Child Disability, Family Labor Supply, and the Value of the Child SSI Program

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The U.S. Supplemental Security Income (SSI) program transfers considerable resources to low-income families with disabled children. This paper measures the extent to which the SSI program provides effective insurance against the additional costs associated with raising a child with a disability, as well as the economic magnitude of the distortions generated by the program's means tests. Estimates from a life cycle model of female labor supply, savings and SSI application imply that the insurance value of the SSI program is sizable, with prospective parents willing to pay premiums equal to 2.7 times their expected claims. Moral hazard due to income- and wealth-contingent eligibility implies that it costs 1.4 dollars to transfer one dollar of benefits to eligible recipients. A policy counterfactual that would raise the program's asset limit to a recently-proposed level would be valued more than its fiscal cost, while policies which decrease screening stringency or increase benefit levels are more effective at increasing welfare.

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1. Introduction

Approximately 1.6% of children are in the United States are enrolled in the Child Supplemental Security Income Program (Child SSI), a federal program which provides cash benefits to low-income families with children who have disabilities, while just over 7% have an activity-limiting disability and are potentially medically eligible.[1] Despite the importance of this program in the broader U.S. social safety net, very little is known about its social value, and in particular, the extent to which it provides adequate insurance against the additional costs associated with raising a child with a disability.

It is well-established that the impact of childbirth on women's labor market outcomes is large and persistent (Kuziemko et al., 2018; Kleven, Landais, and Søgaard, 2019; Cortés and Pan, 2020). These effects may be even greater for parents whose children have disabilities, both through increasing the opportunity cost of work or decreasing its net return.[2] In addition, a disabled child often requires increased medical expenditures or theraputic services.[3] While increased medical expenditures may be defrayed by health insurance, the costs associated with difficulty in engaging in market work are uninsurable in the private market. Moreover, these costs are particularly hard to self-insure, as they are often long-lasting and materialize early in the parent's career. Finally, children who live in lower-income families generally have worse health outcomes than children in higher-income families (Case, Lubotsky, and Paxson, 2002). These factors suggest that a program such as Child SSI, which transfers money to families with disabled children, may be particularly effective at transfering resources to states of the world where the demand for these resources is high.

Of course, Child SSI is costly – due both to the direct cost of the benefits and deadweight loss generated by the program's distortions. Several program features suggest potentially large changes to incentives. First, the payments are means tested and phase out once family income reaches a certain level. The implicit marginal tax rate on earnings in the phase out region is roughly 50%. At the same time, the point at which benefits

[1] 1.2 million children were enrolled in SSI in 2018 (Administration, 2018), among a population of 73.4 million children (Bureau, 2018). The proportion of children with an activity limiting disability are author's calculation using the 2018 National Health Interview Survey (NHIS).

[2] For example, if the child requires higher time investments, if the child requires specialized childcare to meet their needs, or if the child requires care at unpredictable times, thus requiring a parent to accept a lower-paying but more-flexible job. See Gould2004 for a discussion of different channels through which a child's disability may impact labor market incentives.

[3] In a recent review by Stabile and Allin (2012) the former are referred to as direct costs, and the latter are referred to as indirect costs.

begin to phase out is relatively high compared to other welfare programs, and the benefits themselves are relatively generous, on average accounting for approximately half of annual income among participating families (Rupp et al., 2006). These features should decrease labor supply in the short-term, but skill-depreciation when out of work may lead to even larger long-term effects (Keane and Wolpin, 2007; Keane and Wolpin, 2010; Blundell et al., 2016). In addition, families must maintain low asset holding to remain eligible to receive benefits, which generates a strong savings disincentive for both current recipients and potential applicants, who may spend down their savings to qualify.[4] Many of these program features distort behavior via substition effects and thus generate deadweight loss, which may be particularly high as mothers supply labor highly elastically (Keane, 2011; Attanasio et al., 2018), and the majority of SSI recepiets live in female-headed households (Rupp et al., 2006).

This paper asks whether low income families value the insurance provided by Child SSI more than the program's net cost. Addressing these questions requires a quantification of the economic costs associated with having a disabled child. I begin by providing evidence that mothers of disabled children are less likely to work, work less conditional on working, and often receive transfer income from the SSI program. These findings are consistent with prior literature (Salkever (1982), Powers (2001), Powers (2003), Gould (2004), and Gunnsteinsson and Steingrimsdottir (2019) and others referenced in Stabile and Allin (2012)) examining the effects of children's health status on their parent's labor market outcomes. This decline in labor supply is associated with a large increase in active time spent with the child. Taken together, the reduced form work builds on earlier work indicating that childhood disability is costly to families beyond the direct costs of medical care these disabilities may require.

However, these patterns alone are not sufficient to quantify the ex-ante insurance value of the ability to receive transfers should your child develop a disability, nor the economic magnitude of the moral hazard generated by the program's distortions. The answers to these questions depend crucially on household preferences and constraints – how children affect the costs of work, how this varies by child disability status and other available social support programs, as well as one's ability to self-insure. Similarly, simply measuring total SSI outlays is likely to dramatically understate the true fiscal cost

[4]This form of means testing may partially explain the relatively low take-up of the program amongst plausibly medically eligible children, and has come under recent scrutiny from both academics and policymakers (Burkhauser and Daly (2013) and Daly and Duggan (2019)). Sen. Brown (2022) proposes to increase the asset limits to $10,000 for singles and $20,000 for couples, indexed to inflation going forward.

of the program due to the previously mentioned incentive effects, as well as substitute tax and transfer programs.

To answer these questions, I estimate a dynamic life-cycle model of female labor supply, savings and SSI application which incorporates the previously described trade-offs. The model considers the problem of a woman entering the labor market, facing uncertainty regarding her future fertility, the health of any children she might have, her future marital status, and her future labor market outcomes. In the model, women differ ex-ante in their unobserved productivity in the labor market, which also affects the likelihood of becoming or remaining married, their future fertility, as well as the probability that their child will develop a disability. As such, the model incorporates the established reduced-form link between family resources and child health without explicitly modeling the process through which this occurs.[5]

The model is estimated using data from the Panel Study of Income Dynamics (PSID) and the National Health Interview Survey (NHIS). The PSID contains detailed information on household demographics, labor supply, income, wealth, and SSI receipt, and its Child Development Supplement (CDS) contains additional detail on children's chronic conditions and functional limitations. The model translates observed behavior relating to labor supply, savings and SSI receipt into estimates of key preference and policy parameters: allowance rates for SSI amongst the children in the sample, the utility cost of applying for SSI, as well as preferences for consumption and (dis)utility from labor, which vary by household structure, child age and disability status. The model generate plausible responses to economic incentives, both in terms of the labor supply elasticities (i.e. Keane (2011), Blundell et al. (2016), and Attanasio et al. (2018)), the elasticity of SSI application with respect to benefit levels (Kubik, 1999). Family responses to SSI take up and removal are qualitatively similar to findings from previous design-based studies (Duggan and Kearney, 2007; Deshpande, 2016b), [although certain model features preclude a closer fit].

I use the estimated model to assess the extent to which households value the insurance provided by child SSI, to measure the magnitude of the moral hazard generated by the program's distortions, and assess how reforms to the program would affect

[5]Lower-income children are both more likely to develop chronic conditions and more likely to be in poor health given the same chronic conditions. Credibly modeling the process by which childhood disability manifests would require a model of how parental investments affect the stock of possible chronic conditions that a child could develop, as well as how parental inputs affect the activity limitations associated with their child's chronic condition. While important, this is outside the scope of the present paper and is left for future work.

household outcomes such as savings, labor supply, and welfare. My welfare metric is a consumption equivalent, which keeps the household's expected utility at the beginning of life constant while varying the policy.[6] Estimates of the insurance value of the program are generated by comparing women's willingness-to-pay ex-ante to move from a world in which Child SSI does not exist to one in which the program exists, but is actuarially fair and women in the model pay an annual premium priced according to her permanent productivity group. The results imply that the insurance provided by the program is highly valued – women in the model are willing to pay up to 1.6 times the actuarially fair premium. The moral hazard cost of the program is estimated using a counterfactual in which SSI is replaced by an alternative program which distributes resources across exogenous states of the world to the same degree as the current program, but does not condition on the household's labor supply or savings. Household's willingness-to-pay to move to this counterfactual program is an estimate of the excess burden generated by the program. The findings from this exercise indicate that it costs roughly \$1.5 to provide \$1 of Child SSI through the current program. Finally, I use the estimated model to assess the welfare effects of several policy reforms to the program. I find that a policy which raises the asset limit to the level proposed by Sen. Brown (2022) would be valued more than its fiscal cost, while policies which decrease screening stringency or increase benefit levels are more effective at increasing welfare.

1.1. Related Literature

This project relates to several distinct areas of research: (i) the literature that estimates the effect of children's health or disability on family outcomes, typically focusing on the mother's labor supply, (ii) the literature that examines the effects of the Child SSI program on family behavior and outcomes, and (iii) the literature that estimates the welfare effects of social insurance programs using structural life cycle models, and (iv) the literature which studies female labor supply over the life cycle. The first two literatures use reduced-form methods, while the latter two use structural models.

Stabile and Allin (2012) provide a recent review of the literature on the effect of child disability on family outcomes. Comparisons across studies are made difficult by the fact that researchers employ a variety of definitions of disability (Powers (2003)) and estimate

[6]This measure takes the form of an annual tax or subsidy on consumption. When comparing willingness to pay to the fiscal costs of a program, I calculate the expected present discounted cash value of the tax/subsidy.

effects for different samples, but these papers typically find that mothers of children with disabilities are less likely to work, work less conditional on working, and earn less than mothers of children without disabilities, with larger effects among single and less-educated women (Salkever, 1982; Wolfe and Hill, 1995; Powers, 2001; Gould, 2004; Wasi, den Berg, and Buchmueller, 2012). A more recent string of papers (Gunnsteinsson and Steingrimsdottir, 2019; Eriksen et al., 2021; Breivik and Costa-Ramón, 2021; Adhvaryu et al., 2023) use register data to estimate event studies of maternal labor supply surrounding the onset of child health shocks and find large effects. The empirical patterns that I document in the PSID are consistent with these findings, and I complement this literature by assessing the welfare impacts of the SSI program through the lens of a life cycle model which matches these patterns.

There is also a literature studying the effects of the Child SSI program on parents' behavior.[7] Duggan and Kearney (2007) find that parents' short-term earnings seem unaffected by their child's enrollment in the program, while Deshpande (2016b) finds that parents almost fully offset the decline in household income by increasing their labor supply when their children are removed from SSI. While not explicitly targeted in estimation, my model does a reasonable job of matching these patterns. I contribute to this literature by estimating the insurance value and deadweight loss from the program, as well as assessing the welfare impacts of policy reforms.[8]

This paper is also connected to the literature that uses life cycle models to investigate the impact of social insurance programs on household behavior and welfare, as well as the impact of children on female labor supply over the life cycle. Notable examples include Blundell et al. (2016) and Low et al. (2022), who model how social assistance in the UK and US, respectively, affects female labor supply and welfare. It is likely that income support aimed at the general population has different welfare effects and consequences than support for families with disabled children. This difference could be attributed to the screening aspect of the SSI program and the unique constraints faced by families with disabled children. Other research focuses on the value of social insurance targeted at individuals with disabilities, primarily examining Disability Insurance. These papers, which include Bound, Stinebrickner, and Waidmann (2010), Low and Pistaferri

[7] Duggan, Kearney, and Rennane (2015) reviews of the full SSI program and literature.

[8] Hendren and Sprung-Keyser (2020)'s review of the empirical PF literature cites only Deshpande (2016a) as a paper that estimated the Marginal Value of Public Funds (MVPF) for SSI, but this was for children continuing to receive SSI into adulthood. Indeed, both Duggan and Kearney (2007) and Deshpande (2016b) emphasize the normative ambiguity of their findings and emphasize the importance of assessing the normative effects of child SSI in future research.

(2015), Autor et al. (2019), Lee (2023), and Kellogg (2022), study a different form of risk – a health shock which limits one's own ability to work – among men who are typically near-retirement. A few papers have estimated the welfare impacts of SSI reforms for retirees, often in the context of evaluating the value of Medicaid, such as De Nardi, French, and Jones (2016) and Achou (2023). Papers which study the impact of children on lifecycle female labor supply include, amongst others, Hotz and Miller (1988), Adda, Dustmann, and Stevens (2017), and Blundell, Pistaferri, and Saporta-Eksten (2018), but do not differentiate between children with and without disabilities. Broadly, my paper contributes to these areas of research by examining a different source of risk and target population than existing studies on the value of social insurance, and by considering a distinct dimension of heterogeneity than prior papers on effects of children on female labor supply over the life cycle.

2. The Child SSI Program

The Supplemental Security Income (SSI) program is a federal program administered through the Social Security Administration (SSA), which provides cash benefits to low-income individuals who qualify for benefits on the basis of their age or disability status.[9] Beneficiaries fall into three broad groups: blind or disabled non-elderly adults, those 65 or older, and the focus of the present paper, blind or disabled children. Medical eligibility requires the presence of a medically determinable condition, or combination of conditions, that result in "marked and severe functional limitations" and which are expected to last for at least 12 months or result in death. Whether a child's condition meets these criteria is determined by the state Disability Determination Services and based on guidelines provided by the SSA.[10] Rejection rates are fairly high, with only about half of applicants being approved in 2017 (Administration, 2018).[11] Once a child is deemed medically eligible, their eligibly is reassessed at a frequency depending on

[9]Most states administer supplemental SSI payments to Federal SSI beneficiaries. I abstract from this feature of the program throughout my analysis.

[10]Applicants must provide detailed information about the child's medical condition(s), and provide permission for the child's doctors, teachers, therapists, etc. to answer questions pertaining to the child's functioning. The state's Disability Determination Services office review the application and determine whether the child meets the criteria for disability. Determination may be made solely on the basis of the provided records, often also requires an in-person evaluation. Certain severe medical conditions confer automatic eligiblity, but for others the process may take three to six months.

[11]Rejections can be appealed, but reversals are fairly uncommon, with just under 15% being reversed in 2017 (Administration, 2018).

the child's condition, but recommended to occur every three years.[12]

In addition to medical eligibility, eligibility depends on household income and assets.[13] In most cases, a child is asset-eligible to receive SSI payments if they live in a single-parent household with less than $4,000 or a two-parent household with less than $5,000 in assets.[14] Families with sufficiently low income receive the maximum benefit, after which benefit amounts are reduced by 50 cents for each dollar of income. SSI payments are quite generous relative to other US income support programs, accounting for more than half of family income among most recepients (Rupp et al., 2006). In 2015 the maximum benefit was $733 per month for single-parent households, and $1,100 for two-parent households. In addition, the phaseout region begins at a high income level relative to other social insurance programs. In a single-parent household the child will receive the full benefit amount if the parent earns less than $1,591 per month. In a two-parent household, this figure is $2,322 per month.

