

Disability Insurance and the Dynamics of the Incentive-Insurance Tradeoff*

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Abstract

We provide a lifecycle framework for comparing the insurance value and the incentive cost of disability benefits. We estimate the risks that individuals face and the parameters governing the disability insurance program using longitudinal US data on consumption, health, disability insurance, and wages. We characterize the economic effects of disability insurance and study how policy reforms impact behavior and household welfare. Disability insurance is characterised by high rejection rates of disabled applicants; acceptances of healthy applicants is less widespread. Welfare increases as: (1) the program becomes less strict, reducing rejection rates among the disabled, despite the worsening of incentives; (2) generosity is reduced or reassessments increased because false applications decline; (3) the generosity of unconditional means-tested benefits is increased.

JEL Codes: D91, H53, H55, J26

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1 Introduction

The Disability Insurance (DI) program in the US is a large and rapidly growing social insurance program offering income replacement and health care benefits to people with work limiting disabilities. In 2007, the cash benefits paid by the DI program were three times larger than those paid by Unemployment Insurance (UI) (\$99.1 billions vs. \$32.5 billions)¹ and between 1985 and 2007 the proportion of DI claimants in the US has almost doubled (from about 2.5% to almost 5% of the working-age population, see Duggan and Imberman, 2009). The key questions in thinking about the size and growth of the program are whether program claimants are genuinely unable to work, whether those in need are receiving insurance, and how valuable is the insurance provided vis-à-vis the inefficiencies created by the program.

In this paper we evaluate the welfare consequences of reforming some key aspects of the DI program that are designed to alter the dynamics of the trade-off between costs and insurance aspects of the program. This evaluation exercise requires a realistic model of individual behavior; a set of credible estimates of preferences, risks, and of the details of the program; and a way to measure the welfare consequences of the reforms.

We address these aims in three steps. First we propose a life cycle framework that allows us to study savings, labor supply, and the decision to apply for DI under non-separable preferences. We consider the problem of an individual who faces several sources of risk: a disability or work limitation shock which reduces the ability to work, a permanent productivity shock unrelated to health (such as a decline in the price of skills), and labor market frictions. We assume that the DI program screens applicants with errors and re-assesses them probabilistically following award. Second, we obtain estimates of the parameters of the model using microeconomic data from the Panel Study of Income Dynamics (PSID) and the Consumer Expenditure Survey (CEX). We use data on employment, wages, consumption, and self-assessed reports of disability which allow us to distinguish between no, moderate, and severe work limitations. Identification is in three stages: first, we estimate health risk directly from transitions across health status over the lifecycle, assuming that health status evolves exogenously; second, we estimate wage risk and the effect of disability on wages by using data on wages and the variance of unexplained wage growth, controlling for selection

¹The relative size of DI is even larger if we add the in-kind health care benefits provided by the Medicare program to DI beneficiaries. After 2007 the differences are less dramatic due to the recession-induced expansion of UI.

into work. Third, we use our model to identify through indirect inference the preference parameters and the parameters of the DI program. This involves using information on the recipients of DI, as well as individuals' participation and consumption decisions across the life-cycle. We show that the model replicates well salient features of reality both internally in terms of matching targeted moments, as well as externally in terms of matching from the literature reduced form elasticities measuring the costs of the program, screening errors, exit flows, and wealth patterns. In the final step of the paper, we analyze the impact on welfare and behavior of varying key policy parameters: (a) the generosity of disability payments, (b) the stringency of the screening process, (c) the generosity of alternative social insurance programs, and (d) the re-assessment rate. The ability to evaluate these questions in a coherent, unified framework is one of the main benefits of the paper. Our metric for household welfare is the consumption equivalent that keeps expected utility at the start of life constant as policy changes. We show that the welfare effects are determined by the dynamics of insurance for disabled workers ("coverage") and of application rates by non-disabled workers ("false applications") as the policy changes.

We document a number of important findings. First, the disability insurance program is characterized by substantial false rejections. Our distinction between those with no work limitation versus a moderate limitation highlights that false acceptances exist among the moderately disabled, but are small for those without any limitation. Second, in terms of policy reforms, the high fraction of false rejections associated with the screening process of the disability insurance program leads to an increase in welfare when the program becomes less strict, despite the increase in false applications. This is because coverage among those most in need goes up (for example, those with less savings and so less self-insurance). Second, welfare is higher if the generosity of DI is reduced and if reassessment is more frequent. Both of these reforms have a large impact reducing the number of applications from those with only a moderate disability at little cost in terms of reduced coverage for those in need. It is this difference in responsiveness to incentives among the moderately disabled compared to the severely disabled which underlies our policy conclusions. This distinction is novel to our paper and explains the difference between our findings and those elsewhere in the literature where responsiveness is not disaggregated by the severity of disability. Finally, DI interacts in important ways with other welfare programs. We show that an increase in generosity of means-tested programs reduces DI application rates by non-disabled workers

and increases insurance coverage among disabled workers. This positive combination arise because marginal undeserving applicants use the means-tested program as a *substitute* for DI (they switch to a program that is increasingly as generous as DI but has less uncertainty), while truly disabled workers used it as a *complement* (they use the more generous income floor to finance their consumption in case of rejection).

The literature on the DI program, surveyed in the next Section, contains both reduced form papers attempting to separately estimate the extent of inefficiencies created by the program and its insurance value, as well as sophisticated structural analyses geared towards assessing the consequences of reforming the program. As with most structural models, the value of our approach relative to reduced form analyses is that we can evaluate the consequences of potential reforms to the DI program, i.e., we can examine counterfactual cases that have not been experienced in the past or that are too costly to assess in a randomized evaluation context. Relative to existing structural analyses, we stress the importance of a number of model features: different degrees of work limitation, early life cycle choices, non-separable preferences, fixed costs of work that depend on work limitation status, permanent skill shocks, and interactions between different welfare programs. Further, we study the effects of novel policy reforms, and subject our model to various validity tests. For our structural model to deliver credible policy conclusions, we require that it fits the data in a number of key dimensions (internal validity) and that it can replicate the estimates prevailing in the reduced form literature without targeting these estimates directly (external validation). We show to what extent our model passes these tests.

The rest of the paper is structured as follows. Section 2 reviews the relevant literature on the DI program. Section 3 presents the life-cycle model and discusses how we model preferences, the sources of risk faced by individuals, and the social insurance programs available to them. Section 4 summarizes the data used in the estimation of the model, focusing on the data on disability status and on consumption. Section 5 discusses the identification strategy, presents the estimates of the structural parameters, and discusses both the internal and external fit of the model in a number of key dimensions. Section 6 carries out counter-factual policy experiments, reporting the effects on behavior and average household welfare of potential reforms of DI, along with sensitivity tests of these experiments. Section 7 concludes and discusses limitations and directions for future work.

2 Literature Review

The literature on DI has evolved in three different directions: (1) papers that estimate, typically in a reduced form way, the disincentive effects of the DI program; (2) papers that estimate, again using reduced form strategies, the welfare benefits of the program; and (3) papers that estimate structural models in order to evaluate the welfare consequences of reforming the program. Our paper belongs to the third line of research but we stress the importance of matching evidence from the first and second lines.

Incentive Effects of DI. There is an extensive literature estimating the costs of the DI program in terms of inefficiency of the screening process and the disincentive effects on labor supply decisions.

Since disability status is private information, there are errors involved in the screening process. The only direct attempt to measure such errors is Nagi (1969), who uses a sample of 2,454 initial disability determinations. These individuals were examined by an independent medical and social team. Nagi (1969) concluded that, at the time of the award, about 19% of those initially awarded benefits were undeserving, and 48% of those denied were truly disabled. To the extent that individuals recover but do not flow off DI, we would expect the fraction falsely claiming to be higher in the stock than at admission. This is the finding of Benitez-Silva et al. (2006a), using self-reported disability data on the over 50s from the Health and Retirement Study (HRS): over 40% of recipients of DI are not truly work limited. We compare these estimates of the screening errors to the estimates of our model. These errors raise the question of whether the “cheaters” are not at all disabled or whether they have only a partial work limitation. With our distinction between severe work limitations and moderate limitations, we are able to explore this issue. Moreover, we assume that disability evolves over the lifecycle, which allows for both medical recoveries and further health declines.

In terms of labor supply effects, the incentive for individuals to apply for DI rather than to work has been addressed by asking how many DI recipients would be in the labor force in the absence of the program.² Identifying an appropriate control group has proved difficult

²Some of the costs of the program derive from beneficiaries staying on the program despite health improvements. Evidence on the effectiveness of incentives to move the healthy off DI is scant: Hoynes and Moffitt (1997) conclude *via* simulations that some of the reforms aimed at allowing DI beneficiaries to keep

(see Parsons, 1980; Bound, 1989). Bound (1989) uses rejected DI applicants as a control group and finds that only 1/3 to 1/2 of rejected applicants are working, and this is taken as an upper bound of how many DI beneficiaries would be working in the absence of the program. This result has proved remarkably robust. Chen and van der Klaauw (2008) report similar magnitudes. As do French and Song (2011) and Maestas et al. (2011), who use the arguably more credible control group of workers who were not awarded benefits because their application was examined by “tougher” disability examiners (as opposed to similar workers whose application was examined by more “lenient” adjudicators). Von Wachter et al. (2011) stress that there is heterogeneity in the response to DI, and that younger, less severely disabled workers are more responsive to economic incentives than the older groups usually analyzed. Further, this growth in younger claimants has been a key change in the composition of claimants since 1984.³ We compare the implied elasticity of employment with respect to benefit generosity that comes from our model with the estimates of such elasticity in the literature.

A further dimension of the incentive cost of the program is the possibility that poor labor market conditions (such as declines in individual productivity due to negative shocks to skill prices or low arrival rates of job offers), increase applications for the DI program. Black et al. (2002) use the boom and bust in the mining industry in some US states (induced by the exogenous shifts in coal and oil prices of the 1970s) to study employment decisions and participation in the DI program. They show that participation in the DI program is much more likely for permanent than transitory skill shocks. In our framework, we distinguish between these different types of shock.

Estimates of the benefits of the program The literature on the welfare benefits of DI is more limited. Some papers (e.g. Meyer and Mok, 2007, and Stephens, 2001, for the US; and Ball and Low, 2012, for the UK) first quantify the amount of health risk faced by workers and then measure the value of insurance by looking at the decline in consumption that follows

more of their earnings on returning to work are unlikely to be successful and may, if anything, increase the number of people applying for DI.

³These incentive effects have implications for aggregate unemployment. Autor and Duggan (2013) find that the DI program lowered measured US unemployment by 0.5 percentage points between 1984 and 2001 as individuals moved onto DI. This movement was firstly because the rise in wage inequality in the US, coupled with the progressivity of the formula used to compute DI benefits, implicitly increased replacement rates for people at the bottom of the wage distribution (increasing demand for DI benefits). Secondly, in 1984 the program was reformed and made more liberal (increasing the supply of DI benefits).

a poor health episode. Chandra and Sandwick (2009) use a standard life cycle model, add disability risk (which they model as a permanent, involuntary retirement shock) and compute the consumer’s willingness to pay to eliminate such risk. These papers interpret any decline in consumption in response to uninsured health shocks as a measure of the welfare value of insurance, ignoring the question of whether preferences are non-separable and health-dependent. However, consumption may fall optimally even if health shocks are fully insured, for example because consumption needs are reduced when sick, leading to consumption and poor health being substitutes in utility. We allow explicitly for health-dependent preferences which provides a better assessment of the welfare benefits of the DI program.

The value of reforming the DI program The broader issue of the value of DI and the effects of DI reform requires combining estimates of the risk associated with health shocks alongside the evaluation of the insurance and incentives provided by DI. Similar to our paper, previous work by Bound et al. (2004, 2010), Benitez-Silva et al. (2002), and Waidmann et al. (2003) has also highlighted the importance of considering both sides of the insurance/incentive trade-off for welfare analysis and conducted some policy experiments evaluating the consequences of reforming the program. These papers differ in focus and this leads to differences in the way preferences, risk, and the screening process are modeled; and in the data and estimation procedure used.⁴

Benitez-Silva et al. (2006b) use the HRS and focus on older workers. Their model is used to predict the implications of introducing the “\$1 for \$2 benefit offset”, i.e., a reduction of \$1 in benefits for every \$2 in earnings a DI beneficiary earns above the “substantial gainful activity” (SGA) ceiling. Currently, there is a 100% tax (people get disqualified for benefits if earning more than the SGA). The effect of the reform is estimated to be small. While the model is very detailed, non-employment rates by age in the data are substantially lower than in the simulations, while the stocks on DI are overpredicted, and there is no disaggregation by health. Disaggregation by health may be important. As stressed by von Wachter et al. (2011), behavioral responses to incentives in the DI program differ by age and by health

⁴There is a purely theoretical literature on optimal disability insurance, such as the model of Diamond and Sheshinski (1995) and the Golosov and Tsyvinsky (2004) result on the desirability of asset testing DI benefits. Rather than optimality, our focus is on the estimation of the value and incentives of the actual DI program and the aim is to provide welfare analysis of possible program reforms. We relate our results to the theoretical literature in section 6.

status, with the young being the most responsive.

The paper closest to ours is Bound et al. (2010). They specify a dynamic programming model that looks at the interaction of health shocks, disposable income, and the labor market behavior of men. The innovative part of their framework is that they model health as a continuous latent variable for which discrete disability is an indicator. This is similar to our focus on different degrees of severity of health shocks. However, the focus of their paper is on modelling behavior among the old (aged 50 and over from the HRS), rather than over the whole lifecycle. Further, the decline in labour market participation among the old is not disaggregated by health status and does not match the decline in the data. The point of our paper is that we need a life-cycle perspective to capture fully the insurance benefits, and we need an accurate characterization of labor supply behavior and applications to the program to capture fully the incentive costs of the program.

3 Life-Cycle Model

3.1 Individual Problem

We consider the problem of an individual who maximizes lifetime expected utility:

$$\max_{c, P, DI^{App}} V_{it} = E_t \sum_{s=t}^T \beta^{s-t} U(c_{is}, P_{is}; L_{is})$$

where β is the discount factor, E_t the expectations operator conditional on information available in period t (a period being a quarter of a year), P a discrete $\{0, 1\}$ employment indicator, c_t consumption, and L_t a discrete work limitation (disability) status indicator $\{0, 1, 2\}$, corresponding to no limitation, a moderate limitation and a severe limitation, respectively. Work limitation status is often characterized by a $\{0, 1\}$ indicator (as in Benitez-Silva et al., 2006a). We use a three state indicator to investigate the importance of distinguishing between moderate and severe work limitations. Individuals live for T periods, may work T^W years (from age 23 to 62), and face an exogenous mandatory spell of retirement of $T^R = 10$ years at the end of life. The date of death is known with certainty and there is no bequest motive.

The intertemporal budget constraint during the working life has the form

$$A_{it+1} = R \left[\begin{array}{c} A_{it} + (w_{it}h(1 - \tau_w) - F(L_{it}))P_{it} \\ +(B_{it}Z_{it}^{UI}(1 - Z_{it}^{DI}) + D_{it}Z_{it}^{DI} + SSI_{it}Z_{it}^{DI}Z_{it}^W)(1 - P_{it}) \\ +W_{it}Z_{it}^W - c_{it} \end{array} \right]$$

where A are beginning of period assets, R is the interest factor, w the hourly wage rate, h a fixed number of hours (corresponding to 500 hours per quarter), τ_w a proportional tax rate that is used to finance social insurance programs, F the fixed cost of work that depends on disability status, B unemployment benefits, W the monetary value of a means-tested welfare payment, D the amount of disability insurance payments obtained, SSI the amount of Supplemental Security Income (SSI) benefits, and Z^{DI} , Z^{UI} and Z^W are reciprocity $\{0, 1\}$ indicators for disability insurance, the means-tested welfare program and unemployment insurance, respectively.⁵ We assume that unemployment insurance is paid only on job destruction and only for one quarter; the means-tested welfare program is an anti-poverty program providing a floor to income, similar to Food Stamps, and this is how we will refer to it in the rest of the paper. Reciprocity Z_{it}^W depends on income being below a certain (poverty) threshold. The way we model both programs is described fully in the Appendix.

The worker's problem is to decide whether to work or not. When unemployed, the decision is whether to accept a job that may have been offered or wait longer. The unemployed person will also have the option to apply for disability insurance (if eligible). Whether employed or not, the individual has to decide how much to save and consume. Accumulated savings are used to finance consumption at any time, particularly during spells out of work and retirement.

We assume that individuals are unable to borrow: $A_{it} \geq 0 \forall t$. This constraint has bite because it precludes borrowing against social insurance and means-tested programs. At retirement, people collect social security benefits which are paid according to a formula similar to the one we observe in reality, and is the same as the one used for DI benefits (see below). Social security benefits, along with assets that people have voluntarily accumulated over their working years, are used to finance consumption during retirement. The structure of the individual's problem is similar to life-cycle models of savings and labour supply, such as Low et al. (2010). The innovations in our set-up are to consider the risk that arises

⁵We do not have an SSI reciprocity indicator because that is a combination of receiving DI and being eligible for means-tested transfers.

from work limitation shocks, distinguishing between the severity of the shocks, the explicit modelling of disability insurance, and the interaction of disability insurance with other social insurance programs.

While eligibility and receipt of disability insurance are not means-tested, in practice high education individuals are rarely beneficiaries of the program. In our PSID data set individuals with low and high education have similar DI reciprocity rates only until their mid-30s (about 1%), but after that age the difference between the two groups increases dramatically. By age 60, the low educated are four times more likely to be DI claimants than the high educated (16% vs. 4%).⁶ Figure 4 in the Appendix provides the details. Given these large differences, in the remainder of the paper we focus on low education individuals (those with at most a high school degree), with the goal of studying the population group that is more likely to be responsive to changes in the DI program and most likely to value the insurance.

While our model is richer than existing characterizations in most dimensions, there are certain limitations of our model. First, we model individual behavior rather than family behavior and hence neglect insurance coming from, for example, spousal labor supply. On the other hand, we assume that social insurance is always taken up when available. Second, in our model health shocks result in a decline in productivity which indirectly affects consumption expenditure, but we ignore direct health costs (i.e., drugs and health insurance) that may shift the balance across consumption spending categories.⁷ Third, we do not allow for health investments which may reduce the impact of a health shock. This assumption makes health risk independent of the decision process and so can be estimated outside of the model. As we shall discuss, however, we do allow health shocks to affect non-health related individual productivity shocks through shifts in the variance of such shocks. Moreover, we focus on a group of relatively homogeneous individuals (with low education), while in practice most heterogeneity in health investment occurs between education. We discuss how our results may depend on these assumptions in the concluding section.

We now turn to a discussion of the three key elements of the problem: (a) preferences, (b) wages, and (c) social insurance.

⁶The low DI participation rates among the high educated is partly due to the vocational criterion used by the SSA for awarding DI (described later).

⁷Our measure of consumption in the data excludes health spending.

3.2 Preferences

We use a utility function of the form

$$u(c_{it}, P_{it}; L_{it}) = \frac{(c_{it} \exp(\theta L_{it}) \exp(\eta P_{it}))^{1-\gamma}}{1-\gamma} \quad (1)$$

We set $\gamma = 1.5$ based on papers in the literature (see footnote 20), and estimate θ and η . To be consistent with disability and work being “bads”, we require $\theta < 0$ and $\eta < 0$, two restrictions that as we shall see are not rejected by the data. The parameter θ captures the utility loss for the disabled in terms of consumption. Employment also induces a utility loss determined by the value of η . This implies that consumption and work are Frisch complements (i.e. the marginal utility of consumption is higher when working) and that the marginal utility of consumption is higher when suffering from a work limitation.⁸

If individuals are fully insured, individuals will keep marginal utility constant across states. $\theta < 0$ implies that individuals who are fully insured want more expenditure allocated to the “disability” state, for example because they have larger spending needs when disabled (alternative transportation services, domestic services, etc.).⁹

3.3 The Wage Process and Labour Market Frictions

We model the wage process for individual i as being subject to shocks to work limitation status, general productivity (skill) shocks, as well as the contribution of observable characteristics X_{it} :

$$\ln w_{it} = X'_{it}\alpha + \varphi_1 \mathbf{1}\{L_{it} = 1\} + \varphi_2 \mathbf{1}\{L_{it} = 2\} + \varepsilon_{it} \quad (2)$$

where

$$\varepsilon_{it} = \varepsilon_{it-1} + \zeta_{it}$$

The work limitation status of an individual, L_{it} , evolves according to a three state first-order Markov process. Upon entry into the labor market, all individuals are assumed to

⁸In addition to the non-separable effect of disability, there may be an additive utility loss associated with disability. Since disability is not a choice, we cannot identify this additive term. Further, such an additive utility loss would be uninsurable because only consumption can be substituted across states.

⁹Lillard and Weiss (1997) also find evidence for $\theta < 0$ using HRS savings and health status data. On the other hand, Finkelstein et al. (2008) use health data and subjective well-being data to proxy for utility and find $\theta > 0$.

be healthy ($L_{i0} = 0$). Transition probabilities from any state depend on age. We assume that these transition probabilities are exogenous. We interpret ε_{it} as a measure of individual unobserved productivity that is mean-independent of health shocks - examples would include shocks to the value and price of individual skills - and interpret ζ_{it} as a permanent productivity shock. Besides allowing health shocks to affect mean offered wages through the φ_1 and φ_2 parameters, we also allow the process determining the wage innovations to vary by health status. In particular, since individuals with different realizations of their disability process may face a different distribution of permanent productivity shocks, we assume that $\text{var}(\zeta_{it}|L_{it}) = \sigma_{\zeta,L}^2$. The idea is that, after the realization of the disability shock, individuals will draw shocks to their productivity from distributions with different degrees of dispersion.

Equation (2) determines the evolution of individual productivity. Productivity determines the offered wage when individuals receive a job offer. The choice about whether or not to accept an offered wage depends in part on the fixed costs of work, which in turn depend on the extent of the work limitation, $F(L)$. In addition, there are labour market frictions which means that not all individuals receive job offers. First, there is job destruction, δ , which forces individuals into unemployment for (at least) one period. Second, job offers for the unemployed arrive at a rate λ and so individuals may remain unemployed even if they are willing to work.

This wage and employment environment implies a number of sources of risk, from individual productivity, work limitation shocks, and labor market frictions. These risks are idiosyncratic, but we assume that there are no markets to provide insurance against these risks. Instead, there is partial insurance coming from government insurance programs (as detailed in the next section) and from individuals' own saving and labor supply.

3.4 Social Insurance

The DI Program The Social Security Disability Insurance program (DI) is an insurance program for covered workers, their spouses, and dependents that pays benefits related to average past earnings. The purpose of the program is to provide insurance against persistent health shocks that impair substantially the ability to work. The difficulty with providing this insurance is that health status and the impact of health on the ability to work is imperfectly observed.

The award of disability insurance depends on the following conditions: (1) An individual

must file an application; (2) There is a work requirement on the number of quarters of prior employment: Workers over the age of 31 are disability-insured if they have 20 quarters of coverage during the previous 40 quarters; (3) There is a statutory five-month waiting period out of the labour force from the onset of disability before an application will be processed; and (4) the individual must meet a medical requirement, i.e. the presence of a disability defined as “*Inability to engage in any substantial gainful activity by reason of any medically determinable physical or mental impairment, which can be expected to result in death, or which has lasted, or can be expected to last, for a continuous period of at least 12 months.*”¹⁰

The actual DI determination process consists of sequential steps. After excluding individuals earning more than a so-called “substantial gainful amount” (SGA, \$900 a month for non-blind individuals as of 2007), the SSA determine whether the individual has a medical disability that is severe and persistent (per the definition above).¹¹ If such disability is a listed impairment, the individual is awarded benefits without further review.¹² If the applicant’s disability does not match a listed impairment, the DI evaluators try to determine the applicant’s residual functional capacity. In the last stage the pathological criterion is paired with an economic opportunity criterion. Two individuals with identical work limitation disabilities may receive different DI determination decisions depending on their age, education, general skills, and even economic conditions faced at the time the determination is made.

In our model, we make the following assumptions in order to capture the complexities of the disability insurance screening process. First, we require that the individuals make the choice to apply for benefits. Second, individuals have to have been at work for at least the period prior to becoming unemployed and making the application. Third, individuals

¹⁰Despite this formal criterion changing very little, there have been large fluctuations over time in the award rates: for example, award rates fell from 48.8% to 33.3% between 1975 and 1980, but then rose again quickly in 1984, when eligibility criteria were liberalized, and an applicant’s own physician reports were used to determine eligibility. In 1999, a number of work incentive programs for DI beneficiaries were introduced (such as the Ticket to Work program) in an attempt to push some of the DI recipients back to work.

¹¹The criteria quoted above specifies “any substantial gainful activity”: this refers to a labour supply issue. However, it does not address the labour demand problem. Of course, if the labour market is competitive this will not be an issue because workers can be paid their marginal product whatever their productivity level. In the presence of imperfections, however, the wage rate associated with a job may be above the disabled individual’s marginal productivity. The Americans with Disability Act (1990) tries to address this question but that tackles the issue only for incumbents who become disabled.

