)	(0.335)	(0.022)	(0.019)
Intensive	-0.007	-0.017	-0.006	0.021	0.031	0.030	-0.630	-1.168	0.159*	0.120*
	(0.021)	(0.019)	(0.025)	(0.024)	(0.022)	(0.024)	(1.089)	(1.026)	(0.087)	(0.070)

Robust standard errors in parentheses.

Significance Levels: *** 1% level, ** 5% level, * 10% level

[a] Marginal effects shown.

Chapter 2

Dynamic Wage and Employment Effects of Elder Parent Care

How does caregiving for an elderly parent affect a woman's current and future labor force participation and wages? Working less to provide care clearly affects a woman's current income, but it is also clear that her future labor market opportunities can be affected. Women who spend time away from work to provide care may later struggle to find a job or return to their previous wage. In addition, caregiving often involves a significant time commitment. On average, caregivers provide 10 to 20 hours of care per week for four years (MetLife 2009a, National Alliance for Caregiving and AARP 2009). Thus, the decision to provide care may mean a substantial loss of current and future earning capacity. These considerations make clear the potential long-term labor market effects of caregiving and underscore the inherent forward-looking nature of caregiving and work decisions.

Understanding the short and long-term effects of caregiving on work and wages is an important policy issue given the large and growing population of disabled elderly and the prevalence of informal care provided by adult daughters, most of whom have a history of working. Currently in the United States there are 9 million men and women over the age of 65 who need help with basic personal activities, household chores or errands. By 2020, 12 million older Americans are projected to need long-term care.[1] About 70 percent of the elderly rely solely on informal care from family or friends, and about two-thirds of elder parent caregivers are women, a group which has experienced increasing labor force participation rates. In light of these trends and the fact that a typical caregiver is in her fifties or early sixties, still in her prime working years, providing care may involve a considerable loss of current and future human capital and job opportunities.

Despite the intertemporal nature of caregiving and work, the existing literature has overlooked the dynamics of these decisions. Most models are static and focus only on current foregone wages, which could seriously underestimate the costs of caregiving. In contrast to most earlier studies, I model caregiving and work decisions in an explicitly intertemporal framework in which women make these decisions considering how they will affect future outcomes. I build and estimate a dynamic discrete choice model of caregiving and work that incorporates dynamic elements such as health changes of elderly parents, human capital accumulation and labor market frictions. These features allow for long-term labor market effects of informal care that may arise due to foregone or lower wages and/or decreased job opportunities during and after a caregiving spell. By incorporating these elements in a dynamic framework, I can identify various channels through which caregiving affects a woman's labor market outcomes over the short and long-term.

I estimate the structural parameters of the model using eight waves of data from the *Health and Retirement Study* by efficient method of moments. The results highlight various static and dynamic labor market tradeoffs faced by caregivers. Women who begin care provision are likely to continue to do so, especially if their parent is in poor health. Thus, when a woman makes caregiving and work decisions, she not only considers the tradeoff between caregiving and work today, but also the potential long-term tradeoffs generated by the persistence in caregiving. In addi-

[1] Medicare.gov: http://www.medicare.gov/longtermcare/static/home.asp and US Department of Health and Human Services' National Clearinghouse for Long-Term Care: http://www.longtermcare.gov/LTC

tion, women are more likely to provide large amounts of care when their parents are in poor health, and these intensive care providers are less likely to be working, especially full-time.

The estimates also underscore the importance of labor market frictions. Women who do not work face low probabilities of receiving job offers in the future. For example, the probability a non-working woman younger than 62 will receive a part-time (full-time) offer next period is 7-9 (9-12) percent. Thus, those who leave work to provide care may find it difficult to return. The estimates also reveal that women cannot move frictionlessly between full and part-time work. As a result, a woman may not always have the option to decrease her work hours while providing care. If she does work part-time while caregiving, she is not guaranteed to be able to move to full-time work in the future. The wage estimates show that there are returns to experience, there is a wage penalty for not working in the prior period and that part-time jobs are associated with lower wages. Thus, women who leave work to provide care forgo experience and the associated wage returns, and face a lower expected wage if they return to work. In addition, caregivers are more likely to work part-time than non-caregivers, and earn a lower wage than had they worked full-time.

I use the parameter estimates and model to calculate the value (equivalently, the cost) of elder parent care, which reflects both the static and dynamic value of caregiving. The median value of initiating care provision is $66,370 over a two-year period, about half the cost of two years of nursing home care. This estimate is two to three times larger than the values found in the previous literature, which are calculated using the replacement wage approach or current foregone wages due to caregiving. Thus, calculations that ignore forward-looking behavior and the intertemporal nature of caregiving and work decisions underestimate the value of elder parent care.

The estimated structural parameters are then used to analyze how various government sponsored programs for elder parent care affect a woman's caregiving and labor market decisions. I analyze three counterfactual policy experiments: (1) A two-year unpaid work leave to provide intensive care for a parent; (2) A two-year paid work leave to provide intensive care where the caregiver receives a payment that is tied to the health of the parent; (3) A caregiver allowance where those who provide intensive care receive a payment that is tied to the health of their parent, is not linked to their employment status and can be received indefinitely. The first policy experiment is a lengthier version of the Family and Medical Leave Act (FMLA) of 1993 which allows workers to take up to a 12-week unpaid leave to care for an ill family member and guarantees the worker will return to his/her job at the same wage. The second policy experiment is of particular interest as paid leaves have recently received much attention both at the national and state-level.[2] The caregiver allowance experiment may inform about the labor market effects of policies similar to that of the recently suspended CLASS Act.

The results of the policy experiments show that both the unpaid and paid leaves generate modest increases in intensive care provision, and encourage more work, especially full-time, among women who ever provide intensive care to a parent. On the other hand, the caregiver allowance generates substantial increases in intensive care provision, but leads to an increase in non-work among women who ever provide intensive care. A comparison of the welfare gains generated by the policies shows that about half the value of the paid leave can be achieved with the unpaid leave, and the caregiver allowance and the unpaid leave generate comparable welfare gains. The gains generated by the leaves emphasize the value of guaranteeing a caregiver can return to work, and underscore the importance of taking an intertemporal approach to modeling caregiving and work.

The paper proceeds as follows. Section 2.1 discusses the literature. The structural model is presented in Section 2.2. Identification is discussed in Section 2.3. Section 2.4 describes the data, discusses empirical implementation and provides descriptive statistics. Estimation is discussed in Section 2.5. Section 2.6 presents the

[2]For example, H.R. 1723 The Family Leave Insurance Act of 2009 was introduced in the 111^{th} Congress to provide for a paid family and medical leave insurance program. Also, the federal budget for fiscal year 2011 establishes a $50 million State Paid Leave Fund within the Department of Labor to provide competitive grants to help states launch paid family leave programs similar to those already established in California and New Jersey.

main results, model fit and the value of elder parent care calculation. Section 2.7 discusses the counterfactual policy experiments and results, and Section 2.8 concludes.

2.1 Related Literature

This paper contributes to two strands of the literature. The first examines the relationship between elder parent care and labor market outcomes such as labor force participation, work hours and wages. Most US and European studies find there is a negative correlation between female labor force participation and caregiving (Ettner 1995, Pavalko and Artis 1997, Heitmueller 2007, Bolin et al. 2008, Crespo and Mira 2010, Van Houtven, Coe, and Skira 2010).[3] However, the magnitude of this negative correlation varies across studies, ranging from an almost negligible effect to a 30 percentage point decrease in the probability of working. In addition, this negative correlation is stronger among intensive caregivers, or those with a greater commitment of caregiving time (Ettner 1995, Carmichael and Charles 1998, Heitmueller 2007, Casado-Marín et al. 2011).

There is less consensus concerning whether caregivers who remain in the labor force reduce their work hours. Wolf and Soldo (1994), Bolin et al. (2008) and Casado-Marín et al. (2011) find little evidence of caregiving reducing work hours, while Ettner (1996), Johnson and LoSasso (2000) and Van Houtven, Coe, and Skira (2010) find female caregivers in the US do reduce their work hours. In terms of wage effects, Carmichael and Charles (2003) find caregiving for more than 10 hours per week reduces current wages by 9 percent for women in the UK, and Heitmueller and Inglis (2007) find caregivers in the UK earn 3 percent less than non-caregivers with similar characteristics. Van Houtven, Coe, and Skira (2010) find caregiving leads to a 2.3 to 2.6 percent reduction in a woman's hourly wage in the US. While this literature examines several tradeoffs between caregiving and female labor supply, the tradeoffs are analyzed in isolation. In addition, these studies only evaluate

[3] Wolf and Soldo (1994) is a notable exception which finds no evidence of informal care reducing the propensity of married women to be employed.

the effect of caregiving today on a woman's current labor market outcomes.[4] This is the first paper to examine the effects of caregiving on current and future labor force participation, at the intensive and extensive margins, as well as wages in one comprehensive framework.

This paper also contributes to the literature that formulates theoretical models of caregiving and work. Almost all of the models are static time allocation models where the adult child makes caregiving and work decisions at a single point in time and the only cost of caregiving is current foregone wages (for example, Börsch-Supan et al. 1992, Johnson and LoSasso 2000, Crespo and Mira 2010, Knoef and Kooreman 2011). There is no forward-looking behavior, no parental health dynamics and no long-term costs of caregiving. Fevang et al. (2009) is the only study which provides a theoretical model of caregiving and work with multiple periods. In that model, however, perfect foresight is assumed—with certainty a parent is healthy in the first period, sick and in need of care in the second period, and passes away in the third period. The adult child can freely adjust her work hours over these three periods and the wage is assumed to be constant over all periods.

I expand upon the literature by modeling caregiving and work decisions in an intertemporal framework which includes a forward-looking adult daughter, parental health changes and uncertainty, human capital accumulation and labor market frictions. The model allows informal care to have long-term labor market effects through several channels, such as foregone or lower wages over time and decreased job offers. With the recent exception of Knoef and Kooreman (2011), the structural parameters of the theoretical models are not estimated in the above-mentioned studies.[5] By estimating the structural parameters of the model, I can simulate counterfactual policy experiments such as the work leave and caregiver allowance programs

[4]Heitmueller et al. (2010) and Moscarola (2010) allow last year's caregiving decision to affect current labor force participation but do not allow for direct contemporaneous effects of caregiving on employment. Spiess and Schneider (2003) find recently terminating care provision is insignificantly related to changes in work hours in Europe.

[5]Knoef and Kooreman (2011) estimate the structural parameters of their static model using only children, and then use those estimates to assess the nature of interactions between siblings. Börsch-Supan et al. (1992) jointly model employment and "time spent with parents," which is a much broader concept than time spent providing care. They estimate equations based on the underlying structural model.

described above. No studies have attempted to analyze the impact of government sponsored elder parent care programs on the caregiving and labor supply decisions of adult children in the US or the welfare gains generated by such policies.

2.2 Model

To answer the questions posed above, I propose a one-child one-parent structural dynamic discrete choice model in which an adult daughter makes joint decisions about caregiving and work.[6] The optimization problem, consistent with the data available for estimation, begins at a point in the middle of the daughter's lifecycle.[7] At any period t, the daughter has up to two choices to make. She makes an employment decision $E = \{0, PT, FT\}$ for non-employment, part-time work and full-time work, respectively, and a caregiving decision (given a parent is alive) $CG = \{0, 1, 2\}$ for no caregiving, light caregiving and intensive caregiving, respectively.

2.2.1 Preferences

The woman is forward-looking and at any time t, her objective is to maximize her expected lifetime utility, U_t, given the choice set she faces. A woman's period utility, u_t, is determined by her consumption, C_t, leisure time, L_t, and caregiving decision, CG_t. The daughter receives direct utility from light and intensive caregiving which varies with the health state of her parent, H_t^p.[8] This captures the idea that when a parent is very sick, a child may derive relatively more utility from caregiving than when the parent is healthy. In addition, there is a utility cost to initiating care which varies with the health of the parent. This captures the idea that beginning care provision may involve substantial adjustments (in the daughter's schedule, for

[6] I abstract from the other parent since less than 7 percent of female caregivers care for both parents simultaneously. If both parents are alive, spousal caregiving is the most prevalent form of informal care (Spillman and Pezzin 2000). I abstract from other adult children since among families with at least one informal care provider and at least two adult children, only 14 percent include multiple caregiving adult children (Byrne et al. 2009). Modeling a dynamic sibling bargaining game is currently beyond the scope of this paper but is a promising avenue for future research.