Since the 1990 Supreme Court case of *Sullivan vs. Zebley*, CHild SSI has been expanded by decreasing the stringency of medical eligibility criteria for children. This effect has been most pronounced for children whose primary disabling condition is a mental health condition, who currently make up the majority of the caseload (Table A3). As part of the 1996 welfare reform, medical eligibility was tightened and roughly 1/3 of recepients had their eligibility reassessed, but as shown in Figure 1 the program saw steady growth through the mid 2010s, after which the number of children receiving benefits has slightly declined, although outlays remain flat.

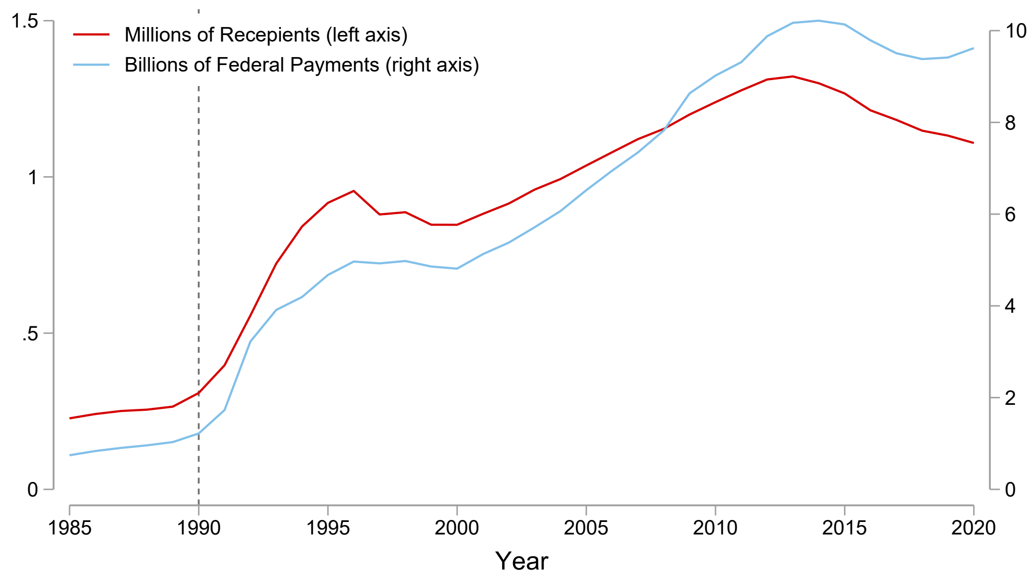
In this paper, I consider the economic risk, particularly for mothers, of having a disabled child that limits work capacity. In its current form, the Child SSI program insures families with disabled children against future poor health shocks. Prior to having a child, however, parents are not likely to be able to purcahse adequare private insurance or self-insure, because child disability is a rare event, and its realization

[12]This process is called Continuing Disability Reviews (CDRs). For conditions not expected to result in improvements, the CDR can just be filling out a mailer. For others a full reassessment is required. In the mid-2000s CDRs occured much less frequently than the three-year recommendation due to limited funding (Aizer, Gordon, and Kearney, 2013). However, subsequent funding increases have allowed the SSA to catch up on the backlog of CDRs, and the SSA now reports that CDRs are occuring at the recommended frequency (**SocialSecurityAdministration2020**).

[13]Technically, in the SSI means test a portion of the parent's income and assets are assigned to the child through a process called *deeming*, after which the child's eligibility is determined. Section H provides more detail about the deeming process. The figures presented here are for the typical case in which the SSI child has no income or assets of their own.

[14]These categories include assets such as a house, one vehicle, personal effects such as wedding rings.

FIGURE 1. Child SSI Recepients and Outlays, 1985-2020



Note. This figure displays the number of children receiving SSI benefits, as well as the total outlays for the program, in each year from 1985 to 2020. The red line reports the number of children receiving SSI benefits, in millions, while the dashed blue line reports the total outlays for the program. The vertical dashed line indicates the year of the Zebley decision, which is the year in which I begin my analysis.

likely occurs early in the career when wages are low relative to average lifetime wages. As with Social Security Disability Insurance and Unemployment Insurance, it is also likely that any private SSI-style insurance scheme would be too adversely-selected to be profitable. At any given price, those most likely to have a child who develops a disability would be most willing to purchase the insurance, thus limiting the ability of such a firm to remain profitable. Even if these firms were able to price-discriminate, there is empirical evidence that in markets such as that for long term care (Hendren (2013)) or college financing (Herbst and Hendren (2021)), the degree of private information is sufficiently large such that insurance companies would be unable to break even if they were able to price on observable characteristics.

In comparison, a public insurance program is able to overcome the issue of adverse selection, by requiring participation of both high and low-risk individuals. However, the mandatory nature of a public insurance program is not able to alleviate issues of moral hazard. In the context of child SSI, these concerns typically manifest as relating to parents presenting their child as disabled or not investing in the human capital of their child (Kristof (2012)). On the other hand, Deshpande and Dizon-Ross (2023) find that parents do not increase investments in their children's human capital when mistaken beliefs about the likelihood their child will continue to receive SSI in adulthood are corrected. The overall welfare effects of Child SSI with thus depend on whether the sum of costs of these distortions and the direct costs outweigh the benefits to recipients, as well as the insurance value to non-beneficiaries.

3. Data and Motivating Empirics

3.1. Data

My main source of data is the Panel Study of Income Dynamics (PSID), which I supplement with the National Health Interview Survey (NHIS). The PSID began in 1968 and was collected annually through 1997, and biannually thereafter. The survey contains detailed information on household demographics, labor supply, income, wealth, and SSI receipt, and its Child Development Supplement (CDS) contains additional information on children's chronic conditions and functional limitations. Important for my context, interviewees are asked about hours worked and income for each of the previous two years in the biannual surveys, which allows me to generate annual measures of labor force activity. I use data collected from 1990 (the year of the Zebley decision) through 2019, linked to the PSID's childbirth history file to construct the number and ages of children in the household. To create my analysis sample, I exclude individuals with missing values for education, race or state of residence, and drop years in which an individual is self-employed. I further exclude women who ever reported having adopted a child, who have their first child before age 20, or their last child after age 40. To remove the influence of outliers, I drop observations in which an individual experiences very high wage growth or declines in consecutive periods, or reports an implied hourly wage below half of the state minimum wage. [15] In order to focus my analysis on the sample of women most likely to meet the SSI income and asset means tests, I restrict the sample to women without a college degree. In addition, I drop women who have their first child before 1990, so as to ensure my sample consists only of women who have children in the post-Zebley regime. The final analytical sample is an unbalanced panel of 1894 mothers linked to 4,527 CDS children. Unless otherwise specified, I use the longitudinal weights provided by the PSID to adjust for differential attrition and the initial oversample of low-income households.

[15] I exclude the PSID's Latino oversample. Individuals in this sample were added in 1990 but were only followed until 1995, when the sample was removed due to a lack of funding (McGonagle et al. (2012)).

While the PSID asks about SSI receipt, it does not ask about eligibility for the program.[16] As such, I use information from the CDS to identify respondents whose children may medically qualify. As per SSA guidelines, this requires both the presence of a medically determinable condition, and “marked and severe functional limitations”. I therefore utilize a combination of questions relating to the presence of chronic conditions, as well as the presence of activity limitations, in order to identify potentially-SSI eligible children. For each child in the CDS, their primary caregiver is asked whether a medical professional has ever said that their child has a given condition. In addition, parents are asked whether the child has any physical or mental condition which limits their ability to do usual childhood activities, their ability to attend school, or their ability to do school work.[17] Details about the exact wordings of the questions are in Section B.5.

Table 1 reports the prevalence of each condition in the CDS sample, as well as the prevalence of the condition in combination with an activity limitation. Less than a third of children with any condition have an activity limitation, highlighting the importance of considering both conditions and activity limitations when identifying potentially-SSI eligible children.

TABLE 1. Chronic Conditions in the Child Development Supplement

	Share w/ Condition (x100)	Share w/ Condition and Activity Limitation (x100)
Mental Health Conditions	11.52	3.89
Serious Emotional Disturbance	2.84	1.12
Autism	1.40	0.82
Learning/Developmental Disability	6.40	2.69
Hyperactivity	5.72	1.92
Physical or Intellectual Conditions	6.92	1.93
Diabetes	0.27	0.07
Orthopedic Impairment	2.47	0.82
Hearing	1.92	0.72
Seeing	2.46	0.41
Birth Defect	0.27	0.03
Heart Condition	1.08	0.17
Intellectual Disability	0.60	0.53

Note. The left column reports the share of children in the CDS who ever are reported as having a given chronic condition. The right column reports the share of children in the CDS who are reported to have a given chronic condition, and also having an activity limitation. The total number of children across all CDS waves is 10169.

There are a few limitations of the PSID, which I address by supplementing the data

[16]This is also the case with the NLSY, the Fragile Families Study and the SIPP. The NHIS asks whether individuals have ever applied for SSI, but does not indicate whether the application was accepted or rejected.

[17]The questions about the presence of chronic conditions are not pre-screened by whether a child is reported to have an activity limitation.

with the National Health Interview Survey (NHIS), an annual survey conducted by the National Center for Health Statistics.[18] A first limitation is that the Child Development Supplement does not ask about the age of onset or diagnosis of the sample children's disabiling conditions. This is problematic for two reasons. The first is that restricting the sample to only CDS years would reduce the number of observations in my sample considerably. The second is that in the model parents will have expectations about the likelihood that their child develops a disability by a given age. Transition probabilities generated using only cross-sectional data from the CDS years are likely to be quite noisy. I therefore impute the children's disability status in off-CDS years using a combination of information from the CDS and the NHIS. If a child is reported to have a disability in a given CDS interview, I assign them as having a disability in each of their remaining years in the household. For the years prior to the report of their disability, I impute the age of condition onset using the modal age at which the condition is reported to have manifested in the National Health Interview Survey. For conditions whose age of onset is not reportedin the NHIS, I draw from the medical literature. As a concrete example, the modal age of onset of hyperactivity is age 5 in the NHIS. If a child is first interviewed at age 10 and is reported to have hyperactivity which is categorized as disabling, they will be assigned to having a disability from 5 onwards. More details about this procedure, including the ages used for each condition, are described in Section B.5.

A second limitation of the PSID is that it does not ask whether individuals have applied for SSI. This is an issue because the structural model features both psychic costs of applying for SSI (as in Moffitt (1983)), and rejection of applications. Studies that observe Disability Insurance applications (Autor et al., 2019; Lee, 2023) identify the program's acceptance probability using the observed acceptance rate, then use application rates to identify the application costs. Other studies assume that the application costs are zero (Low and Pistaferri, 2015; Kellogg, 2022) and identify SSI acceptance probabilities . Without additional information, I cannot identify whether a low share of individuals receiving SSI is due to high application costs or a low acceptance rate. I could simply set acceptance rates for SSI using the acceptance rate reported by SSA, but it is likely that the composition of applicants for SSI is different than children who I report as having a disability in the PSID. Fortunately, the NHIS asks whether individuals have ever applied for SSI. I therefore calculate the share of children in the NHIS with a disability who report having ever applied for SSI, and target this lifetime application rate when estimating the model. When calculating this statistic, I similarly restrict to children

[18] I use data harmonized by IPUMS Health Surveys (Blewett et al., 2022).

whose mothers do not have a college degree, and who were born after 1990, and use the weights provided by the NHIS to make the sample nationally representative.

3.2. Sample Statistics

Table 2 reports characteristics of women in my analytical sample who give birth to a child interviewed in the CDS, which reduces the number of women in the sample from 1894 to 984. The first column reports outcomes of women whose children are never observed having a child with a disability. The second column report outcomes for women ever observed having a child with a disability. The third column reports the difference-in-means p value.

Panel A reports potentially time varying characteristics – age, marital status and health – while Panel B reports permanent characteristics. We see that sample who ever have a disabled child are more likely to be white and have more children on average. However, average age at first birth and educational attainment are similar. Panel C reports covariates from the most recent year the woman is observed in the PSID prior to the birth of her first child. The restriction that the mother is observed prior to the birth of the first child further reduces the sample of mothers from 984 to 526. This is partially because many women enter the PSID sample by cohabiting with a PSID sample member in the year they give birth. In addition, many women do not meet the requirement of being either a household head or spouse of the household head in the year prior to the birth of their first child, and so I do not observe their labor market outcomes. Labor force attachment does not appear to be significantly different across the three groups, although labor earnings and wages for those who ever have a child with a disability are lower on average. This highlights a major challenge in the literature studying the effect of children's health on their mother's labor market outcomes. Namely, given the established relationship between family income and children's health (Case, Lubotsky, and Paxson, 2002), it is difficult to distinguish between the effect of having a child with a disability on maternal labor supply, and correlated factors which may affect both the probability of having a child with a disability and maternal labor supply.[19] An advantage of the structural model in this context is that I am able to explictly allow for the possibility that the probability of having a child with a disability is correlated with

[19] Using similar data, Case, Lubotsky, and Paxson (2002) find that family income is strongly predictive of children's current health, even income measured prior to the child's birth. They show that the relationship between parent's income and children's health is driven in part by chronic conditions being more likely to be disabling for children in lower-income families.

the woman's permanent income.

TABLE 2. Summary Statistics

	No Children Disabled	Any Disability	Equality of means p-value
Panel A: Average Characteristics			
Age	29.80	30.18	0.50
Married	0.58	0.61	0.58
Health Very Good or Excellent	0.57	0.58	0.96
Panel B: Permanent Characteristics			
Age at first birth	24.28	23.93	0.47
White	0.67	0.76	0.11
Total # Kids	2.12	2.58	0.00
Years of education	12.88	12.83	0.77
Panel C: Pre First-Birth Average			
Employment rate	0.87	0.84	0.62
Employed Full-time	0.68	0.76	0.34
Labor Income (2010 ks)	24.57	20.43	0.14
Wage (2010s)	14.35	10.93	0.03
N Mothers	923	61	
N observed before first child	499	27	

Note. Sample is all women without a college degree who are mothers of a CDS child and have their first child after age 19. Bottom panel reports outcomes from the most recent year the woman is observed prior to her first birth. p value is test where the null is that group means are equal.

3.3. Regression Results

Next, I will compare the outcomes of mothers with and without disabled children, focusing on maternal employment, earnings, and family SSI receipt. These specifications are run separately by whether the woman is single or married.

In addition to indicators for whether there is a child with a disability in the household, all specifications include a full set of year dummies, controls for characteristics of the mother (a cubic in age, education categories, race, and an indicator for whether she reports having a work-limiting disability), for the family structure (the age of the youngest child in the household and the number of children in the household), the state unemployment rate in that year, and controls to summarize the state welfare regime (the maximum TANF/AFDC, EITC, and SNAP benefits that a woman with a given family structure in that state and year). When estimating effects for married women I also include controls for the characteristics of the husband (a cubic in age, education dummies, and an indicator for whether he has a work-limiting disability). To partially account for a measure of permanent income, I also include a cubic in the average of the mother's earnings in the years prior to the birth of her first child, interacted with an indicator for having observed the woman prior to her first birth.

The Panel A of Table 3 reports results for single women. The estimates are suggestive of declines in labor force participation and earnings for women who have a child with a disability in the household. Effect sizes for married women, reported in Panel B, are smaller, and are often not statistically significant. This is consistent with the prior literature (i.e. Powers (2003), Wasi, den Berg, and Buchmueller (2012)) which typically finds larger effect sizes for single women, although definitions of disability vary across studies.