¹²The listed impairments are described in a blue-book published and updated periodically by the SSA (“Disability Evaluation under Social Security”). The listed impairments are physical and mental conditions for which specific disability approval criteria has been set forth or listed (for example, Amputation of both hands, Heart transplant, or Leukemia).

must have been unemployed for at least one quarter before applying. Successful applicants begin receiving benefits in that second quarter. Unsuccessful individuals must wait a further quarter before being able to return to work, but there is no direct monetary cost of applying for DI. Finally, we assume that the probability of success depends on the true work limitation status and age:

$$\Pr \left(DI_{it} = 1 \mid DI_{it}^{App} = 1, L_{it}, t \right) = \begin{cases} \pi_L^{Young} & \text{if } t < 45 \\ \pi_L^{Old} & \text{if } 45 \leq t \leq 62 \end{cases} \quad (3)$$

We make the probability of a successful application for DI dependent on age because the persistence of health shocks is age dependent.¹³ Individuals leave the disability program either voluntarily (which in practice means into employment) or following a reassessment of the work limitation and being found to be able to work (based on (3)). We depart from the standard assumption made in the literature that DI is an absorbing state because we want to be able to evaluate policies that create incentives for DI beneficiaries to leave the program. The probability of being reassessed is 0 for the first year, then is given by P^{Re} , which is independent of L and age.

DI benefits are calculated in essentially the same fashion as Social Security retirement benefits. Beneficiaries receive indexed monthly payments equal to their Primary Insurance Amount (PIA), which is based on taxable earnings averaged over the number of years worked (known as AIME). Benefits are independent of the extent of the work limitation, but are progressive.¹⁴ We set the value of the benefits according to the actual schedule in the US program (see Appendix).

We assume that the government awards benefits to applicants whose signal of disability exceeds a certain stringency threshold. Some individuals whose actual disability is less severe than the threshold may nonetheless wish to apply for DI if their productivity is sufficiently low because the government only observes a noisy measure of the true disability status. In contrast, some individuals with true disability status above the threshold may not apply because they are highly productive despite their disability. Given the opportunity cost of

¹³The separation at age 45 takes also into account the practical rule followed by DI evaluators in the the last stage of the DI determination process (the so-called Vocational Grid, see Appendix 2 to Subpart P of Part 404—Medical-Vocational Guidelines, as summarized in Chen and van der Klaauw, 2008).

¹⁴Caps on the amount that individuals pay into the DI system as well as the nature of the formula determining benefits make the system progressive. Because of the progressivity of the benefits and because individuals receiving DI also receive Medicare benefits after two years, the replacement rates are substantially higher for workers with low earnings and those without employer-provided health insurance.

applying for DI, these considerations suggest that applicants will be predominantly low productivity individuals or those with severe work limitations (see Black et al., 2004, for a related discussion).

Supplemental Security Income (SSI) Individuals who are deemed to be disabled according to the rules of the DI program and who have income (comprehensive of DI benefits but excluding the value of food stamps) below the threshold that would make them eligible for food stamps, receive also supplemental security income (SSI). The definition of disability in the SSI program is identical to the one for the DI program, while the definition of low income is similar to the one used for the Food Stamps program.¹⁵ We assume that SSI generosity is identical to the means-tested program described in the Appendix.

3.5 Solution

There is no analytical solution for our model. Instead, the model must be solved numerically, beginning with the terminal condition on assets, and iterating backwards, solving at each age for the value functions conditional on work status. The solution method is discussed in detail in the Appendix, which also provides the code to solve and simulate the model.

4 Data

The ideal data set for studying the issues discussed in our model is a longitudinal data set covering the entire life cycle of an individual, while at the same time containing information on consumption, wages, employment, disability status, the decision to apply for DI, and information on receipt of DI. Unfortunately, none of the US data sets typically used by researchers working on DI satisfy all these requirements at once. Most of the structural analyses of DI errors have used data from the HRS or the Survey of Income and Program Participation (SIPP). The advantage of the HRS is that respondents are asked very detailed questions on disability status and DI application, minimizing measurement error and providing a direct (reduced form) way of measuring screening errors. However, there are three important limitations of the HRS. First, the HRS samples only from a population of older

¹⁵In particular, individuals must have income below a “countable income limit”, which typically is slightly below the official poverty line (Daly and Burkhauser, 2003). As in the case of Food Stamp eligibility, SSI eligibility also has an asset limit which we disregard.

workers and retirees (aged above 50). In Figure 6 of the Appendix, we show that in recent years an increasing fraction of DI awards have gone to younger individuals, which highlights that capturing the behavior of those under 50 is an important part of our understanding of disability insurance, as also discussed in von Wachter et al. (2011). Second, the HRS asks questions about application to DI only to those individuals who have reported having a work limitation at some stage in their life course. Finally, the HRS has no consumption data. The SIPP has the advantage of being a large data set covering the entire life cycle, but it also lacks consumption data. This is problematic because an important element of our model is the state dependence in utility induced by health. Moreover, the longitudinal structure of the SIPP makes it difficult to link precisely the timing of wages with those of changes in work limitations.

Our choice is to use the 1986-1996 PSID.¹⁶ The PSID offers repeated, comparable annual data on disability status, disability insurance reciprocity, wages, employment, and food consumption. The quality of the data is comparable to SIPP and HRS and the panel is long. However, there are also disadvantages from using the PSID, and here we discuss how important they are and what we do to tackle them. The first problem is that the sample of people likely to have access to disability insurance is small. Nevertheless, estimates of disability rates in the PSID are similar to those obtained in other, larger data sets (CPS, SIPP, NHIS - and HRS conditioning on age, see Bound and Burkhauser, 1999). Moreover, PSID DI rates by age compare well with aggregate data (see the Appendix, Figure 3), and also in the time series. For example, in the population, the proportion of people on DI has increased from 2.4% to 4.3% between 1985 and 2005, whereas in the PSID the increase over the same time period is from 2.4% to 4.5%.

The second problem is that consumption in the PSID refers only to food. By contrast, in the model, the budget constraint imposes that, over the lifetime, all income is spent on (non-durable) consumption. To compare consumption in the model to consumption in the data, we obtain non-durable consumption in the data with an imputation procedure that uses a regression for nondurable consumption estimated with CEX data. The imputation procedure

¹⁶Due to the retrospective nature of the questions on earnings and consumption, this means our data refer to the 1985-1995 period. We do not use data before 1985 because major reforms in the DI screening process were implemented in 1984 (see Autor and Duggan, 2003, and Duggan and Imberman, 2009). We do not use data after 1996 primarily because the welfare reform of that year may have changed the nature of the interaction among the various welfare programs, and hence also affected the decision to apply for DI (see e.g., Blank 2004).

is described in detail in the Appendix. To summarize, there are two types of variation we use. First, there is variation in tastes (which we capture with demographic characteristics) and total nondurable consumption. Second, there is variation in health variables. In particular, we use variables that in the CEX and PSID capture health status: an indicator of whether the head is “ill, disabled, or unable to work”, and an indicator for receipt of DI payments. The R^2 of the imputation regression is quite high (0.75).

The third problem is that the PSID does not provide information on DI application. We use our indirect inference procedure to circumvent this problem: For a given set of structural parameters, we simulate DI application decisions and the resulting moments that reflect the DI application decision (such as DI reciprocity by age and disability status, disability state of DI recipients by age, and transitions into the program). These moments, crucially, can be obtained both in the actual and simulated data and the fit of these moments is an explicit way of checking how well our model approximates the decision to apply for DI.

The PSID sample we use excludes the Latino sub-sample, female heads, and people younger than 23 or older than 62. Further sample selection restrictions are discussed in the Appendix.¹⁷

Disability Data We define a discrete indicator of work limitation status (L_{it}), based on the following set of questions: (1) *Do you have any physical or nervous condition that limits the type of work or the amount of work you can do?* To those answering “Yes”, the interviewer then asks: (2) *Does this condition keep you from doing some types of work?* The possible answers are: “Yes”, “No”, or “Can do nothing”. Finally, to those who answer “Yes” or “No”, the interviewer then asks: (3) *For work you can do, how much does it limit the amount of work you can do?* The possible answers are: “A lot”, “Somewhat”, “Just a little”, or “Not at all”.

¹⁷While PSID data are annual, our model assumes that the decision period is a quarter, as events like unemployment, wage shocks, etc., happen at a frequency that is shorter than the year. We match timing in the model with that available in the data by converting quarterly data in our simulations into the annual frequency of the PSID. To give an example of how we do this, people report their disability state in the PSID at the time of the interview, which typically occurs in the 2nd quarter of the year. In the simulations disability states are updated every quarter. To create a consistent match between data and simulations, we match 2nd quarter statistics only. Similarly, in the data $DI = 1$ if any DI payments were received in the year. In the simulations, we have four DI observations per year. We set $DI = 1$ in the simulations if $DI = 1$ in any of the quarters. Hence, in both the data and the simulations, $\Pr(DI = 1|L = 2)$ is the fraction of people who reported to be severely disabled in the second quarter and who reported to have received some DI payments during the year.

We assume that those without a work limitation ($L_{it} = 0$) either answer “No” to the first question or “Not at all” to the third question. Of those that answer “Yes” to the first question, we classify as severely limited ($L_{it} = 2$) those who answer question 2 that they “can do nothing” and those that answer question 3 that they are limited “a lot”. The rest have a moderate limitation ($L_{it} = 1$): their answer to question 3 is that they are limited either “somewhat” or “just a little”. This distinction between severe and moderate disability enables us to target our measure of work limitation more closely to that intended by the SSA.¹⁸ In particular, we interpret the SSA criterion as intending DI for the severely work limited rather than the moderately work limited.¹⁹

The validity of work limitation self-reports is somewhat controversial for three reasons. First, subjective reports may be poorly correlated with objective measures of disability. However, Bound and Burkhauser (1999) survey a number of papers that show that self-reported measures are highly correlated with *clinical* measures of disability. We provide additional evidence in support of our self-reported measure of work limitation in Table 3 in the Appendix.

Second, individuals may over-estimate their work limitation in order to justify their disability payments or their non-participation in the labour force. Benitez-Silva et al. (2004) show that self-reports are unbiased predictors of the definition of disability used by the SSA (“norms”). In other words, there is little evidence that, for the sample of DI applicants, average disability rates as measured from the self-reports are significantly higher than disability rates as measured from the SSA final decision rules. However, Kreider (1999) provides evidence based on bound identification that disability is over-reported among the unemployed.

Third, health status may be endogenous, and non-participation in the labour force may affect health (either positively or negatively). Stern (1990) and Bound (1991) both find pos-

¹⁸Our three-way classification uses the responses to the multiple questions (1)-(3), and hence reduces the measurement error associated with using just the "Yes/No" responses associated to question (1). An alternative way to reduce such error is to classify as disabled only those who answer "Yes" to question (1) for two consecutive years, as in Burkhauser and Daly (1996).

¹⁹The distinction between moderate and severe disability is a key step in achieving identification of the error rates in the DI application process. However, our distinction does not take into account that the vocational criterion of DI implies that eligibility potentially varies across time and space for workers with similar disabilities because of market conditions. On the other hand, as noticed by Benitez-Silva et al. (2004), these measures have the unique advantage of being sufficient statistics for use in the structural modeling of individual behavior under disability risk.

itive effects of non-participation on health, but the effects are economically small. Further, Smith (2004) finds that income does not affect health once one controls for education (as we do implicitly by focusing on a group of homogenous individuals with similar schooling levels). Similarly, Adda et al. (2009) find that innovations to income have negligible effect on health.

Sample Summary Statistics Table 1 reports descriptive statistics for our sample, stratifying it by the degree of work limitations. The severely disabled are older and less likely to be married or white. They have lower family income but higher income from transfers (most of which come from the DI or SSI program). They are less likely to work, have lower earnings if they do so, are more likely to be a DI recipient, and have lower food spending than people without a disability.

These statistics underpin the moments used in the indirect inference estimation. Two particularly important descriptive statistics are the fraction of DI recipients who are not severely disabled (“false claimants”) and the fraction of individuals with a severe disability who receive DI (“coverage”). Figure 1 plots the life cycle patterns for each: the fraction of claimants who are healthy is particularly high early in the life cycle, while “coverage” becomes more effective at the end of the working life cycle.

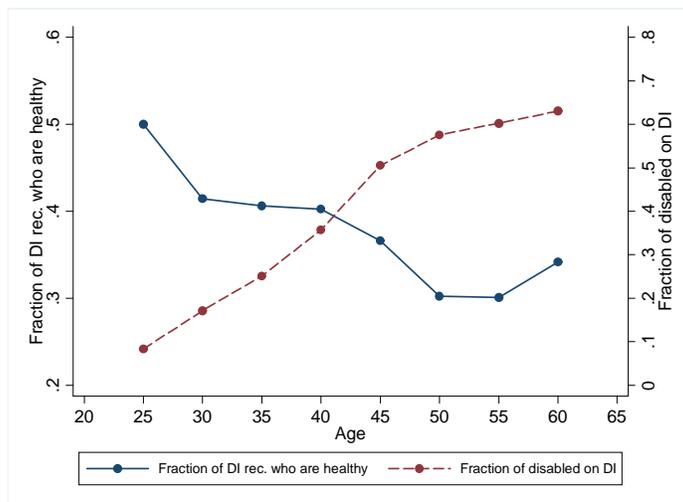


Figure 1: Coverage vs. False Claimants

Table 1: Sample Summary Statistics by Work Limitation Status

	$L = 0$	$L = 1$	$L = 2$
Age	38.41	43.99	47.74
% Married	0.82	0.82	0.73
% White	0.62	0.70	0.54
Family size	3.24	3.23	2.97
Family income	46,418	41,204	25,623
Income from transfers	1,772	5,381	10,365
% Working now	0.91	0.64	0.15
% Annual wages > 0	0.96	0.73	0.19
Hours Hours>0	2,158	1,935	1,487
Wages Hours>0	31,048	26,701	17,213
Hourly wage	14.85	14.34	12.53
% DI recipient	0.01	0.14	0.47
Food spending	5,645	5,469	4,160
Number of obs.	12,820	1,102	878

Note: monetary values are in 1996 dollars.

5 Identification and Results

Identification of the unknown parameters proceeds in three steps. First, some parameters are pre-determined or calibrated using established findings from the literature. We check the sensitivity of our policy experiment results to assuming different values for key pre-determined parameters. Second, some parameters are estimated outside the structure of the model. For some parameters, this is because no structure is needed: disability risk can be estimated directly from transitions between disability states because of the exogeneity assumption. For other parameters, we use a reduced form approach to reduce the computational burden when there are plausible selection correction processes, as is the case for the wage parameters. The remaining parameters are estimated structurally using an Indirect Inference procedure.

This mixed identification strategy is not novel to our paper. For example, to make estimation feasible, Bound, Stinebrickner and Waidmann (2010) estimate, in a context very similar to ours, the parameters of the earnings equations and health equations outside the behavioral model. This mixed strategy has been used more generally in a number of papers

looking at consumption choices under uncertainty: Gourinchas and Parker (2000); Attanasio et al. (1999); Low et al. (2010); Alan and Browning (2009); and Guvenen and Smith (2011).

5.1 Pre-determined and calibrated parameters

We fix the relative risk aversion coefficient γ and the intertemporal discount rate β to realistic values estimated elsewhere in the literature. In principle, one could identify γ and β using asset data. During the sample period we use, however, data on assets are available only for two waves, 1989 and 1994. Instead, we use these limited asset data to test the out-of-sample behavior of our model.

We set $\gamma = 1.5$ in our baseline and we later examine the sensitivity of our results to setting $\gamma = 3$.²⁰ As for the estimate of β , we use the central value of estimates from Gourinchas and Parker (2000) and Cagetti (2003), two representative papers of the literature and set $\beta = 0.025$.²¹ In principle, the arrival rate of offers when unemployed (λ) parameter could be identified using unemployment duration by age. This is the strategy taken in Low, Meghir and Pistaferri (2010), and thus we use their estimate of a quarterly arrival rate $\lambda = 0.73$.

DI beneficiaries have their disability reassessed periodically through Continuing Disability Reviews (CDR).²² To obtain an estimate of the reassessment probability we use aggregate statistics. During the fiscal years 1987-1996, the SSA conducted a total of 1,777,277 CDRs. Using the stock of disabled workers in receipt of DI, we calculate a probability of re-assessment $P^{\text{Re}} = 0.0613$.²³

Finally, we set the interest factor to a realistic value, $R = 1.016$ (on an annual basis), and assume that a life-span is 50 years, from age 22, with the last 10 years in compulsory retirement.

²⁰Attanasio et al. (1999), Blundell et al. (1994), Attanasio and Weber (1995), and Banks et al. (2001), report estimates of 1, 1.35, 1.37, 1.5, and 1.96 respectively. Our choice $\gamma = 1.5$ is a central value of these estimates.

²¹Both use annual data and we convert their annual discount rate in a quarterly discount rate. The estimates we use from their papers refer to their low education (high school or less) sample. The Gourinchas and Parker's estimate is 0.012; Cagetti's estimates range between 0.013 and 0.051 depending on the definition of wealth, the data set used (PSID and SCF), and whether mean or median assets are used.

²²By law, the SSA is expected to perform CDRs every 7 years for individuals with medical improvement not expected, every 3 years for individuals with medical improvement possible, and every 6 to 18 months for individuals with medical improvement expected. In practice, the actual number of CDRs performed is lower.

²³While we could use transitions out of the DI program as moments to identify P^{Re} , these moments are very noisy.

5.2 Disability Risk

Disability risk is independent of any choices made by individuals in our model, and is also independent of productivity shocks. This means that the disability risk process can be identified structurally without indirect inference. By contrast, the same is not true for the variance of wage shocks: because wages are observed only for workers, wage shocks are identified using a selection correction.

In principle, since we have three possible work limitation states, there are nine possible transition patterns $\Pr(L_{it} = j | L_{it-1} = k)$. These are reported in full detail in the Appendix. Here (Figure 2) we plot only selected estimates of the transition probabilities $\Pr(L_{it} = j | L_{it-1} = k)$.²⁴ These estimates are informative about work limitation risk. For example, $\Pr(L_{it} = 2 | L_{it-1} = 0)$ is the probability that an individual with no work limitations is hit by a shock that puts him in the severe work limitation category. Whether this is a persistent or temporary transition can be assessed by looking at the value of $\Pr(L_{it} = 2 | L_{it-1} = 2)$.

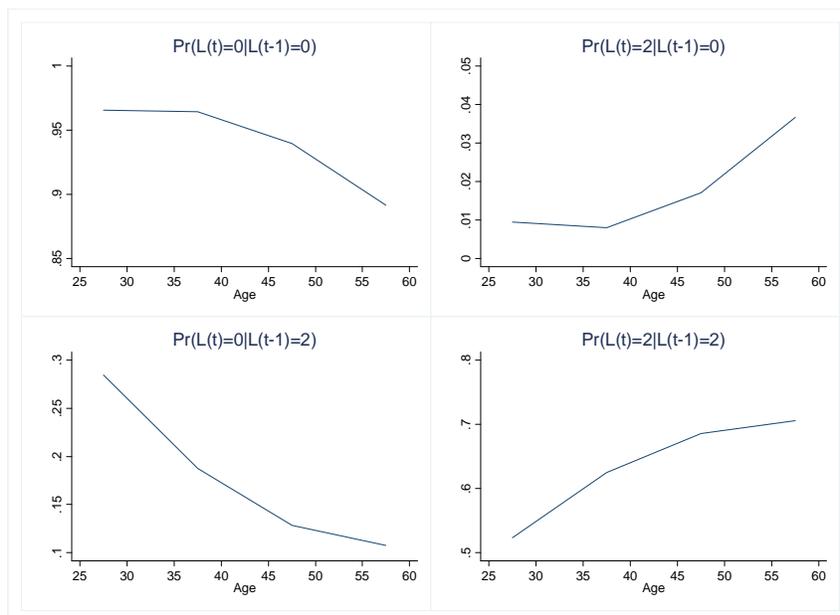


Figure 2: Selected transitions

The top left panel of Figure 2 plots $\Pr(L_{it} = 0 | L_{it-1} = 0)$, i.e. the probabilities of staying

²⁴To obtain these plots, we first construct a variable that equals the mid-point of a 10-age band (23-32, 33-42, etc.), call it mid-age. We then regress an indicator for the joint event $\{L_{it} = j, L_{it-1} = k\}$ on a quadratic in the mid-age variable, conditioning on the event $\{L_{it-1} = k\}$ (that is, focusing on the sample of individuals with $\{L_{it-1} = k\}$). The predicted value of this regression is what we plot in the figure.

healthy by age. This probability declines over the working part of the life cycle from 0.96 to about 0.88. The decline is equally absorbed by increasing probabilities of transiting in moderate and severe work limitations. The top right panel plots the latter, $\Pr(L_{it} = 2 | L_{it-1} = 0)$. This probability increases over the working life, and the increase is fast: from 1% to almost 4%. The probability of full recovery following a severe disability (shown in the bottom left panel) declines over the life-cycle. Finally, the probability of persistent severe work limitations, $\Pr(L_{it} = 2 | L_{it-1} = 2)$ (bottom right panel) increases strongly with age (from about 0.5 to about 0.7).²⁵

5.3 The Wage Process and Productivity Risk

We augment the wage process (2) to include an additional error term ω_{it} :

$$\ln w_{it} = X'_{it}\alpha + \varphi_1 \mathbf{1}\{L_{it} = 1\} + \varphi_2 \mathbf{1}\{L_{it} = 2\} + \varepsilon_{it} + \omega_{it} \quad (4)$$

with $\varepsilon_{it} = \varepsilon_{it-1} + \zeta_{it}$ as before. We assume that ω_{it} reflects measurement error. We do this because measurement error is not separately identifiable from transitory shocks. Despite the lack of transitory shocks in wages, there will be transitory shocks to *earnings* because of the frictions which induce temporary loss of income for a given productivity level. We make the assumption that the two errors ζ_{it} and ω_{it} are independent.²⁶ Our goal is to identify the variance of the productivity shock $\sigma_{\zeta,L}^2$ (for $L = \{0, 1, 2\}$) as well as φ_1 and φ_2 . A first complication is selection effects because wages are not observed for those who do not work and the decision to work depends on the wage offer. Further, the employment decision may depend directly on disability shocks as well as on the expectation that the individual will apply for *DI* in the subsequent period (which requires being unemployed in the current period). We observe neither these expectations, nor the decision to apply.

Our selection correction is based on a reduced form rather than on our structural model, although the structural model is consistent with the reduced form.²⁷ We assume that “po-

²⁵Low educated individuals face worse health risk than high educated individuals, with higher probabilities of bad shocks occurring and a lower probability of recovery (see Figure 10 in the Appendix). These differences across education, alongside the much greater prevalence of DI among the low educated, are the reasons why we focus our analysis on the subsample of individuals with low education.

²⁶Based on evidence from e.g., Bound and Krueger (1995), we assume that the measurement error ω_{it} may be potentially serially correlated (an MA(1) process).

²⁷Estimating the wage process jointly with preferences and DI parameters is computationally burdensome, as it would require adding seven additional parameters.

tential” government transfers and the interaction of potential government transfers with disability status serve as exclusion restrictions. The interaction account for the fact that the disincentive to work that government transfers are intending to capture may be different for people who have a physical cost to work. “Potential” transfers are the sum of food stamps benefits, AFDC benefits, EITC benefits, and unemployment insurance benefits individuals would receive in case of program application. These potential benefits are computed using the formulae coded in the federal (for food stamps and EITC) and state (for AFDC and UI) legislation of the programs.²⁸ The use of this variable is in the spirit of the “simulated IV” literature in empirical public finance. In general, realized public income transfers are endogenous because the individual’s take-up decision is a choice. Since the parameters behind these public programs are exogenous, however, we use the amount of benefits individuals are potentially eligible for (before any take up decision is made).²⁹

In Table 2 column (1) we report marginal effects from a probit regression for employment. Throughout the exercise, standard errors are clustered at the individual level. Employment is monotonically decreasing in the degree of work limitations. Absent potential transfers, the probability of working declines by 23 percentage points at the onset of a moderate work limitation, and by 74 percentage points at the onset of a severe work limitation. Regarding our exclusion restrictions, the signs are correct: higher (potential) income from transfers induced by a more generous welfare system increase the opportunity cost of work, and the effects are statistically significant. We also find that for individuals with some disabilities this opportunity cost effect is smaller, consistent with the idea that lack of work among the disabled may not always reflect an “option value” argument. We will revisit this important issue in the policy experiment section.

Estimation of the probit for employment allows us to construct an estimate of the inverse Mills’ ratio term. We then estimate the wage equation only on the sample of workers. The resulting estimates of φ_1 and φ_2 , with the selection correction through the inverse Mills’

²⁸We ignore asset limits on Food Stamps and AFDC since we have data on assets only for two waves. Full details on how we construct potential benefits for these four programs are in the Appendix.

²⁹To check the robustness of our findings, in the online Appendix we report results under a variety of different exclusion restrictions, including (a) received (public and private) transfers, (b) an index of generosity of the local UI program; and (c) interactions of state and year dummies to capture reforms to local welfare systems. We find that the use of these different exclusion restrictions induce only small changes in the effect of disability variables on wages and virtually no effects on the estimated variances of the permanent shock (the only structural parameters in this exercise). Our results are also robust to using lagged wages or sample average wages when computing potential transfers.

Table 2: **The Log Wage Equation**

Variable	Employment equation (1)	Wage w/out selection (2)	Wage with selection (3)
$1\{L_{it} = 1\}$	-0.225*** (0.026)	-0.160*** (0.034)	-0.211*** (0.044)
$1\{L_{it} = 2\}$	-0.738*** (0.031)	-0.262*** (0.052)	-0.470*** (0.136)
Potential transfers	-0.091*** (0.012)		
Potential transfers $\times 1\{L_{it} = 1\}$	0.037* (0.020)		
Potential transfers $\times 1\{L_{it} = 2\}$	0.041* (0.023)		
Mills ratio			0.176* (0.106)
N	14,800	13,332	13,332

Note: Clustered standard errors in parenthesis. *, **, *** = significant at 10, 5, and 1 percent, respectively.

ratio, should be interpreted as the estimates of the effect of work limitations on *offered* wages.