[7] Initial conditions are those that prevail at that lifecycle point, and are addressed in Section 2.4.3.

[8] The parental health states and the health transition process are discussed in detail in Section 2.2.5.

example) and may be more difficult when the parent is already in poor health. Utility from caregiving also varies with whether the woman has a sister, sis_t, since she may derive relatively less utility from caregiving when there are other adult daughters who could potentially provide care.[9,10] I allow for permanent unobserved heterogeneity in preferences through differences in the utility from leisure.[11] The period utility function is assumed to be linear in its arguments with some interaction terms and is given by

$$u_t = u\left(\ln(C_t), \ln(L_t), CG_t; H_t^p, sis_t, CG_{t-1}, \ell, \nu_{t,E,CG}\right) \tag{2.1}$$

where ℓ denotes the woman's unobserved type and $\nu_{t,E,CG}$ denotes time-varying unobserved utility from each choice in the model. The unobserved utility arguments, $\nu_{t,E,CG}$, are assumed to be additively separable, serially uncorrelated and normally distributed with mean zero and covariance matrix Σ_ν to be estimated.[12] The assumed utility function specification is provided in the Appendix.

2.2.2 Time and Budget Constraints

The daughter's leisure, L_t, is constrained to equal the time that remains in a period given her work and caregiving choices. Caregiving is a use of time that is valued differently than leisure since a woman gets direct utility from caregiving, but the time constraint makes it clear that the direct opportunity cost of caregiving is

[9] I abstract from allowing utility from caregiving to vary with whether the woman has a brother since Engers and Stern (2002), Checkovich and Stern (2002), Byrne et al. (2009) and several others find that all else equal, daughters are significantly more likely than sons to provide care.

[10] I assume the utility from informal care provision does not vary with the parent's financial needs. McGarry (1998) finds no significant difference between more and less wealthy parents in the conditional probability of receiving informal care from children. Brown (2007) finds no evidence that children provide care in response to their parents' financial need, but rather to their parents' care needs in a dynamic structural model of parents' retirement asset choices and family care arrangements.

[11] I allow for two types, $\ell \in \{1, 2\}$, who differ in permanent features unobserved to the econometrician. In addition to having different leisure preferences, the types have different wage offer intercepts as discussed in Section 2.2.4.

[12] More precisely, two covariance matrices are estimated. A 9×9 covariance matrix governs the unobserved utility from each joint caregiving and work choice for those with a parent alive. A 3×3 covariance matrix governs the unobserved utility from each work choice for women without a parent alive (since they no longer make a caregiving choice).

foregone leisure time. The time constraint is given by

$$L_t = \overline{T} - h_t^E - h_t^{CG} \tag{2.2}$$

where $\overline{T}$ is the total time available per decision period, h_t^E denotes the hours associated with the woman's employment choice and h_t^{CG} denotes the hours associated with her caregiving choice.

The daughter's consumption, C_t, is constrained by the sum of her hourly wage, w_t, times hours worked, h_t^E, and non-labor income, y_t.[13] Non-labor income varies with the woman's education, age and marital status, and is included because the woman may receive income from other sources such as her spouse or retirement benefits.[14] Thus, non-labor income captures the influences of spousal labor supply. The Appendix describes how non-labor income is formulated. The budget constraint is given by

$$C_t = w_t h_t^E + y_t \tag{2.3}$$

[13]I abstract from including savings behavior directly in the model. This may be a concern if those with more savings substitute away from informal care provision and purchase care for their parents. However, in the data, there is no descriptive evidence of a lower probability of informal care provision for those with more liquid wealth or savings. In addition, Byrne et al. (2009) find among families where elderly parents receive formal health care, only 9 percent of these parents receive financial contributions for this care from their children. There may also be a concern that those with more wealth can afford to caregive by consuming their savings; however, there is no evidence that light nor intensive caregivers experience significantly different changes in assets or savings than non-caregivers. This descriptive evidence cannot be interpreted causally, and savings would need to be included directly in the structural model to test its behavioral impact. Savings is currently incorporated in the model in that the woman's initial liquid assets enter the unobserved type probabilities, which is discussed in more detail in Section 2.4.3. This allows for persistent differences in behavior based on wealth that operate through the permanent unobserved heterogeneity, but not intertemporal adjustments in consumption and savings behavior.

[14]I abstract from inheritances and inter-vivos transfers between the parent and daughter; thus, caregiving decisions are not motivated by such financial considerations in the model. Most recent studies do not support the bequest motive. For example, Brown (2007) finds no evidence that children's caregiving behavior is influenced by parents' planned bequests; Norton and Van Houtven (2006) find informal care has no effect on the equality of intended bequests; and, Checkovich and Stern (2002) conclude that children do not compete for bequests through their provision of informal care. The evidence on inter-vivos transfers is mixed. McGarry and Schoeni (1997) and Brown (2006) find parents do not transfer significantly more to their caregiving children than their non-caregiving children on average. Norton and Van Houtven (2006), however, find a child who provides care is 11 to 16 percentage points more likely to receive an inter-vivos transfer than a sibling who does not provide care. If such financial considerations motivate caregiving decisions for some women, this will be reflected in the utility from caregiving parameters.

2.2.3 Job Dynamics

If a woman worked part-time in period $t-1$, she is assumed to receive a part-time offer with certainty in period t, and if she worked full-time in period $t-1$, she is assumed to receive a full-time offer with certainty in period t.[15] If the woman was not working part-time in period $t-1$, either because she was not working or was working full-time, she receives a part-time offer in period t with probability $\lambda^{PT}(\mathbf{Z}_t)$, where $\mathbf{Z}_t$ is a vector of the woman's characteristics. If she was not working full-time in period $t-1$, either because she was not working or was working part-time, she receives a full-time offer in period t with probability $\lambda^{FT}(\mathbf{Z}_t)$.[16] The offer arrival rates are assumed to come from a logistic distribution and are given by

$$\lambda^E(\mathbf{Z}_t) = \frac{\exp[\lambda^E \mathbf{Z}_t]}{1+\exp[\lambda^E \mathbf{Z}_t]} \quad E \in \{PT, FT\} \tag{2.4}$$

where

$$\lambda^E \mathbf{Z}_t = \lambda_0^E + \lambda_1^E I(E_{t-1}=0) + \lambda_2^E I(age_t \geq 62) + \lambda_3^E I(educ_t = 2) + \lambda_4^E I(educ_t = 3)$$

The vector $\mathbf{Z}_t$ includes whether the woman worked last period or not, $I(E_{t-1}=0)$, whether she has reached the age of 62, $I(age_t \geq 62)$, and her education.[17] The job offer probabilities depend on whether the woman has reached age 62 since Social Security retirement benefits can be claimed at this age and could consequently affect search and job offer probabilities. I assume job offer arrival rates are constant over calendar time; thus, the offer probabilities do not account for business cycle effects.

[15] Since transitions from full-time to part-time work, and vice versa, are infrequent in the data, job holding is assumed. About 16.7 percent of those working part-time in period t transition to full-time work the next period, and 10.6 percent of those working full-time in period t transition to part-time work the following period.

[16] The offer arrival rates reflect both search by the woman and contact made by the firm. The model assumes identical women (in terms of observables) face the same arrival rates. If there are differences in search intensity that are not captured in $\mathbf{Z}_t$, this can be introduced in the model by including a search decision with a cost attached.

[17] Education is discretized into three categories: (1) Less than a high school degree; (2) High school degree/GED; and (3) At least some college.

2.2.4 Wages

If a woman receives a job offer, she also receives an hourly wage offer given by

$$\begin{aligned} \ln w_t =& \beta_{0,\ell} + \beta_1 age_t + \beta_2 age_t^2 + \beta_3 exper_t + \beta_4 exper_t^2 + \beta_5 I(educ_t = 2) \\ & + \beta_6 I(educ_t = 3) + \beta_7 I(E_t = PT) + \beta_8 I(E_{t-1} = 0) + \epsilon_t \end{aligned} \tag{2.5}$$

where $exper_t$ is actual years of work experience, $I(educ_t = 2)$ and $I(educ_t = 3)$ are education category indicators for having completed high school and at least some college, respectively, and ϵ_t is an i.i.d. wage unobservable which is distributed normal with mean zero and variance σ_w^2 to be estimated. Thus, wages grow if there are substantial returns to work experience and fall if there are penalties for being out of the workforce in the previous period or for working at a part-time job. Permanent unobserved heterogeneity in wages is incorporated by allowing the offer intercept to differ by unobserved type ℓ.

2.2.5 Parental Health Transitions

Parental health is a crucial element in the model as it provides an important channel for dynamics and helps to generate persistence in caregiving. The parent's health is assumed to be unaffected by informal care provided by the daughter.[18] Thus, a woman does not provide care to change the healthy trajectory of her parent, but because she derives direct utility from caregiving which varies with the parent's health state (i.e. caregiving is a consumption good). The health of the parent takes on four discrete states: (1) Healthy; (2) Has any activities of daily living (ADL) limitations or has a memory or cognition problem; (3) Cannot be left alone for an hour or more; and (4) Death.[19] Parental health is modeled as a Markov process, which helps capture the fact that a parent's need for care may be sporadic, sustained

[18] In the data, informal care provision is positively correlated with poor parental health. Health transition estimates with informal care as an input imply that caregiving has no significant effect on parental health or leads to worsening parental health. Byrne et al. (2009) estimate elderly health-quality production functions and find informal care provided by children is relatively ineffective. Thus, I abstract from allowing informal care to affect parental health.

[19] Activities of daily living include bathing, dressing and eating. The choice of health states is motivated by the parental health information available in the HRS data.

or intensified over the course of a caregiving episode. π_{jk} denotes the probability that the parent enters health status k where $k \in \{healthy, ADL, alone, death\}$ in period $t+1$, conditional on having been in health state j where $j \in \{healthy, ADL, alone\}$ in period t. The transition probabilities vary with the parent's age and education. Let $\mathbf{X}_t^p$ be a vector of these parental characteristics. I then define the index variables $v(k|j)$ as follows:

$$\begin{aligned} v(k|j) &= \exp(\gamma'_{jk}\mathbf{X}_t^p) \qquad \text{for } k = ADL, alone, death \\ &= \exp(0'\mathbf{X}_t^p) = 1 \quad \text{for } k = healthy \end{aligned} \tag{2.6}$$

The Markov transition probabilities for the health status of the elderly parent in $t+1$ are then defined by

$$\pi_{jk} = \frac{v(k|j)}{\sum_k v(k|j)}$$

The parameters of the health transition probabilities are estimated with a multinomial logit specification. The health transition matrix takes the following form[20]

		$t+1$		
t	*Healthy*	*ADL*	*Alone*	*Death*
Healthy	$\pi_{healthy,healthy}$	$\pi_{healthy,ADL}$	$\pi_{healthy,alone}$	$\pi_{healthy,death}$
ADL	$\pi_{ADL,healthy}$	$\pi_{ADL,ADL}$	$\pi_{ADL,alone}$	$\pi_{ADL,death}$
Alone	$\pi_{alone,healthy}$	$\pi_{alone,ADL}$	$\pi_{alone,alone}$	$\pi_{alone,death}$
Death	0	0	0	1

2.2.6 Dynamic Programming Problem

A woman's objective in any period t is to maximize her expected lifetime utility given by

$$\max_{d_t \in D_t} U_t = E\left[\sum_{t'=t}^{T} \beta^{t'-t} u_{d_{t'}} | \mathbf{S}_t\right] \tag{2.7}$$

[20] In the data there is recovery to better health states, so I do not restrict the transition matrix to be diagonal. See the Appendix for a detailed discussion of the health transition estimation and the average predicted transition matrix.

where d_t is the woman's decision at time t, D_t is her decision set at time t which varies depending on whether her parent is alive and her available job offers, u_{d_t} is the period utility from her decision at time t, T is the terminal period of the model,[21] β is the discount factor and $\mathbf{S}_t$ is a vector of the woman's state variables. A woman's state variables include her last period's employment decision, E_{t-1}, her last period's caregiving decision, CG_{t-1}, her age, age_t, her years of work experience, $exper_t$, her education, $educ_t$, her marital status, mar_t, whether she has a sister, sis_t, the vector of her parent's characteristics, $\mathbf{X}_t^p$, her parent's realized health state at time t, H_t^p, and her type, ℓ. In addition, utility from each choice depends on the realized wage unobservable and unobserved utility arguments, denoted by vector $\boldsymbol{\epsilon}_t$. The vector of state variables at time t is given by

$$\mathbf{S}_t = \{E_{t-1}, CG_{t-1}, age_t, exper_t, educ_t, mar_t, sis_t, \mathbf{X}_t^p, H_t^p, \ell, \boldsymbol{\epsilon}_t\} \tag{2.8}$$