TABLE 3. Regression Results: Labor Market Outcomes

	Employment Rate	Log Weekly Hours	Labor Income (ks)	Log Labor Income	Receiving Child SSI
Panel A: Unmarried Women					
Disabled Child in Household	-0.17***	-0.13*	-7.44***	-0.28**	0.19***
	(0.07)	(0.07)	(1.65)	(0.11)	(0.05)
Control Mean	0.81	3.50	18.66	9.76	0.02
R2	0.19	0.11	0.32	0.25	0.12
N	3561	2826	3561	2826	2443
Panel B: Married Women					
Disabled Child in Household	-0.03	0.00	-1.48	-0.07	0.06***
	(0.06)	(0.06)	(2.19)	(0.12)	(0.02)
Control Mean	0.69	3.42	18.97	9.89	0.01
R2	0.19	0.13	0.20	0.22	0.08
N	6942	4759	6942	4759	5152

Note. All specifications include controls for survey year, state UR and welfare characteristics, a cubic in the mother's age, race, years of education, work-limiting disability, a cubic in earnings prior to first birth if observed. If the woman is married, the same covariates for the husband are included. In addition, indicators for the number of children in the household, and age of the youngest child in the household. SEs are clustered at the mother's level.

A potential mechanism for the decline in labor force participation and earnings is that children with disabilities require greater time inputs. Previous work has been unable to directly test for this mechanism due to a lack of data on time use.[20] I supplement my analysis using the detailed time diary information contained in the CDS. These diaries report what the child was doing throughout the day and with whom. I follow Del Boca, Flinn, and Wiswall (2014) and denote time that a parent was "actively participating" with the child as "active time", and all other time as "passive time". Each child submits a diary for one weekday and one weekend day. Again following Del Boca, Flinn, and Wiswall (2014), I adjust reported hours so that the average number of hours across

[20]An exception is Rupp et al. (2006), which utilized data from a unique survey of SSI recepients to show a high prevalence of family caregiving of children with disabilities, with a large degree of heterogeneity. Relative to this paper, I am able to observe caregiving of all disabled children, not just those receiving SSI, and am able to compare to the amount of caregiving of children without disabilities. In addition, the data used in Rupp et al. (2006) contain "stylized time use" questions rather than detailed time diaries, which are thought to be of lower quality (Juster and Stafford, 1991).

weekdays and across weekend days is equal for children of the same age. I then multiply the number of weekday hours by 5 and the number of weekend hours by 2 to obtain a weekly measure of time spent with the child. I restrict the sample to children who are younger than 18 years old, whose mother has less than a college degree, and whose mother reports more than 5 active hours with the child.

Table 4 reports the results of a regression in which the outcome variable is the log of the number of hours spent with the child, either actively or passively, and the key explanatory variable is an indicator for whether the child has a disability. I additionally control for a cubic in the mother's age, whether the mother has a partner in the household, dummies for the survey year, education dummies, dummies for the child's age, the number of children in the household, and race. I weight these regressions using the CDS sampling weights. The results indicate that mothers of children with disabilities spend more time with their children, both actively and passively. The effect sizes are economically large, with the presence of a child with a disability being associated with a 14 to 21% increase in the total amount of time spent with the child, and just over 15 percent more active time per week.

TABLE 4. Time Diary Regression Results

	Log(Active Time)	Log(Passive Time)	Log(All Time)
Disabled Child	0.214***	-0.023	0.146**
	(0.080)	(0.143)	(0.059)
Observations	2175	1988	2175
Mean (Level)	22.28	18.60	40.89

Note. Outcome variable is the log of a given type of time spent with the child. All specifications control for the age of the child, the survey year, education dummies, whether the mother is married, the number of children in the household, and race. CDS sampling weights are used. SEs are clustered at the mother's level.

4. A Life-Cycle Model of Female Labor Supply, Saving and SSI

The empirical patterns described in the previous section indicate that mothers whose children have a disability have generally worse labor market outcomes and spend more time providing care to their children. These empirical outcomes are a function of preferences, costs and the policy environment. Moreover, they may be driven in part by unobserved heterogeneity, as indicated by the lower wages of mothers who have a disabled child even before the arrival of the child. In order to map these empirical patterns onto estimates of preferences and costs, I develop and estimate a life cycle model of female labor supply which incorporates costs associated with raising children, costs compounded by childhood disability, (exogenous) fertility, marriage and divorce, as well as a realistic model of the Child SSI program and the general U.S. tax and transfer system. In particular, Child SSI is imperfectly screened and eligibility requires satisfying an asset test. The latter feature of the program generates a strong savings disincentive for current and potential applicants. Receiving SSI benefits distort labor supply decisions both through an income and substitution effect – transfers can reach up to $13k/year for a two-parent household, but the phaseout generates the implicit marginal tax rate for earnings above $28k/year of 50%.

4.1. Model Outline

The model begins at age 20 and follows the working period life of a woman, who may be married or single, and may or may not have a child. Each year, women in the model choose their consumption, whether to supply labor, and whether to apply for SSI. If the woman is married, I assume that her husband always works. Households may save, but are not allowed to borrow.[21] When making these decisions, she faces several forms of uncertainty: her future family structure, her wage, whether her child will develop a disability, and whether her child will be accepted for SSI should she apply. Fertility can occur in every period until the age of 40, and children live in the household until they turn 18 years old. Individuals retire with certainty at age 62[22], then live off of their savings and Social Security income for 10 years. There is no bequest motive.

Children affect household decisions by affecting the utility cost of work, which changes as the child ages. Child SSI transfers resources to families who have a child with a disability, but is means-tested and imperfectly-screened. Wages depend on labor market experience, and individual productivity is subject to persistent shocks. Choices are further influenced by the tax and transfer system, which provides partial insurance against idiosyncratic shocks. Individuals differ ex-ante in their permanent "type", which affects their wage, the process underlying their future family structure, and the probability that their child develops a disability. They also differ ex-post due to the

[21] This is a standard assumption which prevents borrowing against future pension wealth or social insurance.

[22] This is the age at which households become eligible for early Social Security retirement benefits.

realizations of the stochastic shocks.

4.2. Preferences

In each year, a woman maximizes her expected lifetime utility taking as given her current state variables. These are her age t, her permanent type g, her accumulated assets A, work experience E, idiosyncratic productivity F, the presence of a partner m, his idiosyncratic productivity $\tilde{F}$, whether there is a child in the household k, the age of the youngest child in the household z, the child's disability status $\theta \in \{0, 1\}$, and whether the family is receiving Child SSI, SSI.

Utility is intertemporally separable, and flow utility depends on equilivized consumption, the woman's labor supply – which is nonseparable with consumption – and the choice of whether to apply for SSI. At age t it is given by

$$u(c_t, l_t, \text{App}_t; \theta_t, X_t) = ((c_t/n_t)\exp\{-P_t\gamma_{z_t,\theta,m}\})^{1-\sigma}/(1-\sigma) - \eta_m \text{App}_t \tag{1}$$

where n_t is the equivalence scale[23], c_t is consumption, P_t is female labor supply, and App_t is the choice of whether to apply for SSI.[24] This specification of preferences allows for nonseparability of consumption and leisure and is standard in the literature on labor supply over the life cycle.[25]

The parameter σ governs both risk aversion and intertemporal substitution. Because σ will be calibrated to be greater than 1, higher values of γ will imply that working reduces the utility from consumption relatively more. γ varies by whether the mother is married, the disability status of any child in the household, and whether the child is school-aged.

With full insurance, women in the model would equalize their marginal utility of consumption

$$\frac{\partial u(c_t, l_t, \text{App}_t; \theta_t, X_t)}{\partial c_t} = c_t^{-\sigma}\exp\{-P_t\gamma_{z_t,\theta,m}\}^{1-\sigma}$$

[23] I follow Blundell et al. (2016) in setting n = 1 for singles, 1.4 for single mothers, 1.6 for a married couple, and 2 for a couple with children.

[24] This term is standard in the modeling of government programs with incomplete take-up, and can be interpreted to represent stigma attached with program participation (Moffitt, 1983) or transaction costs associated with the application process (Currie, 2006).

[25] See, for instance Low, Meghir, and Pistaferri (2010), Low and Pistaferri (2015), Blundell et al. (2016), Autor et al. (2019), and Low et al. (2022)

across potential health and work states within each year and allocate resources across time to satisfy the Euler equation. Work being a "bad" requires that $\gamma_{z_t,\theta,m}$ be positive, with higher values increasing the marginal utility of consumption. If work is more costly when a child has a disability – which is consistent with the evidence presented in the previous section – then Child SSI transfers resources to states in which the marginal utility of consumption when working is higher.

I assume there is an exogenous retirement period beginning at age T_r.[26] In the retirement period, I assume households only decide how much to consume/save, and that households live off of their accumulated savings and Social Security benefits.[27] I assume households live for 10 years after retirement, and die with certainty at age $T_r + 10$. For simplicity, I assume there is no uncertainty during the retirement period. I multiply the value function in retirement by an adjustment factor which is allowed to vary by marital status, χ_s and χ_m. This approach of differentiating the periods of interest (in my case the pre-retirement periods) from the periods which are not of interest to the researcher, but are taken into account by the modeled agents (in my case the retirement period) has been used by, for example, Keane and Wolpin (1997), Gourinchas and Parker (2002), and Jakobsen, Jørgensen, and Low (2023).[28]

4.3. The SSI Program

Eligibility for SSI requires satisfying the SSI income and asset tests

$$y_t + rA_t - y_d \leq \underline{\mathrm{Y}}(\mathrm{m}) \quad \text{and} \quad A_t \leq \underline{\mathrm{A}}(\mathrm{m})$$

where $\underline{\mathrm{Y}}(\mathrm{m})$ is the SSI income limit, and $\underline{\mathrm{A}}(m)$ is the asset limit. Both of these depend on the presence of a spouse. y_t is total sum of family income, and y_d is the income disregard. Conditional on meeting the SSI income and asset tests, families must apply for child SSI. Applicants for SSI are accepted with probability $\pi = Pr(SSI_{t+1} = 1|\theta)$, which will be estimated. Those on the SSI program rolls are reassesed for eligibility with probability $P^{Re}(\theta)$, which are set to match reassessment rates for applicants implied by the program statute.

[26] I include a retirement period to match the age profile of asset holdings. Without a retirement period, households begin to dissave during the working life, which does not match the data.

[27] See appendix D.1 for details about how I model social security benefits.

[28] Jørgensen and Tô (2020) study the robustness of this approach relative to a full-solution estimator, and find that the two approaches yield similar results in the context they study.

4.4. Wages

Wages are a function of labor market experience, exp_t, an intercept term that is common amongst all members of group g, $f_{g(i)}$ and a permanent wage innovation whose cumulative value at time t is F_t. The permanent wage innovations follow a random walk with normally distributed innovations ε_t.

$$\ln(w_t) = \alpha_1 \text{exp}_t + \alpha_2 \text{exp}_t^2 + f_{g(i)} + F_t \tag{2}$$

$$F_t = F_{t-1} + \varepsilon_t, \quad \varepsilon_t \sim \mathcal{N}(0, \sigma_\varepsilon) \tag{3}$$

Experience increase by one if a woman works full time and depreciates at rate δ if she does not participate in the labor market:

$$\text{exp}_{t+1} = \text{exp}_t + \mathbb{1}(P_t = 1) + \delta\, \mathbb{1}(P_t = 0) \tag{4}$$

As men always work in the model, their labor market experience is given by their age:

$$\ln(\tilde{y}_t) = \tilde{\alpha}_0 + \tilde{\alpha}_1 t + \tilde{\alpha}_2 t^2 + \tilde{F}_t \tag{5}$$

$$\tilde{F}_t = \tilde{F}_{t-1} + \tilde{\varepsilon}_t, \quad \tilde{\varepsilon}_t \sim \mathcal{N}(0, \sigma_{\tilde{\varepsilon}}) \tag{6}$$

4.5. Budget Constraint

Let A_t denote the household's assets at the beginning of period t, and r denote their return. Total post-tax income for a woman with marital status m and presence of a child k is $\tau_y(\tilde{y}_t + w_t P_t, m, k, \tau)$, with the vector τ summarizing the tax system and approximated for with a log-linear function (Feldstein, 1969):

$$\tau_y(y, m, k, \tau) = y - \lambda_{mk} * y^{(1-\tau_{mk})} \tag{7}$$

where the scale λ and progressivity τ of the tax function vary by marital status and presence of a child.

Means-tested transfers other than SSI are dispursed through a consumption floor,

$tr_t()$ (Hubbard, Skinner, and Zeldes (1995))[29] which is parameterized as:

$$tr_t(k) = \max\{0, \bar{c} * n_t - (\tau_y(\tilde{y}_t + w_t P_t, m, k, \theta) + (1+r)A_t)\} \tag{8}$$

Household consumption is constrained to be above the consumption floor:

$$c_t \geq \bar{c} \tag{9}$$

The budget constraint is:

$$A_{t+1} = (1+r)(A_t + \tau_y(.) + tr_t(.) + SSI_t(.) - c_t). \tag{10}$$

For those applying for SSI, and those on SSI who wish to remain eligible in the next period, an additional constraint is that savings must remain below the asset limit,

$$A_{t+1} \leq \underline{\text{A}}(m) \tag{11}$$

If the final constraint is violated, the household is removed from SSI. Finally, household are unable to borrow:

$$A_{t+1} \geq 0 \tag{12}$$

4.6. Recursive Formulation

I describe the recursive formulation for a single woman with a child in the household. As men do not make any decisions in the model, the problem of a married woman differs only through the additional state variable relating to the husband's permanent income and the uncertainty regarding becoming divorced in the next period, rather than becoming married.

For unmarried women without a child, the state variables are $\Omega_t = \{g, \exp, A, F\}$, with next-period values denoted by a prime. These variables are her permanent income group g, her labor market experience exp, her assets A, and her productivity F. She

[29] See also French (2005), Scholz, Seshadri, and Khitatrakun (2006), and De Nardi, French, and Jones (2016), and many others.

chooses how much to work, $P_t \in \{\emptyset, FT\}$, and consume, c_t to maximize

$$V_t^S(\Omega_t) = \max_{c_t, P_t} \left\{ \begin{array}{c} u(c_t, P_t) \\ +\beta E_t \left[\begin{array}{c} (1-m_{g,t}) \left[\begin{array}{c} (1-f_{g,t}) \cdot V_{t+1}^S(\Omega_{t+1}) \\ +f_{g,t} \cdot V_{t+1}^S(\Omega_{t+1}) \end{array} \right] \\ +m_{g,t} \left[\begin{array}{c} (1-f_{g,t}) \cdot V_{t+1}^M(\Omega_{t+1}, \text{SSI}_{t+1}=1) \\ +f_{g,t} \cdot V_{t+1}^M(\Omega_{t+1}, \text{SSI}_{t+1}=0) \end{array} \right] \end{array} \right] \end{array} \right\}$$

s.t. eqns (2), (7), (8), (9), (10), (12)

where $f_{g,t}$ and $m_{g,t}$ are the group-by-age specific fertility and marriage rates.

