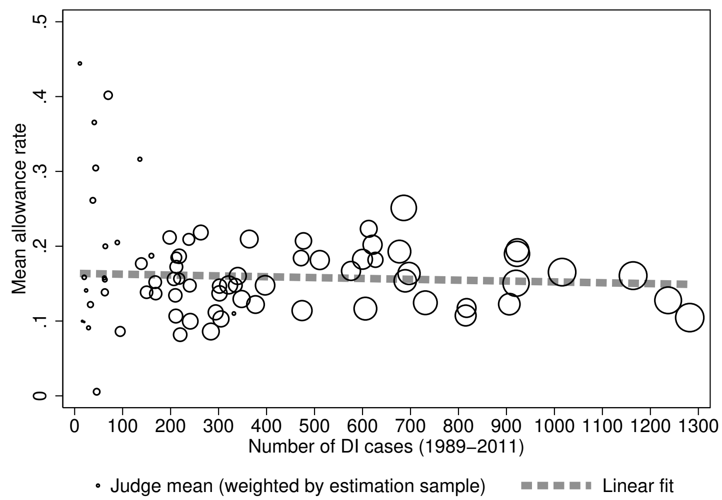
Online Appendix: "Disability Benefits, Consumption Insurance, and Household Labor Supply"

By David Autor, Andreas Kostøl, Magne Mogstad, and Bradley Setzler

Figure A1. : **Judge Leniency versus Number of Cases Handled**

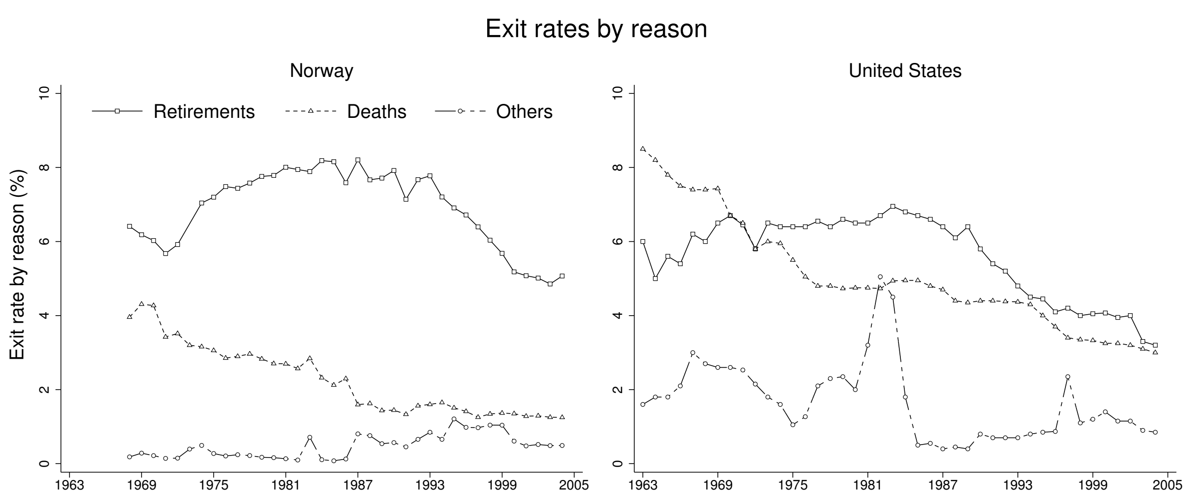


Notes: The figure plots judge allowance rate against the total number of cases handled by each judge. There are 75 unique judges, and on average, each judge has handled a total of 325 cases. Allowance rates are normalized by subtracting off year $\times$ department deviations from the overall mean. Cases are restricted to claimants appealing their first denied case during the period 1994-2005. Dot size is proportional to the number of cases a judge handles in the estimation sample (which is weakly smaller than the number of cases they have ever handled, as plotted on the x-axis).