The lifetime utility maximization problem given in equation 2.7 can be rewritten in terms of value functions. The maximum expected value of discounted lifetime utility at time t can be represented by the period t value function

$$V_t(\mathbf{S}_t) = \max_{d_t \in D_t} \left[V_{d_t}(\mathbf{S}_t)\right] \tag{2.9}$$

where $V_{d_t}(\mathbf{S}_t)$, the choice-specific expected lifetime value function, obeys the Bellman equation

$$V_{d_t}(\mathbf{S}_t) = u_{d_t} + \beta E(V_{t+1}\left(\mathbf{S}_{t+1} | d_t, \mathbf{S}_t\right)) \quad \text{if } t < T$$

$$V_{d_t}(\mathbf{S}_t) = u_{d_t} \quad \text{if } t = T \tag{2.10}$$

Thus, the value of any decision at time t is a function of the period utility from that choice plus the discounted expected value of future behavior given the woman's choice at time t. The expectation is taken over the distribution of future unobserved

[21]The terminal period occurs at age 70. At that time I do not allow the woman to work, but she may make a final caregiving decision.

utility from each choice and future wage unobservables as well as the parental health transition probabilities and job offer probabilities.[22]

2.2.7 Solution Method

The dynamic programming problem is solved by backward recursion given a set of model parameters. In the last period, expected values of the optimal choice are calculated for each reachable state space $\mathbf{S}_T$ and each potential choice set via Monte Carlo simulation. For example, for a set of terminal period state variables $\mathbf{S}_T$, n draws of the wage unobservable and unobserved utility arguments are drawn and the maximum of the choice-specific value functions is calculated and recorded for each draw.[23] The average of the maximum value functions over the n draws is the expected maximum value of arriving at time T with that choice set available and state space $\mathbf{S}_T$. Moving back one period, that expected value is used to do the same calculation for period $T-1$, and this procedure is repeated until the first period is reached. This process is described in greater detail in Keane and Wolpin (1994).

2.2.8 Model Summary

The model allows for current and long-term labor market effects of caregiving in several ways. First, job offer probabilities depend on the woman's prior work decision. Thus, if a woman leaves work or decreases her work hours at some point during a caregiving episode, she may face a reduced probability of receiving job offers in future periods, and hence find it difficult to return to work or increase her work hours. Second, wage offers depend on a woman's years of work experience, whether she worked last period and whether the offer is associated with a part-time job. Thus, women who leave work while caregiving forgo returns to experience and may face lower future wage offers due to human capital depreciation. In addition, if women make adjustments on the intensive margin while caregiving and transition

[22] Women make decisions assuming their marital status will be the same next period, and that whether they have a sister will be the same next period since fewer than 4 percent of women in the data experience a change in marital status and fewer than 2 percent experience a change in whether they have a living sister. This assumption can be relaxed in future work.

[23] Currently $n = 175$.

to part-time work, they may face a lower wage offer. Third, the health transitions are modeled in such a way that the parent's health could improve, be sustained, or deteriorate. As a result, the caregiving trajectory is uncertain and the associated work adjustments (for example to non-work or part-time work) could potentially last several periods.

2.3 Identification

Since only accepted job offers are observed, the econometrician typically cannot distinguish whether a woman's decision not to work was the result of rejecting a job offer or not receiving an offer. Furthermore, if she receives a job offer, it is typically difficult to distinguish whether rejection occurs because she has a high preference for leisure or she received a low wage offer. A variety of assumptions allow for separate identification of the utility from leisure, the wage offer parameters and the parameters of the job offer probabilities. Exclusionary restrictions and functional form assumptions both help. For example, the job offer probabilities depend non-linearly on whether the woman has reached age 62, but the utility from leisure is the same for all women of a given type ℓ, and wage offers depend continuously on age and aged squared. Thus, if women age 62 and over are observed to work infrequently, this would be explained by low job offer probabilities, not a higher preference for leisure or lower wage offers. In addition, the job holding assumption helps to separately identify the utility from leisure from the job offer parameters. A woman who works full-time (part-time) is assumed to have a full-time (part-time) job offer with certainty in the next period, which means when a woman moves from full or part-time work to non-work, the econometrician knows a job was available and the expected wage offer. Thus, the utility from leisure can be identified by women transitioning from full or part-time work to non-work, since non-work was chosen over an offered wage. The offer probabilities are then separately identified by observed transitions from non-work to full or part-time work, from part-time to full-time work, and from full-time to part-time work.

The utility from caregiving parameters are separately identified from the utility from leisure in several ways. First, women who no longer have a parent alive only make work choices, thus their leisure time is only a function of their work choice, and their work decisions help to identify the utility from leisure. The assumed exogeneity of parental death allows the utility from leisure to be pinned down by this subgroup of women. Second, the utility from leisure is assumed to be the same for all women of a given type ℓ, while utility from caregiving varies with the health of the woman's parent. Thus, if women with parents in a certain health state are observed to caregive more than women with parents in another health state but who are otherwise similar, this would be explained by differences in the utility from caregiving over different health states, not by a lower preference for leisure.[24] In addition, utility from caregiving varies with whether the woman has a sister or not. If women without sisters are observed to caregive more frequently than women with sisters, this again would be explained by differences in the utility from caregiving, not by a lower preference for leisure.

Identification of the wage offer parameters can be viewed as a sample selection problem since only accepted wage offers are observed in the data. The solution to the dynamic programming problem generates the sample selection rules (i.e. generates an implicit reservation wage). The functional form, distributional and exclusionary assumptions made in the model serve the same purpose as a sample selection correction in either a two-step or full information maximum likelihood procedure (Eckstein and Wolpin 1999). The distributional assumption is the normality of the time-varying wage unobservable, ϵ_t, in the log wage offer function. In addition, the model generates selection into work that is driven by observables besides those of the wage offer. First, non-labor income which enters consumption varies with whether the woman has reached age 62, her marital status and the interaction between the two, but wage offers do not. Second, women with parents alive make a caregiving

[24] It is important to keep in mind that I assume caregiving does not affect the health transition probabilities. Thus, observing differences in caregiving frequency and intensity over different parental health states is explained by differences in the utility from caregiving over these health states, not by care provision affecting health transitions.

choice which depends in part on their parents' realized health state and whether they have a sister, neither of which affect the wage offer. The caregiving choice is made simultaneously with the work choice and different joint choices lead to different amounts of leisure time. The caregiving choice, however, does not have a direct impact on wage offers.

Last, permanent unobserved heterogeneity enters the model in two places. Unobserved types differ in their utility from leisure and their wage offer intercept.[25] The idea is to allow women to differ in permanent ways unobserved to the econometrician and estimate the distribution of types to fit the persistence of their choices and observed wages. When two women who are equivalent in their observable characteristics persistently make different choices or have persistently different accepted wages, this implies they likely differ in unobservable characteristics. Thus, identification of the unobserved type proportions is achieved through across group variation in caregiving and work choices and wages. It is important to note that the inclusion of unobserved heterogeneity introduces serially correlated state variables. For example, the sum of the permanent heterogeneity component in the wage offer, $\beta_{0,\ell}$, and the i.i.d. wage unobservable, ϵ_t, is a serially correlated state variable. Thus, women can select into caregiving and work on the basis of persistent differences in the utility from leisure and wage offers which are unobserved by the econometrician. It should be noted that the assumption that the wage unobservable, ϵ_t, is i.i.d. is important for identification of the wage penalty for not working in the prior period (parameter β_8).

2.4 Data and Empirical Implementation

The data are drawn from the *Health and Retirement Study* (HRS) which is representative of the non-institutional US population born between 1931 and 1941 and their spouses. The HRS is a panel survey which provides longitudinal informa-

[25] I follow the usual convention in the dynamic programming literature of allowing for a small number of types. The correlation in the two dimensions (i.e. leisure preferences and wage offers) is restricted by allowing for two types.

tion on labor supply, family structure, intergenerational transfers, health, income and assets. The baseline interviews were completed for 12,654 individuals in 7,702 households in 1992. At that time, respondents were approximately 51 to 61 years old or were married to individuals in that age range. Follow-up interviews took place biennially. The HRS is well-suited for this study since it follows a large sample of individuals at midlife over time, many of whom have elderly parents alive. In addition, it contains information on parents of all respondents, regardless of whether the parent needs or is receiving care. Thus, I am able to examine the behavior of women who do and do not provide care.

I restrict the sample to female HRS respondents between the ages of 42 and 70. In addition, I restrict potential care recipients to be mothers and there are several reasons for this restriction. First, only 21 percent of the women in the HRS report having a father alive in the 1992 wave of the survey, whereas about 47 percent report having a mother alive.[26] In addition, fathers are less likely to receive care than mothers (Hiedemann and Stern 1999, Byrne et al. 2009). In the HRS data, less than one-third of the fathers ever receive care, but over one-half of the mothers receive care at some point in the sample period. The sample is restricted to women who report having a mother alive in the 1992 wave of the survey, and I use the 1994 through 2008 data for estimation of the model. The sample size is 3,094 women with 18,066 person-wave observations.

2.4.1 Caregiving and Work Measures

Since the HRS interviews occur biennially, a decision period in the model corresponds to two calendar years. In implementing the model, the total time available in a decision period, $\overline{T}$, is equal to 10,200 hours (14 hours per day times 730 days). Thus, time allocated to caregiving and work is assigned based on two-year decision periods.

The HRS asks respondents "Have you (or your husband/partner) spent 100 or

[26] By the 2000 survey wave, only 10 percent have a father alive, whereas 30 percent have a mother alive.

more hours in the past two years helping your parent(s)/step-parents with basic personal needs like dressing, eating, and bathing?" The survey then asks who was helped and how many hours of care the respondent and, separately her spouse provided. After 1992, respondents were also asked whether they or their spouses spent a total of 100 or more hours in the past two years helping "with other things such as household chores, errands, transportation, etc." Again, the survey then asked who was helped and how many hours of care were separately provided by the respondent and her spouse. A woman is considered a caregiver if she has provided either type of care, and the hours she has spent providing both types of care are summed to determine whether she is a light or intensive caregiver. In the data, light caregivers are defined as women who provide less than 1,000 hours of care over a two-year period, and intensive caregivers are defined as those who provide 1,000 or more hours of care over a two-year period. In the model, those who lightly caregive are assumed to caregive for 300 hours per period, while those who intensively caregive provide 2,000 hours of care per period.[27]

Regarding employment status, a woman is considered to be working full-time if she works 35 or more hours per week for 36 or more weeks per year; less than this is considered part-time. In the model, those who work full-time are assumed to work 4,000 hours over the two-year period, while those who work part-time work 2,000 hours per period.[28] A woman is considered to be not working if she is retired, unemployed, or reports not being in the labor force. Respondents are asked to report hourly wages if they are working. If the respondent reports her pay at a different frequency, the RAND HRS data files adjust the pay rate appropriately using the respondent's reported usual hours worked per week and usual weeks worked per year.

[27]Among those classified as light (intensive) caregivers the median hours of care over two years is 300 (2,000) hours.

[28]In the data, the median hours worked per week by part-time (full-time) workers is 20 (40) hours. For both types of workers, the median number of weeks worked per year is 50.

2.4.2 Demographic and Parental Measures

The HRS contains detailed information on other variables that enter the estimation such as the respondent's education, years of work experience, non-labor income and family structure. In terms of family structure, in each survey wave, the woman reports her marital status, how many living siblings she has and the gender breakdown of those siblings. The woman reports various sources of non-labor income including capital income, income from pensions and annuities, income from Social Security Disability Insurance or SSI, income from Social Security retirement, spouse or widow benefits, income from unemployment or worker's compensation, income from other government transfers and her spouse's labor earnings (if she is married).

In terms of parental information, the HRS contains age and education data for each respondent's parent. The mother's education is discretized into two categories—less than a high school education versus high school graduate. In addition, the HRS reports for each respondent's parent whether he/she needs help with activities of daily living, whether he/she can be left alone for an hour or more and in waves after 1996 whether the parent has a memory or cognition problem. The HRS does not contain information about how many or which activities of daily living the parent needs help with, but only that help is required with at least one activity.