If a child is in the household, the state variables are augmented with the age of the child, z, their disability status θ, and whether the family has been accepted onto SSI SSI: $\Omega_t = \{g, \exp, A, F, z, \theta, SSI\}$ and an additional choice variable is the decision of whether to apply for SSI App_{t+1}. Her recursive problem is:

$$V_t^S(\Omega_t) = \max \left\{ V_t^{S,\text{Apply}}(\Omega_t), V_t^{S,\text{No Apply}}(\Omega_t) \right\}$$

where

$$V_t^{S,\text{Apply}}(\Omega_t) = \max_{c_t, P_t} \left\{ \begin{array}{c} u(c_t, P_t, \text{App}_t = 1) \\ +\beta E_t \left[\begin{array}{c} (1-m_{i,t}) \left[\begin{array}{c} \pi(\theta_t) \cdot V_{t+1}^S(\Omega_{t+1}, \text{SSI}_{t+1}=1) \\ +(1-\pi(\theta_t)) \cdot V_{t+1}^S(\Omega_{t+1}, \text{SSI}_{t+1}=0) \end{array} \right] \\ +m_{i,t} \left[\begin{array}{c} \pi(\theta_t) \cdot V_{t+1}^M(\Omega_{t+1}, \text{SSI}_{t+1}=1) \\ +(1-\pi(\theta_t)) V_{t+1}^M(\Omega_{t+1}, \text{SSI}_{t+1}=0) \end{array} \right] \end{array} \right] \end{array} \right\}$$

s.t. eqns (2), (7), (8), (9), (10), (11), and (12)

and

$$V_t^{S,\text{No Apply}}(\Omega_t) = \max_{c_t, P_t} \left\{ \begin{array}{c} u(c_t, P_t, \text{App}_t = 0) \\ +\beta E_t \left[\begin{array}{c} (1-m_{i,t}) \cdot V_{t+1}^S(\Omega_{t+1}, \text{SSI}_{t+1}=0) \\ +m_{i,t} \cdot V_{t+1}^M(\Omega_{t+1}, \text{SSI}_{t+1}=0) \end{array} \right] \end{array} \right\}$$

s.t. eqns (2), (8), (9), (10), and (12)

4.7. Model Solution

The solution of the model consists of policy functions for consumption, labor supply and SSI application as a function of the exogenous state variables. There is no closed form solution for these, and so the model is solved numerically using backward induction. I begin with the terminal condition for savings then iterate backwards, solving for the value function and policy functions at each age. The presence of the discrete choices and means-tested social insurance imply that consumption will not be continuous in assets, and the continuation value may not be globally concave in the savings decision. Accordingly, I use a modified version of the Endogenous Grid Method (Carroll, 2006), extended to problems with a mix of discrete and continuous choices by Iskhakov et al. (2017), to solve the model.[30] More details about the solution method are included in Section C.

5. Estimation

I estimate the model using a three-step procedure commonly employed in this context. First, I set certain parameters based on estimates from other studies, such as the discount rate and the coefficient of relative risk aversion. I also set certain features of the SSI program to match program rules. The two remaining steps fit model parameters to my analytical PSID sample. In the second step, I estimate marriage, divorce, and fertility transitions directly from the data, and estimate the parameters governing the wage equations, as well as the tax function. Finally, I estimate the remaining preference parameters and the latent SSI acceptance probability using the method of simulated moments.

5.1. Predetermined and Directly Estimated Parameters

The parameters calibrated or estimated in the first two steps are reported in Table 5

I set the coefficient of relative risk aversion γ and the discount rate β using values estimated in previous studies. In particular, I set $\gamma = 1.5$, following Blundell, Browning, and Meghir (1994) and Attanasio and Weber (1995) and $\beta = 0.98$. I set the reassessment

[30] I am grateful to Thomas Jørgensen for his helpful correspondence regarding implementing this method.

TABLE 5. Parameters Calibrated or Estimated Outside the Model

Parameter	**Value/Source**
Panel A: Externally Set Parameters	
Relative risk aversion (σ)	1.5
Discount Factor, risk-free rate (β, r)	0.98, 1/(1+0.98)
Equiv. Scale (S, SK, M, MK)	1, 1.4, 1.6, 2.0 Blundell et al. (2016)
SSI Benefits + Asset/Income Limits	Statutory rules
SSI Reassessment Rate	Avg. 3 yr CDR rate
Panel B: Directly Estimated Parameters	
Family Transitions	See text
θ Distribution	See text
Tax and Transfer system ($T(.)$)	See text
Variance of women/men's wage shocks	.04, .05
Experience depreciation from year out of work (δ)	-1.07
Experience profile log(female wages) (α_1^w, α_2^w)	.05, -.0005
Life cycle profile log(male earnings) (α_0^m, α_1^m, α_2^m)	10, .05, -.0009

rates for disability status at 1/3 so that a child on SSI can be expected to be reassessed every three years.[31] The SSI asset limits are set to \$4,000 for singles and \$5,000 for couples, which has been their value for the entirety of my sample period. I take the maximum benefit, and phaseout regions for singles and couples from the 2015 program rules. I assume mandatory retirement at age 62, after which individuals live off of their savings and pension income for ten years.

5.1.1. The Wage Process and Productivity Risk

When estimating the parameters of the equation for male annual earnings (Equation 5) and female hourly wages (Equation 2), I follow the common approach of augmenting each with an additional term which I interpret as measurement error.

Denote exp_t^{FT} and exp_t^{O} as years of accumulated experience for work and time out of the labor force, respectively. Given the law of motion for experience, the augmented wage equation can be written as:

$$\ln(w_t) = \alpha_1(\text{exp}_t^{FT} + \delta\text{exp}_t^{O}) + \alpha_2(\text{exp}_t^{FT} + \delta\text{exp}_t^{O})^2 + f_{g(i)} + F_t + \varepsilon_t$$

[31]Modeling CDRs this way allows me to only keep track of whether a child is currently on SSI, rather than also tracking the length of a child's SSI spell. In practice CDRs occur less frequently (Deshpande, 2016b).

I estimate this equation using a two-step procedure to address the selection into work (Heckman (1979)). In the first step I estimate a Probit model of employment using the maximum SNAP, EITC and AFDC/TANF benefits available to the woman – which vary across state and time and within-state due to difference in family status – as excluded instruments. This is similar in spirit to simulated IV (Currie and Gruber (1996)). In the second step I estimate the augmented wage equation, including the inverse Mills ratio. This provides me with estimates for α_1, α_2 and δ.

The estimation of the variance of the productivity shocks and the group-specific fixed effects make use of the residual log-wage, which is defined as

$$u_t = \ln(w_t) - \hat{\alpha}_1 \hat{\text{exp}}_t + \alpha_2(\hat{\text{exp}}_t)^2$$

I estimate the type-specific fixed effects by calculating the average value of u_t for each individual in the data, $\bar{u}$, and then grouping individuals into terciles by their average value. The group-specific fixed-effect is the median value of the $\bar{u}$ for each group.

Finally, the variance of the productivity shocks are indentified by the first moment, second moment and autocovariance of u_t. I estimate these parameters using GMM, again controlling for selection. More details about this procedure are included in Section I.

For men, I estimate equation 5 while allowing for iid measurement error in earnings. As labor force participation of married men is quite high, selection bias in this estimation is likely to be small. More details of the estimation are reported in Section E.2.

Estimates of the parameters governing the law of motion for experience, the labor market return of experience, and the variance of the permanent income shocks are reported in Table 5. The general patterns are consistent with previous studies. I estimate a concave return to experience and significant human capital depreciation when out of the labor force.[32] As expected, I estimate a concave age profile in labor earnings for men.

[32]As in Attanasio, Low, and Sánchez-Marcos (2008), I impose a floor of zero in the level of experience.

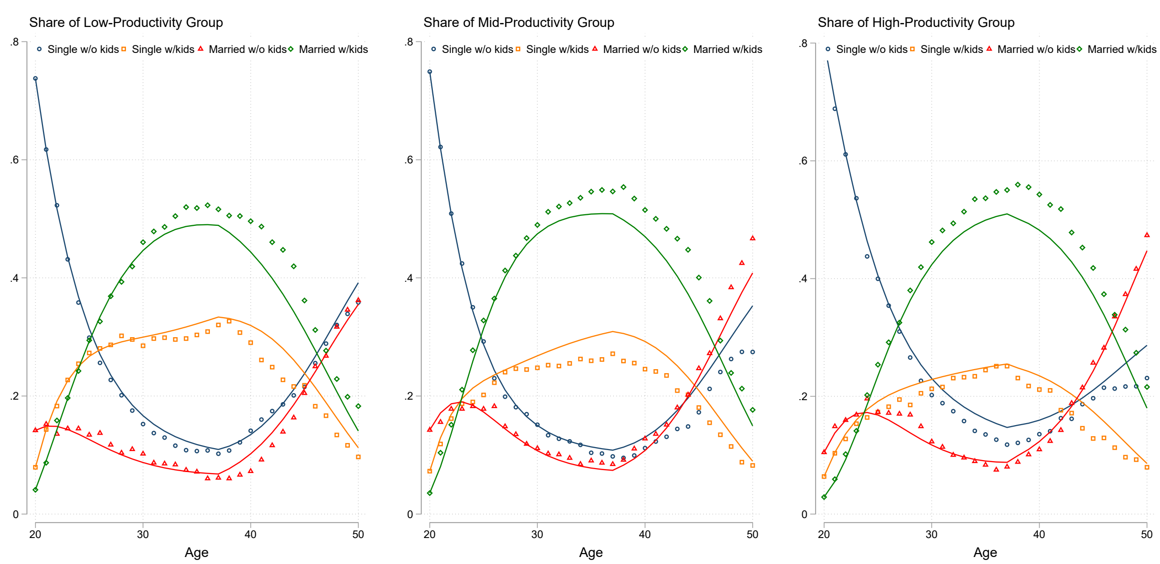
5.1.2. Family Transitions

I assume that fertility, marriage and divorce transitions are independent of household choice. Accordingly, they can be estimated without imposing the structure of the model.

I estimate the probability of a partner arriving, a partner leaving, and of having a child – separately by household type – using a probit. Each marriage transition probabilty is estimated using a fourth-order polynomial in age, separately by the presence of a child in the household. The fertility probability is estimated using a square in age and, if there is a child in the household, a linear term in the child's age and an interaction with the mother's age. These are estimated separately by whether the woman is married. These probabilities form the basis of household's expectations about future family transitions within the model. However, when the model is simulated during the estimation stage, each simulated household experiences the actual family transitions that occurred in the data.

Figure 2 plots the distribution of family composition by female age and permanent productivity type for the observed data and the simulations. The simulated profiles match their data counterparts reasonably well. For each group, the probability of being partnered with a child rises with age, although women in the low-productivity group are more likely to spend time as single mothers.

FIGURE 2. Family Status over the Life Cycle by Productivity Type



A. Low Productivity B. Medium Productivity C. High Productivity

5.1.3. Disability Transitions

I calibrate a relatively simple process for child disability transitions. I allow for two time periods over the child's life when disabilty status can change. The first is at birth. I take the share of children prior to school age who are reported to have a disability in the PSID, separately by the mother's type. This is the fraction that I assign as having a disability at birth in the model. Next I take the share of children who are school-aged who are reported to have a disablity. From this, I calculate the rate of onset of disability between birth and school age, again separately by mother's type. I then assume disability is an absorbing state throughout the rest of childhood. See Table 6 for the estimated transition probabilities. Consistent with previous work (e.g. Case, Lubotsky, and Paxson (2002)) the incidence of childhood disability is higher for women in the lower productivity groups.

TABLE 6. Disabililty Transition Probabilities

	Low Productivity	Medium Productivity	High Productivity
Disability rate at birth	0.050	0.038	0.048
Disability transition rate at age 5	0.037	0.041	0.014
Share w/disablility by age 6	0.085	0.077	0.061

Note. Table reports the estimated probabilities that a child of a woman will develop a disability at different ages, as well as the probability the child has a disability by the time they are school-aged.

5.1.4. Tax Function

Recall that the tax function is specified as

$$\tau_y(y, m, k, \tau) = y - \lambda_{mk} * y^{(1-\tau_{mk})}$$

I estimate the parameters λ_{mk} and τ_{mk} by regressing the log of post-tax income on the log of pre-tax income, using the extracts of the CPS ASEC provided by IPUMS (Flood et al., 2023).[33] I run this regression separately for the four types of family structure allowed in my model, using the sample of women without a college degree from the years 1990 to 2020. Table 7 reports the estimated parameters and R^2 of the four regressions. As shown

[33] I use the CPS because the PSID does not report tax liabilities after 1992. The IPUMS data have post-tax income generated by the Census Bureau's tax model. It is also possible to use the NBER TAXSIM model to approximate the tax system with the PSID. Kimberlin, Kim, and Shaefer (2015) provide code to generate the necessary inputs to TAXSIM from the PSID through 2011. Updating this code to fully cover my sample period is in progress.

by the high R^2, this functional form appears to provide a reasonable approximation to the tax schedule these households face.

TABLE 7. Tax Function Parameter Estimates

	λ	τ	R^2
Singles, no kids	0.66	0.083	0.97
Singles, w/kids	0.44	0.060	0.98
Couples, no kids	0.45	0.060	0.97
Couples, w/kids	3.39	0.325	0.88

5.2. Simulation Procedure and Estimation

I estimate the remaining preference parameters and latent SSI acceptance probabilities using the Method of Simulated Moments (Gourieroux, Monfort, and Renault (1993), Pakes and Pollard (1989), and McFadden (1989)). Denote the parameters to be estimated as Ω. For each candidate parameter vector $\Omega.$, along with the first stage parameters estimated in the previous section, I solve the model separately for women in each of the three productivity groups. I then use the resulting policy functions to simulate the consumption, labor supply and SSI application decisions for each individual in the simulated dataset, described below. I next calculate the moments from the simulated dataset, using the same procedure as for the empirical moments.

When simulating the model, I use the observed histories of marital status, fertility, and child's disability status of each woman in my analytical sample, and simulate the uncertainty the she faces – wage shocks, SSI acceptance probabilities – using random draws from the estimated distributions. For years in which there is a child in the household, but the child's disability status is unknown, I simulate the child's disability status using the disability transition probabilities I calculated in the next section.[34] I replicate the simulated PSID dataset 20 times in this way, which generates the sample used to compute the simulated moments. I incorporate the effect of the sampling design of the PSID on the estimated moments by only using simulated observations in the years in which the individual's PSID counterpart was observed.

The MSM estimator minimizes the difference between simulated and observed

[34]These observations are not included when calculating simulated moments which condition on the child's disability status.

moment conditions using a GMM criterion function

$$\hat{\Omega} = \arg\min_{\Omega} g(\Omega)' W g(\Omega)$$

where $g(\Omega) = m^{data} - m^{sim}(\Omega)$ is a $J \times 1$ vector of differences between the J empirical moments calculated from my analytical sample and their simulated counterparts. W is a $J \times J$ weighting matrix. Altonji and Segal (1996) show that the theoretically optimal weighting matrix has poor small-sample properties, and so I use a diagonal weighting matrix, where the elements of the diagonal are the variances of the empirical moments, generated by block bootstrap.