Figure A2. : **DI Awards and DI Exits in Norway and the U.S.**

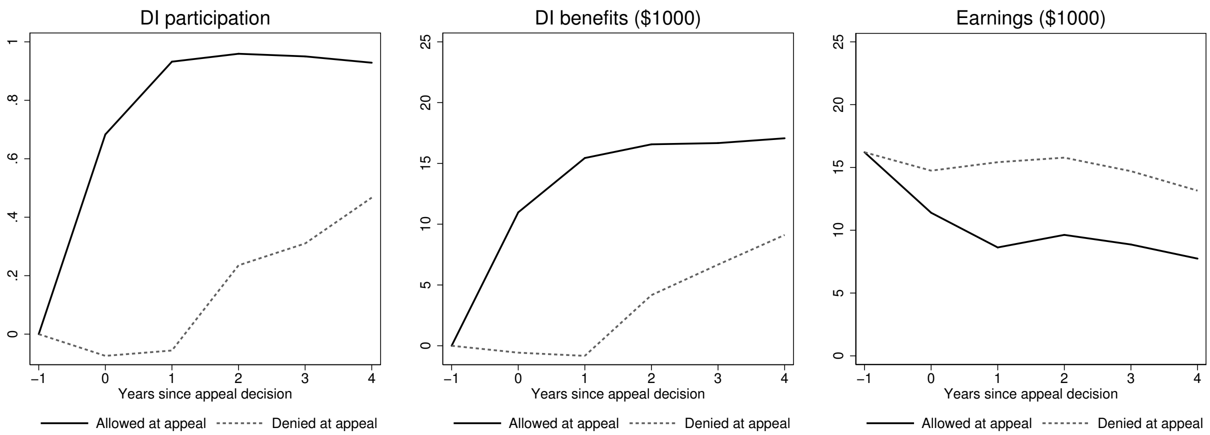
Notes: The U.S. trends are based on Autor and Duggan (2006), while the Norwegian trends are collected from various issues of the SSA Supplement. The graphs show award rates in the insured population and exit rates from the DI program in both countries.

Figure A3. : **DI Exits by Reason in Norway and the United States**



Notes: The U.S. trends are based on Autor and Duggan (2006), while the Norwegian trends are collected from various issues of the SSA Supplement. The graphs show exit rates because of death, retirement or other reasons (including eligibility-based exits).

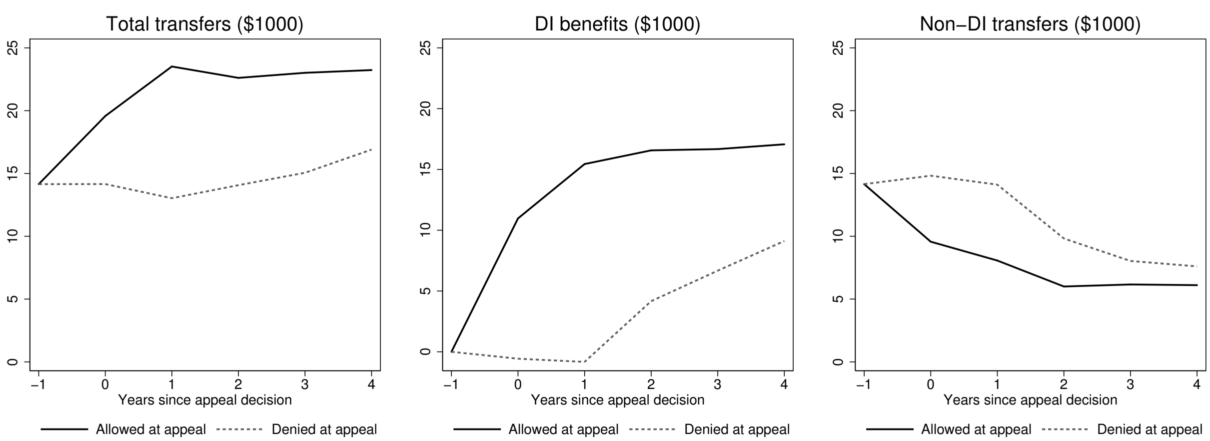
Figure A4. : **Potential Outcomes: Labor Earnings and DI benefits**



(a) (b) (c)

Notes: These figures display the decomposition of our LATE estimates into potential outcomes for allowed and denied complier appellants (see Dahl, Kostøl and Mogstad 2014 for details).