2.4.3 Permanent Unobserved Heterogeneity

Women enter the HRS sample at various ages during midlife. Thus, I observe decisions beginning in the middle of the lifecycle that are conditioned on state variables that arise from prior unobserved decisions. If these "initial" conditions are not exogenous (i.e. if there is unobserved heterogeneity in preferences or constraints) direct estimation will lead to bias.[29] To account for this problem, I assume the probabilities of the unobserved heterogeneity types can be represented by parametric functions of the initial state variables. If the wage unobservables and unobserved utility arguments are serially uncorrelated, the initial state variables are exogenous

[29] "Initial" conditions are those that exist at the time the woman is first observed in the sample.

given type.[30]

The unobserved type probabilities also depend on initial conditions that are not in the woman's state space. Specifically, the type probabilities depend on the woman's initial log wage and initial discretized liquid assets. Liquid assets are composed of the net value of the woman's stocks, mutual funds and investment trusts, her checking, savings and money market accounts, and her CDs and bonds. Thus, savings enter the model through the unobserved heterogeneity, which allows women who enter the model with low or high wealth to exhibit persistent differences in caregiving and work choices. The specification of the type probability function is given in the Appendix.

2.4.4 Descriptive Statistics

Table 2.1 provides descriptive statistics for those without a mother alive and for non-caregivers, light caregivers and intensive caregivers conditional on the woman's mother being alive.[31] Light caregivers are about 2 percentage points less likely to be working than non-caregivers whereas intensive caregivers are 11 percentage points less likely to be working than non-caregivers. Both light and intensive caregivers are about 2 percentage points more likely to be working part-time than non-caregivers. While non-caregivers and light caregivers who are working appear to earn about the same hourly wage, the average accepted wage for intensive caregivers is about two dollars lower. Thus, the data seems to suggest a negative relationship between caregiving and labor force participation that is particularly large for intensive caregivers. Those with a mother no longer alive are older which likely explains why almost 60 percent of this group is not working.

The data indicates that caregiving frequency and intensity vary with the health of the mother. Non-caregivers are more likely to have healthy mothers than light caregivers and intensive caregivers. Light caregivers are about 10 percentage points more likely to have a mother who needs help with ADLs or has a memory or cog-

[30] Aguirregabiria and Mira (2010) provide a detailed discussion of this initial conditions problem and possible solutions, including the one described above.

[31] All dollar amounts are adjusted by the Consumer Price Index using 2008 as the base year.

nition problem than non-caregivers. About two-thirds of intensive caregivers have non-healthy mothers, and intensive caregivers are 16 percentage points more likely to have a mother who cannot be left alone compared to both non- and light caregivers. Table 2.2 shows the percentage of mothers in each health state that receive light or intensive care from their daughters. Less than 30 percent of healthy mothers receive informal care from their daughters and almost all care provided is light. Over half the mothers with ADL needs or a memory or cognition problem receive care, and of those receiving care, about a quarter of them are receiving intensive care from their daughter. Caregiving for a mother who cannot be left alone for an hour or more is less common than caring for a mother with ADL needs or a memory problem which may reflect the increased caregiving burden when a parent cannot be left alone.[32] However, over half the women providing care to a mother who cannot be left alone are providing intensive care. By allowing the direct utility from caregiving and the utility cost from initiating care to vary with the parent's health state, the model should be capable of matching these statistics.

Table 2.1 also indicates that non-caregivers are more likely to have a sister than light and intensive caregivers, and light caregivers are more likely to have a sister than intensive caregivers. By allowing the utility from caregiving to vary with whether the woman has a sister, the model should be able to match these statistics. Caregivers are slightly better educated than non-caregivers and have more years of work experience than non-caregivers, but are also slightly older on average.

[32]This may also reflect the mother receiving formal care either from a home aide or a nursing home. The HRS does not contain data on formal home health care utilization by parents, but does contain information about whether the mother resides in a nursing home at the time of the survey. Formal home health care utilization is somewhat rare—approximately 13 to 14 percent of the non-institutionalized elderly rely on formal (or paid) home health care (Johnson 2007, Kaye et al. 2010), but generally in combination with informal care. In 2002, only 4 percent of the disabled elderly relied solely on paid help (Johnson 2007). Nursing home usage is also rare, with only 8 percent of the mothers in the estimation sample residing in a nursing home. The model has been estimated including nursing home utilization, and the results are qualitatively and quantitatively similar to those from the model presented.

2.5 Estimation

I pursue a non-likelihood-based estimation strategy, efficient method of moments (EMM), which is a type of indirect inference (see Gourieroux et al. 1993, Gallant and Tauchen 1996). The basic idea is to fit simulated data obtained from the structural model to an auxiliary statistical model. This auxiliary statistical model can be easily estimated and must provide a complete enough statistical description of the data to be able to identify the structural parameters. Following Tartari (2006) and van der Klaauw and Wolpin (2008), the auxiliary model I use in estimation consists of a combination of approximate decision rules that link endogenous outcomes of the model and elements of the state space as well as structural relationships such as the wage equation and job offer probabilities.

Specifically, using the actual data, y_A, I estimate a set of M_A auxiliary statistical relationships with parameters θ_A. By construction, at the maximum likelihood estimates, $\widehat{\theta}_A$, the scores of the likelihood function, L_j for $j = 1, \ldots, M_A$, are zero. That is, $\frac{\partial L_j}{\partial \theta_{A,j}} = 0$ where $\theta_{A,j}$ is the vector of model j's parameters. Denoting θ_B the parameters of the behavioral model, the idea behind EMM is the choose parameters that generate simulated data, $y_B(\theta_B)$, that make the score functions as close to zero as possible. This is accomplished by minimizing the weighted squared deviations of the score functions evaluated at the simulated data. Thus, the EMM estimator of the vector of structural parameters θ_B is

$$\widehat{\theta}_B = \underset{\theta_B}{\operatorname{argmin}} \frac{\partial L}{\partial \theta_A} \left(y_B(\theta_B); \widehat{\theta}_A \right) \Lambda \frac{\partial L}{\partial \theta'_A} \left(y_B(\theta_B); \widehat{\theta}_A \right) \tag{2.11}$$

where Λ is a weighting matrix and $\frac{\partial L}{\partial \theta_A} \left(y_B(\theta_B); \widehat{\theta}_A \right)$ is a vector collecting the scores of the likelihood functions across auxiliary models. The weighting matrix Λ is a block diagonal matrix where each block is a consistent estimate of the inverse Hessian of the corresponding auxiliary model evaluated at the actual data.

2.5.1 Auxiliary Statistical Models

The solution of the optimization problem described is a set of decision rules in which the optimal choice made in any period is a function of the state space in that period. One class of auxiliary models used consists of parametric approximations to these decision rules.[33] Following van der Klaauw and Wolpin (2008), to keep these approximations parsimonious, I do not include all the state variables. Instead, I specify the decision rules as parametric functions of subgroups of state space elements. A second set of auxiliary models comprises quasi-structural relationships related to the wage equation and job offer probabilities. The following list consists of auxiliary models used in estimation:

1. Multinomial logits of non-work, part-time work and full-time work on combinations of age, age squared, experience, experience squared, education indicators, indicators for last period's employment decision, an indicator for reaching age 62 and a marital status indicator.

2. Logits of caregiving (any intensity) versus not caregiving on combinations of parental health status indicators, an indicator for having a sister and lagged caregiving for those with a mother alive.

3. Multinomial logits of no care, light care and intensive care on combinations of parental health status indicators, an indicator for having a sister and lagged caregiving for those with a mother alive.

4. Multinomial logits of the combined work-caregiving decision (9 choices total) on combinations of experience, education indicators, lagged caregiving, indicators for last period's employment decision, an indicator for reaching age 62, a marital status indicator, an indicator for having a sister and parental health status indicators for those with a mother alive.

[33] For example, the utility function is unobserved to the econometrician so it is impossible to provide auxiliary models which approximate the utility function itself. However, the outcome of the utility function is a set of caregiving and work choices each period. Thus, auxiliary models that are related to these choices will identify the utility function parameters.

5. Logit of transitions from not caregiving to caregiving (any intensity) on parental health status indicators for those with a mother alive.
6. Logit of transitions from caregiving (any intensity) to not caregiving on parental health status indicators for those with a mother alive.
7. Multinomial logits of transitions from non-employment to no work, part-time work or full-time work; from part-time work to no work, part-time work or full-time work; from full-time work to no work, part-time work or full-time work on experience, education indicators and an indicator for reaching age 62.
8. Logits of transitions from non-full-time work to full-time work and from non-part-time work to part-time work on an indicator for not working last period, education indicators and an indicator for reaching age 62.
9. Regressions of log accepted wages on combinations of age, age squared, experience, experience squared, education indicators and indicators for last period's employment decision.

The auxiliary models imply 435 score functions which are used to identify 67 structural parameters.[34] The structural parameters being estimated include the parameters of the utility function, job offer probabilities, wage offers, unobserved type probabilities as well as the covariance matrix of the unobserved utility from each choice and the variance of the wage unobservable.[35]

2.5.2 Simulating Data for Estimation

I perform path simulations as follows. At a given set of structural parameters, having solved the optimization problem conditional on those parameters, I simulate one-step-ahead decisions. That is, given the state variables of a woman in a given period, I simulate her decisions by drawing a vector of the disturbances and choosing

[34]Estimates of the auxiliary parameters are not reported but are available upon request.

[35]As mentioned before, the parameters of the health transition probabilities are estimated outside the structural model (i.e. outside the estimation algorithm).

the alternative with the highest value function. The permanent unobserved heterogeneity is incorporated as follows. The probability that a simulated individual is of a given type depends on her initial state variables. Given that probability, each simulated observation is assigned a particular type by drawing randomly from the type probability function. The score functions from the auxiliary models are then evaluated using the simulated decisions and the criterion function is calculated.[36] I iterate on the parameters using the Nelder-Mead simplex method until the criterion function is minimized.

2.6 Results

2.6.1 Parameter Estimates

Parameter estimates and standard errors are provided in Table 2.3. The model allows for two types of women who differ in their utility from leisure and wage offer intercept. The estimated distribution of types is 50.5 percent type 1 and 49.5 percent type 2. A number of estimates are worth highlighting and make clear the static and dynamic labor market tradeoffs faced by caregivers. First, the estimates suggest initiating care provision is costly regardless of the mother's health. In addition, direct utility from providing care is greater (or less negative) when mothers are not healthy, and in particular when they have ADL needs or a memory or cognition problem.[37] Thus, those who start caregiving are likely to continue to do so, especially if their mother is no longer healthy, since they have already incurred the initiation cost. As a result, the model generates persistence in caregiving, an important dynamic channel. A woman considers that if she provides care today, she will

[36] For the purpose of calculating the score function, I perform 60 simulations for each sample observation and average that observation's score functions over the simulations.

[37] The model was also estimated with nursing home utilization to see if nursing home use of mothers who cannot be left alone was generating the observed ordering of caregiving utilities (for example, $\alpha_3 > \alpha_4$). Nursing home use was modeled as follows. Nursing home utilization occurred with some probability which depended on the mother's realized health state and last period's nursing home use. A (dis)utility parameter from caregiving while the mother is in a nursing home was introduced and estimated. The remaining caregiving utility parameter estimates were nearly identical to those presented here without nursing home use incorporated. Results from estimation of the model with nursing home use are available upon request.

likely to do so again next period, and she will make a work decision today which accounts for this persistence in caregiving and the long-term tradeoffs it generates.

The estimates of the job offer probabilities underscore the importance of the labor market frictions. The probability of receiving a part-time job offer given a woman did not work in the previous period ranges from 7 to 13 percent, and the probability of receiving a full-time job offer given a woman did not work in the previous period ranges from 1 to 12 percent.[38] Thus, women who do not work are unlikely to receive offers the following period, making it difficult to return to work. The probability of receiving a part-time job offer given a woman worked full-time last period ranges from 27 to 41 percent. This probability is larger for women who have reached the age of 62, which captures the observed fact that many women transition from full to part-time work before retirement. The probability of receiving a full-time job offer when a woman worked part-time in the previous period ranges from 6 to 52 percent, and is larger for women who are younger than 62. These job offer probability estimates highlight important dynamic tradeoffs for caregivers. Those who leave work to provide care face low probabilities of receiving future offers, particularly full-time offers when over the age of 62, potentially leading to withdrawal from the labor force earlier than desired or expected. In addition, if a woman wishes to move from full to part-time work while providing care, such an option is not always available, and she may have to choose between combining full-time work with care responsibilities or not working. If she does work part-time while caregiving, she is not guaranteed to be able to move to full-time work in the future, but is more likely to do so if she is younger.