5.3. Targeted Moments and Identification

My targeted moments can be classified into three sets. All moments jointly contribute to the estimation of the structural parameters, but some parameters are more naturally linked to specific moments. In this section, I provide a heuristic argument for which moments are likely to provide the most identifying information for a given parameter.

The first set of moments I match relate to female labor supply. I match the share of women employed by marital status, whether there is a child in the household, the child's disability status, and whether the child is school-aged.[35] These moments are informative about the disutility from work parameters. Take, for instance, the probability that a single woman with no children is employed. This moment is matched by finding the disutility of labor supply which is consistent with the observed participation rates for women in this demographic category, holding fixed the other preference parameters and the returns from working generated by the wage equation and the tax code.

The second set of moments I match are the share receiving and entering onto SSI by marital status and disability group, as well as the fraction of women with a disabled child who ever apply for SSI. These moments should be especially informative about the cost of applying for SSI, as well as the probability of being accepted onto SSI. Recall that I do not observe applications for SSI in the PSID. However, for a given acceptance rate, the flows onto SSI should inform the magnitude of the application cost. Intuitively, the application decision is determined by weighing the expected discounted benefit of applying for SSI, which depends on the acceptance probabilities and the other preference parameteters,

[35]The school age calculation in the analytical sample is defined by the age of the youngest child in the household, while in my model I only track the age of the youngest child.

with the cost of applying. All else equal, a higher application cost will lead to fewer applications. Similarly, the higher the acceptance rate the more applications.[36]

The final set of moments I match are the median level of assets in 10 year age bins, separately by family structure. I exclude housing and vehicle wealth, as the primary residence and the value of one car do not enter the SSI asset test. These moments are informative about the retirement adjustment factor, as well as the consumption floor. Individuals in the model save to self-insure against economic shocks, as well as to finance consumption in retirement. As the consumption floor increases, individuals desire to self-insure will decrease, and they will save less. This is motive is particularly salient early in life. Later in life, the retirement savings motive becomes more operative, and the retirement adjustment factor will determine the level of assets with which households enter retirement.

6. Results

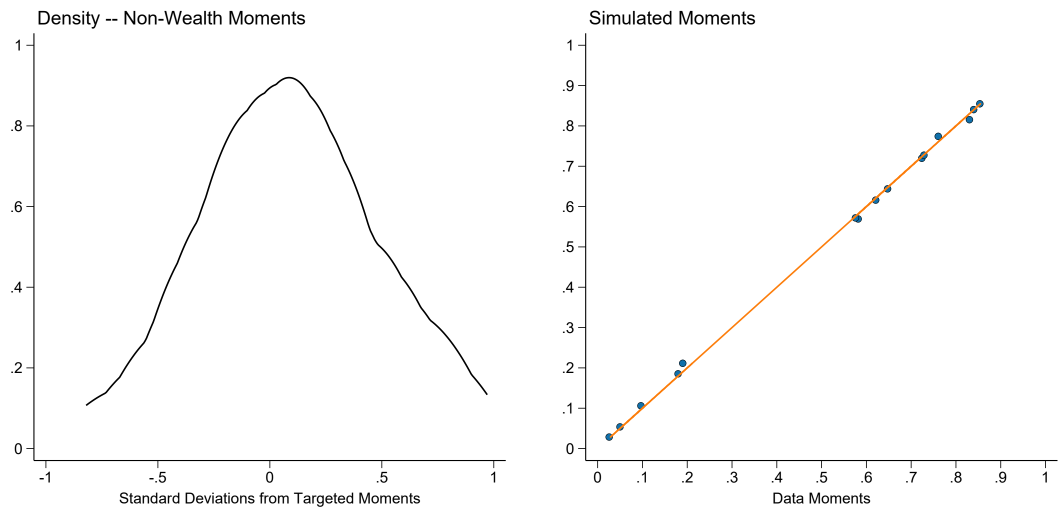
This section presents the fit of the model to targeted moments and untargeted responses. Parameter estimates are reported in Section A.1. The parameter estimate with the most interpretable analogue is the SSI acceptance probability, which is estimated to be just under 54%. Aizer, Gordon, and Kearney (2013) report that the acceptance probability for children applying with a mental health condition is around 45%, and around 65% for those with a physical condition. The fact that the pooled elasticity is in this range suggests that the sample of children I am identifying as disabled in the PSID is not significantly less disabled than the population that applies for SSI benefits in the data.

6.1. Fit of model to targeted moments

Figure 3 reports the model's fit of the targeted moments, excluding moments relating to asset accumulation. Overall, the model does an excellent job of fitting these moments. Panel A shows that each simulated moment falls within a standard deviation of its data counterpart. Some moments are estimated imprecisely due to the relatively small sample size of the PSID, but Panel B confirms that the estimated values of the simulated moments align closely with their data counterparts. Figures **??**-**??** in Section A.2 report the fit of each moment.

[36] This argument is formalized in Section G.

FIGURE 3. Model Fit to Targeted Moments – Non-Asset Moments



A. Standardized Deviations from Data Moments

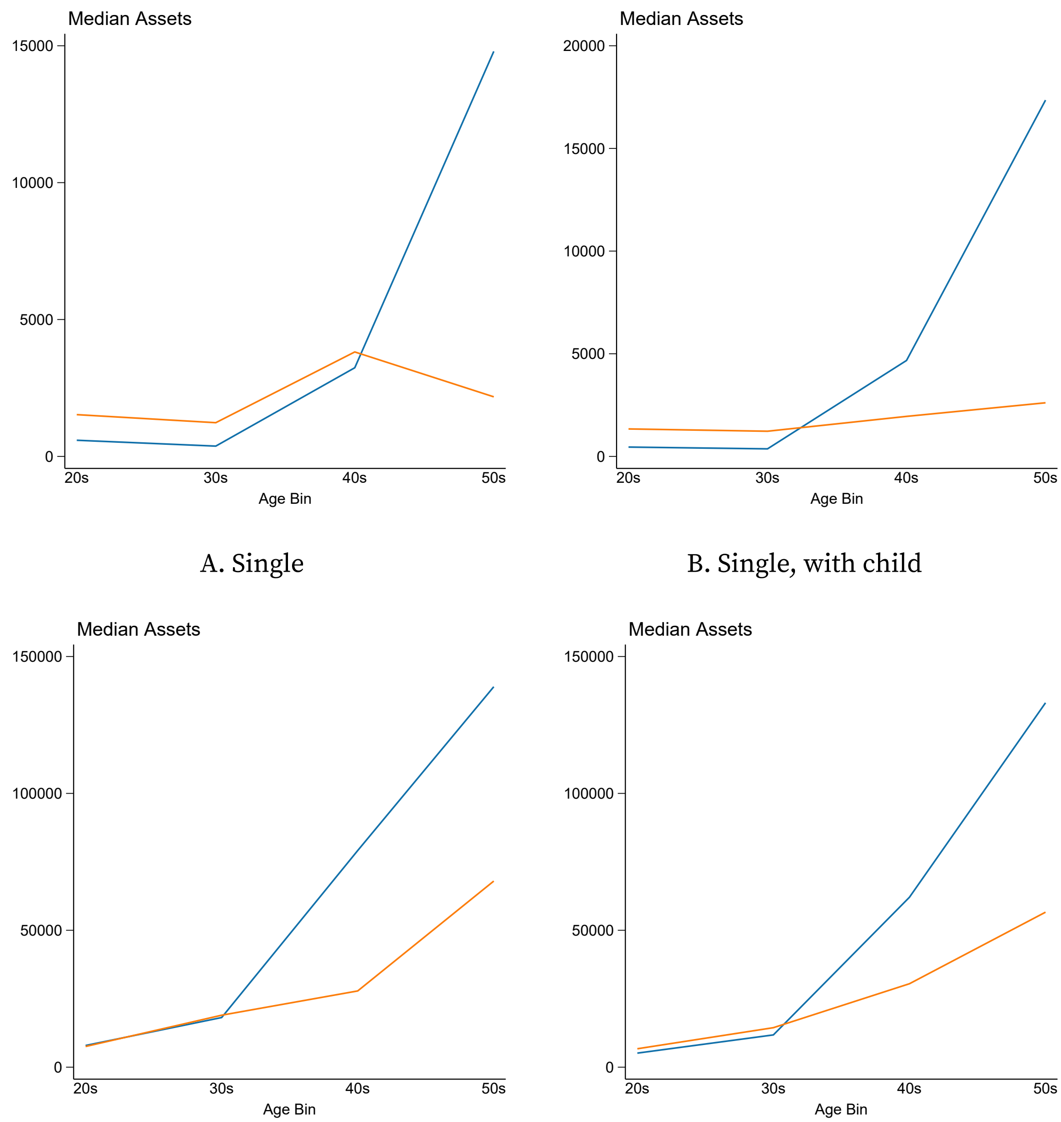
B. Model vs. Simulated Moments

The model fits moments related to asset accumulation less well. Figure 4 plots the median level of assets by age and family structure. For singles (Panels A and B) and couples (Panels C and D) the model slightly underpredicts savings in early life, but overpredicts savings in later life. The difficulty of the life cycle model in matching asset levels is well-established[37], particularly at the low end of the wealth distribution. The model only has one type of asset, which is liquid and simultaneously used to self-insure and finance consumption in retirement. In the data, individuals' wealth is held in a variety of asset types, some of which are liquid (bank deposits), some are illiquid (pension wealth), and some which provide nontrivial flow utility (vehicles). At the low end of the asset distribution, the timing assumptions implicit in the model also drive a wedge between savings in the model and the data. The concept of wealth in the model is the amount of resources left over after the period's consumption has occured, before income is next realized. There is no such concept in the data – in the case of checking accounts, individuals are simply asked how much is currently in the account – and so many people whose behavior could be described as "hand-to-mouth" will likely have nonzero wealth at any given time. Finally, the poor fit of near the end of life in particular is likely driven by the highly stylized retirement period. However, the portion of single and married women for whom the SSI asset limit is likely to bind, especially in their

[37]See, for instance, Hubbard, Skinner, and Zeldes (1995), Bernheim, Skinner, and Weinberg (2001), De Nardi (2004), and Lockwood (2018)

20s and 30s, is reasonably well matched.

FIGURE 4. Model Fit to Targeted Moments – Asset Moments



A. Single

B. Single, with child

C. Married

D. Married, with child

6.2. External Validity

In this section I analyze the model's ability to replicate patterns observed in the data that are not explicitly targeted in the estimation procedure. In particular, I assess the model's ability to generate plausible responses to incentives for work, the take-up of

SSI, and the effects of SSI on household income.

Table 8 reports model-implied Marshallian wage elasticities. I calculate these by simulating a permanent 5% wage increase for the women in the model, and calculate the increase in employment relative to the baseline simulations. My estimated elasticities are well within the range of empirical estimates surveyed in Keane (2011), as well as the recent structural estimates in Blundell et al. (2016) and Jakobsen, Jørgensen, and Low (2023). In addition, the qualitative patterns are consistent with prior literature. Women with children are more responsive to increases in wages than women without children, and the labor supply of single women is more elastic than is that of married women.

TABLE 8. Labor Supply Elasticities

	Own-Wage	Husband's Wage
Single women w/ no children	0.646	–
Single women w/children	1.203	–
Married women w/ no children	0.688	-0.574
Married women w/ children	0.877	-0.610

Next, I assess how well my model is able to replicate empirical estimates from existing studies which use design-based approaches. Table 9 reports the results. See Section **??** for more detail on the design of these studies, and how I calculate the simulated elasticities. Kubik (1999) uses state-level variation in SSI benefit generosity driven by interactions between AFDC and SSI benefits in the early 1990s to estimate the elasticity of SSI takeup with respect to benefit levels, finding an elasticity of 0.5.[38] My simulated elasticity, which is identical to that in Kubik (1999) is generated by comparing the number of SSI recepients in a simulation in which the SSI benefit schedule has been increased by 10% to the number of SSI recepients in the baseline simulation. The next set of estimates concern changes in family resources surrounding entry and exit from the child SSI program. The first study is Duggan and Kearney (2007), which studies the effect of child SSI entry using fixed effect regressions in the SIPP. The second study is Deshpande (2016b) which, using administrative data of child SSI recepients, studies program exit due to failing a continuing disability review, cohort-based variation in the likelihood

[38] Kubik (1999) also finds that higher SSI benefit levels also lead to an increase in the number of children diagnosed with chronic conditions, which he interprets as evidence that these policies promote the detection and treatment of underlying disabilities. My model is not able to speak to this result. In addition, Kubik (1999) is unable to distinguish between families receiving SSI due to a child's disability and those receiving SSI due to a parent's disability.

of receiving a review generated by a cut to the SSA's budget. These papers calculate the impact of SSI entry and exit on a variety of outcomes including parent's earnings, disability applications for other programs, and the fraction of children living in poverty. The fact that my model only includes a binary work decision, and that the father's labor supply is unable to adjust, means that the model has difficulty matching the change in parent's labor income surrounding program transitions. Indeed, Deshpande (2016b) the earnings response of parents to their child's SSI loss is driven by the intensive margin. In addition, the model's parsimonious measure of support from other government programs will have difficulty matching the extent to which changes in SSI income are offset by changes in other government transfers. I instead assess how well the model is able to match the change in family income that occurs upon SSI entry or exit. Overall, the model overstates the importance of SSI to total family income, but the qualitative patterns are consistent with the empirical estimates.

TABLE 9. Comparison to External Estimates

Paper	Estimated Quantity	External Estimate	Model Estimate
Kubik (1999)	Elasticity of SSI Takeup wrt Benefits	0.5	0.50
Duggan and Kearney (2007)	Δ Log(Family Income) upon SSI Entry	0.20	0.41
Deshpande (2016b)	Δ Log(Family Income) upon SSI Loss		
	All families	-.17	-0.19
	Single mothers	-.23	-0.31

Note. External estimates come from page 212 of Kubik (1999), Table 5 of Duggan and Kearney (2007) and the Treatment-on-the-Treated column of Table 3 of Deshpande (2016b) for the All Review group.

7. Simulation Analysis

In this section, I use the estimated model to analyze the insurance value and moral hazard cost of the Child SSI program, and to simulate the effects of a number of potential reforms.[39]

The welfare metric I utilize in this section is an ex-ante consumption equivalent. It is generated by first solving and simulating the model under a baseline policy regime, yielding for each simulated individual a set of consumption, labor supply and SSI application decisions, $c_{it}, P_{it}, \text{App}_{it}$. These can be used to calculate the present discounted

[39] All counterfactuals use a sample of 100,000 simulated individuals, as opposed to the estimation sample described in Section 5.2. This is because the counterfactuals require me to simulate the full life history of each individual, which I do not observe in the PSID.

lifetime utility in the baseline economy:

$$EV_0 \equiv \sum_{i=1}^{N}\sum_{t=1}^{T} \beta^t((c_{it}/n_{it})\exp\{-P_{it}\gamma_{z_{it},\theta it,m_{it}}\})^{1-\sigma}/(1-\sigma) - \eta_{m_{it}}\text{App}_{it}$$

Next, I simulate the model under a counterfactual policy regime, generating new consumption, labor supply and SSI application decisions, c^*_{it}, P^*_{it}, App^*_{it}. The consumption equivalent willingness to pay to live in the counterfactual regime is level of the consumption tax π^* such that total utility in the two regimes are equal:

$$\pi^* = \pi \quad \text{s.t.} \sum_{i=1}^{N}\sum_{t=1}^{T} \beta^t(((1-\pi)c^*_{it}/n_{it})\exp\{-P^*_{it}\gamma_{z_{it},\theta it,m_{it}}\})^{1-\sigma}/(1-\sigma) - \eta_{m_{it}}\text{App}^*_{it} = EV_0$$

This calculation can be performed for different subgroups of the population by taking the summation over all individuals in a given group, or for the population as a whole.