In columns (2) and (3) of Table 2, we report estimates of the log wage process with and without correcting for endogenous selection into work. The key coefficients are the ones on $\{L = 1\}$ and $\{L = 2\}$, which are estimates of φ_1 and φ_2 , the effect of the work limitation on wages. A moderate work limitation reduces the observed wage rate by 16 percentage points, whereas a severe limitation reduces the offered wage by 26 percentage points. The selection correction to recover the offered wage from the observed wage makes a substantial difference. The effect of a severe work limitation on the observed wage is 20 percentage points less than on the offered wage: those who remain at work despite their work limitation have higher-than-average permanent income.³⁰ This is confirmed by the positive sign of the Mills ratio.

³⁰We check that our results do not depend on the normality assumption. In the online Appendix we repeat our wage equation estimates using a non-parametric approach. In the first step we estimate a univariate employment model using the semi-nonparametric estimator of Gallant and Nychka (1987) and save the predicted value \hat{s}_{it} . In the second step, we estimate our wage regression controlling for a 2^{nd} degree polynomial in \hat{s}_{it} . We find that the results remain very similar.

Table 3: **Variances of the Productivity Shocks**

Parameter	$\sigma_{\zeta,L=2}^2$	$\sigma_{\zeta,L=1}^2$	$\sigma_{\zeta,L=0}^2$
Estimate	0.110** (0.048)	0.041* (0.021)	0.016** (0.007)
P-value test $\sigma_{\zeta,L=2}^2 = \sigma_{\zeta,L=0}^2$		5.1%	

Note: Clustered standard errors in parenthesis. *, **, *** = significant at 10, 5, and 1 percent, respectively.

Productivity Risk To identify the variance of productivity shocks, we define first the “adjusted” error term:

$$g_{it} = \Delta \left(\ln w_{it} - X'_{it} \alpha - \sum_{j=1}^2 \varphi_j L_{it}^j \right) = \zeta_{it} + \Delta \omega_{it} \quad (5)$$

From estimation of α , φ_1 and φ_2 described above we can construct the “adjusted” residuals, and use them as they were the true adjusted error terms (5) (MaCurdy, 1982). We can then identify the variance of productivity shocks by health status and the variance of measurement error using the first and second moments and the autocovariances of g_{it} (conditioning on disability status), as discussed fully in the Appendix. The identification idea is simple. Neglect for a moment the issue of selection. With measurement error, the variance of g_{it} reflects two sources of innovations: permanent productivity shocks and measurement error. The autocovariances identify the contribution of measurement errors (which are mean-reverting), and hence the variance of productivity shocks is identified by stripping from the variance of wage growth the contribution of measurement error. Without selection, second moments conditional on working would just reflect variances of shocks. With selection, conditional variances are less than unconditional variances (which are the parameters of interest) by a factor that depends on the degree of selection in the data. First conditional moments help pin down the latter. See the Appendix for a formal proof.

The results are in Table 3. As before, we report standard errors clustered at the individual level. The estimates of the variance of productivity shocks vary by health status. We find that work limitations increase the dispersion of shocks, making the likelihood of more extreme realizations of productivity shocks higher when people become work limited.

5.4 Identification of Preferences and Disability Insurance Parameters

Identification of the remaining structural parameters of interest $(\eta, \theta, \delta, F_{L=0}, F_{L=1}, F_{L=2})$ and the DI policy parameters $(\pi_{L=0}^{Young}, \pi_{L=1}^{Young}, \pi_{L=2}^{Young}, \pi_{L=0}^{Old}, \pi_{L=1}^{Old}, \pi_{L=2}^{Old})$ is achieved by Indirect Inference (see Gourieroux et al, 1993).³¹ Indirect inference relies on matching moments from an approximate model (known as *auxiliary model*) which can be estimated on both real and simulated data, rather than on moments from the correct data generating process. The moments of the auxiliary model are related (through a so-called binding function) to the structural parameters of interest. The latter are estimated by minimizing the distance between the moments of the auxiliary model estimated from the observed data and the moments of the auxiliary model estimated from the simulated data. Any bias in estimates of the auxiliary model on actual data will be mirrored by bias in estimates of the auxiliary model on simulated data, under the null that the structural model is correctly specified. However, the closer the link between the moments of the auxiliary equations and the structural parameters, the more reliable is estimation.

How to choose which auxiliary moments to match? In our theoretical model, individuals make three decisions: how much to consume, whether to work, and whether to apply for DI. We choose auxiliary moments that reflect the choices individuals make.³² In particular, we use: (1) a regression of log consumption on work limitation, disability insurance, employment (and interactions), controlling for a number of other covariates; (2) employment rates, conditional on disability status and age; (3) the stock of recipients of DI, conditional on disability status and age; (4) the DI status of people of different age and health status; and (5) the flows into the DI program by age and disability status. These choices give us 36 moments overall, which we discuss next.

Moments: Disability Insurance There are three ways in which we calculate moments involving DI recipients. First, we consider the composition of DI recipients by health status. This identifies the fraction of DI recipients who are not truly disabled and helps to

³¹Indirect Inference is a generalization of the more traditional method of simulated moments, MSM, or the Efficient Method of Moments, EMM. Indirect Inference is becoming a standard estimation method in analyses of the type we conduct in our papers. See for recent examples Alan and Browning (2009); Guvenen and Smith (2011); Altonji, Smith and Vidangos (2011).

³²We do not have data on DI application, and hence use moments reflecting participation in the DI program.

pin down the incentive cost of the program. Second, we consider the DI status of individuals within work limitation-types. For the severely work limited, this identifies the fraction of the truly needy who benefit from DI. Third, we consider the flow rates onto DI by individuals within work limitation types.

These moments can be directly related to the probabilities of a successful application, the structural parameters of the DI program. Information on stocks on DI and flows into DI is the kind of variability in the data that we use to identify success probabilities by type (age and health status). Intuitively, a higher probability of success for a given type would generate higher flows into the program and larger stocks on DI for that type. For example, consider how we use the fraction of those with a severe limitation not on DI who move onto DI to help identify $\pi_{L=2}^{Old}$. The fraction we observe, and use as auxiliary moment, is $Fr(DI_t = 1|DI_{t-1} = 0, L = 2, Old)$. We can show that:

$$\begin{aligned} Fr(DI_t = 1|DI_{t-1} = 0, L = 2, Old) &= \Pr(DI_t = 1|DI_{t-1} = 0, L = 2, Old, DI^{App} = 1) \\ &\quad * \Pr(DI_t^{App} = 1|DI_{t-1} = 0, L = 2, Old) \\ &= \pi_{L=2}^{Old} \Pr(DI_t^{App} = 1|DI_{t-1} = 0, L = 2, Old) \quad (6) \end{aligned}$$

The observed fraction would be particularly informative if all $L = 2$ individuals applied (i.e., if $\Pr(DI_t^{App} = 1|DI_{t-1} = 0, L = 2, Old) = 1$). However, because not everyone applies, the moment we use (the left hand side of (6)) is a lower bound on the probability of acceptance, the structural parameter of interest. To move from a bound on the probability of acceptance to the actual probability requires a model of the application decision, which will itself be affected by the probabilities of acceptance, as well as the availability of other insurance programs and wage offers.

Consider the following example: the flow fraction $Fr(DI_t = 1|DI_{t-1} = 0, L = 2, Old) = 0.21$ in the data. Suppose we start the iteration with $\pi_{L=2}^{Old} = 0.1$. This probability will not match the data regardless of what the application probability is. Since the probability of applying for DI is not greater than 1, it is clear that $\pi_{L=2}^{Old}$ must exceed 0.21 to make sense of the data, and this is indeed the area where the algorithm will search. For any value of $\pi_{L=2}^{Old}$, the structural model simulates a different $\Pr(DI_t^{App} = 1|DI_{t-1} = 0, L = 2, Old)$, where at the margin more people apply as $\pi_{L=2}^{Old}$ increases. If the fraction (6) were the only moment to match, the algorithm would pick the $\pi_{L=2}^{Old}$ such that $\pi_{L=2}^{Old} \Pr(DI_t^{App} = 1|DI_{t-1} = 0, L = 2, Old)$

is as close as possible to 0.21. In practice, the probabilities and application rates also affect the stock of DI recipients, which are more precisely measured, but which are affected by the flows off DI and by changes in health status over time. We use both flows and stocks by work limitation status as our auxiliary moments.

Moments: Consumption Regression

A work limitation is likely to have two separate effects on consumption: first, the work limitation affects earnings and hence consumption through the budget constraint. The size of this effect will depend on the persistence of the shock and the extent of insurance, both self-insurance and formal insurance mechanisms such as DI. The second effect of the work limitation is through non-separabilities in the utility function (measured by the parameter θ in (1)). For example, if being disabled increases the marginal utility of consumption (e.g. through increased needs) then consumption will rise on disability even if there is full insurance and marginal utility is smoothed over states of disability. It is important to separate out these two effects. Stephens (2001) calculates the effect of the onset of disability on consumption, but does not distinguish whether the effect is through non-separability or through the income loss directly.

The identification of θ comes from a regression of consumption on work limitation. Of course, the presence of income/budget constraint effects means this does not identify the non-separability effect θ . However, if we can identify a (control) group of individuals who are fully insured against disability shocks, then the consumption response to the work limitation for those individuals should capture only preference effects. We assume that people who are in receipt of DI represent such group.³³

Our method for separating out the two effects is to use the parameters of the following auxiliary regression:

$$\begin{aligned} \ln c_{it} = & \alpha_0 + \alpha_1 L_{it}^1 + \alpha_2 L_{it}^2 + \alpha_3 L_{it}^1 DI_{it} + \alpha_4 L_{it}^2 DI + \alpha_5 DI_{it} \\ & + \alpha_6 P_{it} + \alpha_7 t + \alpha_8 t^2 + v_{it} \end{aligned}$$

³³The extent of insurance from DI obviously depends on being admitted onto the program, but conditional on receiving DI, the extent of insurance is greater for low income individuals because replacement rates for our low educated sample can be fairly high: (1) DI payments are progressive (the replacement rate is about 85% for people at the 25th percentile of the AIME distribution, and about 65% at the median); (2) DI covers medical expenses through the Medicare program after two years on the program; (3) unlike wages, benefits are untaxed up to a certain limit; (4) lifetime replacement rates may potentially be higher because DI payments are received with certainty while employment is random due to labor market frictions.

The effect of a (severe) work limitation on consumption for individuals who are not in receipt of DI is given by the parameter α_2 . This captures both the income effect and the non-separability effect. For individuals who are in receipt of DI, however, the effect of a severe disability on consumption is $(\alpha_2 + \alpha_4)$. If DI provided full insurance, $(\alpha_2 + \alpha_4)$ would capture the effect of the non-separability, with the parameter α_4 negating the income effect in α_2 . The split between α_2 and α_4 is less clear if insurance is partial; in which case $(\alpha_2 + \alpha_4)$ captures both the non-separable part and the lack of full insurance for those receiving *DI*. Indirect inference exploits this identification intuition without putting a structural interpretation directly on the α parameters. The coefficients α_1 and α_3 correspond to the effects of a moderate disability. We use an adult-equivalent measure of consumption and control for a quadratic in age to account for life-cycle evolution of family composition and tastes.^{34 35}

Employment can also provide insurance against disability shocks. In addition, employment has a direct effect on the marginal utility of consumption (the parameter η). We use the auxiliary parameter α_6 to help capture this non-separability between consumption and labor supply. Intuitively, whether consumption and employment covary positively or negatively (controlling for health status and point on the life cycle) is informative about whether they are Frisch complements or substitutes in utility.

Moments: Employment Rates over the Life-Cycle We calculate employment rates by age and by work limitation status, using four 10-year age bands: 23-32, 33-42, 43-52, and 53-62. The moments that we use are the employment rates for the three work limitation groups in each age band, giving 12 moments overall. These moments are related to fixed cost of work with different work limitations, $F(L)$, the utility cost of working, η , and the labor market frictions.

In particular, unemployment rates among the healthy in the early life cycle are informative about the job destruction rate δ because assets are very low at young ages and so very few decide voluntarily not to work. The differences in employment by disability status is

³⁴Our measure of consumption is per adult equivalent (using the OECD equivalence scale $1 + 0.7(A - 1) + 0.5K$, where A is the number of adults and K the number of children in the household).

³⁵We need to add two caveats to our identification strategy. First, as stressed by Meyer and Mok (2008), consumption is measured at the family level, but we observe changes in disability at the individual level. To partly account for this, we use a measure of adult equivalent consumption. The second caveat is that disability insurance is only one form of insurance against disability risk (SSI and workers' compensation being others). We replicated the regression reported in section B of Table 4 using a more comprehensive measure of insurance against disability risk (comprising DI, SSI and WC) and find qualitatively similar results.

informative about the extent that work is more costly for disabled than for healthy workers and thus how the fixed cost of work differs by work limitation status.

5.5 Indirect Inference Results

In this section we present results on the moments matched by Indirect Inference in Table 4, and the estimates of the structural parameters in Table 5. For each targeted moment, we present its value in the data, its simulated value (evaluated at the estimated structural parameters), and the 95% confidence interval of the difference between the value in the data and that in the simulation.³⁶ Targeted moments are divided into five panels: consumption moments, employment moments, DI coverage moments, moments related to the composition of DI recipients, and DI flows moments.

Starting with Panel A, we find that our auxiliary model estimates of the consumption regression suggest that consumption falls when people become disabled and there is no insurance. However, those who are insured against the disability shock (those who are receiving DI) increase their consumption, consistent with the idea that consumption and poor health are Frisch complements ($\theta < 0$ in our utility specification). This may arise, for example, because a disability that induces a work limitation may also reduce an individual's opportunities for home production, such as in preparing food, housework and in accessing the cheapest shops. These auxiliary regression results are very closely replicated by our simulated moments. None of the health and DI-related moments are statistically different in the data relative to the simulations.³⁷

Turning to Panel B, the model is capable of matching well the employment behavior of people with severe and moderate disabilities, but it does not fit perfectly well the employment behavior of older non-disabled workers.³⁸ Nevertheless, the differences appear economically

³⁶We compute standard errors of the auxiliary moments estimated in the data by the block bootstrap. Call $s_{\hat{\beta}_{data}}$ this standard error. The standard error of the difference $(\hat{\beta}_{data} - \hat{\beta}_{sim.s})$ is computed (using asymptotic results) as: $\sqrt{(1 + \frac{1}{S}) s_{\hat{\beta}_{data}}^2}$, where S is the number of simulations ($S = 40$ in our case).

³⁷We repeated our consumption regression using food data and find qualitatively very similar results as far as the non-separability issue between consumption and health is concerned. The results also remain qualitatively similar if we control for individual fixed effects (see Table 9 in the Appendix for both sets of results).

³⁸Some of the employment rejections are due to the fact that the employment proportions are very high and hence even small differences get magnified by small standard errors. For example, in the data the fraction of 33-42 years old who work is 94.6%, while we simulate it to be 91%. However, even if we had simulated an economically undistinguishable 93.5%, we would still have found a statistical rejection of the

Table 4: Targeted Moments

Variable/Moment	Data	Simulations	95% C.I. diff.	Variable/Moment	Data	Simulations	95% C.I. diff.
Panel A: The Log Consumption Regression							
$\{L_{it} = 1\}$	-0.047 (0.031)	-0.060	(-0.048; 0.074)*	$\text{Fr}\{DI_{it} = 1 L_{it} = 2, t < 45\}$	0.293 (0.0376)	0.295	(-0.077; 0.072)*
$\{L_{it} = 2\}$	-0.186 (0.037)	-0.174	(-0.086; 0.062)*	$\text{Fr}\{DI_{it} = 1 L_{it} = 2, t \geq 45\}$	0.599 (0.0319)	0.574	(-0.038; 0.089)*
$\{L_{it} = 1\} \times DI_{it}$	0.070 (0.101)	0.133	(-0.265; 0.138)*	$\text{Fr}\{DI_{it} = 1 L_{it} = 1, t < 45\}$	0.075 (0.0142)	0.058	(-0.012; 0.045)*
$\{L_{it} = 2\} \times DI_{it}$	0.291 (0.101)	0.361	(-0.271; 0.131)*	$\text{Fr}\{DI_{it} = 1 L_{it} = 1, t \geq 45\}$	0.211 (0.0291)	0.213	(-0.060; 0.055)*
DI_{it}	-0.248 (0.091)	-0.263	(-0.165; 0.196)*	$\text{Fr}\{DI_{it} = 1 L_{it} = 0, t < 45\}$	0.0024 (0.0007)	0.0026	(-0.002; 0.001)*
Employed	0.235 (0.022)	0.112	(0.078; 0.167)	$\text{Fr}\{DI_{it} = 1 L_{it} = 0, t \geq 45\}$	0.0144 (0.0035)	0.0182	(-0.011; 0.003)*
Panel B: Employment by Disability Status							
$\text{Fr}\{P_{it} = 1 L_{it} = 0, 23-32\}$	0.921 (0.0061)	0.911	(-0.002; 0.022)*	$\text{Fr}\{L_{it} = 2 DI_{it} = 1, t < 45\}$	0.607 (0.0479)	0.636	(-0.124; 0.066)*
$\text{Fr}\{P_{it} = 1 L_{it} = 0, 33-42\}$	0.946 (0.0054)	0.910	(0.025; 0.047)	$\text{Fr}\{L_{it} = 2 DI_{it} = 1, t \geq 45\}$	0.683 (0.0270)	0.630	(-0.001; 0.107)*
$\text{Fr}\{P_{it} = 1 L_{it} = 0, 43-52\}$	0.947 (0.0062)	0.909	(0.025; 0.050)	$\text{Fr}\{L_{it} = 1 DI_{it} = 1, t < 45\}$	0.258 (0.0349)	0.201	(-0.011; 0.127)*
$\text{Fr}\{P_{it} = 1 L_{it} = 0, 53-62\}$	0.837 (0.0163)	0.895	(-0.090; -0.026)	$\text{Fr}\{L_{it} = 1 DI_{it} = 1, t \geq 45\}$	0.224 (0.0221)	0.229	(-0.049; 0.039)*
$\text{Fr}\{P_{it} = 1 L_{it} = 1, 23-32\}$	0.715 (0.0375)	0.864	(-0.223; 0.075)	$\text{Fr}\{L_{it} = 0 DI_{it} = 1, t < 45\}$	0.135 (0.0326)	0.164	(-0.093; 0.036)*
$\text{Fr}\{P_{it} = 1 L_{it} = 1, 33-42\}$	0.775 (0.0333)	0.802	(-0.093; 0.040)*	$\text{Fr}\{L_{it} = 0 DI_{it} = 1, t \geq 45\}$	0.093 (0.0194)	0.141	(-0.087; -0.010)
$\text{Fr}\{P_{it} = 1 L_{it} = 1, 43-52\}$	0.675 (0.0435)	0.660	(-0.071; 0.102)*	Panel E: Flows into DI			
$\text{Fr}\{P_{it} = 1 L_{it} = 1, 53-62\}$	0.450 (0.0449)	0.367	(-0.006; 0.172)*	$\text{Fr}\{DI_{it} = 1 DI_{it-1} = 0, L_{it} = 2, t < 45\}$	0.1225 (0.0216)	0.1539	(-0.074; 0.011)*
$\text{Fr}\{P_{it} = 1 L_{it} = 2, 23-32\}$	0.233 (0.0493)	0.202	(-0.068; 0.128)*	$\text{Fr}\{DI_{it} = 1 DI_{it-1} = 0, L_{it} = 2, t \geq 45\}$	0.2063 (0.0266)	0.3049	(-0.151; -0.046)
$\text{Fr}\{P_{it} = 1 L_{it} = 2, 33-42\}$	0.196 (0.0365)	0.234	(-0.110; 0.034)*	$\text{Fr}\{DI_{it} = 1 DI_{it-1} = 0, L_{it} = 1, t < 45\}$	0.0144 (0.0060)	0.0151	(-0.012; 0.011)*
$\text{Fr}\{P_{it} = 1 L_{it} = 2, 43-52\}$	0.109 (0.0243)	0.146	(-0.085; 0.011)*	$\text{Fr}\{DI_{it} = 1 DI_{it-1} = 0, L_{it} = 1, t \geq 45\}$	0.0412 (0.0114)	0.0561	(-0.038; 0.008)*
$\text{Fr}\{P_{it} = 1 L_{it} = 2, 53-62\}$	0.060 (0.0173)	0.049	(-0.023; 0.045)*	$\text{Fr}\{DI_{it} = 1 DI_{it-1} = 0, L_{it} = 0, t < 45\}$	0.0009 (0.0004)	0.0005	(-0.000; 0.001)*
				$\text{Fr}\{DI_{it} = 1 DI_{it-1} = 0, L_{it} = 0, t \geq 45\}$	0.0045 (0.0014)	0.0019	(-0.000; 0.006)*

Note: Block bootstrap s.e. in parenthesis. An asterisk indicates a statistically insignificant difference (at 5 percent level).

small and not systematic (the model underpredicts employment at age 33-42 and overpredicts it in the last 10 years before retirement).³⁹ We also notice that these discrepancies arise for the group of healthy individuals that for the most part is unaffected by the type of policy experiments we are going to run later. It would have been much more worrying for the credibility of our policy experiments if the discrepancies between data and model had emerged for groups (those with moderate or severe disabilities) whose behavior is most likely affected by changes in benefit generosity or screening procedures.

In Panel C and D we look at the two sides of the insurance/disincentives trade-off of DI. Our model is capable of matching almost all the moments with great accuracy. For example, it matches quite closely the proportions of “false recipients”, $\text{Fr}(L = 0|DI = 1, t)$, as well as the proportion of workers “insured” by the DI program, $\text{Fr}(DI = 1|L = 2, t)$, which are the reduced form equivalents of the incentive cost/insurance benefit tradeoff. In the final Panel E we examine the flows into the program by work limitation and age. Once more, the model fits these moments quite well statistically.

In Table 5 we report the Indirect Inference parameter estimates corresponding to these moments. We estimate that a moderate (severe) disability induces about a 22% (44%) loss of utility in terms of consumption. Working induces a 20% loss. The fixed costs of work per quarter rise substantially with the degree of work limitation. We estimate that a job is destroyed on average every 15 quarters. The probability of success of DI application increases with age and disability status. The estimates of the success probabilities by type (age and work limitation status) provide information on the extent of type I and type II errors, which we discuss further in the next section. All estimates are statistically significant except for the probabilities of success among those without any work limitation at all, which are however economically insignificant.

null of no difference given a standard error of 0.005.

³⁹One exception is employment among very young people reporting a moderate disability. In the data, only 72% work, while in the model 86% do. In the simulations, these individuals have low acceptance rates onto DI and no assets, and so they must work in order to finance their consumption. In reality, they may have access to sources of support that we do not explicitly model - such as insurance provided by parents or other relatives.

Table 5: **Estimated Parameters**

Frictions and Preferences			Disability Insurance Program	
Parameter		Estimate	Parameter	Estimate
θ	Cost of disability	-0.224*** (0.051)	$\pi_{L=0}^{Young}$	0.004 (0.485)
η	Cost of part.	-0.197*** (0.053)	$\pi_{L=0}^{Old}$	0.0095 (0.409)
δ	Job destruction	0.068*** (0.027)	$\pi_{L=1}^{Young}$	0.148* (0.078)
			$\pi_{L=1}^{Old}$	0.148*** (0.041)
$F_{L=0}$	Fixed cost	0.0002 [\$0] (0.046)	$\pi_{L=2}^{Young}$	0.232*** (0.029)
$F_{L=1}$	Fixed cost	0.276*** [\$839] (0.108)	$\pi_{L=2}^{Old}$	0.510*** (0.078)
$F_{L=2}$	Fixed cost	0.524*** [\$1592] (0.056)		

Note: Fixed costs are reported as the fraction of average offered wage income at age 23 and also in 1992 dollars per quarter. Standard errors in parenthesis (see the Appendix for definitions). *, **, *** = significant at 10, 5, and 1 percent, respectively.

5.6 Implications

In this section we discuss the implications of our estimates for the success of the DI screening process, for behavioral responses to DI program parameters, and the extent of self-insurance. We also show the importance of our estimates about the role of work limitations. We compare predictions of our model with evidence from the predominantly reduced form literature. This is a way to verify that the model can reproduce statistics about the DI program that were not explicitly targeted by the estimation procedure (external validity).

5.6.1 Success of the DI Screening Process

One important issue is to evaluate the success rate of the existing DI Screening Process. We first look at the award rate at the point of entry in the system (i.e., award of initial application). We simulate this rate (using our structural model and estimated parameters) to be 0.34. French and Song (2010) use administrative SSA data on the outcome of DI applications and report a very similar success rate for the initial application (0.39). In practice, applicants who are rejected can appeal at four different successive levels: DDS reconsideration, Administrative Law Judges (ALJ), Federal Court, and at the Council Review level. While we do not model the appeal process formally, we do allow individuals to re-apply for

DI following rejections. This allows us to compare award rates in the short and long run in the model and in reality. According to French and Song (2011) the award rate after 2 years from the initial application is 53% (52% in our model); after 4 years is 61% (and is the same in our model); and after 10 years is 67% (74% in our model). Hence, our model captures quite well short- and long-run award rates.

Those reported above are unconditional award rates (i.e., they do not condition on the applicant's health). Given that the true disability status of an applicant is private information, SSA evaluators are likely to commit two types of errors: Admitting onto the DI program undeserved applicants and rejecting those who are truly disabled. Our structural estimates of the success rates show how large these errors are. Consider first the extent of false positives (the proportion of healthy applicants who receive DI). From Table 5, these type II errors have probabilities ranging from 0.4% (young non disabled) to 15% (those with a moderate disability). Similarly, we can use our model to estimate the Award Error: the fraction of successful applicants to DI who are not severely disabled, given by $Pr(L = \{0, 1\} | DI = 1, DI^{App} = 1) = 0.157$. In the literature, one finds reduced form estimates that are fairly similar, 0.16 to 0.22 in Benitez-Silva et al. (1999), depending on the statistical assumptions made, and 0.19 in Nagi (1969).