The wage offer parameters are reasonable and as expected. There is a wage penalty for not working in the previous period—a woman who did not work last period can expect a 13 percent lower wage offer than an otherwise similar woman who worked last period. These estimates also make clear static and dynamic trade-offs between caregiving and work. Women who leave work to provide care forgo

[38]The 1 percent probability of receiving a full-time offer corresponds to women who have reached the age of 62. Thus, the model can implicitly generate retirement (from full-time work) without modeling an explicit retirement choice.

experience and the associated wage returns, and also face a lower expected wage if they return to work. The estimates suggest that part-time jobs are associated with lower wage offers ($\beta_7 = -0.253$), which is important since both light and intensive caregivers are more likely to work part-time than non-caregivers. In addition, if a woman is considering decreasing her work hours while caregiving she must consider first that such an option may not be available (i.e. she may not receive a part-time offer) and second that the decrease in hours will lead to a lower expected wage.

2.6.2 Model Fit

The parameter estimates are used to create a simulated sample consisting of 15 replicas of each sample individual's initial state space variables. The model should fit well the proportion of individuals working full-time, part-time or not all, the proportion of individuals lightly and intensively caregiving and the proportion of combined caregiving and work choices. Table 2.4 reports actual and simulated statistics of the proportion of women working full-time, part-time or not at all by their caregiving status, conditional on the woman's mother being alive. The model predictions match the observed fact that light and intensive caregivers are more likely to be in part-time work than non-caregivers, and that intensive caregivers are less likely to be in full-time work than both non- and light caregivers. Table 2.5 reports the actual and simulated proportions of combined caregiving and work choices, conditional on the woman's mother being alive. Generally, the model fits these choice proportions well, but slightly overstates the proportion of women not working, regardless of caregiving choice. Table 2.6 compares actual and simulated statistics for the proportion of women lightly and intensively caregiving by the mother's health status. The model fits very well along these dimensions. In particular, it is able to match the fact that intensive caregiving is more frequent for mothers who are non-healthy, and that caregiving is most prevalent when a mother has ADL needs or a memory or cognition problem. The model also fits accepted wages well, predicting an average accepted log wage of 2.622 compared to 2.669 in the actual data.

Importantly, the model should not only fit choice proportions, but also transitions in caregiving and work status. Table 2.7 shows observed caregiving transitions in the actual and simulated data. The model fits very well along these dimensions. Specifically, the model matches the fact that about two-thirds of caregivers continue caregiving (regardless of intensity) in the next period, conditional on the mother being alive next period. This prediction explicitly shows the persistence in caregiving generated by the model. The model also fits well the proportion of women with mothers alive who did not provide care in the previous period but caregive in the current period (regardless of intensity). Last, the model matches well the proportion of women who stop caregiving, due to either the death of the mother or the woman stopping care provision. Table 2.8 compares observed employment transitions in the actual and simulated data. The model fits these transitions well. The model matches the fact that transitions from non-work to full or part-time work are rare, and transitions from part-time to full-time work and vice versa occur with slightly higher probability.

2.6.3 The Value of Elder Parent Care

The structural approach adopted in this paper allows for calculation of the value (equivalently, the cost) of elder parent care, which reflects both the static and dynamic value of caregiving. To determine the value of elder parent care I implement a counterfactual scenario in which women who would otherwise begin care provision are not allowed to do so. Specifically, the parameter estimates are used to create a simulated baseline sample consisting of 15 replicas of each sample individual's initial state space variables. The parameter estimates are then used again to create a simulated sample of 15 replicas of each sample individual, but a woman is not allowed to provide care (of either intensity) in the period in which she initiated care provision in the baseline scenario. The removal of caregiving choices from the decision set comes as a surprise to the woman in that period, and she must make the best choice that does not involve providing care.[39] She makes this decision expecting the caregiving

[39] Since women are surprised when they have the caregiving choices removed and the same draws for the idiosyncratic shocks and unobserved utility arguments are used in the baseline and counterfactual scenarios, all pre-caregiving outcomes are unchanged, in particular prior work decisions.

choices to be available in all future periods. I then calculate the lump-sum transfer needed to make a woman indifferent between her choice in the non-caregiving counterfactual and her choice in the baseline in the period in which she initiated care (i.e. the transfer needed to equalize the realized period value function in the non-caregiving counterfactual to the realized period value function in the baseline when she initiated care).[40]

Figure 2.1 shows the distribution of transfer payments, excluding the top 90th percentile of transfers. The median transfer is \$66,370 per two-year period, which is about half the cost of two years of nursing home care in a semi-private room (MetLife 2010b). The transfers vary with the mother's health in that period. The median value of initiating care is \$63,501 when a mother is healthy, \$75,539 when a mother has ADL needs or a memory problem and \$64,929 when a mother cannot be left alone. The value of initiating care provision is larger when a mother has ADL needs or a memory problem for several reasons. First, the direct utility from both light and intensive caregiving is largest for those with mothers in this health state compared to the others. Second, mothers who have ADL needs or a memory problem remain in that health state with 43 percent probability, transition to the cannot be left alone health state with 18 percent probability, and transition to death with 26 percent probability on average. Thus, the daughter is likely to provide care next period since she will be able to again enjoy the direct utility from providing care if her mother remains in that health state and the initiation cost will have already been incurred. When a mother cannot be left alone she remains in that health state with about 42 percent probability and transitions to death with about 39 percent probability on average. As a result, the probability of providing care again next period is lower for these women. If her mother remains in the cannot be left alone health state, she derives less direct utility from the second period of caregiving than a woman whose mother has ADL needs or a memory problem. The transfers reflect these dynamic channels that operate via the caregiving initiation

[40]The transfer is necessarily positive since the woman is forced to make a choice from a constrained decision set in which the optimal choice is removed.

costs and the parental health transitions.

The transfers described above incorporate the option value of initiating care in a particular period since they are based on value function differences. If the transfers were instead based only on period utility differences, the future benefits of starting care would not be captured. I also calculate the transfer needed to equalize the realized period utility function in the non-caregiving counterfactual to the realized period utility function in the baseline when she initiated care. The median transfer based on utility differences is $5,759 per two-year period, about eleven times smaller than the transfer based on value function differences. These transfers are lower since they incorporate the utility cost from initiating care, but not the benefits from providing care in the future having already incurred this initiation cost. The large difference between the static and dynamic transfers highlights the importance of the forward-looking behavior in the model and the intertemporal nature of caregiving and work decisions.

Several previous studies, particularly in the gerontology literature, have also assigned a monetary value to informal care. However, these studies typically calculate this value by multiplying the average hours of care provided by the average or median wage of a home health aide (the replacement wage approach), the minimum wage or some average of the two (Ernst and Hay 1994, Arno et al. 1999, Chappell et al. 2004, Feinberg et al. 2011). For example, Feinberg et al. (2011) estimate the economic value of informal care based on caregivers providing an average of 18.4 hours of care per week at an average value of $11.16 per hour, which amounts to an approximate value of $21,356 over two years. This value is substantially lower than the median transfer I calculate above based on value function differences. Johnson and LoSasso (2000) perform a back of the envelope calculation and find the loss in annual work hours for female caregivers in the US translates on average into about $7,800 in lost wages per year in 1994 dollars, or $22,663 over two years in 2008 constant dollars, similar to that found in Feinberg et al. (2011). Ernst and Hay (1994) find the net cost of informal care for an Alzheimer's patient is $20,900 per year in 1991 dollars, or $66,076 over two years in 2008 dollars. This value is larger than those of the other studies since they estimate the weekly hours of informal care per week at 52.5, which is substantially higher than that found in most studies and the sample used in this paper. Their methodology based on 20 hours of care provision per week produces a value of $33,866 over two years. The structural approach employed in this paper allows for calculating a value of caregiving which incorporates the direct utility from providing care, the utility cost from initiating care, parental health transitions and the option value of providing care. These features are not reflected in the approaches used in the above-mentioned studies, and it appears calculations based on the replacement wage approach or current foregone wages substantially underestimate the value of elder parent care.

2.7 Policy Experiments

One of the goals of this paper is to use the structural estimates to analyze how various government sponsored elder care policies affect a woman's caregiving and work decisions. For each policy I simulate a dataset using 15 replicas of each sample individual's initial state space variables and compare the results to those of the baseline dataset simulated without the policy experiments.[41] I consider 3 policies: a two-year unpaid leave, a two-year paid leave (under different payment schemes) and a caregiver allowance for intensive caregivers.[42]

2.7.1 Unpaid Leave

Currently in the US, the Family and Medical Leave Act (FMLA) of 1993 allows workers to take up to a 12-week unpaid leave to care for an ill family member and guarantees the worker will return to his/her job at the same wage. According to the US Department of Labor, only 10.6 percent of leave-takers utilized the FMLA to care for an ill parent in 2000 (Cantor et al. 2001) and most studies attribute this

[41] I use the same draws for the idiosyncratic shocks and unobserved utility arguments in the baseline and policy simulations.

[42] Throughout the analysis of the policy experiments, it is important to keep in mind the partial equilibrium setup of the model. The demand side of the labor market is considered completely exogenous. Thus, I assume employers do not adjust their behavior in response to the counterfactual policies.

low take-up to the short duration and unpaid status of the leave time. Motivated by the fact that an average caregiving spell lasts about four years (National Alliance for Caregiving and AARP 2009), the first policy experiment involves an unpaid work leave longer than the 12 weeks currently allowed under the FMLA. The policy experiment allows a woman to take a two-year unpaid leave from work to caregive intensively for her mother. Family work leaves of such lengths (and sometimes longer) are common in several European countries, such as Austria, Bulgaria and Germany. The policy is implemented as follows: Women who worked in the previous period (either full or part-time) have the option of caregiving intensively and not working during the current period with a guarantee that they will have a job offer (for the type of job they left) with certainty in the following period with no wage penalty for not working during the leave.[43] Thus, the leave alleviates a woman from combining work and intensive caregiving for a period, but she forgoes her labor income for that period. At the same time, the leave eliminates the uncertainty about returning to work since her job is held for her during the leave.

About 33 percent of women who are eligible take the unpaid leave, where eligible means the woman worked last period and is intensively caregiving in the current period. About 19 percent of women who intensively caregive are doing so while on leave. Columns 1 and 2 of Table 2.9 report the proportion of women providing intensive care by the mother's health status in the baseline simulation and in the unpaid leave simulation. The unpaid leave generates modest increases in intensive care provision.

There is evidence that the leave helps women to better maintain employment during and after a caregiving spell. Columns 1 and 2 of Table 2.10 report the employment status of women during and after intensive care provision in the baseline simulation and the unpaid leave simulation. The leave induces more work, especially full-time work, among these ever intensive caregivers compared to the baseline where women do not have the unpaid leave available. Figure 2.2 shows the proportion of

[43]The leaves are aimed at women facing substantial caregiving burden and are not available to light caregivers.

unpaid leave-takers in full and part-time work in the years before and after they take the leave compared to the corresponding periods in the baseline when the leave is not available. Women seem to take the unpaid leave at a time in the baseline when intensive care provision induces them to leave work, particularly full-time work. About 39 percent of those who take the leave left work in the equivalent period in the baseline, and there is no evidence in the baseline simulation that these women return to work. The unpaid leave, however, returns women to work and many of them continue working for several periods. There is a 49 (27) percent increase in the proportion of women in full-time (part-time) work in periods after the leave is taken compared to the corresponding periods in the baseline. Thus, it appears allowing women to take a leave to intensively caregive but removing the uncertainty about the availability of job offers after the leave encourages more full and part-time work for these women compared to when such a leave is unavailable. These results highlight the importance of labor market frictions for these caregivers.

2.7.2 Paid Leave

The second policy experiment is similar to the leave described above except the woman receives a lump-sum payment while on leave to intensively caregive, and the payment is linked to the health of the care recipient. Currently in the US, California and New Jersey have implemented paid family leave programs, but caregivers can only take a leave for a maximum of 6 weeks, and payment is tied to the worker's wage. Payments to caregivers are very common in Europe and Canada,[44] and payments to care recipients that are indexed to their health or level of need are also common.[45] I consider a combination of these pre-existing policies in that the payment is provided directly to the caregiver while on leave, and the payment varies with the health of her mother.

[44]For example, the Swedish Temporary Care Leave pays a caregiver 80 percent of her normal labor income for a maximum leave of 60 days. Canada's Compassionate Care Benefit pays 55 percent of a caregiver's average earnings for up to six weeks while she cares for a terminally ill family member. Ireland's Carer's Benefit pays a maximum of 205 euros per week for up to 104 weeks to caregivers who leave work to "care for a person in need of full-time care and attention."