When comparing the welfare gains or losses from a policy relative to its effect on the goverment's budget, I calculate the present discounted cash value of the consumption equilavent:

$$\text{WTP} = \sum_{i=1}^{N}\sum_{t=1}^{T} \beta^t \pi c^*_{it}$$

7.1. The Insurance Value of the SSI Program

I first estimate the value of the insurance provided by the Child SSI program. To do so, I compare household's willingness-to-pay to move from a world in which SSI does not exist, to a world in which SSI does exist but is actuarially fair. I report results for a counterfactual under which everyone pays the same premium, and another where premiums are generated separately by permanent productivity group. This latter comparison is attractive because it eliminates the value the program may have ex-ante by redistributing between different productivity groups.

A necessary input into this experiment is the actuarially fair premium. This is generated by first calculating the expected present discounted value of SSI payments, starting from age 20, either the full population or sepatately by productivity group. Actuarial fairness requires that each woman "pay into" the program the same amount they expect to receive. However, I need to take a stand on the payment structure. It seems most natural to require that the premium is paid out annually over the time period that the woman is exposed to the risk insured by the program. Accordingly, I require the women in the sample to pay an annual premium each year it is possible for them to have a disabled child in the household which, given that fertility may occur until age 40, covers ages 20-57. The willingness-to-pay measures are also calculated over this range. I first calculate the willingness-to-pay for insurance for all women in the sample, then repeat the experiment including only those who eventually become parents.[40] In the second case, the annual premiums will be higher, but the probability that woman eventually has a disabled child will be higher as well.

Table 10 reports the results of this analysis. In the left-most column, the actuarially fair premium is calculated assuming no price differentiation between productivity groups, while in the latter three premiums are differentiated by productivity group. Row (1) reports the actuarially fair premium. Unsurprisingly, the premium necessary to ensure actuarial fairness is decreasing in productivity. This is due both to the fact that women in the higher-productivity groups are less likely to have a disabled child, and also to the progressivity of the SSI payment schedule. Row (2) reports the mean share of annual consumption these women are willing to give up in order to live in a world with actuarially fair SSI, relative to a world with no SSI. Row (3) reports this measure in dollar terms, calculated by multiplying the value from row (2) with present discounted lifetime consumption, then converting to an equivalent annual value to make comparable with the premium.[41] Finally, Row (4) reports the maximum implicit price the women in the sample are willing to pay for SSI. This term is simply the ratio of the annual premium necessary for the willingness-to-pay to be equal to zero, divided by the actuarially fair premium. The bottom panel (rows (5)-(8)) repeats the same exercise for the sample who eventually becomes a mother. These women are by definition more likely to have a child with a disability which increases the likelihood that they will receive SSI, which accordingly means they will face higher premiums.

The results indicate that the insurance value from SSI is sizeable. The women in the full sample are willing to pay 2.3-3.4 times the value of the benefits they expect to receive in order to be insured through the program. For the group of women who eventually become mothers, this implicit price is 1.8-2.6, reflecting their higher baseline premium. Perhaps surprisingly, the implicit price is higher for the high-productivity

[40]This subset analysis is valid to the extent that fertility decisions are not influenced by the SSI program.

[41]Letting *PDV* be the present discounted value, r the interest rate and T the number of periods in the lifecycle, I report $\frac{PDV*r}{1-(1+r)^{-T}}$.

groups, who are less likely to have a child with a disability. This occurs for two reasons. The first is that their annual premium is lower, both in absolute terms due to their lower likelihood of having a disabled child and recieving SSI benefits, and also in relative to their expected family income due both to their higher wages and higher likelihood of being married. The second is that, for these women, the states of the world in which they are able to meet the income and asset tests are worse relative to their lifetime average than for the lower productivity groups. This pattern is consistent with Bound et al. (2004), who find that the willingness-to-pay for disability insurance is increasing in education.

TABLE 10. Willingness to Pay for Actuarially Fair SSI

			Premium Priced By Productivity Group		
		No Price Differentiation	Low Prod.	Medium Prod.	High Prod.
	Full Sample				
(1)	Actuarially Fair Premium ($s/yr)	60.13	106.00	40.31	9.05
(2)	WTP (ppt)	0.23	0.42	0.15	0.06
(3)	WTP ($s/yr)	121.03	135.97	76.38	43.37
(4)	Implicit Price ($s)	2.74	2.33	1.96	3.39

7.2. Quantifying the Excess Burden Generated by Child SSI

Results from the previous section indicate that the insurance value of SSI is sizeable, net of the distortions generated by the program. A natural question is how economically important these distortions are. This section quantifies these distortions by calculating the excess burden, or efficiency cost, of the program. We might expect the excess burden associated with the program to be large for at least two reasons. The first is that female labor supply is thought to be highly elastic (Keane, 2011). The second is that the distortions generated by the program are potentially sizeable (i.e. the 50 percent marginal tax rate on earnings, and the asset limit).

If SSI were a tax, the calculation of the excess burden would be straightfoward – simply remove the program, and the difference between the change in tax revenue and the change in household welfare is the excess burden. This setting is more complicated because removing child SSI will remove both the distortions generated by the program and the value of the insurance recieve from the program, which the previous section indicates is likely to be non-trivial. I proceed by estimating the willingness-to-pay of women to replace the current SSI program with one which maintains the insurance value of the program, but eliminates the distortions generated by the program.

I calculate the non-distortionary SSI payment schedule by simulating the model under the baseline regime, then calculating the average SSI payment for each combination of the exogenous state variables.[42] Next, I calculate individual's willingness-to-pay to move from the current SSI program to the non-distortionary program. To the extent to which SSI payments alter labor supply in this regime, it will only be through income effects. Moreover, this counterfactual program does not distort savings behavior. Expected lifetime SSI payments are unchanged in these two regimes, so any willingness-to-pay will be due to the removal of the distortions generated by the program.

The results are reported in Table 11. Rows (1) and (2) generate the willingness-to-pay of annual consumption the women in the sample are willing to pay to remove the distortions generated by SSI. Row (3) reports the amortizated present discounted value of SSI payments, and row (4) reports the ratio of (2) to (3). This is the ratio of the behavioral cost of the program to its mechanical cost, as in Schmieder and Von Wachter (2017). These results indicate it costs roughly an additional $0.38 to transfer a dollar of income through the SSI program. For context, a survey of the UI literature finds that the median value of the behavioral cost of increasing benefit durations (levels) is roughly $0.60 ($0.35) (Schmieder and von Wachter, 2016), while the excess burden associated with an increase in the personal tax rates has been estimated to be roughly $0.75 (Feldstein, 2006). Overall, the excess burden generated by SSI appears to be well in the range of other government programs.

Table 11. The Excess Burden Generated by SSI

		Full Sample	Low	Median	High
	Sample: All Women				
(1)	Excess Burden (ppt)	0.03	0.05	0.02	0.01
(2)	Excess Burden ($s)	15.73	17.42	11.50	4.55
(3)	PDV SSI ($s)	41.44	85.13	33.76	5.43
(4)	Ratio	0.38	0.20	0.34	0.84

[42]The exogenous state variables are the woman's age, the age of her youngest child, the child's disability status, the woman's marital status, her permanent productivity group, and the cumulative realization of her wage shocks. The wage shocks are continuous, and so I discretize their values into age-specific quintiles. In order to reduce noise, I bin the womans age into 5 year bins and the age of her youngest child into school aged and not school aged.

7.3. Reforms To The Program

Finally, I use the estimated model to analyze the effects of changing the structure of the Child SSI program on behavior and welfare. I consider four reforms: (i) raising the asset limits to $10k for singles and $20k for couples, following Sen. Brown (2022); (ii) increasing the generositiy of payments by 10%; (iii) making the program "less strict" by increasing the likelihood an applicant will be accepted onto the program.

The results are reported in Table 12. Each column reports the results from a different policy counterfactual. The first row reports the willingness to pay for the reform in percentage point terms, while the next row reports the willingness to pay in dollar terms, as calculated in the previous section. Finally, I report the change in the government's budget as a result of the reform, and finally the raio of the willingness to pay to the change in the government's budget. The willingness to pay for each reform outweighs the cost to the government. However, the total cost to the government is understated, as these calculations do not incorporate the efficiency cost of paying for these reforms, if the government were to raise taxes to finance them. Of the three reforms, the asset limit is the least effective at raising welfare per dollar spent. This is likely because, given the low level of assets held by women in the model, the asset limit is unlikely to be binding, and those newly eligible for SSI are likely to be relatively better-off. An important caveat to these calculations is that it is only the behavior of women without a college degree who are modeled. It is plausible that raising the asset limit, in particular, would widen the scope of the program. The model is not equipped to quantify the importance of this margin.

TABLE 12. The Value of Reforms to the Program

	Asset Limit	Benefit Levels Up %10	Acceptance Probability to 60%
WTP ($s/yr)	46.35	84.35	99.59
Δ PDV G ($s/yr)	32.13	43.22	41.71
Ratio	1.44	1.95	2.39

8. Discussion

This paper assesses the insurance value and moral hazard cost of the Child SSI program. The Child SSI program provides generous transfers to families whose children have disabilities, but its means tests may both limit its insurance value and generate economically meaningful deadweight loss. Given the growth of the program in recent decades, it is important to understand whether the program effectively serves its purpose of insuring families against the additional costs associated with raising a child who has a disability. I estimate a life cycle model of female labor supply, savings and SSI applications in order to estimate the insurance value of the SSI program, the deadweight loss generated by the program, and the efficacy of several reforms to the program. I find that the insurance value generated by the program is sizeable – women in the model are willing to pay 2.7 times the actuarially fair premium in order to be able to access the insurance. Moreover, I find that the deadweight loss generated by the program is in line with studies analyzing other programs. This latter finding is potentially surprising, due both to the potentially large distortions generated by the program's rules, and the extent to which the population whose behavior is likely distorted supplies labor highly elastically. Finally, I find that a series of policy counterfactuals are generally valued at more than their cost, but increasing the asset limit is the least cost-effective.

The estimated model makes several simplifying assumptions in the interest of tractability that should be considered when interpreting the results. I have abstracted from the fact that Child SSI often automatically grants Medicaid eligibility,[43] which would lead estimates of the program's value to recepients to be understated. In addition, the fact that the model abstracts from health production means that it cannot capture any positive effects associated with increased family resources on the child's health, or for peverse incentives associated with suboptimal investments so that the child may be eligible for benefits. Also, the model does not include any direct costs associated with the child's disability, such as increased expenditures due to medical care or special education, although the literature on childhood disability (Stabile and Allin, 2012) suggests that these are quantitatively less important than the effect of limiting work capacity. Finally, the program's rules – in particular the only $1k higher asset limit for married couples – plausibly alter incentives to become or remain married. These are all exciting opportunities for future work.

[43]This is true for most states, but is not uniform. Duggan and Kearney (2007) show that upwards of 60% of children who enter onto SSI were already recieving Medicaid before applying.

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A. Appendix Tables and Figures

A.1. Tables

	Single	Married
No children	0.50	0.51
Child aged 0-5		
No Disability	0.48	0.78
Disability	1.15	0.81
Child aged 6-17		
No Disability	0.43	0.49
Disability	0.89	0.48

Appendix Table A1. Work Related Parameters

	Single	Married
SSI Application Cost η		
	10.878	12.458
Retirement Adjustment Factor χ	0.950	0.950
Acceptance Probability	0.538	
Consumption Floor	4675	

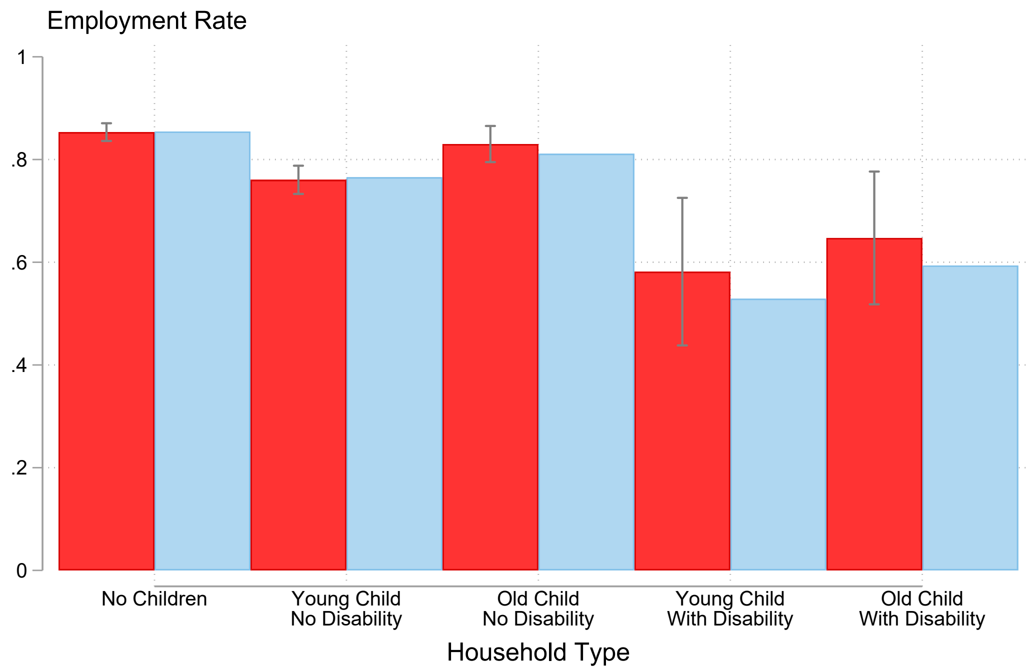
Appendix Table A2. Other Parameters

Mental Disorders	62.4
Autism	*18.6*
Developmental disorders	*19.2*
Mood disorders	*3.0*
Organic mental disorders	*1.7*
Other mental disorders	*0.8*
Unclassified	*19.1*
Physical or Intellectual Disorders	27.3
Intellectual disability	*9.2*
Congenital abnormalities	*5.6*
Nervous system and sense organs	*7.3*
Circulatory system	*1.3*
Digestive system	*1.4*
Genitourinary system	*0.2*
Musculoskeletal system	*0.8*
Respiratory system	*1.3*
Skin	*0.2*
Injuries	0.5
Cancers	0.8
Endocrine, nutritional, metabolic diseases	0.7
Other	5.5
Unknown	1.1