Consider next the probability of false negatives (i.e., the proportion of severely disabled who apply and do not receive DI). From Table 5, our estimate is that the type I errors are 77% for the younger and 49% for the older workers. The fraction of rejected applicants who are disabled, the Rejection Error, is given by $Pr(L = 2 | DI = 0, DI^{App} = 1) = 0.574$. This is again similar to Benitez-Silva et al. (1999), who report 0.52-0.58, and Nagi (1969), 0.48. These comparisons confirm that our structural model is capable of replicating reduced form estimates obtained using direct information on the application and award process. Taken together, these estimates suggest substantial inefficiencies in providing coverage for the severely work limited, but less inefficiencies in terms of identifying false claimants.⁴⁰

⁴⁰One caveat to this conclusion is the possibility of non-classical measurement error. This might arise for example if people tend to exaggerate their report of work limitations if in receipt of DI or unemployed. If that was the case, our estimates of type I error will be overestimated and our estimates of type II error underestimated.

5.6.2 Elasticities

The reduced form literature on DI has attempted to establish the incentive cost of DI by looking at a number of behavioral responses, in particular the response of DI application and labor force participation (or employment) to an increase in generosity of the DI program. In Table 6 we report elasticity estimates from representative papers in the literature (surveyed in the authoritative survey of Bound and Burkhauser, 1999) and we compare these estimates with those that we can compute in our model. These are obtained by simulating individual response as we marginally change the generosity of the DI program.

In column 1 we report the elasticity of DI applications with respect to benefit generosity. As surveyed by Bound and Burkhauser (1999), empirical analyses using aggregate time series data from the 1960s and 1970s (such as Halpern, 1979; Lando et al., 1979) in general tend to find smaller elasticities (around 0.5) than those obtained from cross-sectional data (such as Kreider, 1998, and Halpern and Hausman, 1986), which however display more variability. A central estimate from Table 13 of Bound and Burkhauser (1999) is about 0.6 (with a 0.2-1.3 range). Our estimate (using all individuals) is 0.45. However, this figure masks considerable heterogeneity by health. The moderately disabled are very elastic in their response to generosity (1.11), whereas the severely disabled have very little response (0.12). As we shall see, this difference plays an important role when assessing the welfare implications of changing DI benefits generosity.

The second column shows the elasticity of the non-employment rate with respect to benefit generosity. In the literature, the response of non-employment to benefits is generally estimated to be smaller than the response of DI applications. For example, the range of estimates reported by Bound and Burkhauser (1999) in their Table 16 and by Haveman and Wolfe (2000) in their Table 10 is between 0.06 and 0.93. In our model this elasticity is on the lower end of the range of estimates from the literature (our estimate is 0.12). We also break our sample by work limitation and find a differential effect on the moderately and severely disabled: the moderately disabled are more sensitive but the differences are small except for the under 40s. For moderately work limited under 40, the elasticity is about 0.24, whereas for the severely disabled, the elasticity remains close to zero.

Table 6: **Relevant Reduced Form Elasticities**

	Elasticities	
	DI Application w.r.t. DI generosity (1)	Non-Employment w.r.t. DI generosity (2)
Range of estimates from lit.	0.2 – 1.3	0.06 – 0.93
Our model:		
All Individuals	0.45	0.12
Mod. disab. $L = 1$	1.11	0.049
Sev. disab. $L = 2$	0.12	0.011

Note: The range of estimates from the literature in column (1) come from Bound and Burkhauser (1999, Table 13); those in column (2) from Bound and Burkhauser (1999, Table 16) and Haveman and Wolfe (2000, Table 10).

Table 7: **Flows off DI**

Moment	Data	Simul.	95% C.I. difference
$\text{Fr}(DI_t = 0 DI_{t-1} = 1, t < 45)$	0.137 (0.035)	0.089	$(-0.021, 0.117)^*$
$\text{Fr}(DI_t = 0 DI_{t-1} = 1, t \geq 45)$	0.080 (0.015)	0.062	$(-0.012, 0.048)^*$

Note: Block bootstrap s.e. in parenthesis. An asterisk indicates a statistically insignificant difference (at 5 percent level).

5.6.3 Flows off DI

We use our model to simulate the rate of flows off the DI program by work limitation status, and we compare these to rates in the data. We did not use these rates in the estimation because these moments are imprecisely estimated given the size of our sample. However, we reproduce in Table 7 the main annual flow statistics and the simulated counterparts as an indication of the performance of the model. Simulated flows off DI match the decline by age observed in the data. The difference between actual and simulated outflows is statistically insignificant.

5.6.4 Asset Accumulation

An important part of the model is individuals' ability to self-insure through asset accumulation. Unfortunately, it is difficult to compare asset accumulation when there is only one liquid asset available (as in the model), with data where individuals have both liquid financial wealth (bank deposits and stocks) as well as illiquid assets (housing and pension

wealth). It is precisely for this reason that we use data on consumption and income, rather than assets, in our estimation. Moreover, during the sample period covered by our data, asset information was asked only at five year intervals (in 1989 and 1994). However, we can still compare simulated lifecycle asset profiles and health-specific asset transitions with those we obtain in the data as a form of external validation.

Our definition of assets in the data includes both housing wealth and liquid financial wealth.⁴¹ Median asset holdings around retirement (in the five age interval centered at 60) in the simulations are close to the data both for the healthy and for the work limited: for the severely work limited, median asset holdings are 2.9 times median earnings in the data and 3.7 times in the simulations; for the healthy, the median is 4.9 times median earnings in the data and 5.2 times in the simulations.⁴² Another useful statistics is wealth dynamics by health status. We regress the 5-year change in wealth against a quadratic in age, and dummies for severe and moderate disability (the no disability is the excluded category) in the data and in the simulations. We find that the model approximates well asset changes we observe in the data. Wealth changes decline monotonically with poor health: those in poor health have run down their assets, those in good health have accumulated. We cannot reject the null that data and simulations predict the same health and age gradients (full details are in the Appendix).

5.6.5 Sensitivity: the Importance of Health

In our structural model, health status affects behavior in two ways: it shifts preferences (non-separability) and it changes the fixed cost of work.⁴³ We consider here whether both of these mechanisms are necessary. First, we consider the case where the fixed cost of work does not vary with health status. Second, we consider switching off the non-separability between consumption and health. In both cases, we reestimate the structural model to match the same set of moments as in the baseline. Estimation details are in the Appendix.

When the fixed cost of work does not vary with health, the structural estimates of

⁴¹We calculate median asset holdings at different ages and for different work limitation status. We normalise median asset holdings by the median of annual earning across individuals and across the lifetimes.

⁴²While the model matches the ratios at retirement fairly well, it does less well in matching the speed of accumulation early in the life cycle. The accumulation is faster in early part of the lifecycle in the simulation (below age 40), while in the data the acceleration happens primarily after age 40. These differences partly arise because in the model there are no age-dependent consumption needs (i.e., children).

⁴³There is also the effect of health on wages and the effect of health on the variance of productivity shocks which are estimated directly.

the model imply large and numerous deviations between data and simulated moments (or auxiliary parameters). In particular, the null of no difference between moments in the data and in the simulation is rejected for 28 of the 36 moment conditions. The very poor fit of the model is because without heterogeneity in the fixed cost of work by health status it is very difficult to generate differences in employment across disability groups: too many of the disabled remain at work compared to the data. The bad fit for the employment numbers cascades onto the number of DI applicants and this in turn affects the DI moments and so forth.

When we assume separability between consumption and work limitations, or $\theta = 0$, we also obtain a much worse fit relative to the baseline (17 rejections out of 36 moments). The minimized criterion is 10.5 (as opposed to 3.1 in the baseline). The poor fit in this case is coming from the consumption equation. The coefficients on the work limitations variables $L = 1$ and $L = 2$ are much more negative: statistically we reject the null that data and simulations produce similar estimates of the auxiliary parameters of the consumption regression. This is expected: our estimate of θ implies that the marginal utility of consumption is higher when disabled and so resources are moved into periods in which people suffer a disability shock to keep consumption smoothed. When θ is set to 0 and the non-separability is removed, there is a larger negative effect on consumption because there is only an income effect with no offsetting substitution.

6 Reform of the DI Process

The most important use of our model and structural estimates is the ability to analyze the effects on welfare and behavior of changing the main parameters of the DI program. We consider four main changes: (a) changing the generosity of disability payments; (b) making the program “stricter” by increasing the threshold that needs to be met in order to qualify for benefits; (c) changing the generosity of the means-tested (food stamp-type) program, and (d) changing the reassessment rate of disability recipients. For each scenario, we show the implications for the coverage of the severely disabled, the extent of false applications by the non-disabled, welfare, aggregate output, and asset accumulation. We calculate the welfare implications by measuring the willingness to pay for the new policy through a proportional reduction in consumption at all ages which makes the individual indifferent ex ante between

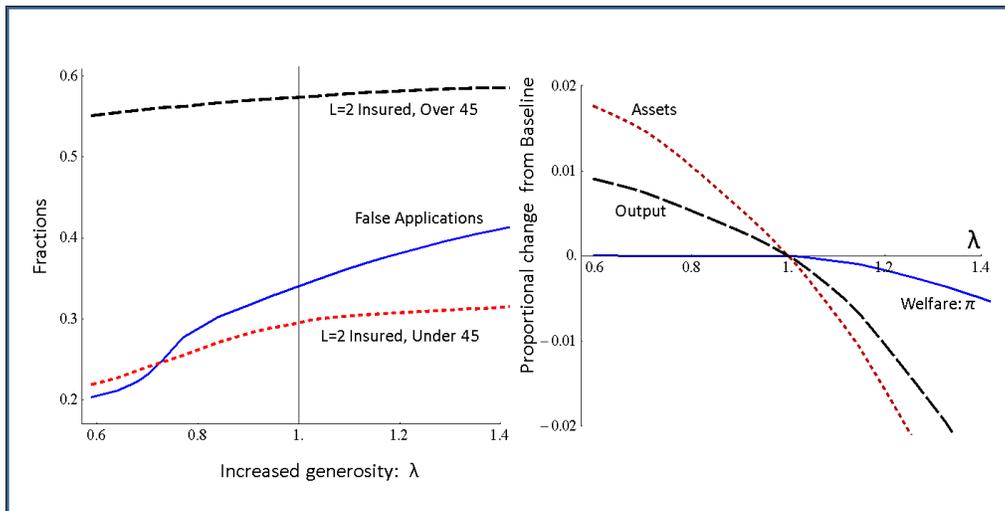


Figure 3: Changing DI Generosity

the status quo and the policy change considered.⁴⁴ In all the experiments below the impact on the government budget is neutralized by adjusting the proportional wage tax iteratively (see equation (4) in the Appendix). We also examine the sensitivity of our policy experiment conclusions to changes in the value of risk aversion, one of the key exogenous parameters.

We stress that we cannot draw conclusions about optimal policy from these experiments. Our policy experiments are best seen as showing partial effects of reform because, although reform is revenue neutral, we do not take account of general equilibrium effects, nor do we consider introducing multiple reforms simultaneously.

6.1 Generosity of DI Payments

In the first experiment, we consider the effects of revenue-neutral, proportional changes in DI generosity, with the proportional changes ranging from a cut to 60% of its current value to a 40% increase. Figure 3 shows the effects of these changes.

The left hand side of Figure 3 shows the effects of the policy on the fraction of applications that are from $L = 0$ or $L = 1$ individuals (the solid line labelled “False Applications”) and on the fraction of severely disabled who are receiving insurance (the dashed lines labelled “ $L = 2$ Insured”, plotted separately for older and younger workers). Both false applications

⁴⁴This is obtained by calculating expected utility at the start of the life-cycle before the resolution of any uncertainty (“behind the veil of ignorance”).

and coverage of the severely disabled increase as generosity increases. However, the fraction of false applicants is much more responsive to changes in generosity than the coverage of the old severely disabled (as also evident from the first column of Table 6).⁴⁵ This fast rise in false applications generates the welfare losses associated with increased generosity shown on the right-hand side graph. On the other hand, reduced generosity from its current level produces negligible welfare benefits: while there are less false applications and a lower tax rate, those who are severely disabled and on DI are less well insured. Further, the welfare losses as generosity increases are quantitatively small: a 10% increase in generosity implies a welfare loss of 0.12% of consumption.⁴⁶

The greater false applications are associated with lower labor force participation and so lower output. Output falls more than welfare partly because of the utility value associated with increased leisure and partly because there is better insurance associated with increased generosity. The assets line shows the effect of generosity on the maximum assets held over the lifetime. The fall in assets with generosity partly reflects the fall in output reducing saving for consumption smoothing and, to the extent that assets are more sensitive than output, the additional crowding out of self-insurance.

6.2 Strictness of DI Admissions

Increases in the strictness of the screening process for DI implemented in 1980 led to sharp declines in inflows onto DI and significant removal of DI recipients, although the criteria were relaxed again in 1984. The issue is whether the benefit induced by greater strictness in terms of reduced incentives for false applications outweighs the worsening insurance of truly disabled workers. To tackle this issue, we need first to define a measure of strictness of the program.

As mentioned in Section 3.4, DI evaluators decide whether to award DI as a function

⁴⁵The fraction of the severely disabled aged under 45 receiving insurance is at a lower level, but similarly varies with generosity much less than the number of false applicants.

⁴⁶Our results differ from Meyer and Mok (2008), who apply a variant of the benefit optimality formula derived by Chetty (2008) to conclude that the current level of DI benefits is lower than the optimal level (i.e., that it is welfare improving to increase DI generosity). Their formula requires estimates of risk aversion and prudence, of the fall of consumption on disability, and an estimate of the elasticity of DI application with respect to DI benefit generosity. Hence, there are three reasons why our results differ from theirs. First, the formula imposes a common elasticity of DI application to benefits without distinguishing between the disability status of applicants. But as shown in Table 6, elasticities are very different when conditioning on work limitation status. Second, with non-separabilities, the fall of consumption upon disability understates the value of insurance. Finally, we assume a more moderate degree of risk aversion.

of a noisy signal about the severity of the applicant’s disability status, which has some distribution f :

$$S_{it} \sim f(L, t)$$

Our estimates of the success probabilities imply that the properties of the distribution of the signal S vary by age and by work limitation status L . Assume that the Social Security DI evaluators make an award if $S_{it} > \bar{S}$. The parameter \bar{S} can be interpreted as a measure of the strictness of the DI program: other things equal, an increase in \bar{S} reduces the proportion of people admitted into the program.

We assume that S lies between 0 and 1 and has a Beta distribution, $\beta(q_{L,t}, r_{L,t})$, whose parameters q and r vary with age and work limitation status. The values of $q_{L,t}$ and $r_{L,t}$ and of \bar{S} are pinned down by the six structural probabilities (π_L^t) estimated above:⁴⁷

$$1 - \pi_L^t = \Pr(\text{Rejection} | t, L, \text{Apply}) = CDF(\beta(q_{L,t}, r_{L,t}))$$

Figure 4 illustrates the resulting distributions of S for those over 45 by work limitation status, and illustrates some of the errors under the estimated DI program. The area on the left of \bar{S} under the solid light grey curve (labeled $f(S|L = 2, t \geq 45)$) measures the probability of rejecting a deserving DI applicant. The area on the right of \bar{S} under the dashed grey curve (labeled $f(S|L = 1, t \geq 45)$) measures the probability of accepting into the DI program a DI applicant with only a moderate disability. Increasing the strictness of the test (increasing \bar{S}) reduces the probability of false positives (reduces the extent of the incentive problem), but increases the probability of false negatives (reduces the extent of insurance provided by the program). It also can have substantial effects on who applies. A policy of changing \bar{S} therefore has both benefits and costs, trading off incentives against insurance, and we use our model to determine which dominates when the strictness of the test changes.⁴⁸

⁴⁷We need to impose two normalizations, and choose to normalize the mean of the signal for the severely disabled old and that of healthy young workers (those with the highest and lowest probability of success in the data). We also impose that the parameter r is identical across age and work limitation status. These normalizations, alongside the use of the Beta distribution, impose a particular distribution on the signals which we do not have the data to test. The intuitive advantage of the Beta distribution is that the precision of the signal increases as true disability status worsens. We considered alternative assumptions, such as a lognormal distribution and find qualitatively similar results. See the Appendix for a discussion of the Beta distribution and the results using a lognormal distribution.

⁴⁸An alternative policy might be to reduce the noise involved in the evaluation of the signal. We do not evaluate such a policy. In theory, we could take the cost of extra SSA evaluations as being the same as the cost of a review. However, the difficulty is estimating the effect of evaluations on reducing the noise.

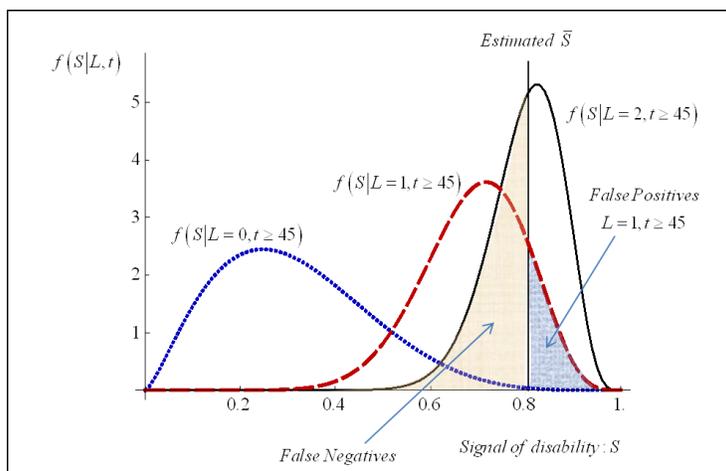


Figure 4: The Distribution of S for the Older Worker by Work Limitation Status

Figure 5 reports the results of changing the level of strictness as measured by \bar{S} . The left-hand graph shows the implications for the DI program in terms of the coverage/disincentive trade-off, while the right-hand graph shows implications for welfare, output, and asset accumulation. Increasing \bar{S} from 0.7 to 0.85 reduces the probability of acceptance for the severely disabled over 45 (under 45) from close to 90% to less than 30% (65% to 5%, respectively). Furthermore, the increase in \bar{S} reduces the proportion of applicants from those with no or only a moderate disability. This is shown in the downward sloping line labelled “False Applications”.⁴⁹

The right hand graph shows the willingness to pay for the alternative \bar{S} in expected utility terms (the welfare measure π). The willingness to pay increases as \bar{S} decreases from its estimated value: the gain in improved insurance from making the program less strict dominates the loss associated with increased numbers of false applicants and a greater award error. The magnitude of the gain in terms of consumption equivalent arising from reducing strictness from its estimated value to $\bar{S} = 0.7$ is about 0.004 (0.4%).

This net gain is the result of two offsetting effects: there is a benefit of increased insurance against disability which individuals are willing to pay for, but this is partly offset by a loss arising from output being lower as individuals work less. Part of the benefit of the relaxed strictness arises from the moderately disabled and the severely-disabled young being offered

⁴⁹Corresponding to this fall in healthy applicants and lower rate of acceptance, there is a clear decline in the fraction of awards being made to the healthy or moderately disabled (the Award Error, not reported).

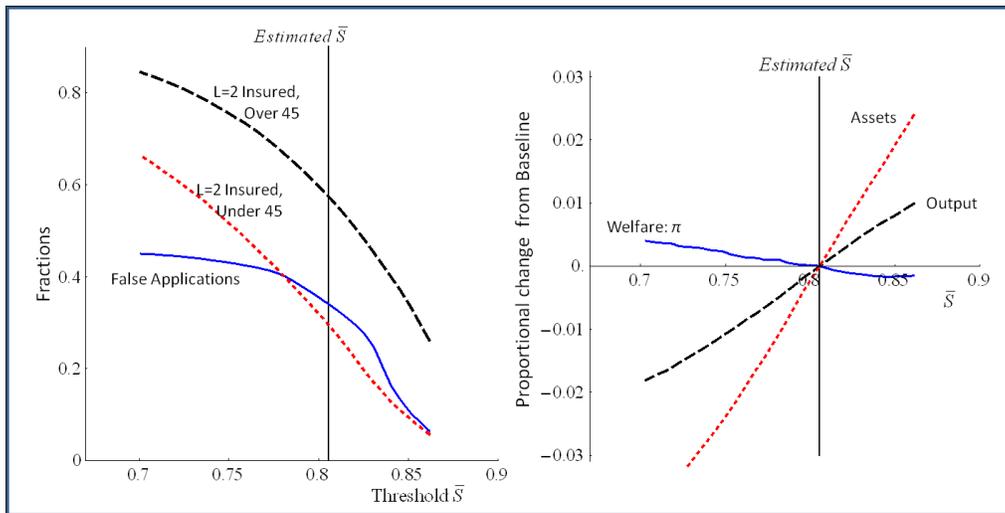


Figure 5: Changing Strictness

better insurance. The key to this conclusion of reduced strictness being welfare increasing is, however, the low acceptance rate of young severely disabled individuals onto DI in the baseline (see Table 5). The subgroup of young severely-disabled individuals are particularly ill-equipped to insure against disability risk because these individuals face high rejection rates when applying for DI and yet have not had time to accumulate enough assets to self-insure. Hence reduced strictness that increases the chance to get into the program is highly valued.⁵⁰

French and Song (2011) and Maestas et al. (2011) consider the extent of labour force participation by DI applicants who have been denied benefits because their application was dealt with by “tougher” disability examiners. We can interpret this empirical strategy as similar to the effect of changing the strictness of the regime in our experiment, as shown in Figure 5. An increase in strictness in our model leads to a fall in DI receipt, and a corresponding rise in labor force participation. For the severely disabled who are over 45, among those who do not receive DI because of greater strictness, we calculate that approximately 15% will be working. Among the moderately disabled over 45, the percentage is only slightly higher at 18%. However, among the moderately disabled under 45, the percentage is 61%. This range is similar to the range found by Maestas et al. (2011).⁵¹

⁵⁰Denk and Michau (2010) obtain a similar result using a dynamic mechanism design approach to the insurance-incentive tradeoff.

⁵¹Some caution is needed in making this comparison: the fraction in the model is calculated by comparing

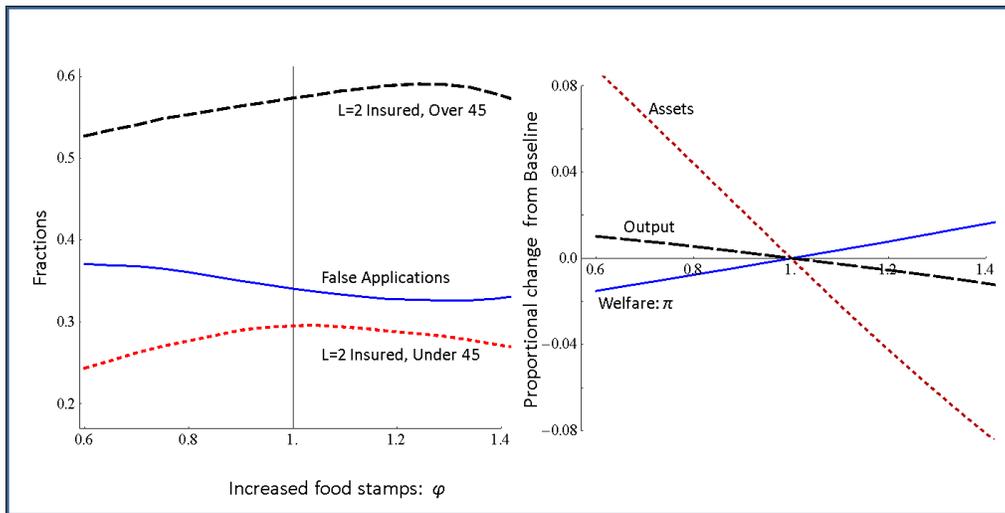


Figure 6: Changing the Generosity of Food Stamps

6.3 Generosity of The Food Stamp Program

The DI program may interact in important ways with other social insurance programs. Here we investigate how important such interactions might be. Figure 6 shows the effects of changing the generosity of food stamps (from a 40% reduction to a 40% increase relative to the status quo). For false applicants, food stamps are substitutes for disability insurance and generally application to DI falls as food stamps' generosity increases. This is because at some point food stamps provide such a sufficiently generous support (without the uncertainty and inconvenience of application for DI) that false applications for DI fall and people with moderate disability substitute application for the generous DI program with the increasingly more generous means-tested program. By contrast, for severely disabled workers food stamps is complementary to DI: We find that the fraction of the severely disabled who receive DI increases as food stamps become more generous. This is because the consumption floor increases, making application for DI less costly for the severely disabled who were marginal between working and applying for DI. In addition, more generous food stamps provide direct insurance against low (permanent) productivity with no risk of rejection. Note, however, that the effect is non-monotonic especially for the younger severely disabled who face high rejection rates from the DI program.

two steady-states, whereas in Maestas et al. (2011) the fraction is calculated using randomisation due to the allocation of lenient assessors.

Together, these effects imply substantial welfare increases as the generosity of food stamps increases. A 10% increase in generosity implies a welfare gain of 1.4% of consumption. This is despite the fall in output and savings that greater generosity induces. It is important to stress that this movement onto food stamps is funded by a change in the tax rate and so, although the saving on DI may appear a false saving because of the greater spending on the food stamp programme, our calculations are that this is welfare increasing despite the tax rise required. What this simulation highlights is the value of food stamps in providing long term support for those whose productivity is too low to be able to work for a reasonable wage. Part of the reason for this result is that the food stamps program is less distortionary than DI because it does not require people to disengage from the labor force and to stop working altogether.