[45]For example, Austria's Cash Allowance for Care, Germany's Cash Allowance for Care, Luxembourg's Cash Allowance for Care and the United Kingdom's Attendance Allowance.

I simulate the paid leave under two payment schemes. The first pays \$6,600 to women who intensively care for mothers with ADL needs or a memory or cognition problem and \$13,200 to women who intensively care for mothers who cannot be left alone. These amounts are loosely based on the range of monthly payments that exist under Germany's Cash Allowance for Care extrapolated to a two-year period. The second payment system pays \$18,250 to women who intensively care for mothers with ADL needs or a memory or cognition problem and \$36,500 to women who intensively care for mothers who cannot be left alone.[46] These amounts are based on the recently suspended CLASS Act, which aimed to create a voluntary government insurance benefit to provide long-term care support. Benefits were to be triggered once a participant needed ADL help or comparable assistance because of cognitive impairment. The law specified the average minimum benefit be \$50 per day with benefit amounts to be scaled based on the level of impairment.[47] I take a conservative approach and provide \$25 per day for two years to women caring for mothers with ADL needs or a memory problem and \$50 per day for two years to women caring for mothers who cannot be left alone.

Under the first payment scheme, about 39 percent of eligible women take the paid leave, and not surprisingly even more take the leave under the second payment scheme (46 percent). Table 2.9 shows that the paid leaves, particularly under the second payment scheme, generate somewhat larger increases in intensive care provision than the unpaid leave. Table 2.10 shows that the employment effects of the paid leave on women during and after intensive care provision are nearly identical to those of the unpaid leave both qualitatively and quantitatively. Figure 2.3 shows the proportion of paid leave-takers under the second payment scheme in full and part-time work in the years before and after they take the leave compared to the corresponding periods in the baseline when the leave is not available. There is a

[46]Under both payments schemes, women who intensively care for healthy mothers can take a leave, but do not receive a payment. I make this assumption since the European and Canadian policies typically require the care recipient to have sufficient need for care.

[47]CLASS Act legislation took effect in January 2011, but in October 2011, the Obama administration announced the program would not be implemented. For a detailed discussion of CLASS Act, see Munnell and Hurwitz (2011).

40 (26) percent increase in the proportion of women in full-time (part-time) work in periods after the paid leave is taken compared to the corresponding periods in the baseline. Again, these results are similar to those of the unpaid leave. Thus, the main differences between the unpaid leave and the paid leaves are the take-up rate and subsequently how much intensive care provision the policies induce and government expenditure on the leave payments.

2.7.3 Caregiver Allowance

The last policy experiment provides a payment to women who intensively caregive for their non-healthy mothers that is not linked to their employment status and may be received indefinitely. This policy experiment can inform about the labor market effects that would have occurred if the care recipient under the CLASS Act transferred the benefit payment in full to her caregiving daughter. The payment amounts are identical to those of the second paid leave payment scheme—\$18,250 for intensively caregiving for a mother with ADL needs or a memory or cognition problem and \$36,500 for intensively caregiving for a mother who cannot be left alone. As seen in Table 2.9, the caregiver allowance generates the largest increase in intensive care provision among all the policies considered compared to the baseline. Two channels may be driving these results—first, the policy does not require the woman to not be working to receive the payment and second, the payment can be received indefinitely. I decompose this policy and simulate it under the leave rules, meaning a woman can receive the payment at most every other period, rather than indefinitely as long as she is providing intensive care. The decomposition shows that the large increases in care provision are due mainly to the fact that unlike the previous policies discussed, the woman does not have to leave work to caregive and receive the payment. At the same time, this policy discourages work among intensive caregivers due to the income effect of receiving this payment indefinitely. Table 2.10 shows that the caregiver allowance leads to a 2.5 percentage point increase in non-work among women who ever provide intensive care, which is mostly due to a reduction in full-time work.

2.7.4 Retirement Effects of Policies

Since a caregiver is typically in her fifties and sometimes in her early sixties, the policy experiments may have important retirement effects. Table 2.11 shows the employment status of women who are between the ages of 62 (the Social Security early entitlement age) and 70 who ever provided intensive care in the baseline simulation, the work leave policy simulations and the caregiver allowance simulation. Both the unpaid and paid leaves slightly increase the proportion of women 62 and over who are working part-time compared to the baseline, and lead to moderate increases in full-time work compared to the baseline. The caregiver allowance slightly decreases the percentage of women working full-time age 62 and over. Thus, it appears the work leaves reduce some early withdrawal from the labor force for women who have ever provided intensive care.

The retirement effects are stronger for the group of women who ever took a leave at some point in the simulations. Table 2.12 compares the employment status of women 62 and over in the baseline simulation and the policy simulations who ever took an unpaid leave or paid leave. The leaves decrease non-work by about 16 to 17 percentage points compared to the baseline, which suggests the leaves are effective in preventing early retirement for many of these leave-takers. Given that the average age of a leave-taker is 57 or 58, these results show that the one period removal of uncertainty regarding the ability of a caregiver to return to work has effects for several periods. In addition, the unpaid leave is just as effective as the paid leaves in encouraging work after age 62 for leave-takers, which is an important consideration for policy makers who may aim to protect the employment of caregivers while minimizing the government expenditure needed to do so.

2.7.5 Welfare Comparison of Policies

Using the structure of the model, I determine the value of the various policy experiments for those who take up the policy. I calculate the lump-sum transfer needed to equalize the woman's realized period value function in the baseline (without any policies available) to her realized value function in the policy experiment scenario in the period in which she takes up the policy being analyzed.[48] Table 2.13 shows the median value of each policy experiment for all women who take up each particular policy, for the subset of women who take up the policy and were already intensively caregiving in the equivalent period in the baseline and for women who were induced to provide intensive care by the policy. About 50 to 60 percent of the median value of the paid leave under the larger payment scheme can be achieved with the unpaid leave, which suggests much of the benefit of the paid leaves comes from the guarantee that the woman can return to work. In addition, the unpaid leave generates comparable welfare gains to the caregiver allowance policy which does not require a woman to leave work to receive the payment. These results further emphasize the importance of the labor market frictions for caregivers and the benefit of eliminating the uncertainty regarding the availability of full and part-time jobs.

Interesting patterns emerge when comparing the welfare gains for the subgroup of women who are induced to intensively caregive by each policy. Those induced to intensively caregive by the paid leave under the smaller payment scheme excluding those caregiving for healthy mothers enjoy about \$10,000 more in welfare than those induced to intensively caregive by the unpaid leave, which lies between the \$6,600 and \$13,200 leave payments. Those induced to intensively caregive by the paid leave under the larger payment scheme excluding those caregiving for healthy mothers enjoy about \$9,000 more in welfare than those induced to intensively caregive by the paid leave with the smaller payments, which is less than the \$11,650 and \$23,300 increase in leave payments. This can be explained in part by the differential take-up of the leaves. As the payments increase across the leaves, more women take them and are induced to intensively caregive. These marginal leave-takers necessarily value the leaves less than women who take all three leaves. The median value of the caregiver allowance for women induced to intensively caregive by this policy

[48]The transfer is calculated for the period in which a woman takes a leave for the unpaid and paid leave experiments and during periods of intensive care provision for an unhealthy mother for the caregiver allowance experiment.

is only slightly larger than the \$18,250 payment and well below the \$36,500 payment for those with mothers who cannot be left alone. This value is also below the median value of the unpaid leave for those induced to intensively caregive by that policy. These results have important implications for policy makers who may be concerned with balancing government expenditure with the welfare gains generated by the policies, particularly for women induced to intensively care by the policies.

2.8 Conclusion

In this paper, I have developed and estimated a dynamic discrete choice model of caregiving and work to study how elder parent care affects a woman's labor force participation and wages over the short and long-term. In contrast to the previous literature, I model caregiving and work decisions in an explicitly intertemporal framework. Women make forward-looking decisions in a model which incorporates several dynamic elements such as parental health changes, human capital accumulation and labor market frictions. I explicitly model the uncertainty women face about their parent's health and the availability of full and part-time jobs.

The model is estimated using data from the *Health and Retirement Study* by efficient method of moments. Based on the estimates, the model was shown to reasonably fit many aspects of the data. The estimates highlight various static and dynamic labor market tradeoffs faced by caregivers. Women who begin care provision are likely to continue to do so, especially if their parent is in poor health. In addition, women are more likely to provide intensive care when their parent is no longer healthy, and intensive caregivers are less likely to be working. The estimates also underscore the importance of labor market frictions. Women who do not work face low probabilities of receiving job offers in the future. As a result, if a woman leaves work while caregiving she may find it difficult to return. If she works part-time while caregiving, she is not guaranteed to be able to increase her hours in the future. The wage offer estimates show women who leave work forgo experience and the associated wage returns, and also face a lower expected wage if they return to work. In addition, part-time work is associated with lower wage offers, and caregivers are more likely to be in part-time work than non-caregivers.

The model structure and estimates were used to calculate the value of elder parent care. The median value of initiating care was found to be $66,370 over two-years, about half the cost of two years of nursing home care, but two to three times larger than the values found in the previous literature. These previous values were calculated using the replacement wage approach or current foregone wages from providing care, and do not reflect the dynamic value of initiating care provision. Thus, calculations that ignore forward-looking behavior and the intertemporal nature of caregiving and work underestimate the value of elder parent care.

The estimates were used to analyze three counterfactual policy experiments: a two-year unpaid work leave, a two-year paid work leave and a caregiver allowance for intensive caregivers. The leaves generate modest increases in intensive caregiving and substantial decreases in non-work among women during and after intensive care provision, further highlighting the importance of the labor market frictions. There is also evidence that the leaves reduce early withdrawal from the labor force. The caregiver allowance on the other hand generates substantial increases in intensive care provision but seems to discourage work among those who ever intensively caregive. A comparison of the welfare gains generated by the policies shows that about half the value of the paid leave can be achieved with the unpaid leave, and the caregiver allowance generates gains comparable to the unpaid leave. The welfare gains generated by the unpaid leave alone emphasize the benefit of guaranteeing a caregiver can return to work. The policy experiments illustrate the existence of potential important tradeoffs faced by policy makers if they wish to both protect the employment of caregivers and encourage informal care provision, as well as balance government expenditure with the welfare gains generated by the policies.

2.9 Chapter 2 Appendix

2.9.1 Utility Function

The period utility function is given by

$$u_t = \ln(C_t) + \alpha_{1,\ell} \ln(L_t) + \alpha_{CG,H^p} + \alpha_{CG,CG_{-1}} + \alpha_{CG,sis} + \nu_{t,E,CG}$$

where

$$\alpha_{1,\ell} = \alpha_{1,1} I(type = 1) + \alpha_{1,2} I(type = 2)$$

and

$$\begin{aligned}\alpha_{CG,H^p} = \alpha_2 I(CG_t = 1)I(H_t^p = healthy) + \alpha_3 I(CG_t = 1)I(H_t^p = ADL)\\ +\alpha_4 I(CG_t = 1)I(H_t^p = alone) + \alpha_5 I(CG_t = 2)I(H_t^p = healthy)\\ +\alpha_6 I(CG_t = 2)I(H_t^p = ADL) + \alpha_7 I(CG_t = 2)I(H_t^p = alone)\end{aligned}$$

and

$$\begin{aligned}\alpha_{CG,CG_{-1}} = \alpha_8 I(CG_t \neq 0)I(CG_{t-1} = 0)I(H_t^p = healthy)\\ +\alpha_9 I(CG_t \neq 0)I(CG_{t-1} = 0)I(H_t^p = ADL)\\ +\alpha_{10} I(CG_t \neq 0)I(CG_{t-1} = 0)I(H_t^p = alone)\end{aligned}$$

and

$$\begin{aligned}\alpha_{CG,sis} = \alpha_{11} I(CG_t \neq 0)I(sis_t = 1)I(H_t^p = healthy)\\ +\alpha_{12} I(CG_t \neq 0)I(sis_t = 1)I(H_t^p = ADL)\\ +\alpha_{13} I(CG_t \neq 0)I(sis_t = 1)I(H_t^p = alone)\end{aligned}$$

The direct utility from not caregiving is normalized to zero across all health states.