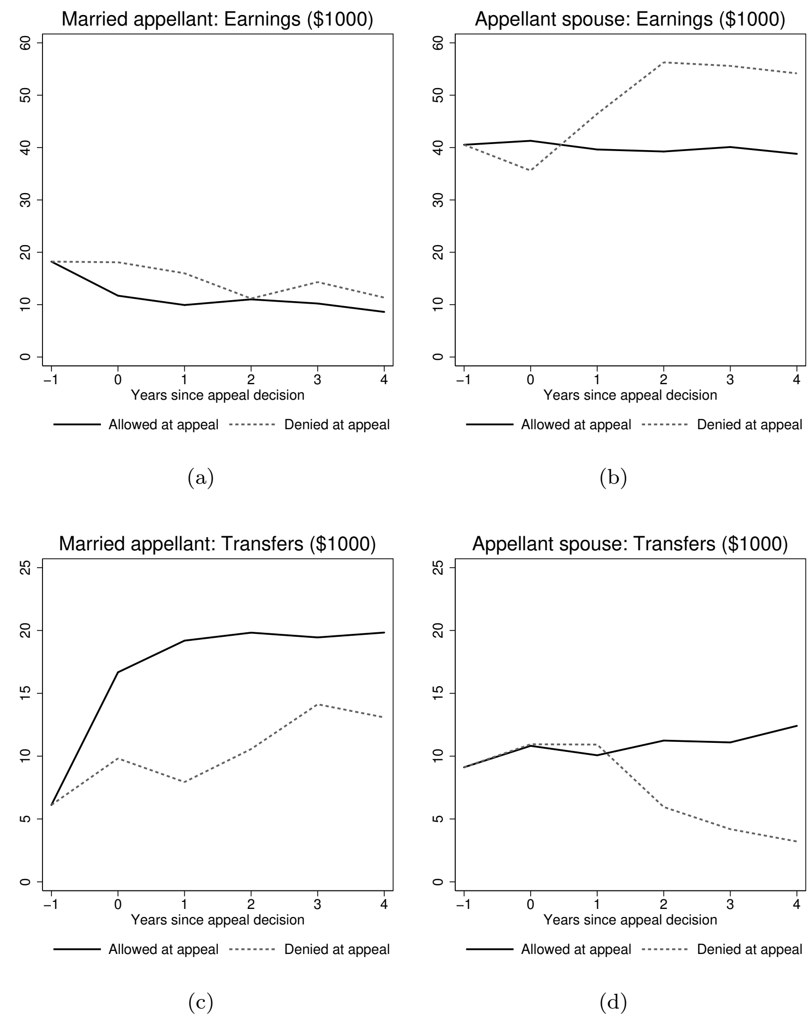
Figure A5. : **Potential Outcomes: Benefit Substitution**



(a) (b) (c)

Notes: These figures display the decomposition of our LATE estimates into potential outcomes for allowed and denied complier appellants (see Dahl, Kostøl and Mogstad 2014 for details).

Figure A6. : **Potential Outcomes: Married appellants and Spouses**



Notes: These figures display the decomposition of our LATE estimates into potential outcomes for allowed and denied complier appellants (see Dahl, Kostøl and Mogstad (2014) for details).

Table A1—: **Characteristics of DI recipients in Norway and the U.S.**

Characteristic	Norway DI Recipients	U.S. SSDI Recipients
Difficult to verify disorder (percent)	59.2	57.3
Age (at decision on initial application)	52.2	49.1
Prior earnings relative to the median (percent)	71.0	69.9

Notes: The U.S. numbers are from Maestas, Mullen and Strand (2013), and the Norwegian numbers are drawn from the sample of DI applicants during the years 2000-2003. Difficult to verify disorders include musculoskeletal and mental diagnoses. Prior earnings are measured in years three through five prior to application or appeal.