6.4 Reassessment Rates

As a final policy change, we consider changing the reassessment rate. This is a policy that instead of affecting the nature of the screening process at the point of entry in the DI program, tries to affect exit rates from the program (which are notoriously quite low). Given our estimate of the cost per reassessment,⁵² this has a direct impact on the budget, as well as the effect induced by changes in the number of recipients and in labour supply. We assume that the probabilities of success, conditional on work limitation status and age, are the same at reassessment as at initial application. The details are in the Appendix, but are briefly summarized here, because the effects are not substantial. An increase in the reassessment rate discourages false applications by those who are not severely disabled, but also reduces coverage for the severely disabled: reassessment causes some severely disabled to be removed from DI and this directly reduces coverage, as well as discouraging applications, as the frequency of reassessment increases. The reduced false applications lead to greater labour force participation and output, and increased asset accumulation as individuals have to self-insure further, as shown on the right hand side graph. The net effect on welfare is negligible.

⁵²For the period 2004-2008, the SSA spent \$3.985 billion to conduct 8.513 million “continuing disability reviews”. This means a review costs on average \$468, and we deflate this back to 1992 prices and include this price in the government’s budget constraint.

6.5 Sensitivity to Risk Aversion

The welfare and behavioral conclusions on policy experiments may be affected by the degree of risk aversion, which we take from previous literature rather than estimating it. In this section, we consider how differences in risk aversion affect the policy conclusions. We set the coefficient of relative risk aversion, γ , to equal 3, (compared to the baseline where $\gamma = 1.5$) and we re-estimate the structural parameters of the model (i.e., those reported in Table 5). We find that the fit of our model is somewhat worse than in our baseline, but that we can still match the moments fairly well. The structural parameter estimates are different, of course. First, the probability of success is higher when γ is higher and individuals are more risk averse. This higher probability is necessary to induce risk averse agents to apply, which is needed to match the DI moments in the data. Similarly, the fixed cost of work is estimated to be higher among the disabled and this is needed to induce the observed non-participation. Full results are in the Appendix. We use these new estimates of the structural parameters to redo our three counterfactual policy experiments, varying generosity, strictness and food stamps.

As the generosity of the program increases, the fraction of the truly disabled who receive DI increases and the fraction of false applicants also increases, much as in the left hand side of Figure 3.⁵³ Similarly, this translates into lower output and lower asset accumulation. However, when risk aversion is higher, the welfare consequences of the increased generosity are reversed: more generous DI increases welfare when individuals are sufficiently risk averse, because the value of the insurance goes up much more.

The effects of changing strictness are qualitatively similar in all dimensions when risk aversion is higher: coverage and false applications both fall as strictness increases; similarly assets and output also increase as individuals work harder and save more in response to the tougher policy. However, the magnitudes are different. In particular, the welfare benefit of reducing strictness is substantially greater than in the baseline: the insurance value of reducing the uncertainty about success for the severely work limited is much greater.

When food stamps become more generous, the fraction of the truly disabled goes up as in Figure 6, but in contrast to our baseline estimates, the number of false applications also rises. Output falls and asset holdings fall as generosity increases in a similar way to the

⁵³Figures 3, 5, and 6 are reproduced in the appendix for the case $\gamma = 3$.

baseline. Further, welfare increases as in the baseline, but much more markedly: the higher risk aversion makes individuals value the insurance provided by food stamps more highly.

7 Conclusions

In this paper, we provide a life-cycle framework for estimating the extent of work-limiting health risk that individuals face and for analyzing the effectiveness of government disability insurance against that risk. Work limitations have substantial effects on wages, with wages falling by about 47% for the severely work limited. Government insurance against these shocks is incomplete: There are substantial false rejections. We estimate that 49% of the older workers with a severe work limitation who apply for benefits are rejected on their first application. This is alongside other negative effects, with some workers discouraged from applying because of the uncertainty surrounding the application process. Similarly, there are significant rates of false acceptances, with around 15% of applications from those who only have a moderate work limitation being accepted.

We use the model to simulate various policy changes aimed at improving the insurance coverage and mitigating the incentive costs of DI. The simulations show that the number of moderately disabled individuals receiving DI is particularly sensitive to the policy parameters, whereas the number of severely disabled is less sensitive. Thus, reducing DI generosity leads to a fall off in false applications and misdirected insurance, without reducing applications from the severely disabled who are essentially inelastic with respect to benefit generosity. Of course, the severely disabled will then receive less insurance, but this reduced generosity increases welfare from an ex-ante perspective in our baseline. On the other hand, increasing the strictness of the DI screening process leads to a decline in welfare because the existing program already suffers from turning down large numbers of severely disabled with little assets enabling them to self-insure. Increasing the generosity of Food Stamps leads to a fall off in false applications for DI and misdirected insurance, leading to better targeting of DI and a substantial welfare improvement despite the extra cost of Food Stamps. More frequent reassessments of recipients directly reduces the number of recipients who are not severely work limited, but equally importantly more frequent reassessments substantially reduces the proportion of false applicants, leading to some (small) welfare gains.

In summary, welfare increases if the threshold for acceptance is lower, disability payments

are lower, reassessment more frequent and food stamp payments more generous. These conclusions arose because these reforms lead to a separation of the severely work limited from the moderately limited for whom work is a realistic option. This highlights the need to have disability classified into more than just a “yes” or “no” state, and raises the question of whether allowing for partial disability and partial DI payments (as in the Netherlands, for example) may be a way to reduce the incentive cost of DI. One limitation of these policy conclusions is the clear non-linearities in behavior apparent from the simulations in section 6. This highlights the value of having careful structural models of behavior in analyzing disability shocks and the DI process.

One of the implications of our simulations is that changes to the DI process can have sizable effects on asset accumulation, both by changing the need for self-insurance and by changing the amount of time that individuals spend out of the labour force. Related to this, Golosov and Tsyvinski (2006) propose that an asset-test should be introduced to the DI award process to identify those applicants who accumulated assets explicitly to smooth consumption while falsely claiming DI. We could in principle explore in our framework whether an asset test discourages applicants among the moderately or severely disabled. However, the difficulty of performing such exercise is that assets in our framework are fully fungible and serve multiple purposes, including retirement saving, general consumption smoothing as well as self-insurance. An asset test for DI applicants would therefore have the unfortunate side effect of reducing retirement saving.

In terms of limitations and further extensions, our model of the disability insurance process is incomplete: Benitez-Silva et al. (2004) and French and Song (2011) have emphasized the importance of the appeal process, whereas we have allowed the social security administration to make just one decision, albeit we assume that individuals in the model are able to reapply. In the context of capturing behavior over the life-cycle this may be less problematic, but it means we cannot examine one dimension of reform, namely the strictness and length of the appeal judgement relative to the initial judgement. A second restriction is in terms of the stochastic process for work limitations, which we take to be exogenous. The probability of receiving a negative shock to the ability to work is likely to be partly under the individual’s control, through occupation choice and other decisions on the job. These decisions may be affected by the properties of the disability insurance scheme. Finally, we have ignored the health insurance component of the program (although our fixed cost for

work process could be partly re-labeled to capture health spending differences by health and employment status). This means we estimate a lower bound of the insurance value provided by the program.

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Disability Insurance and the Dynamics of the Incentive-Insurance Trade-off

Online Appendix: Not For Publication

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In this online appendix we discuss a number of issues that we left out of the main text for reasons of space. Section A describes further details of the model and solution method. Section B provides further information on the data, including comparability between our data and alternative sources, the quality of self-reported measures, and the consumption imputation. Section C describes the estimation method more fully. Section D provides extensive further robustness checks of the estimation results, particularly of the exclusion restrictions, and of the assumed ways that health enters the model. Section E provides more details on the robustness of our policy experiments to changing the distribution of the noisy signal that the government observes and to changes in risk aversion.

A Further Model Details

A.1 Preferences

We use a utility function of the form

$$u(c_{it}, P_{it}; L_{it}) = \frac{(c_{it} \exp(\theta L_{it}) \exp(\eta P_{it}))^{1-\gamma}}{1-\gamma} \quad (1)$$

The parameter θ captures the utility loss for the disabled in terms of consumption. Employment also induces a utility loss determined by the value of η .

The complementarity or substitutability between consumption and the poor health is governed by the sign of θ . To see this, note that from the first-order condition for consumption, $u_c = \lambda$, one can take the total derivative to yield:

$$u_{cc}dc + u_{cL}dL + u_{cP}dP = d\lambda.$$

The Frisch complementarity can be shown by setting $d\lambda = dP = 0$, and rearranging:

$$\left. \frac{dc}{dL} \right|_{d\lambda=0, dP=0} = -\frac{u_{cL}}{u_{cc}}$$

which implies (given concavity):

$$\text{sign} \left(\left. \frac{dc}{dL} \right|_{d\lambda=0, dE=0} \right) = \text{sign}(u_{cL}) = -\text{sign}(\theta),$$

and so consumption and (poor) health are Frisch complements only if $\theta < 0$ (i.e., the marginal utility of consumption is higher when suffering from a work limitation). Similarly, consumption and employment are Frisch complements if $\eta < 0$. In our empirical framework, we pre-set $\gamma = 1.5$ and we lack explicit additive terms in L and P . Hence we require $\theta < 0$ and $\eta < 0$ to be consistent with disability and work being “bads”.

A.2 Unemployment Insurance

We assume that unemployment benefits are paid only for the quarter immediately following job destruction. Unemployment insurance is paid only to people who have worked in the previous period, and only to those who had their job destroyed (job quitters are ineligible for UI payments, and we assume this can be perfectly monitored). We assume $B_{it} = b \times w_{it-1}h$, subject to a cap, and we set the replacement ratio $b = 75\%$. This replacement ratio is set at this high value because the payment that is made is intended to be of a similar magnitude to the maximum available to someone becoming unemployed (i.e., a 75% replacement rate paid over a single quarter is comparable in expectation to the average 45% replacement rate over 2 quarters that we observe in practice).¹ This simplifying assumption means that, since the period of choice is one quarter, unemployment benefit is like a lump-sum payment to those who exogenously lose their job and so does not distort the choice about whether or not to accept a new job offer. Similarly, there is no insurance against the possibility of not receiving a job offer after job loss.

In the US, the UI program varies across states. It would be very complex (in our model, at least) to capture the myriad differences that exist across US states in terms of UI provision. Our modeling choices are instead intended to replicate the most salient features of the program.

A.3 Universal Means-Tested Program

We assume that the universal means-tested program is an anti-poverty program providing a floor to income for all individuals, similar to the actual food stamps program but with three important differences. First, means-testing is on household income rather than on income and assets;² second, the program provides a cash benefit rather than a benefit in kind;³ and third, we assume there is 100% take-up.

The value of the program is given by

$$W_{it} = \begin{cases} \bar{T} - 0.3 \times y_{it} & \text{if } E_{it}^W = 1 \text{ (i.e., if } y_{it} \leq \underline{y}) \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

In reality the maximum value of the payment, \bar{T} , depends on family size and composition. In our model individuals face no heterogeneity in terms of family size or composition, so we do

¹The advantage of this choice is primarily computational: We do not have to keep track of one’s employment status and eliminate moral hazard in job search that is not the direct focus of the paper.

²The difficulty with allowing for an asset test in our model is that there is only one sort of asset which individuals use for retirement saving as well as for short-term smoothing. In reality, the asset test applies only to liquid wealth and thus excludes pension wealth (as well as real estate wealth and other durables).

³See Hoynes and Schanzenbach (2009) for evidence that families react to food stamps as if it were cash.

not model this aspect of food stamps. Instead, \bar{T} is set assuming that the individual lives in the modal household type (two adults and two children). The term \underline{y} is the poverty line and so only people with net earnings y_{it} below the poverty line are eligible. Net income y_{it} is defined as $y = (1 - \tau_w)y^{gross} - d$, where d is the standard deduction that people are entitled to when computing net income for the purpose of determining food stamp allowances. Finally, y^{gross} is given by

$$y_{it}^{gross} = w_{it}hP_{it} + (B_{it}Z_{it}^{UI}(1 - Z_{it}^{DI}) + D_{it}Z_{it}^{DI} + SSI_{it}Z_{it}^{DI}Z_{it}^W)(1 - P_{it}) \quad (3)$$

The amount of food stamp benefits that individuals receive in the model is determined by first computing y_{it}^{gross} (which depends on employment choices and whether the person is receiving other government payments if unemployed), then computing net income y_{it} , and finally using (2). As we discuss in the main text, this means-tested program interacts in complex ways with disability insurance: the Food Stamps program provides a consumption floor during application for DI, and an alternative mechanism for income support for those of low productivity.

A.4 Taxation on Earnings

The government's main source of revenues are the taxes on labor. When people are in the working stage of the life cycle, the government's outlays are given by payments to people on UI, DI, SSI, and on the means-tested welfare program. The government also spend q per each DI beneficiary who is re-assessed (which happens with probability P^{Re}).⁴

When performing the policy experiments we use as a baseline a case in which the tax rate on labor is 0, and hence we let the government run a deficit \bar{D} . When varying parameters of the social insurance programs, we hold the government budget deficit \bar{D} constant. This is achieved by adjusting the proportional payroll tax, τ_w , such that the present discounted value of net revenue flows is constant:

$$\begin{aligned} \sum_{i=1}^N \sum_{t=1}^T \frac{1}{R^t} [(B_{it}Z_{it}^{UI}(1 - Z_{it}^{DI}) + D_{it}Z_{it}^{DI} + SSI_{it}Z_{it}^{DI}Z_{it}^W)(1 - P_{it}) + W_{it}Z_{it}^W + qP^{Re}Z_{it}^{DI}] \quad (4) \\ = \sum_{i=1}^N \sum_{t=1}^T \frac{1}{R^t} \tau_w w_{it} h P_{it} + \bar{D} \end{aligned}$$

This is done iteratively because labor supply and DI application decisions change as a consequence of changes in government policy.

A.5 Disability Insurance Payments and the Award Process

The value of disability insurance received by DI beneficiaries is given by

$$D_{it} = \begin{cases} 0.9 \times \bar{w}_i & \text{if } \bar{w}_i \leq a_1 \\ 0.9 \times a_1 + 0.32 \times (\bar{w}_i - a_1) & \text{if } a_1 < \bar{w}_i \leq a_2 \\ 0.9 \times a_1 + 0.32 \times (a_2 - a_1) + 0.15 \times (\bar{w}_i - a_2) & \text{if } a_2 < \bar{w}_i \leq a_3 \\ 0.9 \times a_1 + 0.32 \times (a_2 - a_1) + 0.15 (a_3 - a_2) & \text{if } \bar{w}_i > a_3 \end{cases} \quad (5)$$

⁴For the period 2004-2008, the SSA spent \$3.985 billion to conduct 8.513 million "continuing disability reviews". This means a review costs on average \$468, and we use this figure deflating it back to 1992 prices.

where \bar{w}_i is average earnings computed before the time of the application and a_1 , a_2 , and a_3 are thresholds we take from the legislation.⁵ We assume \bar{w}_i can be approximated by the value of the permanent wage.

Figure 1 displays the five steps of the DI determination process. These steps are discussed in detail in many papers, including Bound and Burkhauser (1999), to which the interested reader is referred. At step 1 applicants who are working (or more precisely, earning above a limit known as Substantial Gainful Activity) are immediately excluded. At step 2, applicants who do not satisfy a medical requirement ("a determinable impairment that has lasted or can be expected to last 12 consecutive months or to result in death") are also excluded. At step 3, the SSA awards benefits without any further review to applicants who have a "listed impairment", i.e., an impairment that is easily identifiable and recognizable (such as amputation of both hands, leukemia, etc.). At steps 4 and 5 the SSA awards benefits to individuals who, despite not having a listed impairment, have a vocational disability, i.e., are unable to perform their previous jobs and are unable to perform other jobs that "exist in significant numbers in the national economy" and that fit the applicant's age, education and past work experience.

In reality, people may appeal a negative decision by the SSA. We do not model appeals explicitly. However, since individuals in our model can re-apply at any point in the future following a rejection, the appeal option is implicitly available to them and we use this consideration to compute the award rates since time of first application that are reported in Section 5.6.1 in the main text.

A.6 Solution Method

There is no analytical solution for our model. Instead, the model must be solved numerically, beginning with the terminal condition on assets, and iterating backwards, solving at each age for the value functions conditional on work status.

We start by constructing the value functions for the individual when employed and when out of work. When employed, the state variables are $\{A_{it}, \varepsilon_{it}, L_{it}\}$, corresponding to current assets, individual productivity and work limitation status. We denote the value function when employed as V^e . When unemployed, there are three alternative discrete states the individual can be: unemployed and not applying for disability (giving a value V^n), unemployed and applying for disability (giving a value V^{App}), and unemployed and already receiving disability insurance (giving a value V^{Succ}). We consider the specification of each of these value functions in turn.

The value function if working is written as:

$$V_t^e(A_{it}, \varepsilon_{it}, L_{it}) = \max_c \left\{ \begin{array}{l} U(c_{it}, P_{it} = 1; L_{it}) + \\ \beta \delta E_t \left[V_{t+1}^n \left(A_{it+1}, \varepsilon_{it+1}, L_{it+1}, DI_{it+1}^{Elig} = 1 \right) \right] \\ + \beta (1 - \delta) E_t \max \left\{ \begin{array}{l} V_{t+1}^n \left(A_{it+1}, \varepsilon_{it+1}, L_{it+1}, DI_{it+1}^{Elig} = 1 \right) \\ V_{t+1}^e \left(A_{it+1}, \varepsilon_{it+1}, L_{it+1} \right) \end{array} \right\} \end{array} \right.$$

⁵In reality what is capped is \bar{w}_i (the AIME), because annual earnings above a certain threshold are not subject to payroll taxation. We translate a cap on AIME into a cap on DI payments.

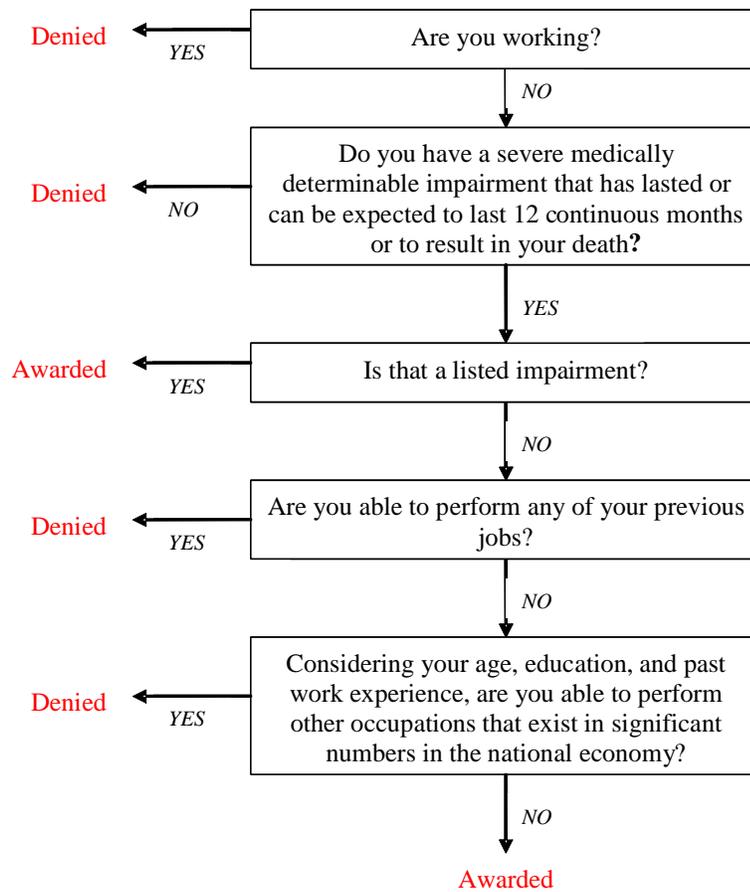


Figure 1: Disability Insurance Determination

where DI_{it+1}^{Elig} is an indicator for whether the individual is eligible to apply for DI.

Consider now the value function for an unemployed individual who is not applying for disability insurance in period t . We need to define as a state variable whether or not an individual has already applied for disability in the current unemployment spell in order to distinguish between those who have the option of applying for disability and those who are ineligible to apply. The value function when eligible for disability is given by:

$$V_t^n \left(A_{it}, \varepsilon_{it}, L_{it}, DI_{it}^{Elig} = 1 \right) = \max_{c, DI^{App}} \left\{ \begin{array}{l} u(c_{it}, P_{it} = 0; L_{it}) \\ +\beta \{1.App = 1\} E_t V_{t+1}^{App} (A_{it+1}, \varepsilon_{it+1}, L_{it+1}) \\ +\beta \{1.App = 0\} \\ \left[\lambda^n E_t \max \left\{ \begin{array}{l} V_{t+1}^n \left(A_{it+1}, \varepsilon_{it+1}, L_{it+1}, DI_{it+1}^{Elig} = 1 \right) \\ V_{t+1}^e (A_{it+1}, \varepsilon_{it+1}, L_{it+1}) \end{array} \right\} \right] \\ + (1 - \lambda^n) E_t \left[V_{t+1}^n \left(A_{it+1}, \varepsilon_{it+1}, L_{it+1}, DI_{it+1}^{Elig} = 1 \right) \right] \end{array} \right.$$

The value function when applying is given by

$$\max_e \left\{ \begin{array}{l} V_t^{App} (A_{it}, \varepsilon_{it}, L_{it}) = \\ u(c_{it}, P_{it} = 0; L_{it}) \\ +\beta \pi_L^t E_t V_{t+1}^{Succ} (A_{it+1}, \varepsilon_{it+1}, L_{it+1}, D_t = 0) \\ +\beta (1 - \pi_L^t) E_t V_{t+1}^n \left(A_{it+1}, \varepsilon_{it+1}, L_{it+1}, DI_{t+1}^{Elig} = 0 \right) \end{array} \right.$$

where D_t is a state variable for the duration of the spell on disability insurance and

$$\pi_L^t = \Pr \left(DI_{it+1} = 1 \mid DI_{it}^{App} = 1, L_{it}, t \right)$$

is the probability of a successful application.

Finally, we have to define the value function if an application for disability has been successful.

$$V_t^{Succ} (A_{it}, \varepsilon_{it}, L_{it}, DI_{it}) = \tag{6}$$

$$\max_c \left\{ \begin{array}{l} u(c_{it}, L_{it}, P_{it} = 0) \\ +\beta (1 - \pi_t^R) E_t \left[\max \left\{ \begin{array}{l} V_{t+1}^{Succ} (A_{it+1}, \varepsilon_{it+1}, L_{it+1}, DI_{it+1}) \\ V_{t+1}^e (A_{it+1}, \varepsilon_{it+1}, L_{it+1}) \end{array} \right\} \right] \\ +\beta \pi_t^R E_t \left[V_{t+1}^n \left(A_{it+1}, \varepsilon_{it+1}, L_{it+1}, DI_{it+1}^{Elig} = 0 \right) \right] \end{array} \right. \tag{7}$$

where

$$\begin{aligned}\pi_t^R &= P^{\text{Re}} \Pr(DI_{it+1} = 0 | L_{it+1}, DI_{it} = 1, t, \text{Re}) \\ &= P^{\text{Re}} (1 - \pi_t^L)\end{aligned}$$

is the probability of being reassessed and removed from the program.

Our model has discrete state variables for: Wage productivity, Work limitation status, Participation, Eligibility to apply for DI (if not working), and Length of time on DI (over 1 year or less than 1 year). The only continuous state variable is assets. We use backward induction to obtain policy functions.

Value functions are increasing in assets A_{it} but they are not necessarily concave, even if we condition on labor market status in t . The non-concavity arises because of changes in labor market status in future periods: the slope of the value function is given by the marginal utility of consumption, but this is not monotonic in the asset stock because consumption can decline as assets increase and expected labor market status in future periods changes. This problem is also discussed in Lentz and Tranaes (2001) and in Low et al. (2010). By contrast, in Danforth (1979) employment is an absorbing state and so the conditional value function will be concave. Under certainty, the number of kinks in the conditional value function is given by the number of periods of life remaining. If there is enough uncertainty, then changes in work status in the future will be smoothed out leaving the expected value function concave: whether or not an individual will work in $t + 1$ at a given A_{it} depends on the realization of shocks in $t + 1$. Using uncertainty to avoid non-concavities is analogous to the use of lotteries elsewhere in the literature. In the value functions above, the choice of participation status in $t + 1$ is determined by the maximum of the conditional value functions in $t + 1$.

B Further Data Issues

B.1 Sample Selection

We focus on male heads because in the PSID, it is the head (almost always the male) who assesses the work limitations of both partners. Using “second-hand” measures of disability status may be misleading. There is now an established literature (see Kapteyn, Smith and van Soest, 2007) arguing that individuals use different response scales when they answer questions about work disability (or any other economic question that involve measurement on a subjective scale, such as assessing the probability of keeping one’s job, etc.). If men are tough critics of disability and they are asked to evaluate someone else’s disability status, their report of the partner’s disability status may be biased downward. Similarly, if men have different subjective assessments of pain than women, their report about the work disability status of their partner may be biased towards their own “pain threshold” (see Mogil and Bailey, 2010, and the references therein).

We exclude those with missing reports on education, the state of residence, the self-employed, those with less than 3 years of data, and some hourly wage outliers (those with an average hourly wage that is below half the minimum wage and those whose hourly wage declines by more than 75% or grows by more than 400%).⁶ Given that the timing of the work limitation question does not coincide with the timing of the DI receipt question (the former refers to the time of the interview, the latter to the previous calendar year), we also lose the first cross-section of data. To identify whether an individual in the PSID is receiving DI, we use a question that asks whether the amount of social security payments received was due to disability.⁷

B.2 Comparison of PSID to Alternative Data Sources

Figures 2 and 3 report a comparison of disability rates in different surveys (the source is Bound and Burkhauser, 1999) and a comparison of trends in DI rates by age as estimated in the PSID and using aggregate statistics, respectively. These figures show that (a) disability rates as estimated in the PSID are not different from those estimated in other, larger data sets, and (b) that the PSID reproduces quite well the fraction of people receiving DI benefits by age.