2.9.2 Non-Labor Income

Non-labor income is assumed to arrive from a degenerate distribution that depends on a woman's education, age and marital status. Outside the structural model, I estimate a linear regression of logged non-labor income on education category indicators, an indicator for whether the woman is married, an indicator for being over the age of 62, an interaction term between marital status and being over the age of 62, and an interaction between not working and being over the age of 62. Non-labor income is measured as the sum of capital income, income from pensions and annuities, income from Social Security Disability Insurance or SSI, income from Social Security retirement, spouse or widow benefits, income from unemployment or worker's compensation, income from other government transfers and her spouse's labor earnings if she is married. Non-labor income depends on whether the woman is over the age of 62 since she can begin claiming Social Security retirement benefits at that age. The interaction term between marital status and achieving the Social Security early entitlement age is meant to capture the drop in her spouse's labor earnings once he retires as well as his potential receipt of Social Security benefits.

Every period in the model, the woman receives non-labor income based on her characteristics as generated by the following equation:

$$\begin{aligned}\ln(y_t) =& \gamma_0 + \gamma_1 I(educ_t = 2) + \gamma_2 I(educ_t = 3) + \gamma_3 I(mar_t = 1) + \gamma_4 I(age_t \geq 62) \\ &+ \gamma_5 I(mar_t = 1) I(age_t \geq 62) + \gamma_6 I(age_t \geq 62) I(E_t = 0)\end{aligned} \tag{2.12}$$

Thus, I provide the daughter with the average non-labor income women with her characteristics have in the data. The estimates from the non-labor income regression are reported in Table 2.14.

2.9.3 Parental Health Transitions

I follow Palumbo (1999) and estimate the coefficients of the parental health transitions for three different multinomial logit models: one for each of the three health states being conditioned upon ($j = healthy, ADL, alone$). That is, I essentially create three different datasets and estimate a different multinomial logit specification for each. The first dataset includes the parent's health status in $t + 1$ and parental characteristics for all parents that were healthy at time t. The second and third datasets include parents that needed ADL help or had a memory problem and those who could not be left alone for an hour or more at time t, respectively. The multinomial logit coefficients are estimated relative to being healthy in $t+1$ since $\gamma_{j,healthy}$ is normalized to zero for $j = \{healthy, ADL, alone\}$ as seen in equation 2.6. The parameters and standard errors from the multinomial logit estimation are reported in Table 2.15. The average predicted health transition matrix is given below.

	$t+1$			
t	*Healthy*	*ADL*	*Alone*	*Death*
Healthy	0.799	0.087	0.045	0.069
ADL	0.124	0.432	0.181	0.263
Alone	0.100	0.095	0.416	0.389
Death	0	0	0	1

2.9.4 Unobserved Type Probability Function

$$Pr(type = \ell) = \frac{\exp(\mu^{\ell}\mathbf{\Omega})}{1 + \sum_{m=2}^{2} \exp(\mu^{m}\mathbf{\Omega})} \qquad \ell \in \{1, 2\} \tag{2.13}$$

where

$$\begin{aligned}\mu^{\ell}\mathbf{\Omega} =& \mu_0^{\ell} + \mu_1^{\ell} I(E_{-1} = PT) + \mu_2^{\ell} I(E_{-1} = FT) + \mu_3^{\ell} I(mar_0 = 1) + \mu_4^{\ell} age_0 \\ &+ \mu_5^{\ell} \ln w_0 + \mu_6^{\ell} I(w_0 = 0) + \mu_7^{\ell} I(asset_0 = 2) + \mu_8^{\ell} I(asset_0 = 3)\end{aligned}$$

where E_{-1} is the work choice of the woman preceding the period in which she enters the sample (period $t = 0$). Recall that I do not use the 1992 survey wave data in the estimation, but the work choice of a woman observed in 1992 serves as her previous period's employment choice when she enters the estimation sample. If the woman enters the model with no wage (either because she did not work or the wage was not reported), she is assigned the average log wage observed in the data, and an indicator variable denotes that she entered without a wage. The woman's initial liquid assets are discretized into terciles. Coefficients for type 1 are all normalized to zero.

2.9.5 Contrast Across Methods

In the first chapter, we examine the effect of informal care on labor force participation, retirement, as well as work hours and wages conditional on working. We allow for permanent unobserved heterogeneity via fixed effects; thus, we allow the time-invariant individual-specific heterogeneity to be correlated with caregiving and other explanatory variables. We address the fact that even after controlling for fixed effects, there may be remaining endogeneity concerns if the individual- and time-varying unobservables are correlated with time-varying caregiving behavior. The identifying instruments we use include “ill-health” of a parent, defined as needing assistance with activities of daily living, having a memory problem, or not being able to be left alone. We also use information about potential alternative sources of informal care provision, mainly through whether the parent or in-law was recently widowed.

We argue that variation in the health of a parent or in-law should directly vary the demand for informal care, but not directly affect work behavior of an adult child other than through the informal care path. Concerns about intergenerational transmission of poor health should be alleviated by the fact that we control for the adult child’s own health and by the inclusion of the fixed effect. Having a parent or in-law who is widowed means their spouse is not available to assume the caregiving role, thereby increasing the demand for care provided by an adult child or child-in-law. The recent passing of a parent or in-law potentially explains much of the termination of care provision. The passing of a parent or in-law should only affect work behavior of an adult child via the termination of care provision for that parent or in-law or the provision of care for the widowed parent or in-law. Coe and Van Houtven (2009) find the death of a parent does not have a direct effect on one’s health or depressive symptoms, which alleviates concerns that the death of a parent or in-law could influence work behavior via the bereavement effect.

In the second chapter, I also rely on the mother's health as a source of exogenous variation that explains caregiving behavior. In the model, women derive utility from light and intensive caregiving that varies with the health of the mother, and I assume caregiving does not affect the parental health transitions. Thus, like in the first chapter, variation in the health of the mother directly varies informal care decisions, but does not directly affect work decisions other than through the informal care path and its expected trajectory. In fact, if I implemented a counterfactual in which women were no longer allowed to make caregiving decisions, the mother's health would no longer have any role in the model.

Most important, in the second chapter, the solution to the dynamic programming problem provides dynamic selection rules into caregiving and work. Selection occurs on observables such as education, age, the mother's health, etc.; time-invariant unobservables via the permanent unobserved heterogeneity that is modeled as two unobserved types who differ in their utility from leisure and wage offer intercepts; and, time-varying unobservables including those of the utility function to each choice in the model and in the wage offer function. The functional form, distributional and exclusionary assumptions embedded throughout the model serve the same purpose as a sample selection correction in either a two-step or full information maximum likelihood procedure.

2.10 Chapter 2 Tables and Figures

Table 2.1: Descriptive Statistics

	Mother Not Alive	Non-Caregiver	Light Caregiver	Intensive Caregiver
Employment				
% Not working	59.35	41.69	43.55	52.54
% Working part-time	16.38	17.47	19.46	19.15
% Working full-time	24.27	40.85	36.99	28.31
Mean accepted wage[a]	$21.09	$20.74	$20.31	$18.16
Mother's Health				
% Healthy		75.25	64.97	35.87
% ADL needs or memory problem		12.63	22.82	35.73
% Cannot be left alone		12.12	12.20	28.39
Demographics and Family Structure				
Mean age	62.07	56.76	58.53	59.81
% Married	77.99	81.90	80.61	74.93
% Has sister	71.90	75.05	69.10	61.22
% Less than HS education	21.81	20.48	14.48	14.27
% HS degree	40.22	38.07	43.04	41.97
% Some college	37.96	41.45	42.48	43.77
Mean years of experience	26.25	23.94	26.21	27.02
N	7,125	7,187	3,032	722

[a] Conditional on working.

Table 2.2: Parental Health and Caregiving

	Healthy	ADL Needs	Alone
% Not caregiving	70.81	48.87	60.23
% Lightly caregive	25.80	37.24	25.59
% Intensively caregive	3.39	13.89	14.18
N	7,637	1,858	1,446

Table 2.3: Main Parameter Estimates

Description	Parameter	Estimate	S.E.
Utility Parameters			
Leisure (Type 1)	$\alpha_{1,1}$	1.532	0.011
Leisure (Type 2)	$\alpha_{1,2}$	2.056	0.067
Light caregiving when $H^p = healthy$	α_2	-0.266	0.021
Light caregiving when $H^p = ADL$	α_3	0.304	0.009
Light caregiving when $H^p = alone$	α_4	-0.225	0.025
Intensive caregiving when $H^p = healthy$	α_5	-1.047	0.037
Intensive caregiving when $H^p = ADL$	α_6	0.156	0.017
Intensive caregiving when $H^p = alone$	α_7	0.022	0.027
Initiating care when $H^p = healthy$	α_8	-1.916	0.016
Initiating care when $H^p = ADL$	α_9	-1.893	0.030
Initiating care when $H^p = alone$	α_{10}	-1.540	0.054
Caregiving and has a sister when $H^p = healthy$	α_{11}	-0.160	0.021
Caregiving and has a sister when $H^p = ADL$	α_{12}	-0.162	0.024
Caregiving and has a sister when $H^p = alone$	α_{13}	-0.318	0.047
Log Wage Offer Parameters			
Intercept (Type 1)	$\beta_{0,1}$	0.351	0.001
Intercept (Type 2)	$\beta_{0,2}$	0.378	0.003
Age	β_1	0.058	9.74E-06
Age squared	β_2	-0.0006	1.01E-06
Experience	β_3	0.046	3.07E-05
Experience squared	β_4	-0.0006	1.44E-06
HS degree	β_5	0.251	0.006
Some college	β_6	0.658	0.005
Part-time	β_7	-0.253	0.004
Did not work last period	β_8	-0.132	0.005
Variance of wage unobservable	σ_w^2	0.437	0.001
Part-Time Job Offer Logit Parameters			
Intercept	λ_0^{PT}	-0.992	0.013
Did not work last period	λ_1^{PT}	-1.556	0.058
Age 62+	λ_2^{PT}	0.376	0.049
HS degree	λ_3^{PT}	0.263	0.030
Some college	λ_4^{PT}	0.072	0.027
Full-Time Job Offer Logit Parameters			
Intercept	λ_0^{FT}	-0.227	0.030
Did not work last period	λ_1^{FT}	-2.101	0.068
Age 62+	λ_2^{FT}	-2.526	0.293
HS degree	λ_3^{FT}	0.289	0.058
Some college	λ_4^{FT}	0.300	0.047

Description	Parameter	Estimate	S.E.
Unobserved Type Probability Parameters			
Type 2: Intercept	μ_0^2	-0.051	0.105
Type 2: Worked part-time before initial period	μ_1^2	1.026	0.997
Type 2: Worked full-time before initial period	μ_2^2	-2.120	0.121
Type 2: Marital status at initial period	μ_3^2	-0.116	0.036
Type 2: Age at initial period	μ_4^2	0.012	4.87E-04
Type 2: Initial log wage	μ_5^2	0.074	0.016
Type 2: No initial log wage	μ_6^2	0.025	0.104
Type 2: Initial asset tercile 2	μ_7^2	0.604	0.130
Type 2: Initial asset tercile 3	μ_8^2	-0.225	0.233
Other Parameters			
Discount factor (not estimated)	β	0.95	

Covariance Matrix for Unobserved Utility Arguments

This matrix governs the unobserved utility from each joint caregiving and work choice when women have a mother alive:

	$\nu_{0,0}$	$\nu_{0,1}$	$\nu_{0,2}$	$\nu_{PT,0}$	$\nu_{PT,1}$	$\nu_{PT,2}$	$\nu_{FT,0}$	$\nu_{FT,1}$	$\nu_{FT,2}$
$\nu_{0,0}$	1.000								
$\nu_{0,1}$	−0.618	1.913							
	(0.019)	(0.023)							
$\nu_{0,2}$	−0.291	0.162	1.335						
	(0.039)	(0.029)	(0.023)						
$\nu_{PT,0}$	−0.010	0.00	0.00	0.563					
	(0.059)			(0.036)					
$\nu_{PT,1}$	0.00	0.00	0.00	0.272	2.525				
				(0.035)	(0.041)				
$\nu_{PT,2}$	0.00	0.00	0.00	0.369	1.175	2.065			
				(0.104)	(0.065)	(0.068)			
$\nu_{FT,0}$	−0.065	0.00	0.00	0.00	0.00	0.00	1.087		
	(0.065)						(0.079)		
$\nu_{FT,1}$	0.00	0.00	0.00	0.00	0.00	0.00	−0.770	1.696	
							(0.042)	(0.023)	
$\nu_{FT,2}$	0.00	0.00	0.00	0.00	0.00	0.00	−0.184	−0.483	1.160
							(0.053)	(0.056)	(0.052)

where the unobserved utility from each choice $v_{E,CG}$ are assumed to be distributed multivariate normal with mean zero and covariance-variance matrix estimated above. The variance of the unobserved utility from not working and not caregiving has been normalized to one. In the estimates reported above, most covariances of unobserved utility across work choices are set equal to zero. This restriction will be relaxed in future work.