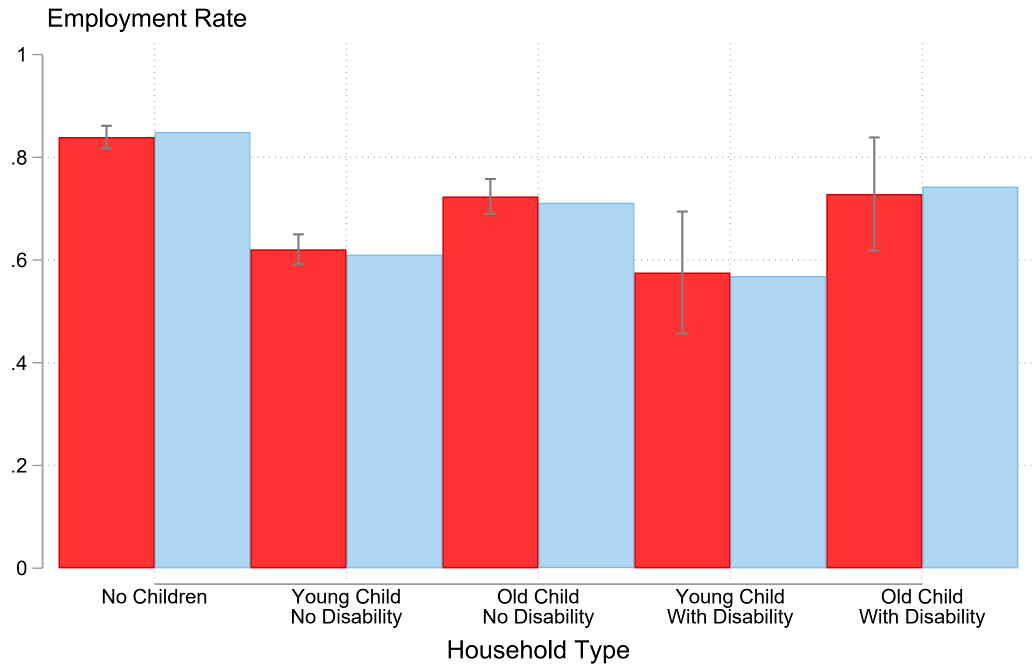
Appendix Table A3. Child SSI Caseload: 2019

A.2. Figures

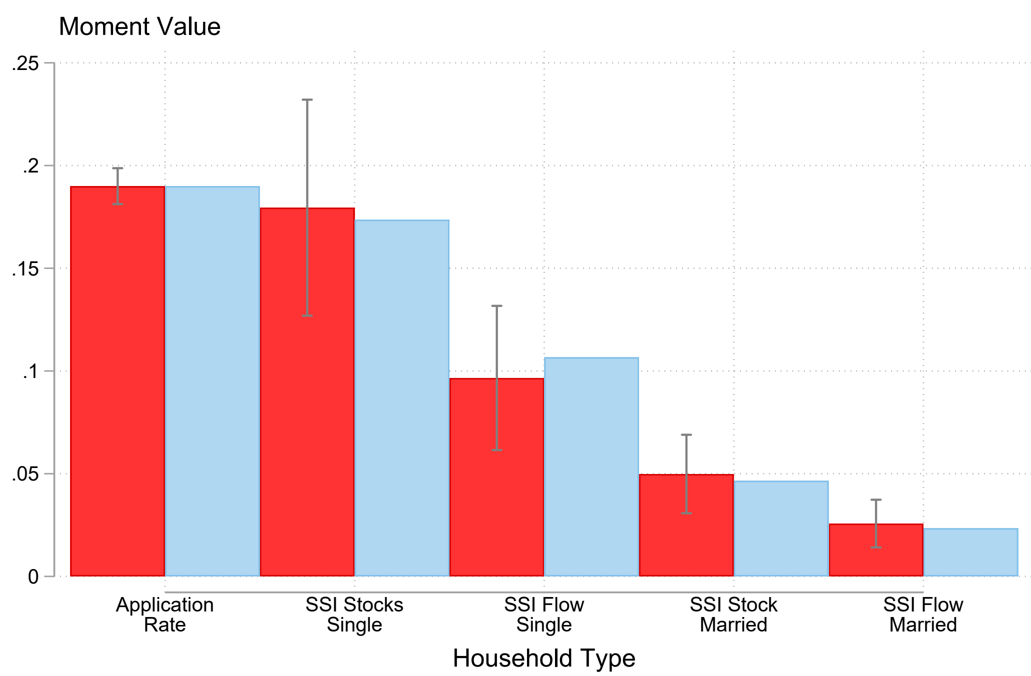
Appendix Figure A1. Employment Moments: Single Women



Appendix Figure A2. Employment Moments: Married Women



Appendix Figure A3. SSI Moments



B. Definitions of PSID Measures

B.1. Income

B.2. Child SSI

This section describes how I construct a variable indicating whether a household has received any income from the child SSI program in a given year.

In each wave from 2005 onwards, the PSID asks about the SSI receipt of each individual in the household in the prior year. From 1999 to 2007, each individual's SSI receipt in the two years prior to the interview was ascertained. If an individual was reported to have received SSI in a year in which they are younger than 18 years old, I code that family as having received child SSI in that calendar year.

In XYZ the PSID asks the reference person and their spouse whether they received SSI, and if so whether they received it for themselves or someone else. These variables are available in each survey wave from 1995. If either the reference person or their spouse reports recieving SSI for someone else, and there is a child in the household, I code this household as having received child SSI.

Finally, there is a variable that asks whether any others in the household received child SSI. If this variable is coded as yes, and there is a child in the household, I assign this family as having received child SSI in that calendar year.

B.3. Consumption

B.4. Wealth

I use wealth information collected in 1994 and biannually since 1999. The wealth information in the PSID covers nine categories: business assets, transaction accounts (including savings), home equity, equity in vehicles, stocks, other real estate equity, retirement acount, other assets and other debts. My sample restriction removes those with self-employment income, who are more likley to hold business assets. Further, to maintain consistency with the asset measure most-relevant for the SSI asset test, I track household's "liquid assets", which are each of the above categories less home equity and equity in vehicles. Broadly speaking the wealth data in the PSID is considered to be high-quality.

B.5. Disability

I construct measures of childhood disability using the Primary Caregiver Child Interview of the PSID's Child Development Supplement. In this interview, each child's primary caregiver is asked detailed questions about the child's health and disability status. In particular, the parent is asked about the child's general health status, the diagnosis of any chronic conditions, and disability. The list of all chronic conditions that are inquired about are listed in table XYZ. In order to generate a concept of child disability that is plausibly informative about eligibility for child SSI, I also include information on the child's activity limitations. While the information about chronic conditions are objective – "has a medical professional ever told you that...." – the questions about a child's activity limitations are ultimately subjective. The questions are as follows: "Does (CHILD) currently have any physical or mental condition that would limit or prevent (his/her) ability to...do usual childhood activities such as play, or participate in games or sports?" "Does (CHILD) currently have any physical or mental condition that would limit or prevent (his/her) ability to attend school regularly?" "Does [CHFName] currently have any physical or mental condition that would limit or prevent (his/her) ability to do regular school work?"

Some of these questions are necessarily age-specific. Accordingly, I require the children in my sample to have been interviewed at least once when school-aged. In order to make the empirical exercise consistent with the model – in which disability status is drawn at birth – I categorize children as having an activity limiting disability if they ever are reported as having one.

Table B1 reports the chronic conditions which are reported in the Child Development Supplement, and which disability group each is assigned to.

Appendix Table B1. Chronic Conditions in the Child Development Supplement

Condition	**Group**
Ever had an epileptic fit or seizure	
Asthma	
Diabetes	
Chronic Ear Infections	
Speech impairment	
Serious difficulty hearing or deafness	Physical or Intellectual Disability
Serious difficulty seeing or blindness	Physical or Intellectual Disability
Intellectual Disability	Physical or Intellectual Disability
Serious emotional disturbance	Other Mental Health Disability
Anemia	
High Lead Levels	
Orthopedic Impairment	Physical or Intellectual Disability
Developmental Delay or Learning Disability	Other Mental Health Disability
Autism	Other Mental Health Disability
Hyperactivity	Other Mental Health Disability
Other	

C. Numerical Solution of the Model

This appendix discusses the details of the numerial solution of the model. I solve the model using backward induction. At each age, I compute the optimal saving, consumption, labor supply and SSI application decision for all possible combinations of the state variables. I then use the policy functions to compute the value function and iterate backwards.

C.1. Discretization

The model has 7 discrete state variables: type, age, experience in the labor market, the presence of a child and their disability status, whether receiving SSI and marital status. There are 3 additional state variables that need to be discretized: assets, and the permanent wage shock of both the woman and her husband (if he exists). Assets are placed on a grid of 60 points over an exponential scale with additional grid points just above and just at each SSI asset limit. I place the permanent component of the husband's labor income and the woman's wage on a grid with 5 points, using the method of the Rouwenhorst (1995), extended by Fella, Gallipoli, and Pan (2019) for nonstationary processes.

There are four control variables in the model; the labor supply decision, the decision of whether to apply for SSI, how much to save and how much to consume. The first two are naturally discrete. Consumption and next-period savings are not placed on a grid –

individuals are allowed to choose any level of consumption or savings which satisfies the budget constraint. This is made possible by the solution method.

C.2. Integration

Calcuating the continuation value of the household's problem requires integrating the value function over the stochastic variables. These are family transitions – marriage and divorce in every period, as well as fertility if there is no child in the household. If the household has applied for SSI, there is also uncertainty regarding the realization of the SSI screening process. I integrate over the possible realization of these shocks by taking a weighted average of the value function realized at each possible outcome, with the weights equal to the probability of that outcome. Finally, there is uncertainty relating to future evolution of the permanent wage shocks. The integration along this dimension is carried out using the node weights provided by the Fella, Gallipoli, and Pan (2019).

C.2.1. Post Retirement Solution

After retirement, the state variables for the household are their current level of assets and their annual retirement benefits, and the only choice is how much to consume or save. The problem thus turns into a standard consumption savings problem without any uncertainty. Define $M_t = A_t + B_t$ as the household's cash-on-hand at the beginning of period t, using the notation of Deaton (1991). The problem can be written in recursive form as

$$\begin{aligned} V_t(M_t, B_t) &= \max_{c_t \in [0, M_t]} u(c_t) + \beta V_{t+1}(M_{t+1}, B_{t+1}) \\ \text{s.t.} \quad M_{t+1} &= (1+r)(M_t - c_t) + B_{t+1} \end{aligned}$$

For households who are not budget constrained, the Euler equation must hold:

$$c_t^{-\sigma} = \beta(1+r)c_{t+1}^{-\sigma}.$$

Applying the inverse of the marginal utility of consumption to both sides of the equation yields

$$c_t = (\beta(1+r))^{\frac{-1}{\sigma}} c_{t+1}.$$

I use the Endogenous Grid Method (EGM) (Carroll (2006)) to solve for the optimal level of period t consumption on an endogenous grid of current-period cash on hand M_t. I then use the budget constraint to back out beginning-of-period assets, which is the state variable.

C.2.2. Pre-Retirement Solution

The pre-retirement solution requires solving for the optimal consumption, savings, labor supply, and SSI application decisions for each possible combination of the state variables. The continuation value of the model in this paper is not globally concave in assets due both to the presence of the consumption floor and also the discrete labor supply and SSI application decisions. Both of these features generate kinks in the value function, which imply that the Euler equation may have multiple solutions, hence being only necessary and not sufficient for finding the optimal consumption rule. Accordingly, I follow a modified version of the EGM described by Iskhakov et al. (2017) to find the optimal policies. This variation of Carroll (2006) generates conditional (on labor supply and SSI application) optimal consumption and savings policies using conditional Euler equation. One additional complication is that the optimal consumption and savings decisions are generated on a grid of total resources M_t conditional on the discrete choices, rather than on a grid of assets, which is the state variable. To get the solution on the grid of assets, I construct an exogenous grid of resources M_t^* using the beginning-of-period grid of assets and the budget constraint, then interpolate the solution from the DCEGM step onto this grid. When performing the interpolation, I use the upper envelope algorithm provided by Druedahl (2021) to select optimal policies in regions of the endogenous cash-on-hand grid where multiple solutions to the Euler equation are detected. This procedure follows the approach in Jakobsen, Jørgensen, and Low (2023).

D. Taxes and Transfers

D.1. Social Security Benefits

This section describes how retirement benefits are computed in the model. The true computation of Social Security benefits is complex, and depends on the age at which the individual retires, their earnings history, and the history of any previous spouse's earnings. The stylized version of social security benefits modeled in this paper is meant to capture the essential features of the program, while avoiding additional state variables. This is particularly important as the state space is already large, and behavior in retirement is not a focus of the paper.

Social Security benefits, both in reality and in the model, are based off of earnings history. In reality, average lifetime earnings are modified by a progressive formula, and then indexed to inflation. In the model I use the most recent year of earnings instead of lifetime earnings in order to not add an additional state variable to the model, capping at the maximum taxable earnings cap e^{max}, which is set at $118, 500.[44] Let this value be denoted Y^*_{it}. Then the Social Security benefit for each spouse is calculated as

$$\begin{aligned} B_{it} =& 0.90 \times \min\{Y^*_{it}, a_1\}+ \\ & 0.32 \times \min\{\max\{Y^*_{it} - a_1, 0\}, a_2 - a_1\}+ \\ & 0.15 \times \max\{Y^*_{it} - a_2, 0\} \end{aligned} \tag{13}$$

Where a_1, a_2 are the bend points which reflect the progressive income replacement factors (90%, 32% and 15%), and are set at $9,912 and $59,760 following the program rules in 2015. For married couples, household benefits are the sum of the benefits of each spouse, calculated according to the above formula. For divorcees, legislative benefits in are calculated based on the earnings history of the ex-spouse, and are equal to 50% of the ex-spouse's benefits if the marriage lasted at least 10 years. I do not track the length of marriages in the model, and instead as a middle ground assume that single retirees receive a benefit equal to one-quarter of the benefits of a husband with the average level of earnings at age 62.

E. Details of the estimation of the wage process and productivity risk

E.1. Female Wage Process

The log wage process for women is

$$\ln(w_t) = \alpha_1 \exp_{it} + \alpha_2 \exp^2_{it} + f_{g(i)} + F_{it} + \omega_{it}$$
$$F_{it} = F_{i,t-1} + \varepsilon_{it}, \quad \varepsilon_t \sim \mathcal{N}(0, \sigma_\varepsilon)$$

[44]See https://www.ssa.gov/oact/COLA/bendpoints.html

where ω_{it} is i.i.d. measurement error.