B.3 Heterogeneity by skills

The empirical analysis in the paper focuses only on the low educated group. Here we report summary statistics on disability status and DI receipt by education groups (which we take as proxies for skill levels). There are important differences by skill level both in terms of probability of disability shocks and disability insurance reciprocity rates. In particular, we find that individuals with low education (at most high school degree) and high education (some college or more) have very similar DI reciprocity rates until their mid 30s, but after that the difference increases dramatically (see Figure 4). By age 60, the low educated are four times more likely to be DI claimants than the high educated (16% vs. 4%). In part, this is due to the fact that low educated individuals are more likely to have some form of disability (moderate or severe) at all ages, as shown in Figure 5.

⁶The hourly wage is defined as annual earnings/annual hours.

⁷The survey first asks the amount of Social Security payments received in year t by the year $t + 1$ head. Then, it asks *Was that disability, retirement, survivor’s benefits, or what?*. Possible responses are: 1) Disability, 2) Retirement, 3) Survivor’s benefits; dependent of deceased recipient, 4) Dependent of disabled recipient, 5) Dependent of retired recipient, 6) Other, 7) Any combination of the codes above.

Data	Year	Survey question	Population	% of population with disabilities
PSID	1989	Do you have any nervous or physical condition that limits the type or the amount of work you can do? (Must have responded yes in both 1988 and 1989)	Men 25-61 Women 25-61	9.2 10.6
CPS	1990	Do you have a health problem or disability which prevents you from working or which limits the kind or the amount of work you can do? Or, Main reason did not work in 1989 was ill or disabled; or Current reason not looking for work is ill or disabled (One period)	Men 25-61 Women 25-61	8.1 7.8
SIPP	1990	Do you have a physical, mental, or other health condition which limits the kind or amount of work you can do? (One period)	Men 21-64 Women 21-64	11.7 11.6
SIPP	1990	Do you have a physical, mental, or other health condition which limits the kind or amount of work you can do? (Must have responded yes in wave 3 and wave 6)	Men 25-61 Women 25-61	9.8 9.8
NHIS	1994	Are you limited in the kind or amount of work you can do because of any impairment or health problem? (One period)	Men 25-61 Women 25-61	10.8 11.4
HRS	1992	Do you have any impairment or health problem that limits the kind or amount of paid work you can do? (One period)	Men 51-61 Women 51-61	27.3 29.8

Figure 2: Survey questions on disability and estimated disability rates (Source: Bound and Burkhauser, 1999).

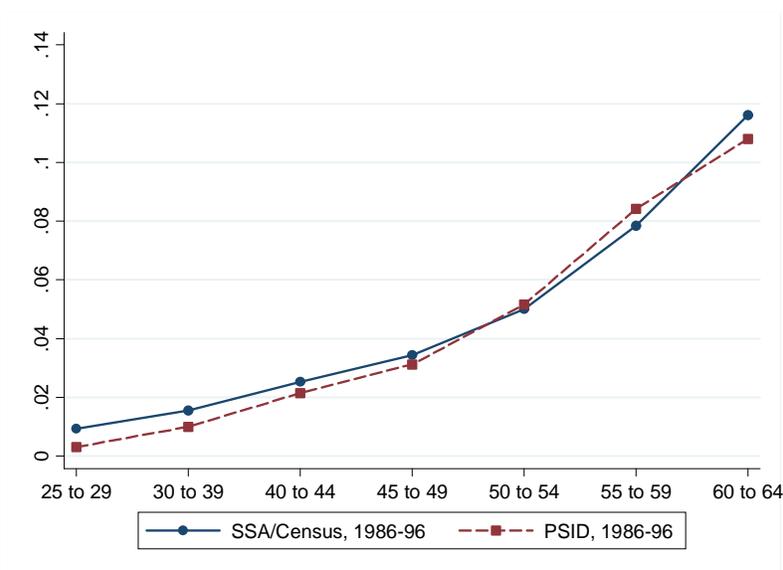


Figure 3: Fraction receiving DI by age, PSID (all males) and aggregate data.

The proportions on DI have varied over time, and particularly there has been a marked increase in reciprocity numbers from the trough in 1984, as documented in Duggan and Imberman (2009) among others. The age composition of those flowing onto DI is shown in figure 6, which highlights that capturing the behavior of those under 50 is an important part of our understanding of disability insurance incentive-insurance dynamic trade-off.

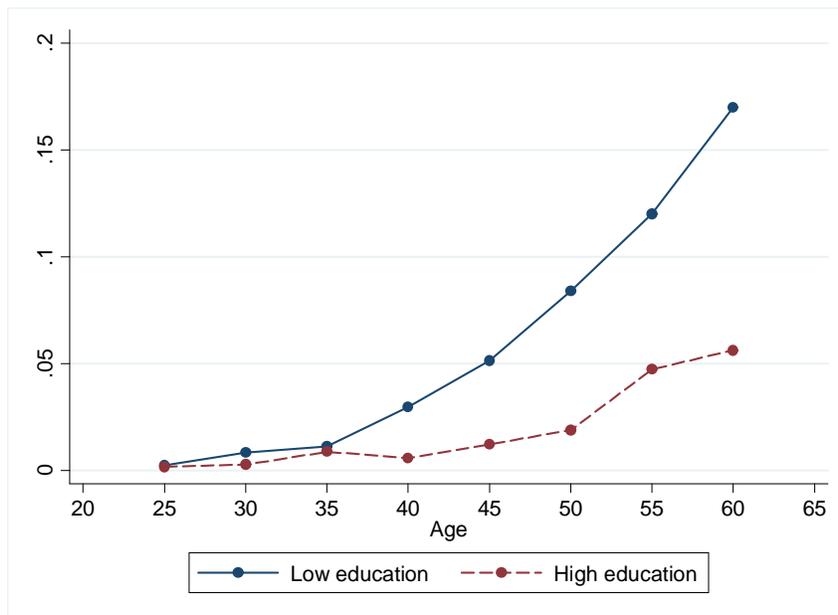


Figure 4: Fraction of individuals receiving disability insurance.

B.4 Self-Reported Disability Measures

Is our self-reported disability measure informative about objective impairment conditions? The 1986 wave of the PSID includes a special module containing detailed information about the respondents' health, including "objective" or "clinical" measures of health, as discussed in Burkhauser and Daly (1986). Table 1 shows that our distinction between a severe and moderate disability is correlated with a wide variety of objective/clinical measures, including Activities of Daily Living (ADLs), hospital stays, extreme BMI values (obesity and being underweight), and subsequent mortality. This confirms that our indicator provides a meaningful and informative classification of work limitations due to disabilities.

B.5 Consumption Data

To compare consumption in the model to consumption in the data, we obtain non-durable consumption in the data with an imputation procedure that uses a regression for nondurable consumption estimated with Consumer Expenditure Survey (CEX) data.

The CEX sample we construct to do the imputation of consumption tries to mimic as closely as possible the sample selections we impose in the PSID. Hence, our CEX sample includes only

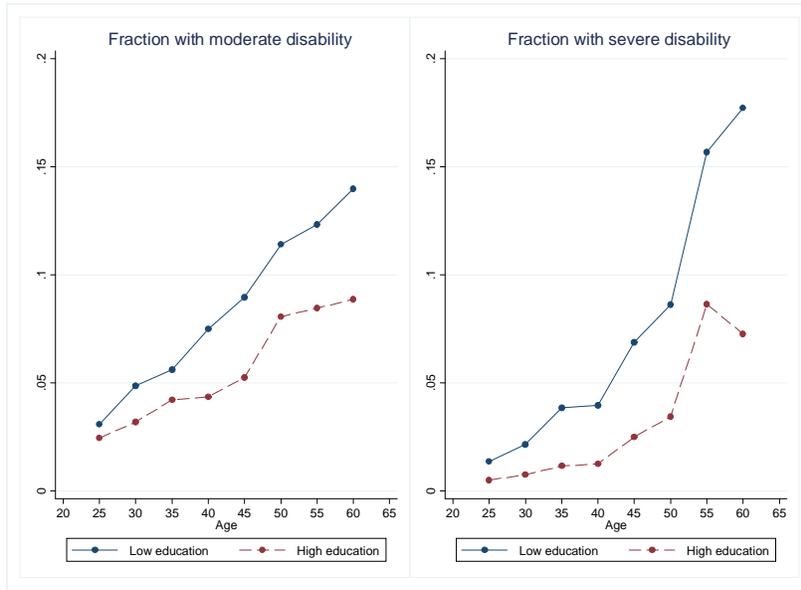


Figure 5: Fraction of individuals with a moderate or severe disability.

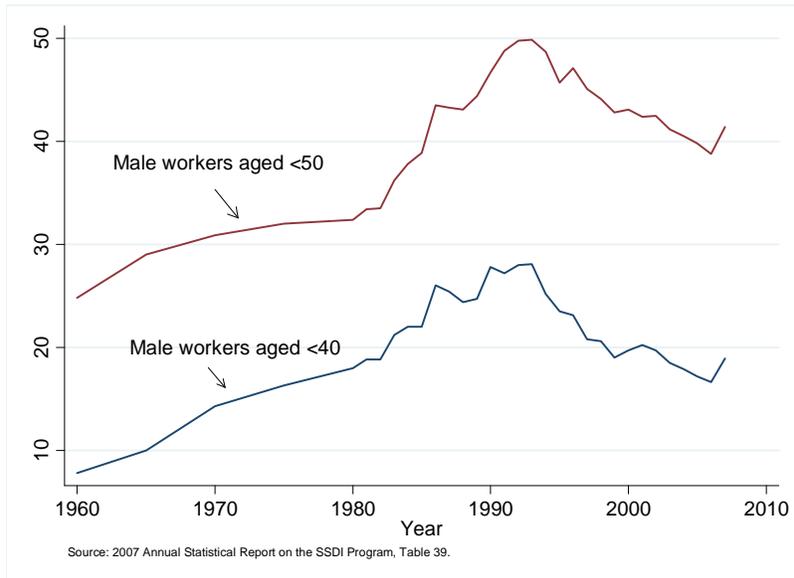


Figure 6: Proportion of DI Awards.

Table 1: **Validity of Self-Reported Disability Status**

Objective indicator	No disability	Moderate	Severe
	$L = 0$	$L = 1$	$L = 2$
Trouble walking/climbing stairs	5%	54%	79%
Trouble bending/lifting objects	7%	61%	83%
Unable to drive car	1%	12%	35%
Trouble with eyesight	2%	6%	15%
Need travel assistance	0%	4%	26%
Need to stay inside	0%	5%	32%
Confined to chair/bed	0%	7%	25%
Limited in physical activity	10%	82%	96%
Spent some time in hospital	6%	27%	34%
Average # of days in hospital	0.96	8.31	8.55
Underweight (BMI < 18.5)	1%	1%	6%
Obese (BMI \geq 30)	14%	22%	18%
Die between 1987 and 2009	15%	30%	43%

Note: The sample is low education male heads of household, aged 23-62. Data refer to 1986.

families headed by a male, reporting data between 1986 and 1996, with no missing data on the region of residence, aged 23 to 62, not self-employed, reporting data for all four interviews (so an annual measure of consumption can be constructed), with complete income responses, non-zero consumption of food, and not living in student housing.

We estimate in the CEX the following regression:

$$\ln c_{it} = \sum_{j=0}^K \theta_j (\ln F_{it})^j + X'_{it}\mu + \xi_{it}$$

where F is food consumption and c_{it} non-durable consumption.

We use a third-degree polynomial in $\ln F$ and control for a cubic in age, number of children, family size, dummies for white, education, region, year, a quadratic in log before-tax family income, labor market participation status, a disability status indicator of whether the head is “ill, disabled, or unable to work”, an indicator for whether the head is receiving social security payments (which for workers aged 62 or less should most likely capture DI), and interactions of the disability status indicator with log food, log income, a dummy for white, the DI indicator, and a quadratic in age. The R^2 of the regression is 0.75. The results are reported fully in Table 2.

We next define in the PSID the imputed value:

$$\widehat{\ln c_{it}} = \sum_{j=0}^K \widehat{\theta}_j (\ln F_{it})^j + X'_{it}\widehat{\mu}$$

This is the measure of consumption we use in the empirical analysis.

Table 2: **The consumption imputation regression**

Regressor	Estimate	Regressor	Estimate
Log food	1.557 (1.036)	Region dummies	Yes
(Log food) ²	-0.157 (0.126)	Year dummies	Yes
(Log food) ³	0.008 (0.005)	Disabled	-1.589 (0.327)
Age	0.050 (0.014)	Disabled×Log food	0.015 (0.023)
Age ²	-0.0011 (0.0003)	Disabled×Log income	0.031 (0.013)
Age ³	8.68e-06 (2.56e-06)	Disabled×White	0.023 (0.025)
Number of children	-0.044 (0.004)	Disabled×DI	0.084 (0.033)
Family size	0.022 (0.003)	Disabled×Age	0.042 (0.012)
White	0.039 (0.008)	Disabled×Age ²	-0.0004 (0.0001)
(Log income)	-.434 (0.024)	DI	0.071 (0.023)
(Log income) ²	0.032 (0.001)	Employed	0.083 (0.012)
		Constant	3.103 (2.851)
N	8097		

Note: Data come from pooled CEX 1986-1996.

C Further Details of the Estimation Process

C.1 Exclusion restrictions in the employment equation

Our reduced form model of employment is:

$$\begin{aligned} P_{it}^* &= X_{it}'\gamma + \sum_{j=1}^2 \delta_j L_{it}^j + \theta G_{it} + \vartheta_{it} \\ &= s_{it} + \vartheta_{it} \end{aligned} \quad (8)$$

where P_{it}^* is the utility from working, and we observe the indicator $P_{it} = \mathbf{1}\{P_{it}^* > 0\}$. The unobserved “taste for work” ϑ_{it} is freely correlated with the permanent productivity shock ζ_{it} , and in particular we define $\rho_{\varepsilon\vartheta, L^j}$ ($\rho_{\zeta\vartheta, L^j}$) the correlation coefficient between ε (ζ) and ϑ for health group L^j .

The vector G_{it} includes exclusion restrictions: They affect the likelihood of observing an individual at work (through an income effect and through affecting the expectation that the individual will apply for DI in the subsequent period), but they do not affect the wage, conditional on X_{it} and L_{it} .

Our employment equation assumes that potential government transfers and the interaction of potential government transfers with disability status serve as exclusion restrictions for the estimation of the wage parameters. Potential benefits are defined next.

Food Stamps Following Wilde (2001), we use the formula:

$$B^{FS} = \max\{M - 0.3 * N_2, 10\}$$

where B are benefits paid, M is the maximum benefit amount (which varies with family size and we take from legislation), and N_2 is net income, defined as:

$$N_2 = \max\{y^G - (D_1 + D_2 + D_3 + D_4 + D_5 + D_6), 0\}$$

where y^G is gross family income (which we take from data), D_1 to D_6 are allowed deductions (standard, earned income, dependent care, medical, child support payment, and excess shelter expense deductions, respectively). We set the dependend care and medical deductions to zero because we have no information on child care or health care expenses. We use information on earned income, child support paid, and rent paid (together with legislation parameters) to compute the other deductions. The shelter deduction is defined as:

$$D_6 = \min\{H^*, \max\{H - 0.5 * N_1, 0\}\}$$

where H are shelter expenses, H^* a cap (from legislation), and N_1 intermediate net income (defined as $N_1 = \max\{y^G - (D_1 + D_2 + D_3 + D_4 + D_5), 0\}$). Finally, we impose eligibility rules (B^{FS} is set to zero if gross income is above 130% of poverty line or net income above poverty line). We ignore the asset test because asset information is available only for two waves.

AFDC Following Solomon (1995), we use the formula:

$$B^{AFDC} = \min \{ \max \{ 0, r^{NS} NS - r^y y \}, M \}$$

where B^{AFDC} are benefits paid, r^{NS} , r^y and M are parameters that vary by state and year, NS are need standards (also varying by state and year, as well as family size) and y is countable income, which we define as the sum of earned income and financial income net of AFDC deductions allowed under the policy. Finally, we impose eligibility rules and set B^{AFDC} to zero for households with no children, or households with before-deductions countable income above 185% of the poverty line or after-deductions countable income above the poverty line.

EITC We set EITC benefits to:

$$B^{EITC} = \tau_1 y \mathbf{1}\{0 < y \leq k_1\} + \tau_1 k_1 \mathbf{1}\{k_1 < y \leq k_2\} + (\tau_1 k_1 - \tau_2 (y - k_2)) \mathbf{1}\{k_2 < y \leq k_3\}$$

where $\mathbf{1}\{\cdot\}$ are indicator functions, τ_1 , τ_2 , k_1 , k_2 and k_3 are policy parameters that vary with family size and time and y is earned income. We add state-specific complementary EITC, and set $B^{EITC} = 0$ for those with 0 earnings or earnings above k_3 . See Hotz and Scholtz (2003).

UI We assume that those who qualify for UI are fully covered and receive it for 26 weeks. We compute UI as:

$$B^{UI} = \max \{ \min \{ r^{UI} y, M \}, m \}$$

where r^{UI} , M , and m vary by state and time and y is "reference" earnings (which also varies by state; some states take it to be annual earnings, others take it to be the average of the best two quarters, and so forth). We add a dependent allowance that is available in certain states and that varies with time and family size. Details come from US D.O.L. (various years).

After estimating (8), we define the inverse Mills ratio $\lambda(s_{it}) = \frac{\phi(s_{it})}{\Phi(s_{it})}$, where $\phi(\cdot)$ and $\Phi(\cdot)$ denote the p.d.f. and c.d.f. of the standard normal distribution, respectively. We incorporate the inverse Mills Ratio into our wage equation and estimate

$$\ln w_{it} = X'_{it} \alpha + \sum_{j=1}^2 \varphi_j L_{it}^j + \sigma_{\varepsilon \vartheta} \lambda(s_{it}) + v_{it} \quad (9)$$

only on the sample of workers, and with $E(v_{it} | P_{it}^* > 0, X_{it}, L_{it}) = 0$. The full set of results are reported in Table 3.

C.2 The variance of productivity shocks

Assuming for simplicity of notation that the measurement error ω_{it} is i.i.d. (when ω_{it} is an MA(1) process one need also consider the second order autocovariances), we can identify the variance of productivity shocks and the variance of measurement error for each health group using the following moment restrictions:

Table 3: **Estimates of the wage equation.**

Variable	Employment equation (1)	Wage w/out selection (2)	Wage with selection (3)
$1\{L_{it} = 1\}$	-0.225*** (0.026)	-0.160*** (0.034)	-0.211*** (0.044)
$1\{L_{it} = 2\}$	-0.738*** (0.031)	-0.262*** (0.052)	-0.470*** (0.136)
Age	0.008*** (0.002)	0.059*** (0.007)	0.064*** (0.008)
Age ² /100	-0.013*** (0.002)	-0.060*** (0.008)	-0.068*** (0.009)
White	0.042*** (0.007)	0.217*** (0.021)	0.226*** (0.022)
Married	0.053*** (0.011)	0.125*** (0.023)	0.139*** (0.025)
Year dummies	Yes	Yes	Yes
Potential transfers	-0.091*** (0.012)		
Potential transfers $\times 1\{L_{it} = 1\}$	0.037* (0.020)		
Potential transfers $\times 1\{L_{it} = 2\}$	0.041* (0.023)		
Mills ratio			0.176* (0.106)
N	14,800	13,332	13,332

Note: Clustered standard errors in parenthesis. *, **, *** indicate statistical significance at 10, 5 and 1 percent level respectively

$$E\left(g_{it}|P_{it} = 1, P_{it-1} = 1, L_{it}^j\right) = \rho_{\zeta\vartheta, L^j} \sigma_{\zeta, L^j} \lambda(s_{it}) \quad (10)$$

$$E\left(g_{it}^2|P_{it} = 1, P_{it-1} = 1, L_{it}^j\right) = \sigma_{\zeta, L^j}^2 \left(1 - \rho_{\zeta\vartheta, L^j}^2 s_{it} \lambda(s_{it})\right) + 2\sigma_{\zeta, L^j}^2 \quad (11)$$

$$-E\left(g_{it}g_{it+1}|P_{it} = 1, P_{it-1} = 1, L_{it}^j\right) = \sigma_{\omega, L^j}^2 \quad (12)$$

(see Low et al., 2010). It follows that the variances are identified by the following expressions:

$$\begin{aligned} \sigma_{\omega, L^j}^2 &= -E\left(g_{it}g_{it+1}|P_{it} = 1, P_{it-1} = 1, L_{it}^j\right) \\ \sigma_{\zeta, L^j}^2 &= E\left(g_{it}^2|P_{it} = 1, P_{it-1} = 1, L_{it}^j\right) + 2E\left(g_{it}g_{it+1}|P_{it} = 1, P_{it-1} = 1, L_{it}^j\right) \\ &\quad + E\left(g_{it}|P_{it} = 1, P_{it-1} = 1, L_{it}^j\right)^2 \frac{s_{it}}{\lambda(s_{it})} \end{aligned}$$

The full set of results are reported in Table 4. In the first column of Table 4 we report results under the assumptions that ω_{it} is MA(1); in the second column, we assume instead that ω_{it} is i.i.d. within each health group. As commented in the main text, the estimate of the variance of productivity shocks vary by health status (the p-value that individuals with no disability and those with severe disability face the same dispersion of productivity shocks is around 5% in both the MA(1) and MA(0) case). While the direction of the effect of poor health on the variance of shocks is an empirical question, we find that disability shifts the degree of dispersion upward – making the likelihood of more extreme realizations of productivity shocks higher when people become disabled. We also find some smaller difference in the variance of measurement error across health groups.⁸ Another interesting feature is that the correlation between unobservables in the wage equation and unobservables in the employment equation is positive and significant only for people with poor health, highlighting the importance of allowing for heterogeneity by health in the wage process. Finally, there is little evidence that an MA(1) process would improve the fit of the wage process much.

C.3 Health Transitions

In this section we discuss estimates of $\Pr(L_{it} = q|L_{it-1} = k)$, for $q, k = \{0, 1, 2\}$. For reason of space, only selected transition probabilities were included in the main text. Figure 7 reports transitions out of the "no disability" state, $L_{it-1} = 0$. The probability of remaining healthy declines over the working life cycle, with 2/3 of the transitions being towards moderate disability and the remaining 1/3 towards severe disability. At the end of the working life cycle individuals with no disability have about a 5% probability of being hit by a severe disability shock.

Transitions out of the moderate disability state $L_{it-1} = 1$ also have interesting life cycle patterns, as shown in Figure 8. Persistence in that state increases, while the probability of health improvement almost halves between age 25 and age 60. Finally, there is a strong increase in the probability of health worsening - almost one quarter of those with moderate disability move onto severe disability at the end of the working life cycle.

⁸Why would measurement error vary across health groups? One possibility is that individuals with a disability have more trouble recalling their last year's earnings, and in fact we find that σ_{ω}^2 slightly increases with poor health (although the difference is statistically insignificant).

Table 4: Estimates of the variance of wage innovations.

Parameter	Wage Process	
	MA(1)	MA(0)
$\sigma_{\varepsilon,L=2}^2$	0.110** (0.048)	0.117** (0.049)
$\sigma_{\varepsilon,L=1}^2$	0.041* (0.021)	0.045** (0.021)
$\sigma_{\varepsilon,L=0}^2$	0.016** (0.007)	0.020*** (0.005)
$\sigma_{\omega,L=2}^2$	0.066*** (0.024)	0.059*** (0.022)
$\sigma_{\omega,L=1}^2$	0.044*** (0.011)	0.040*** (0.010)
$\sigma_{\omega,L=0}^2$	0.038*** (0.005)	0.034*** (0.002)
$\rho_{\varepsilon\pi,L=2}$	0.550*** (0.145)	0.533*** (0.136)
$\rho_{\varepsilon\pi,L=1}$	0.987 (1.535)	0.942 (0.644)
$\rho_{\varepsilon\pi,L=0}$	0.008 (0.128)	0.007 (0.124)
θ	0.053 (0.055)	
P-value test $\sigma_{\zeta,L=2}^2 = \sigma_{\zeta,L=0}^2$	5.1%	5.2%

Note: Clustered standard errors in parenthesis. *, **, *** indicate statistical significance at 10, 5 and 1 percent level respectively

Figure 9 reports transitions out of severe disability. Here, the broad picture is very stark. The probability of complete recovery declines strongly, while mild recoveries only decline slightly. However, there is a strong increase in the persistence of severe disability, from about 50% to almost 75%. This implies a strong increase in disability risk as people age - recoveries become less likely, shocks are more likely, and persistence increases.

In Figure 10 we show that low educated individuals face worse health risk than high educated individuals, with higher probabilities of bad shocks occurring, a slightly lower probability of recovery, and more persistence in poor health.