This matrix governs the unobserved utility from each work choice when women do not have a mother alive:

	ν_0	ν_{PT}	ν_{FT}
ν_0	1.000		
ν_{PT}	0.030	0.343	
	(0.023)	(0.042)	
ν_{FT}	-0.846	0.00	1.272
	(0.039)		(0.120)

where the unobserved utility v_E are assumed to be distributed multivariate normal with mean zero and covariance-variance matrix estimated above. The variance of the unobserved utility from not working has been normalized to one.

Table 2.4: Employment Status by Caregiving Type

	Non-Caregiver		Light Caregiver		Intensive Caregiver	
	Actual	Simulated	Actual	Simulated	Actual	Simulated
% Not working	41.69	46.12	43.55	46.67	52.54	53.35
% Working part-time	17.47	16.34	19.46	18.59	19.15	17.85
% Working full-time	40.85	37.54	36.99	34.74	28.31	28.80

Table 2.5: Joint Caregiving and Work Choices

	Actual	Simulated
% Not working, not caregiving	27.42	29.30
% Not working, light caregiving	12.05	13.77
% Not working, intensive caregiving	3.44	3.72
% Working part-time, not caregiving	11.49	10.38
% Working part-time, light caregiving	5.38	5.49
% Working part-time, intensive caregiving	1.25	1.24
% Working full-time, not caregiving	26.87	23.85
% Working full-time, light caregiving	10.24	10.25
% Working full-time, intensive caregiving	1.85	2.01

Table 2.6: Caregiving by Mother's Health Status

	Healthy		ADL Needs		Alone	
	Actual	Simulated	Actual	Simulated	Actual	Simulated
% Lightly caregiving	25.80	28.13	37.24	36.59	25.59	25.52
% Intensively caregiving	3.39	3.64	13.89	13.92	14.18	14.58

Table 2.7: Caregiving Transitions

	Actual	Simulated
% Caregivers who care again next period	68.00	66.96
% Transitioning from non-caregiving to caregiving	22.40	22.82
% Transitioning from caregiving to non-caregiving	42.43	44.17

Table 2.8: Employment Transitions

	$\mathbf{E_t = 0}$	$\mathbf{E_t = PT}$	$\mathbf{E_t = FT}$
$\mathbf{E_{t-1} = 0}$	89.48 (A) 90.14 (S)	6.64 (A) 6.35 (S)	3.87 (A) 3.51 (S)
$\mathbf{E_{t-1} = PT}$	24.66 (A) 24.21 (S)	58.60 (A) 59.47 (S)	16.75 (A) 16.32 (S)
$\mathbf{E_{t-1} = FT}$	13.91 (A) 16.35 (S)	10.64 (A) 9.98 (S)	75.45 (A) 73.67 (S)

The relative frequency of each cell within its row is reported.
(A): Actual (S): Simulated

Table 2.9: Intensive Care Provision by Mother's Health

	Baseline	Unpaid Leave	Paid Leave I	Paid Leave II	Caregiver Allowance
% Intensively caregiving $\|H^p = healthy$	3.64	4.20	4.21	4.24	3.78
% Intensively caregiving $\|H^p = ADL$	13.92	15.78	16.46	17.67	21.07
% Intensively caregiving $\|H^p = alone$	14.58	16.62	18.23	20.66	27.85

Table 2.10: Employment of Women Who Ever Provide Intensive Care

	Baseline	Unpaid Leave	Paid Leave I	Paid Leave II	Caregiver Allowance
% Not working	58.94	52.58	51.49	50.17	61.50
% Working part-time	16.32	17.53	17.89	18.13	16.19
% Working full-time	24.74	29.89	30.62	31.70	22.31

Employment status shown for women in periods during and after intensive care provision.

Table 2.11: Employment of Women 62 and Over Who Ever Provide Intensive Care

	Baseline	Unpaid Leave	Paid Leave I	Paid Leave II	Caregiver Allowance
% Not working	68.04	62.17	60.94	59.55	70.16
% Working part-time	15.61	16.92	17.37	17.72	15.43
% Working full-time	16.35	20.91	21.69	22.73	14.41

Employment status shown for women in periods during and after intensive care provision.

Table 2.12: Employment Comparison of Women 62 and Over Who Ever Took a Leave

	Unpaid Leave Takers		Paid Leave I Takers		Paid Leave II Takers	
	Baseline	Policy	Baseline	Policy	Baseline	Policy
% Not working	62.02	44.83	60.03	43.29	57.79	41.95
% Working part-time	16.18	20.48	17.06	21.61	17.42	21.84
% Working full-time	21.80	34.69	22.91	35.10	24.79	36.21

Table 2.13: Welfare Comparison of Policy Experiments

	Unpaid Leave	Paid Leave I[a]	Paid Leave I[b]	Paid Leave II[a]	Paid Leave II[b]	Caregiver Allowance
Median value	$27,561	$33,434	$39,999	$43,987	$51,567	$31,033
Always caregivers	$30,582	$38,241	$45,903	$53,333	$67,005	$36,637
Induced caregivers	$25,965	$31,691	$35,948	$39,011	$44,928	$19,818

[a] Includes those on leave caring for a healthy parent, but not receiving a payment.

[b] Excludes those on leave caring for a healthy parent.

Always caregivers are those who were intensively caregiving in the equivalent period in the baseline.

Induced caregivers are those who were not intensively caregiving in the equivalent period in the baseline.

Table 2.14: Non-Labor Income Estimates

Description	Parameter	Estimate
Intercept	γ_0	8.198***
		(0.047)
HS degree	γ_1	0.285***
		(0.034)
Some college	γ_2	0.601***
		(0.035)
Married	γ_3	1.432***
		(0.044)
Age 62+	γ_4	0.813***
		(0.060)
Married and age 62+	γ_5	-0.999***
		(0.061)
Age 62+ and not working	γ_6	0.090**
		(0.041)

Significance Levels: *** 1% level, ** 5% level, * 10% level

Table 2.15: Parental Health Transition Multinomial Logit Estimates

Parameter	Healthy→ADL	Healthy→Alone	Healthy→Dead
Intercept	-10.209***	-7.959***	-7.462***
	(0.514)	(0.725)	(0.591)
Mother's age	0.099***	0.065***	0.062***
	(0.006)	(0.009)	(0.007)
Mother HS graduate	-0.030	-0.390***	-0.145*
	(0.073)	(0.103)	(0.084)

Parameter	ADL→ADL	ADL→Alone	ADL→Dead
Intercept	-4.269***	-8.591***	-5.493***
	(0.962)	(1.136)	(1.072)
Mother's age	0.066***	0.106***	0.073***
	(0.011)	(0.013)	(0.013)
Mother HS graduate	-0.270*	-0.291*	-0.082
	(0.146)	(0.169)	(0.157)

Parameter	Alone→ADL	Alone→Alone	Alone→Dead
Intercept	-13.363***	-10.276***	-11.530***
	(1.436)	(1.095)	(1.218)
Mother's age	0.158***	0.140***	0.153***
	(0.017)	(0.013)	(0.015)
Mother HS graduate	-0.497**	-0.768***	-0.515***
	(0.225)	(0.170)	(0.170)

Significance Levels: *** 1% level, ** 5% level, * 10% level

Figure 2.1: Distribution of the Value of Caregiving

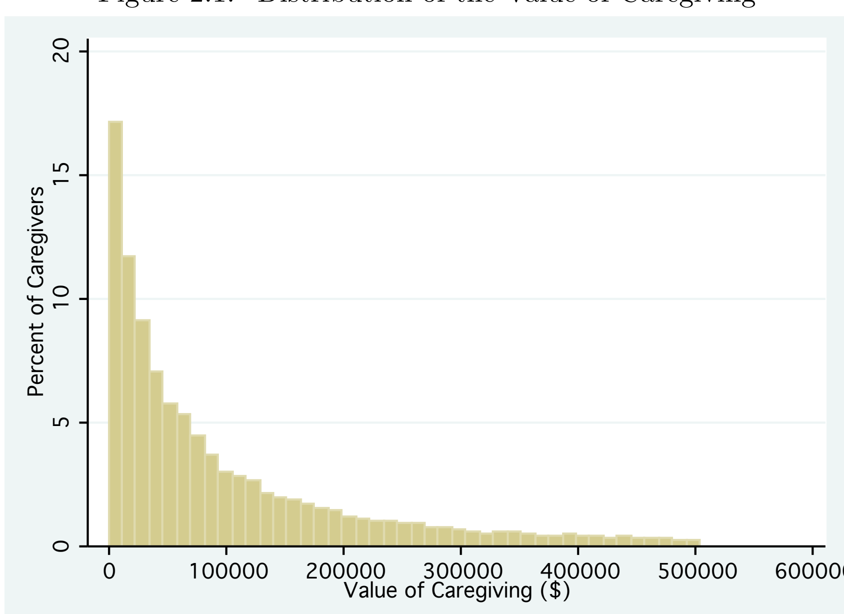


Figure 2.2: Unpaid Leave Results

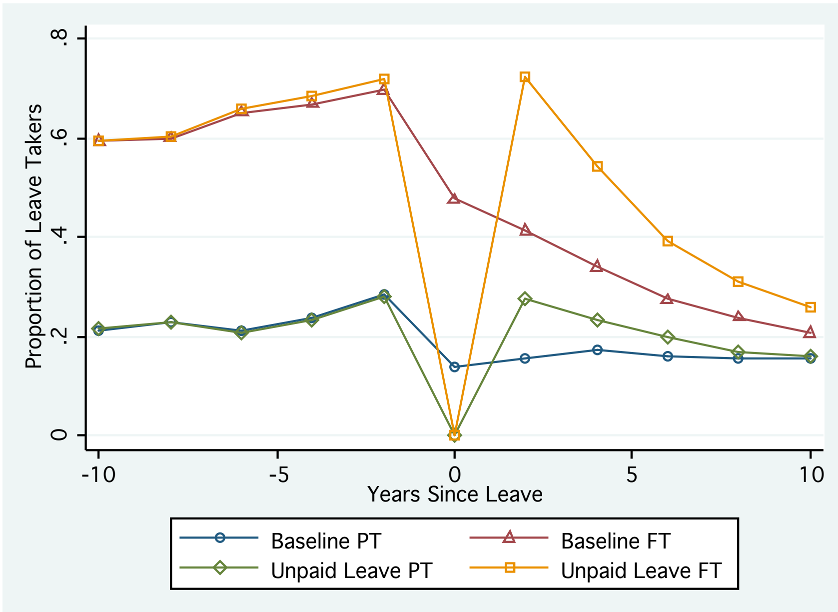
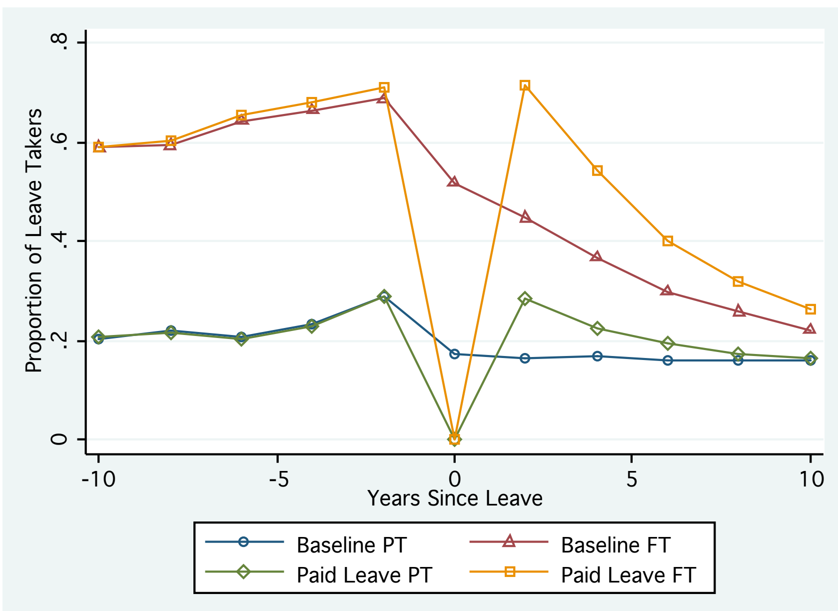


Figure 2.3: Paid Leave Results



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