The results of the first stage regression are reported in Table C1. I report results from a probit of employment on potential government transfers. In particular, for each woman in the sample I calculate the maximum amount of AFDC or TANF transfers, food stamps, and EITC benefits she would be eligible for were she to apply, which are a function of her current state, her family size, and the year. I use potential benefits rather than actual benefits because the take-up decision is itself endogenous. This estimation strategy is essentially a simulated IV in the spirit of Currie and Gruber (1996). When

Appendix Table C1. Female Wages – First Stage

	(1) Employment rate
Employment rate	
Max SNAP (x100)	-0.0108
	(0.106)
Max ADFC/TANF (x100)	-0.0441**
	(0.0212)
Max EITC (x100)	0.0116**
	(0.00506)
Constant	0.884**
	(0.362)
p-value exclusion restrictions	
Observations	0.00
N	36300.00

Note. SE clustered by individual in parentheses. Sample includes all women aged 20-57 w/o a college degree. Restricted to post-1990.

estimating the wage equation, I include the inverse Mills ratio from the employment regression as additional control variables. Further, I estimate the wage equation with individual fixed effects to remove the effect of unobserved permanent heterogeneity. The results are in Table C2. As with male wages, I estimate concave returns to experience.

	(1) lrwage
exp_any	0.0542***
	(0.0149)
exp_NT	-0.0580***
	(0.0223)
exp_any × exp_any	-0.000458***
	(0.0000830)
exp_any × exp_NT	0.0000167
	(0.000502)
exp_NT × exp_NT	0.00380***
	(0.00103)
Constant	1.489***
	(0.398)
Observations	25890

Note. SE clustered by individual in parentheses. Sample includes all women aged 20-57 w/o a college degree. Restricted to post-1990.

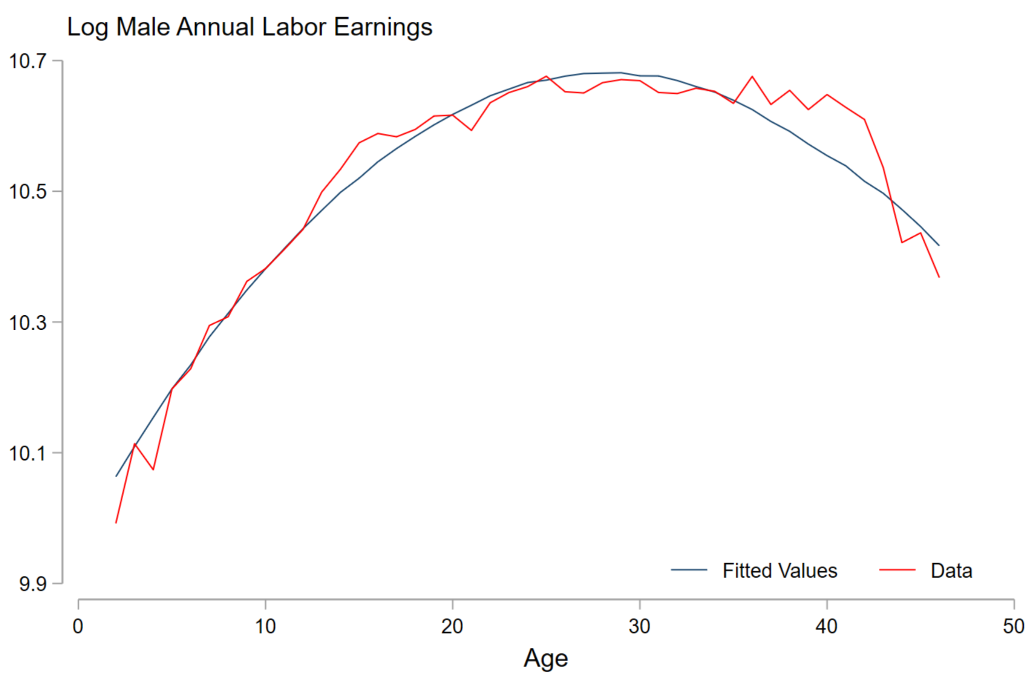
Appendix Table C2. Female Wages

E.2. Male Wage Process

	(1) Labor Income
Age	0.0501***
	(0.00309)
Age sq. (x100)	-0.000889***
	(0.0000725)
Constant	9.921***
	(0.0343)
Observations	43208

Note. SE clustered by individual in parentheses. Sample includes all men aged 20-57 w/o a college degree. Restricted to post-1990.

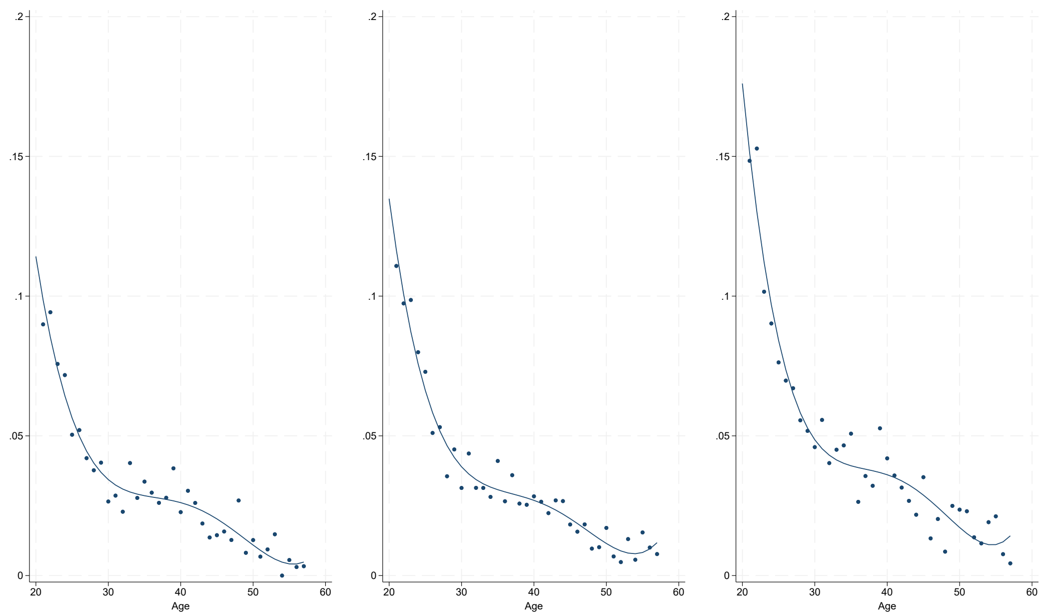
Appendix Table C3. Male Earnings



Appendix Figure C1. Model Fit of Log Male Labor Earnings

F. Second-Stage Estimation

I allow marital transitions to differ by whether there is a child in the household, and fertility to differ by marital status. In addition, each transition probability may vary by household type. However, these transitions are assumed to be independent of any household choices. I therefore estimate the transition probabilities by a fourth-order probit in age, separately by household type and presence of children/marital status.



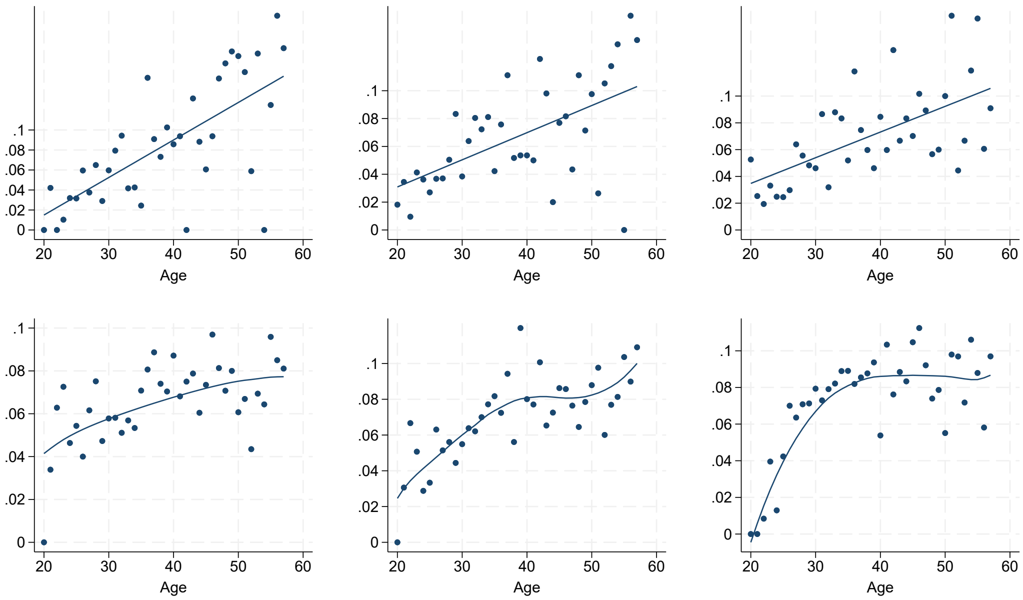
Appendix Figure C2. Marriage Transitions

G. The SSI Application Parameters

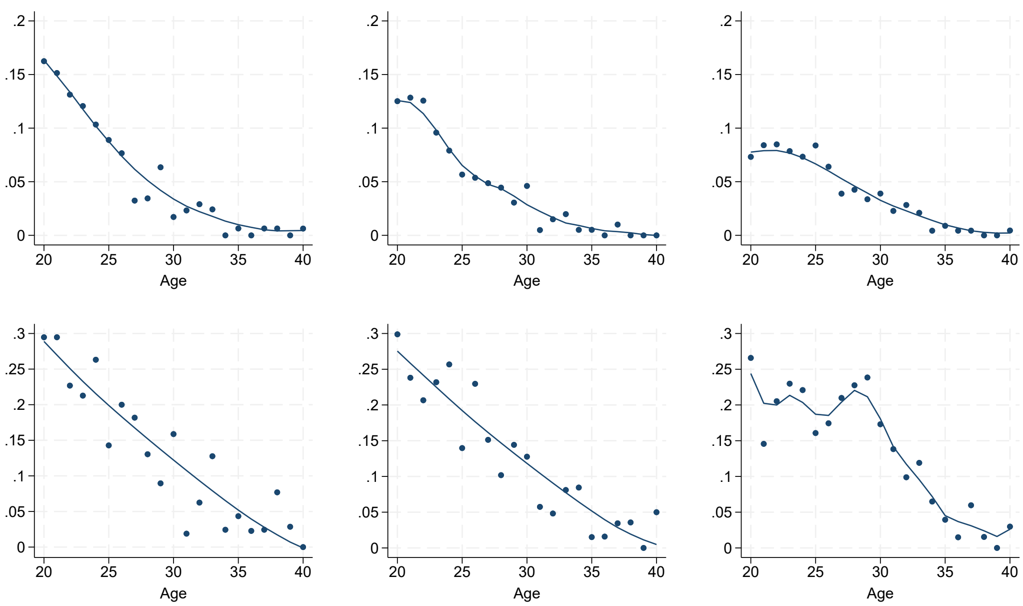
This section demonstrates what is necesary for XYZ. I attempt to match $\eta^{Married}_{\theta=3}$. I use the fraction who moves onto SSI as an auxilary moment. Let $\Gamma = \{SSI_{t-2} = 0, \theta_{t-2} = 3\}$ be the group plausibly eligible for SSI in the relevant group. Then

$$Fr(SSI_t = 1|\Gamma) = Pr(SSI_t = 1|\Gamma, SSI^{App}_{t-2} = 1) * Pr(SSI^{App}_{t-2} = 1|\Gamma)$$

If everyone applied for SSI, then the acceptance probabilities would equal the flow fraction onto SSI. However, not everyone applies for SSI. In the model, $Pr(SSI^{App}_{t-2} =$



Appendix Figure C3. Divorce Transitions



Appendix Figure C4. Fertility Transitions

$1|\Gamma) = Pr(\beta * (EV(SSI) - EV(NoSSI)) > \eta^{Married}_{\theta=3})$. The discounted benefit of applying is a function of preference parameters, and should be roughly flat in η.

H. SSI Policy Details

For children receiving SSI, the income and assets of their parents are counted towards their income and assets through a process called *deeming*. In particular, asset eligibility for children is determined by first calculating the value of the parent's asset holdings net of excludable categories. Applicants then subtract the amount of the adult income limit – $2000 for singles, $3000 for a married couple – from that level of assets, and then apply the individual asset limit for children is the same as that for individual adults ($2000).

Similarly, income eligibility for children is based on whether the child would be income-eligible for SSI if they were adults, with income from parents included in the deeming process. Income eligibility is determined by your "countable income" relative to the maximum Federal Benefit Rate. Countable income is your total income net of income excluded from SSI eligibilty determiniation. This includes, amongst other things, the value of SNAP payments, the first $20 of most income received in each month, the first $65 of earnings and half of all earnings over $65 received per month. If the child's parents would be income-eligible for SSI based off of their own income, then none of the parent's income is deemed to the child. If the parent's income exceeds the threshold for SSI eligibity, then income over the threshold is deemed to the child as unearned income. This income is then added to additional income the child may have, and counted as unearned income. Finally, the earned and unearned income exclusions are applied to the child's calculated income. If the child's income is less than the FBR, then the child receives the full FBR. If it is greater than the FBR, income is phased out at an effective 50% marginal tax rate. In practice, parent's earnings can be quite high before this occurs.

I. Variance

Following Low et al. (2022), the variance of the permanent component of men's earnings $\tilde{\sigma}^2$ are identified by the moment conditions

$$\mathcal{E}[\Delta\tilde{u}_t^2] = \tilde{\sigma}^2 + 2\tilde{\sigma}_{ME}^2$$
$$\mathcal{E}[\Delta\tilde{u}_t\Delta u_{t-1}] = -\tilde{\sigma}_{ME}^2$$

where $\tilde{u}$ are the residuals from the wage equation described in the main text and $\tilde{\sigma}_{ME}^2$ is the portion attributable to measurement error.

The variance of the permanent innovation to female productivity needs to account for selection into work. Again, letting u be the residuals from the wage equation, the variance of the permanent component is

$$E\left[\Delta u_t \mid P_t = 1, P_{t-1} = 1\right] = \sigma_\nu \left[\frac{\phi\left(\alpha_t\right)}{1 - \Phi\left(\alpha_t\right)}\right]$$
$$E\left[\Delta u_t^2 \mid P_t = 1, P_{t-1} = 1\right] = \sigma^2 + \sigma_\nu^2 \left[\frac{\phi\left(\alpha_t\right)}{1 - \Phi\left(\alpha_t\right)}\alpha_t\right] + 2\sigma_{ME}^2$$
$$E\left[\Delta u_t \Delta u_{t-1} \mid P_t = 1, P_{t-1} = 1, P_{t-2} = 1\right] = -\sigma_{ME}^2$$

where $\tilde{\sigma}_{ME}^2$ is the variance of the innovation I attribute to measurement error and σ_ν^2 is the variance of the error term in the selection equation.

J. Minimizing the GMM Objective Function

I minimize the GMM objective function using a nested procedure. I search over the values of the parameters which are most likely to affect savings decisions – the consumption floor and the retirement adjustment factors – in an outer loop. For each guess in this outer loop, I search over the values of the remaining parameters which minimize the non-wealth moments. The labor supply moments are monotonic in the disutility from work parameters, but at which they are able to match the labor supply moments is highly dependent on the consumption floor. This is because the consumption floor sets the level of utility for most non-workers (i.e. those with low assets). Similar dynamics occur with the consumption floor – for a given level of the consumption floor the SSI-related parameters can be set to closely match the data, but these may differ for a different level of the consumption floor.