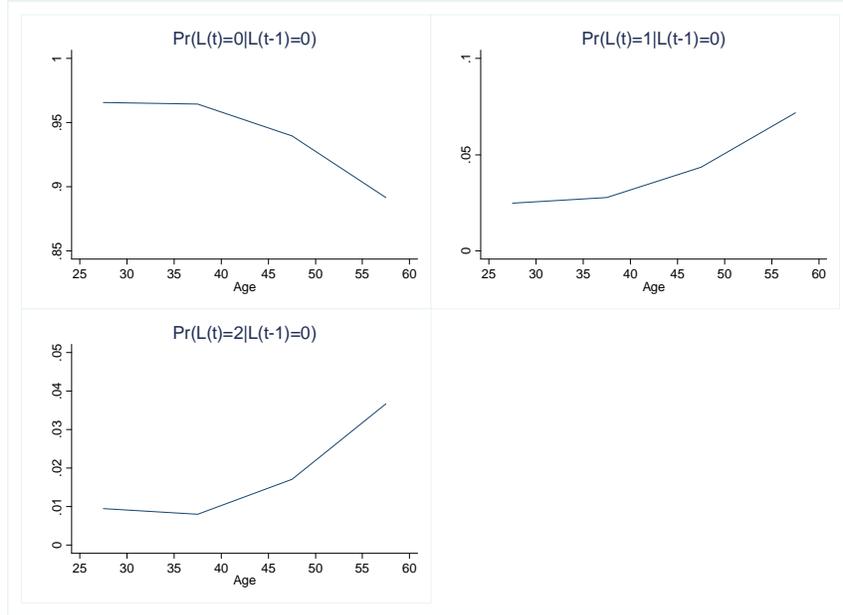


Figure 7: Transitions out of $L = 0$ (Sample: Low education males, aged 23-62).

C.4 Indirect Inference

The Indirect Inference statistical criterion that we use is:

$$\hat{\phi} = \arg \min_{\phi} \left(\hat{\alpha}^D - S^{-1} \sum_{s=1}^S \hat{\alpha}^S(\phi) \right)' \Omega \left(\hat{\alpha}^D - S^{-1} \sum_{s=1}^S \hat{\alpha}^S(\phi) \right)$$

where $\hat{\alpha}^D$ are the moments/parameters of the auxiliary model estimated in the data, $\hat{\alpha}^S(\phi)$ are the corresponding simulated moments/parameters (which we average over S simulations) for given structural parameter values ϕ . The function $\alpha(\phi)$ is the binding function relating the structural parameters to the auxiliary parameters, and Ω is the weighting matrix. The optimal weighting matrix is the the inverse of the covariance matrix from the data, $\hat{\Omega} = \text{var}(\hat{\alpha}^D)^{-1}$.⁹

⁹To reduce computational issues, we use $\text{diag}(\hat{\Omega})$. We compute standard errors using a formula that adjusts for the use of the non-optimal weighting matrix.

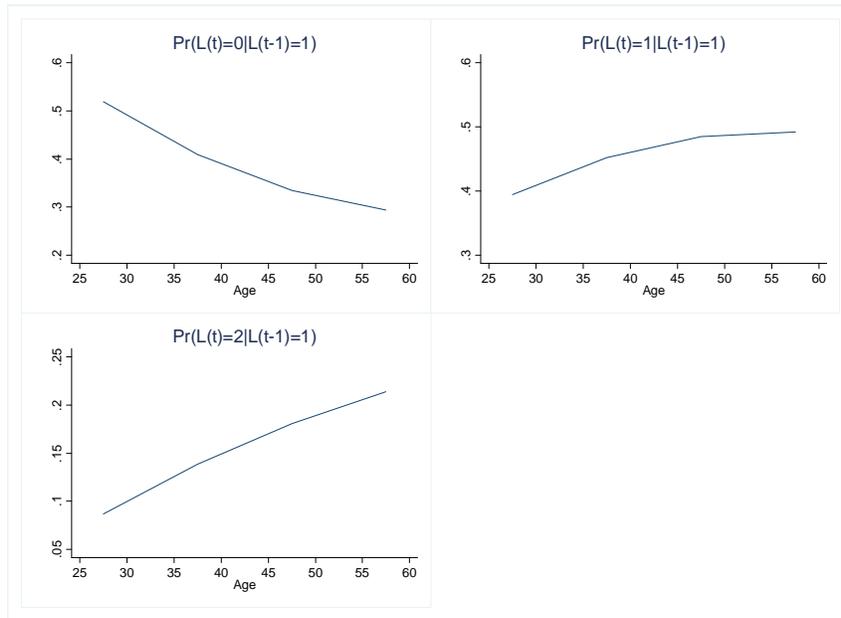


Figure 8: Transitions out of $L = 1$ (Sample: Low education males, aged 23-62).

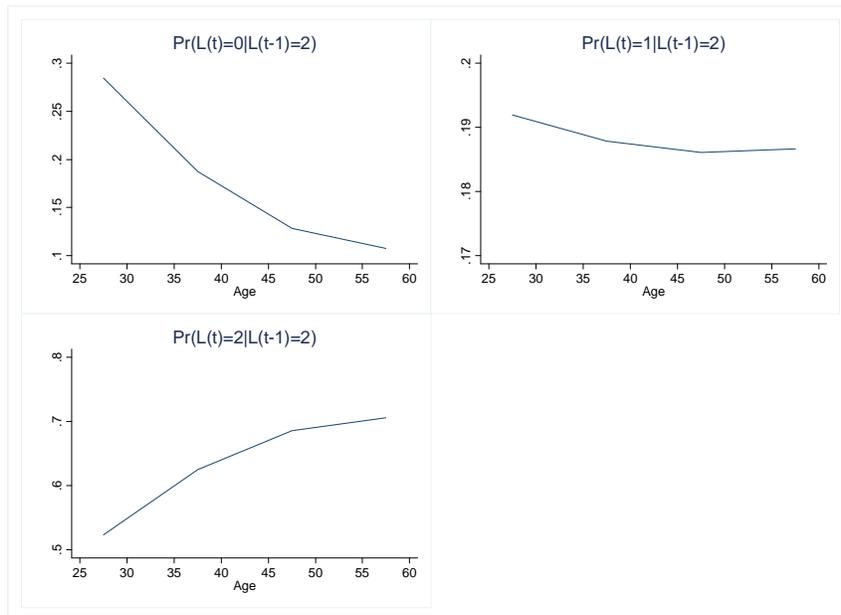


Figure 9: Transitions out of $L = 2$ (Sample: Low education males, aged 23-62).

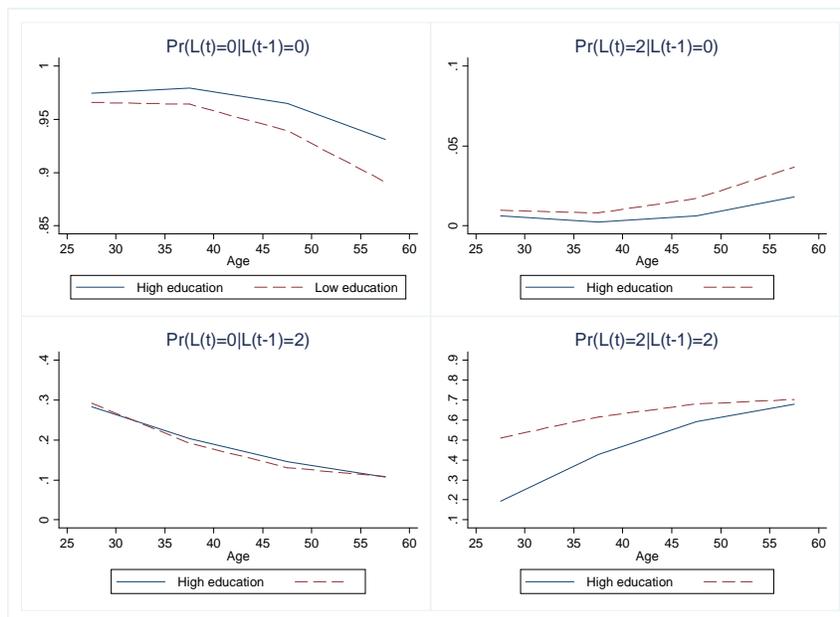


Figure 10: Selected transitions (Sample: All males, aged 23-62).

Standard errors of the structural parameters can be computed using the formula provided in Gourieroux et al. (1993),

$$\text{var}(\hat{\phi}) = (J' \Omega J)^{-1} J' \Omega V \Omega J (J' \Omega J)^{-1}$$

where $J = \frac{\partial \hat{\alpha}^S(\phi)}{\partial \phi}$, and $V = \text{var}(\hat{\alpha}^D - \hat{\alpha}^S(\hat{\phi}))$. Asymptotically, V reduces to $(1 + \frac{1}{S}) \text{var}(\hat{\alpha}^D)$, and we obtain $\text{var}(\hat{\alpha}^D)$ using a block bootstrap procedure. We check that the average of the variance of the simulated moments across the S replications is well approximated by the variance of the moments in the data. We calculate J by finite difference.

Figure 11 gives a graphical account of the match between auxiliary moments/parameters in the data and in the simulations. Cases in which the simulated value is outside the 95% confidence interval are cases in which the gray bar is outside the vertical black line.

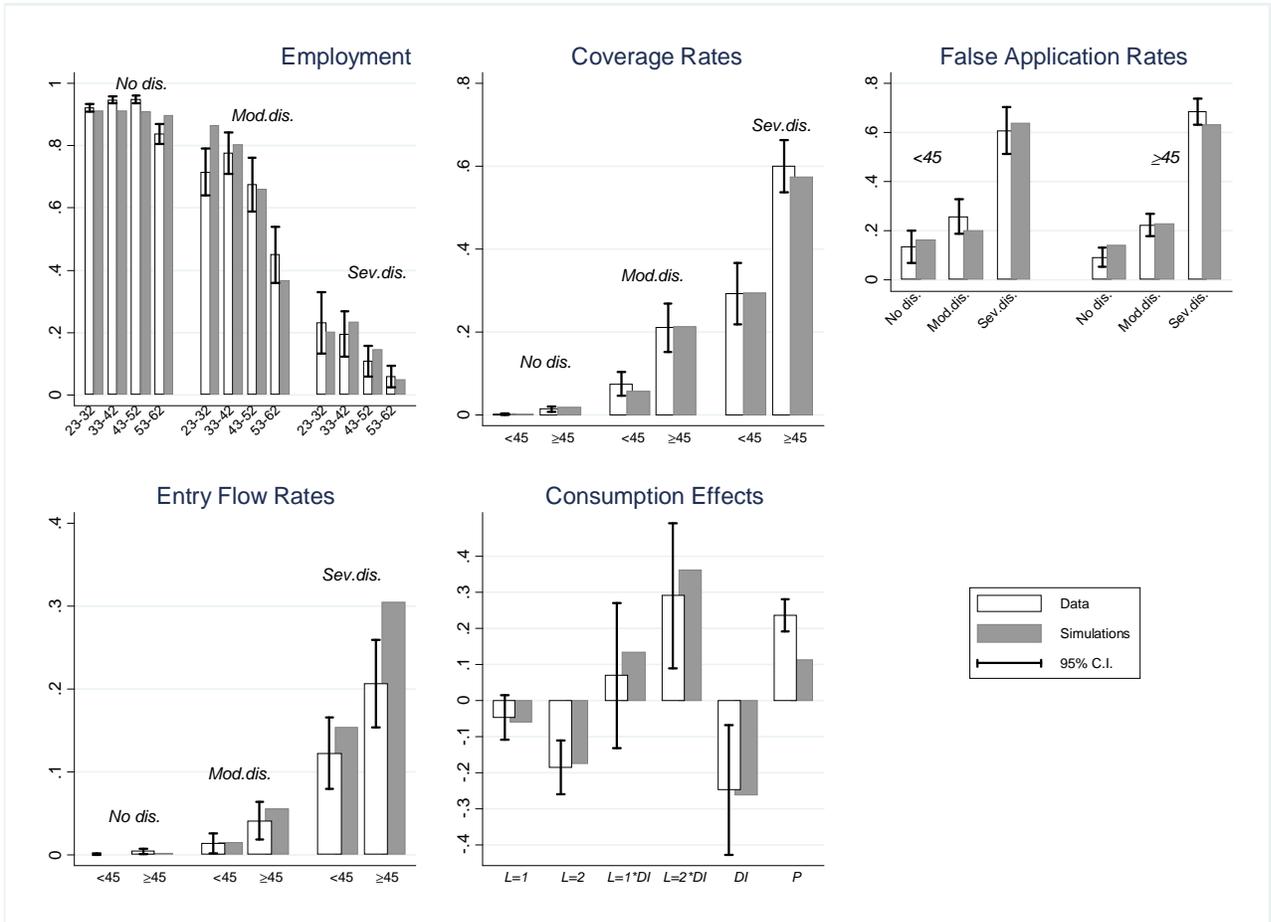


Figure 11: The match between auxiliary moments/parameters in the data and in the simulations.

Table 5: **Sensitivity Analysis on Exclusion Restrictions**

Exclusion restrictions	$\{L = 2\}$ on wage	$\{L = 1\}$ on wage	Mills ratio	$\sigma_{\zeta, L=2}^2$	$\sigma_{\zeta, L=1}^2$	$\sigma_{\zeta, L=0}^2$
Set 1	-0.376 (0.069)	-0.187 (0.036)	0.103 (0.041)	0.094 (0.047)	0.037 (0.021)	0.017 (0.007)
Set 2	-0.278 (0.089)	-0.170 (0.036)	0.037 (0.068)	0.071 (0.047)	0.032 (0.022)	0.019 (0.007)
Set 3	-0.327 (0.158)	-0.176 (0.051)	0.055 (0.126)	0.082 (0.047)	0.047 (0.021)	0.017 (0.007)
Set 4	-0.452 (0.135)	-0.206 (0.043)	0.161 (0.106)	0.103 (0.048)	0.040 (0.021)	0.016 (0.007)
Set 5 - Baseline	-0.470 (0.136)	-0.211 (0.044)	0.176 (0.106)	0.110 (0.048)	0.041 (0.021)	0.016 (0.007)
Set 6	-0.477 (0.145)	-0.213 (0.046)	0.182 (0.115)	0.113 (0.048)	0.042 (0.007)	0.016 (0.007)
Set 7	-0.462 (0.144)	-0.209 (0.045)	0.169 (0.113)	0.106 (0.048)	0.041 (0.021)	0.016 (0.007)

Note: Set 1: Actual transfers and UI generosity; Set 2: State x Time interactions; Set 3: UI generosity; Set 4: Potential transfers; Set 5: Potential transfers and interactions with disability status dummies ("baseline" set). Set 6 (7): Same as in Set 5, but potential transfers computed using lagged earnings (sample average earnings). Clustered standard errors in parenthesis.

D Details of the Robustness of the Estimation

In this section we describe the results of a series of sensitivity analysis on the estimation process.

D.1 Alternative exclusion restrictions

Here we report results under a variety of different exclusion restrictions, including (a) received (public and private) transfers, (b) an index of generosity of the local UI program,¹⁰ and (c) interactions of state and year dummies to capture reforms to local welfare systems. We also show results using alternative ways of computing potential social insurance benefits. We find that the use of these different exclusion restrictions induce only small changes in the effect of disability variables on wages and virtually no effects on the estimated variances of the permanent shock (the only structural parameters in this exercise). See Table 5.

D.2 The normality assumption in the Selection Equation

We checked that our results do not depend on the normality assumption that we make when estimating the wage equation controlling for selection into work. We repeat our wage equation estimates using a non-parametric approach. In the first step we estimate a univariate employment model using the semi-nonparametric estimator of Gallant and Nychka (1987):

$$P_{it}^* = s_{it} + \pi_{it}$$

¹⁰To obtain a measure of the generosity of the UI program in the state where the worker lives, we rank states according to the maximum weekly UI benefit (which we take from current legislation). Our measure of generosity is the rank variable, which varies over time and across states. Income from transfers is the sum of private and public transfers. We also used a measure that excludes transfers received by the head, and find virtually identical results.

Table 6: **Sensitivity Analysis on selection correction**

Selection correction	$\{L = 2\}$ on wage	$\{L = 1\}$ on wage	Selection correction	$\sigma_{\zeta, L=2}^2$	$\sigma_{\zeta, L=1}^2$	$\sigma_{\zeta, L=0}^2$
Non-parametric	-0.474 (0.141)	-0.228 (0.048)	17.6%	0.116 (0.048)	0.060 (0.010)	0.017 (0.007)
Baseline	-0.470 (0.136)	-0.211 (0.044)	9.7%	0.110 (0.048)	0.041 (0.021)	0.016 (0.007)

Note: Non-parametric: First fit univariate participation model using the semi-nonparametric estimator of Gallant and Nychka (1987), then add a second degree polynomial of the predicted value in the wage regression. Clustered standard errors in parenthesis.

Table 7: **Sensitivity Analysis on sample selection**

Sample	$\{L = 2\}$ on wage	$\{L = 1\}$ on wage	Mills ratio	$\sigma_{\zeta, L=2}^2$	$\sigma_{\zeta, L=1}^2$	$\sigma_{\zeta, L=0}^2$
Only SRC	-0.492 (0.194)	-0.190 (0.054)	0.237 (0.163)	0.151 (0.062)	0.031 (0.024)	0.016 (0.009)
Baseline	-0.470 (0.136)	-0.211 (0.044)	0.176 (0.106)	0.110 (0.048)	0.041 (0.021)	0.016 (0.007)

Note: Clustered standard errors in parenthesis.

where s_{it} has been described above (equation (8)), and save the predicted value \hat{s}_{it} . In the second step, we estimate our wage regression controlling for a 2^{nd} degree polynomial in \hat{s}_{it} . We find that the results remain very similar (see Table 6).

D.3 Restricting the Sample

Our sample includes both the SRC and SEO components of the PSID. The SRC was the component of the PSID that was initially representative of the population, while the SEO oversampled individuals close to the poverty line in 1967. Given our focus on the low educated subsample, we have kept in our empirical analysis both the SRC and SEO components of the PSID to have a larger sample. In Table 7 we show results obtained using only the SRC sample. The results are qualitatively similar (there is a greater difference between the severely disabled and the rest of the sample), but all the estimates are less precise, as expected.

D.4 Consumption Regression

With our imputed consumption measure we find that consumption falls when people experience an uninsured severe disability shock; however, consumption rises for people whose shock is insured, consistent with consumption and disability being Frisch complements. The results of the consumption auxiliary regression are reported fully in Table 8.

In this section we check whether our consumption auxiliary regression results are replicated when we use food data and when we control for more general unobserved heterogeneity. We use as a metric the implied “insurance” value of DI, defined as:

Table 8: **The consumption auxiliary regression**

	Estimate
L_{it}^2	-0.186 (0.037)
L_{it}^1	-0.047 (0.031)
$L_{it}^2 \times DI$	0.291 (0.101)
$L_{it}^1 \times DI$	0.070 (0.101)
DI	-0.248 (0.091)
Employed	0.235 (0.022)
Age	-0.007 (0.006)
Age ² /100	0.016 (0.006)
Year dummies	Yes
Constant	8.636 (0.110)
N	12,273

Note: Clustered standard errors in parenthesis.

$$\begin{aligned}
 \varphi &= [E(\ln c|L=2, DI=1, x) - E(\ln c|L=0, DI=0, x)] \\
 &\quad - [E(\ln c|L=2, DI=0, x) - E(\ln c|L=0, DI=0, x)] \\
 &= E(\ln c|L=2, DI=1, x) - E(\ln c|L=2, DI=0, x)
 \end{aligned}$$

namely, the difference between consumption growth experienced by people who face a severe disability shock against which they receive DI and consumption growth experienced by people who face a severe, uninsured disability shock.

The results, reported in Table 9, show that our findings are replicated when using food data (more noisily so) or when controlling for individual fixed effects.

D.5 Assets

In section 5.6.4 in the main text, we discuss the comparison between simulated asset accumulation and asset accumulation in the data. The numbers in the data are calculated using financial and housing wealth combined. We calculate median asset holdings at different ages and for different work limitation status. We normalise median asset holdings by the median of annual earnings across all working age individuals.

Here we discuss the (normalized) asset change regressions. We regress the 5-year change in wealth against a quadratic in age, and dummies for severe and moderate disability ("no disability" is the excluded category) in the data and in the simulations. As shown in Table 10, the data match

Table 9: **Sensitivity Analysis, Consumption regression**

Variable	Baseline	Using food data	Fixed effect
$\{L_{it} = 1\}$	-0.047 (0.031)	-0.036 (0.035)	-0.014 (0.017)
$\{L_{it} = 2\}$	-0.186 (0.037)	-0.189 (0.063)	-0.029 (0.034)
$\{L_{it} = 1\} \times DI$	0.070 (0.101)	0.252 (0.159)	0.083 (0.076)
$\{L_{it} = 2\} \times DI$	0.291 (0.101)	0.495 (0.137)	0.149 (0.070)
DI	-0.248 (0.091)	-0.395 (0.132)	-0.050 (0.064)
Employed	0.235 (0.022)	0.422 (0.059)	0.259 (0.033)
Implied “insurance” value of DI, $L = 2$	0.043	0.043	0.015

Note: Additional controls include Age, Age squared, and Year dummies. Clustered standard errors in parenthesis.

Table 10: **Asset Change Regression**

Variable/Moment	Data	Simulations	95% C.I. diff.
Dependent variable: $((A_{i,t} - A_{i,t-5})/Y)$			
$\{L_{it} = 2\}$	-0.910 (0.396)	-1.324	(-0.36; 1.19)*
$\{L_{it} = 1\}$	-0.530 (0.365)	-0.837	(-0.41; 1.02)*
Age	0.290 (0.047)	0.283	(-0.10; 0.09)*
Age^2	-0.002 (0.101)	-0.004	(-0.20; 0.20)*
Constant	-7.698 (1.084)	-4.027	(-5.80; -1.55)

Note: * denotes that the difference is statistically insignificant at the 5 percent level.

quite well the effect of age and health status on the dynamics of assets. Wealth changes decline monotonically with poor health, and we cannot reject the null that data and simulations predict the same health and age gradients.

D.6 The Importance of Modelling Work Limitations

In section 5.6.5 in the main text, we discussed the importance of allowing the fixed cost of work to vary with work limitation status, and the importance of allowing for non-separability between consumption and health. Each of these components substantially improves our ability to match the moments of disability insurance take-up, participation and the consumption regressions. Table 5 in the text reports the standard errors on these parameter estimates: the statistical significance of θ and the significant difference in the estimates of L by work limitation status shows that these are statistically necessary to explain the moments. To show this more explicitly, we reestimate the

model twice, first forcing the fixed cost to be the same regardless of work limitation status and secondly, switching off the non-separability and so imposing $\theta = 0$. Results are reported in Figure 12. We comment on these results in the main text, so we omit comments here.

Moment	Data	Bootstrap s.e.	Baseline		F(L)=F		θ=0	
			Simulated Moment	T-Stat of Difference	Simulated Moment	T-Stat of Difference	Simulated Moment	T-Stat of Difference
<u>Consumption regression</u>								
L=2	-0.186	0.038	-0.174	-0.30	0.117	-7.93	-0.302	3.06
L=1	-0.047	0.024	-0.060	0.53	0.038	-3.44	-0.157	4.47
L=2*DI	0.291	0.117	0.361	-0.59	0.257	0.29	0.373	-0.70
L=1*DI	0.070	0.111	0.133	-0.56	0.163	-0.83	0.153	-0.74
DI	-0.248	0.104	-0.263	0.15	-0.363	1.10	-0.305	0.55
part	0.235	0.023	0.113	5.34	0.276	-1.80	0.109	5.50
<u>Participation</u>								
L=0, 23-32	0.921	0.006	0.911	1.79	0.909	2.03	0.911	1.80
L=0, 33-42	0.946	0.005	0.910	6.79	0.900	8.64	0.910	6.77
L=0, 43-52	0.947	0.006	0.909	6.47	0.873	12.67	0.910	6.34
L=0, 53-62	0.837	0.014	0.895	-4.17	0.764	5.27	0.907	-5.04
L=1, 23-32	0.715	0.042	0.864	-3.52	0.888	-4.10	0.841	-2.97
L=1, 33-42	0.775	0.034	0.802	-0.76	0.854	-2.29	0.785	-0.28
L=1, 43-52	0.675	0.045	0.660	0.33	0.767	-2.00	0.663	0.26
L=1, 53-62	0.450	0.050	0.367	1.65	0.581	-2.62	0.461	-0.22
L=2, 23-32	0.233	0.050	0.202	0.59	0.763	-10.47	0.176	1.12
L=2, 33-42	0.196	0.033	0.234	-1.14	0.679	-14.45	0.254	-1.72
L=2, 43-52	0.109	0.025	0.146	-1.44	0.526	-16.36	0.187	-3.07
L=2, 53-62	0.060	0.016	0.049	0.69	0.326	-16.61	0.076	-1.02
<u>Coverage</u>								
Fr(DI=1 L=0,t<45)	0.002	0.001	0.003	-0.25	0.003	-1.18	0.003	-0.69
Fr(DI=1 L=1,t<45)	0.075	0.016	0.058	1.02	0.027	2.96	0.068	0.42
Fr(DI=1 L=2,t<45)	0.293	0.041	0.295	-0.06	0.108	4.50	0.309	-0.39
Fr(DI=1 L=0,t>=45)	0.014	0.003	0.018	-1.18	0.048	-10.38	0.014	0.13
Fr(DI=1 L=1,t>=45)	0.211	0.030	0.213	-0.08	0.164	1.54	0.225	-0.47
Fr(DI=1 L=2,t>=45)	0.599	0.035	0.574	0.72	0.421	5.01	0.540	1.67
<u>Composition of DI Recipients</u>								
Fr(L=2 DI=1,t<45)	0.607	0.048	0.636	-0.61	0.436	3.54	0.613	-0.13
Fr(L=2 DI=1,t>=45)	0.683	0.029	0.630	1.78	0.457	7.61	0.629	1.82
Fr(L=1 DI=1,t<45)	0.258	0.036	0.201	1.60	0.173	2.36	0.216	1.19
Fr(L=1 DI=1,t>=45)	0.224	0.025	0.229	-0.19	0.174	1.96	0.256	-1.26
Fr(L=0 DI=1,t<45)	0.135	0.034	0.164	-0.82	0.390	-7.33	0.171	-1.05
Fr(L=0 DI=1,t>=45)	0.093	0.018	0.141	-2.65	0.369	-15.22	0.114	-1.20
<u>Flows into DI</u>								
Fr(DI=1 DI=0,L=2,t>=45)	0.206	0.030	0.305	-3.20	0.187	0.62	0.274	-2.20
Fr(DI=1 DI=0,L=2,t<45)	0.123	0.021	0.154	-1.46	0.049	3.42	0.160	-1.76
Fr(DI=1 DI=0,L=1,t>=45)	0.041	0.011	0.056	-1.33	0.034	0.64	0.068	-2.44
Fr(DI=1 DI=0,L=1,t<45)	0.014	0.007	0.015	-0.08	0.007	0.94	0.019	-0.63
Fr(DI=1 DI=0,L=0,t>=45)	0.005	0.001	0.002	1.92	0.006	-1.15	0.002	1.86
Fr(DI=1 DI=0,L=0,t<45)	0.001	0.000	0.000	1.18	0.000	1.89	0.001	1.00

Note: Bold indicates the difference is statistically insignificant at the 5% level.

Figure 12: Sensitivity Analysis: Moments Varying the Importance of Health

E Robustness of the Policy Counterfactuals

E.1 Welfare Calculations

To define the welfare cost or benefit of reforming DI, we write the lifetime expected utility of an individual as

$$E_0U(k) = E_0 \sum_{t=0}^T \beta^t \frac{(c_{it}(k) \exp(\theta L_{it}) \exp(\eta P_{it}(k)))^{1-\gamma}}{1-\gamma}$$

where k refers to the implied consumption and labor supply stream in the baseline economy ($k = b$) or an alternative economy with different parameters of the DI program ($k = b'$) and E_0 is the expectation at the beginning of working life. Now define π as the proportion of consumption an individual is willing to pay to be indifferent between environment $k = b'$ and $k = b$. This is implicitly defined by

$$\begin{aligned} E_0U(b') |_{\pi} &\equiv E_0 \sum_{t=0}^T \beta^t \frac{((1-\pi) c_{it}(b') \exp(\theta L_{it}) \exp(\eta P_{it}(b')))^{1-\gamma}}{1-\gamma} \\ &= \sum_{t=0}^T \beta^t \frac{(c_{it}(b) \exp(\theta L_{it}) \exp(\eta P_{it}(b)))^{1-\gamma}}{1-\gamma} \\ &\equiv E_0U(b) \end{aligned}$$

We compute π in the different scenarios and use it as our measure of welfare in Section 6.

E.2 Reassessment of DI Recipients

The main text discusses that changing reassessment rates has limited effects. This section provides figure 13 to back up that result. The left-hand graph shows that an increase in the reassessment rate discourages false applications by those who are not severely disabled. The cost of this is the reduced coverage for the severely disabled: reassessment causes some severely disabled to be removed from DI and this directly reduces coverage, as well as discouraging applications, as the frequency of reassessment increases. The reduced false applications lead to greater labour force participation and output, and increased asset accumulation as individuals have to self-insure further, as shown on the right hand side graph. The net effect on welfare is negligible and is not shown.

E.3 The Beta Distribution

In the baseline presented in the main paper, we assume that the signal that the government observes about an individual's health status has a Beta distribution. The Beta distribution is a continuous distribution defined over $x \in [0, 1]$, with the distribution defined by two parameters, q and r . The formula for the PDF is given by:

$$f(x) = \frac{x^{q-1} (1-x)^{r-1}}{B(q, r)}, \quad q > 1, r > 1$$

where $B(q, r)$ is a normalisation to keep the PDF between 0 and 1. This normalisation is

$$\frac{\Gamma(q+r)}{\Gamma(q)\Gamma(r)},$$

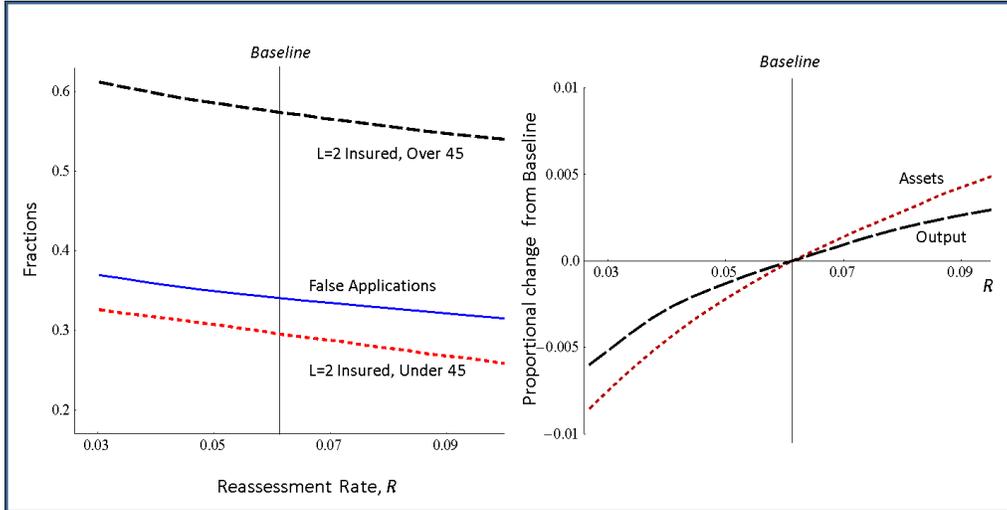


Figure 13: Changing the Reassessment Rate of DI

where Γ is the gamma distribution.

We impose that r is held constant across all types, but that q varies with health and with age. When q and r are equal, the distribution is symmetric around $x = 0.5$. As q increases for a given value of r , the mean of the distribution shifts to the right, and the variance declines. The level of the variance is determined by the absolute size of q and r . We make the assumption that the signal follows a Beta distribution because this implies that the precision of the signal increases as the severity of the true health limitation increases.

To parameterise the Beta distribution and how it changes with health status and with age, we need 6 values of q and 1 value of r . To characterise the government's decision process, we also need the value of the threshold acceptance onto DI, \bar{S} . These 8 parameters are set by the 6 probabilities of acceptance onto DI estimated in the paper, as well as 2 normalisations. The normalisations are to the mean of the signal for the young, healthy individuals, and the mean of the signal for the old, severely disabled individuals (i.e., those with the lowest and highest probability of success in the data). The resulting distribution of the signal is shown in figure 4 in the paper.

E.4 Strictness with lognormally distributed signals

There are alternative assumptions that could be made about the distribution of the signal. For example, the shock could have lognormal distribution. We illustrate this case here. We assume that S lies on the real line and is distributed:

$$\ln S_{L,t} \sim N(\mu_{L,t}, \sigma)$$

where μ varies with age and work limitation status. The six values of μ , the value of σ and \bar{S} are pinned down by the six structural probabilities (π_L^t) estimated.¹¹ The resulting values are mapped into PDFs of the conditional distribution as shown in Figure 14. The fraction of false positives and

¹¹We normalise the mean of the log of the signal, S , for the old who are severely disabled to be 1, and the mean of the log of S for the young who are not at all disabled to being 0.1.

false negatives, as well as the probabilities of success at \bar{S} are held constant with the alternative distribution. The shape of the distribution and the renormalised value of \bar{S} changes.

As in Section 6, we then consider changing the strictness of the regime. We show the implications for coverage, false applications and welfare in figure 15. As strictness increases, the fraction insured falls, the number of false applications falls, and assets and output both rise. The net effect of greater strictness on welfare is, however, negative. These are very similar results to the Beta distribution case in the direction of changes, magnitudes and in the overall effect on welfare. We also find similar results when re-doing the other four experiments (increased DI generosity, increased Food Stamps generosity, and increased re-assessment; results available on request).

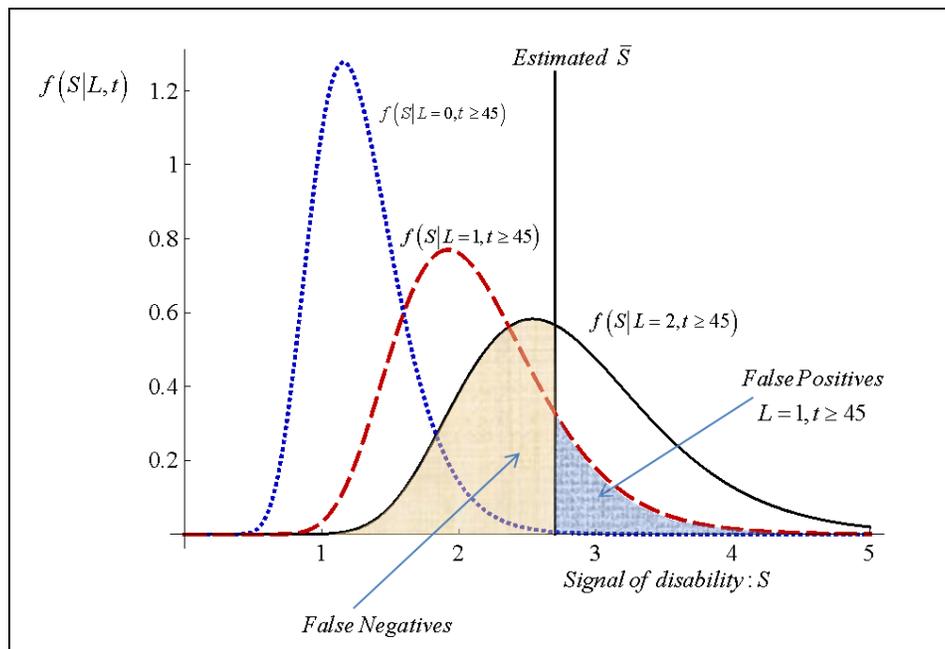


Figure 14: The Distribution of S for the Older Workers: Log Normal Signals

E.5 Sensitivity Analysis: The Importance of Risk Aversion

The value for the coefficient of relative risk aversion is taken as the central estimate from various papers in the literature, $\gamma = 1.5$ (see footnote 20 in the main text). Clearly, how risk averse agents are will have an impact on how they value the insurance benefit of disability insurance. Risk aversion may also alter how individuals respond to policy changes. To explore this possibility and to show the sensitivity of our baseline results to the degree of risk aversion, we reestimated and resimulated all the results assuming a coefficient of relative risk aversion equal to 3.

We first reestimated the structural parameter, using the same set of moments from the data as in the main paper. This resulted in the match shown in Figure 16, with corresponding parameter estimates in Table 11.

We then re-did the three core policy counterfactuals using this new set of parameter estimates and the higher value of risk aversion. First, we changed the generosity of DI payments. Figure

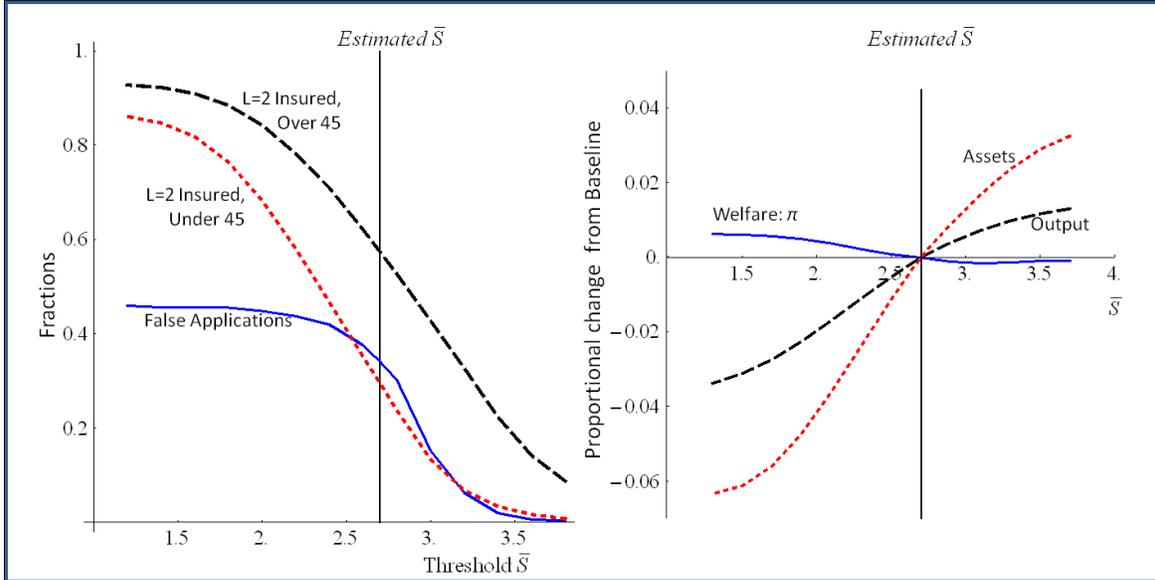


Figure 15: Changing the Strictness of DI: Log Normal Signals

Table 11: **Estimated Parameters when $\gamma = 3$**

Frictions and Preferences			Disability Insurance Program	
Parameter		Estimate	Parameter	Estimate
θ	Cost of disability	-0.22	$\pi_{L=0}^{Young}$	0.004
η	Cost of part.	-0.09	$\pi_{L=0}^{Old}$	0.0095
δ	Job destruction	0.068	$\pi_{L=1}^{Young}$	0.19
			$\pi_{L=1}^{Old}$	0.22
$F_{L=0}$	Fixed cost	0.0002 [\$0]	$\pi_{L=2}^{Young}$	0.32
$F_{L=1}$	Fixed cost	0.52 [\$1580]	$\pi_{L=2}^{Old}$	0.68
$F_{L=2}$	Fixed cost	0.77 [\$2341]		

Note: Fixed costs are reported as the fraction of average offered wage income at age 23 and also in 1992 dollars per quarter. Standard errors in parenthesis.

Moment	Data	Bootstrap s.e.	Baseline		CRRA = 3.0	
			Simulated Mbmnt	T-Stat of Difference	Simulated Mbmnt	T-Stat of Difference
<u>Consumption regression</u>						
L=2	-0.186	0.038	-0.174	-0.30	-0.1881	0.07
L=1	-0.047	0.024	-0.060	0.53	-0.1177	2.86
L=2*DI	0.291	0.117	0.361	-0.59	0.3198	-0.25
L=1*DI	0.070	0.111	0.133	-0.56	0.1442	-0.66
DI	-0.248	0.104	-0.263	0.15	-0.2348	-0.12
part	0.235	0.023	0.113	5.34	0.1019	5.81
<u>Participation</u>						
L=0, 23-32	0.921	0.006	0.911	1.79	0.9106	1.82
L=0, 33-42	0.946	0.005	0.910	6.79	0.9100	6.79
L=0, 43-52	0.947	0.006	0.909	6.47	0.9097	6.34
L=0, 53-62	0.837	0.014	0.895	-4.17	0.9079	-5.10
L=1, 23-32	0.715	0.042	0.864	-3.52	0.8102	-2.25
L=1, 33-42	0.775	0.034	0.802	-0.76	0.7624	0.37
L=1, 43-52	0.675	0.045	0.660	0.33	0.6417	0.73
L=1, 53-62	0.450	0.050	0.367	1.65	0.4614	-0.23
L=2, 23-32	0.233	0.050	0.202	0.59	0.0934	2.74
L=2, 33-42	0.196	0.033	0.234	-1.14	0.1875	0.26
L=2, 43-52	0.109	0.025	0.146	-1.44	0.1530	-1.72
L=2, 53-62	0.060	0.016	0.049	0.69	0.0664	-0.40
<u>Coverage</u>						
Fr(DI=1 L=0, t<45)	0.002	0.001	0.003	-0.25	0.0027	-0.29
Fr(DI=1 L=1, t<45)	0.075	0.016	0.058	1.02	0.0663	0.53
Fr(DI=1 L=2, t<45)	0.293	0.041	0.295	-0.06	0.2536	0.95
Fr(DI=1 L=0, t>=45)	0.014	0.003	0.018	-1.18	0.0125	0.57
Fr(DI=1 L=1, t>=45)	0.211	0.030	0.213	-0.08	0.1949	0.52
Fr(DI=1 L=2, t>=45)	0.599	0.035	0.574	0.72	0.5316	1.90
<u>Composition of DI Recipients</u>						
Fr(L=2 DI=1, t<45)	0.607	0.048	0.636	-0.61	0.5815	0.52
Fr(L=2 DI=1, t>=45)	0.683	0.029	0.630	1.78	0.6560	0.91
Fr(L=1 DI=1, t<45)	0.258	0.036	0.201	1.60	0.2421	0.45
Fr(L=1 DI=1, t>=45)	0.224	0.025	0.229	-0.19	0.2355	-0.44
Fr(L=0 DI=1, t<45)	0.135	0.034	0.164	-0.82	0.1764	-1.19
Fr(L=0 DI=1, t>=45)	0.093	0.018	0.141	-2.65	0.1085	-0.87
<u>Flows into DI</u>						
Fr(DI=1 DI=0, L=2, t>=45)	0.206	0.030	0.305	-3.20	0.2707	-2.09
Fr(DI=1 DI=0, L=2, t<45)	0.123	0.021	0.154	-1.46	0.1256	-0.14
Fr(DI=1 DI=0, L=1, t>=45)	0.041	0.011	0.056	-1.33	0.0513	-0.90
Fr(DI=1 DI=0, L=1, t<45)	0.014	0.007	0.015	-0.08	0.0206	-0.84
Fr(DI=1 DI=0, L=0, t>=45)	0.005	0.001	0.002	1.92	0.0017	2.04
Fr(DI=1 DI=0, L=0, t<45)	0.001	0.000	0.000	1.18	0.0005	1.11

Note: Bold indicates the difference is statistically insignificant at the 5% level.

Figure 16: Moments with High Risk Aversion: $\gamma = 3.0$

17 corresponds to Figure 3 in the main text. The left hand side shows how the fraction insured and the fraction of false applicants increases as generosity increases. The right hand side shows the effects on output, asset accumulation and welfare. The sensitivity of the behaviour of those with only a moderate limitation is again evident from the False Application line. The difference from our baseline is that welfare is increasing in the generosity of the program because the value of insurance is higher. Figure 18 shows the effect of changing the strictness threshold of DI, \bar{S} . The results are qualitatively the same as in the main paper. The difference is in the magnitude of the welfare gains: reducing strictness has much larger welfare gains because of the higher value of the insurance. Figure 19 reports the details of increasing generosity of the food stamp program for the higher risk aversion. Welfare rises with the generosity of food stamps, but again much more markedly because of the higher risk aversion.

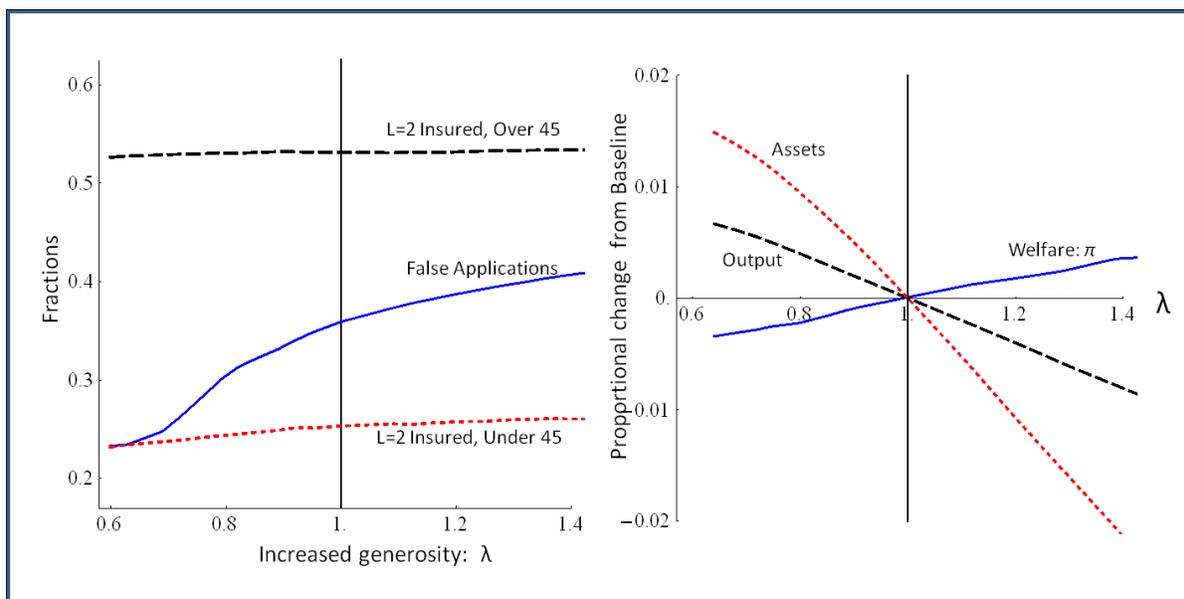


Figure 17: Changing DI Generosity when Risk Aversion is high: $\gamma = 3$

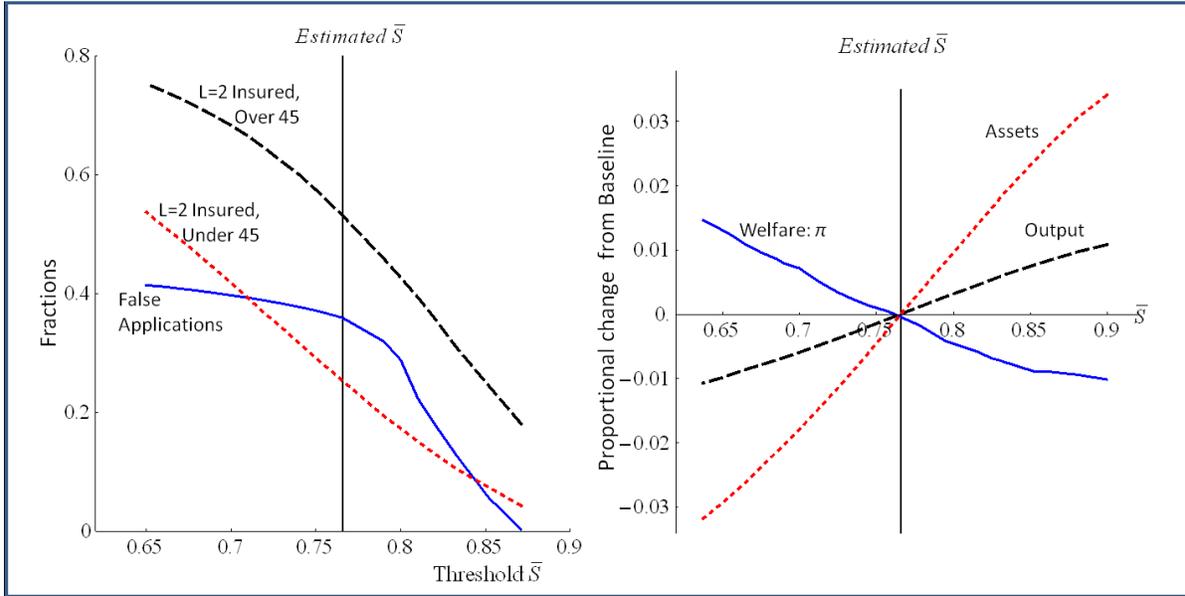


Figure 18: Changing Strictness when Risk Aversion is high: $\gamma = 3$

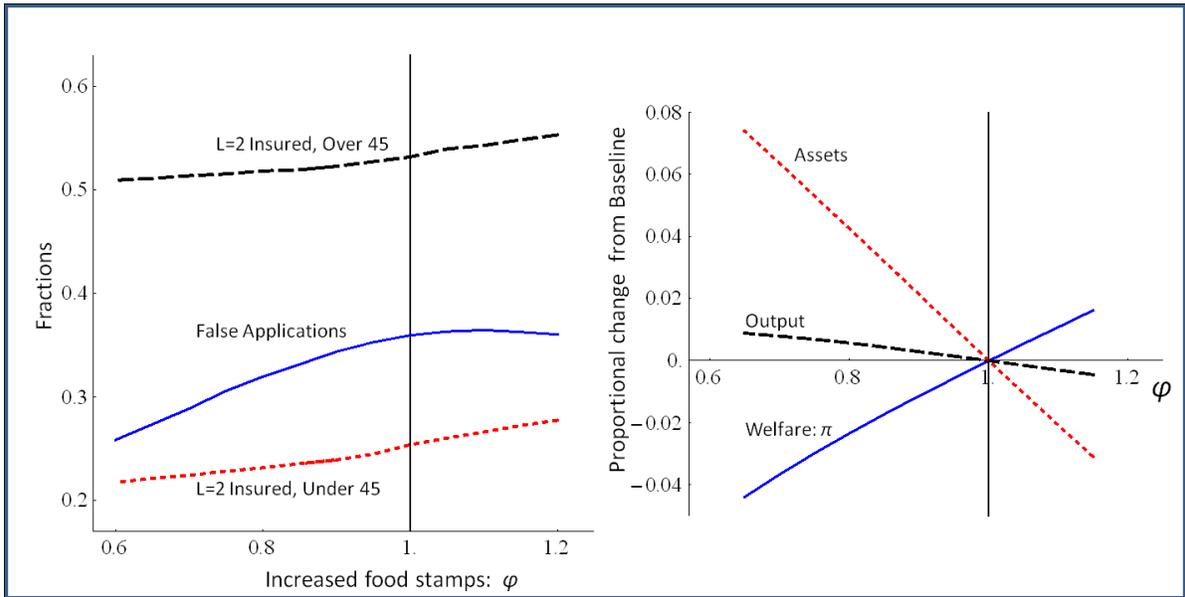


Figure 19: Changing Food Stamp Generosity when Risk Aversion is high: $\gamma = 3$

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