Table A2—: **Characteristics of DI Applicants and Appellants in Norway and the U.S.**

	Norway		U.S.	
Characteristic	Applicants	Appellants	Applicants	Appellants
Difficult to verify disorder (percent)	60.9	69.7	58.5	62.2
Age (at decision on initial application)	51.1	47.1	47.1	46.1
Prior earnings relative to the median (percent)	66.5	50.4	60.5	56.3

Notes: This table reports the key characteristics of DI applicants and appellants discussed in Section I. The U.S. numbers are from Maestas, Mullen and Strand (2013), and the Norwegian numbers are drawn from the sample of DI applicants during the years 2000-2003. Difficult to verify disorder comprise musculoskeletal and mental diagnoses. Prior earnings are measured during years three through five prior to application or appeal.

Table A3—: **Sub-Sample First Stage Estimates**

	Baseline instrument		**Reverse-sample instrument**	
	(1)		(2)	
Dependent variable	$Pr(Allow)$		$Pr(Allow)$	
Younger appellants (age$\leq$ 48)	0.777	Dep. mean: 0.093	0.613	Dep. mean: 0.093
	(0.077)	N: 7,458	(.082)	N: 7,392
Older appellants (age >48)	0.838	Dep. mean: 0.165	0.838	Dep. mean: 0.165
	(0.106)	N: 6,634	(.124)	N: 6,563
Small households ($N \leq 3$)	0.921	Dep. mean: 0.140	0.710	Dep. mean: 0.139
	(0.091)	N: 9,532	(.168)	N: 9,329
Large households ($N > 3$)	0.589	Dep. mean: 0.100	0.474	Dep. mean: 0.099
	(0.097)	N: 4,560	(.090)	N: 4,522
Female appellants	0.837	Dep. mean: 0.134	0.606	Dep. mean: 0.133
	(0.083)	N: 8,851	(.078)	N: 8,700
Male appellants	0.774	Dep. mean: 0.115	0.668	Dep. mean: 0.115
	(0.115)	N: 5,241	(.139)	N: 5,184
Married appellants	0.830	Dep. mean: 0.133	0.666	Dep. mean: 0.133
	(.095)	N: 8,061	(.096)	N: 7,950
Unmarried and single appellants	0.775	Dep. mean: 0.119	0.685	Dep. mean: 0.118
	(0.097)	N: 6,031	(.091)	N: 5,978
Foreign born	0.425	Dep. mean: 0.091	0.373	Dep. mean: 0.090
	(.155)	N: 2,534	(.141)	N: 2,509
Less than high school degree	0.899	Dep. mean: 0.116	0.778	Dep. mean: 0.116
	(0.089)	N: 7,097	(.115)	N: 7,044
At least a high school degree	0.725	Dep. mean: 0.139	0.547	Dep. mean: 0.137
	(.092)	N: 6,995	(.100)	N: 6,897
At least one child below age 18	0.727	Dep. mean: 0.102	0.495	Dep. mean: 0.101
	(0.062)	N: 8,140	(.079)	N: 8,029
No children below age 18	0.927	Dep. mean: 0.162	0.976	Dep. mean: 0.161
	(0.105)	N: 5,952	(.127)	N: 5,888
Musculoskeletal disorders	0.823	Dep. mean: 0.118	0.732	Dep. mean: 0.118
	(0.112)	N: 6,149	(.119)	N: 6,102
Mental disorders	0.810	Dep. mean: 0.134	0.605	Dep. mean: 0.133
	(0.120)	N: 3,666	(.125)	N: 3,624
Circulatory system	0.754	Dep. mean: 0.150	0.829	Dep. mean: 0.150
	(0.367)	N: 512	(.347)	N: 510

Standard errors (in parentheses) are clustered at the judge level.

Notes: This table reports heterogeneity in first stage estimates using the baseline instrument (1) and the reverse-sample instrument (2). The first stage specification in (1) corresponds to panel B in Table 3. The reverse-sample instrument (2) is constructed by calculating judge leniency using all cases except for those in the specified subsample (e.g., judge leniency for the subsample of older applicants is constructed using judges' decisions for younger applicants). We exclude appellants whose judges handled fewer than ten cases in the reverse sample.

Table A4—: **Effect of DI Allowance on Earnings and Transfer Payments Among Married and Unmarried**

	Years after decision			
	1	**2**	**3**	**4**
Panel A.	**Married appellant labor earnings ($1,000)**			
Allowed DI	-5.042	-0.444	-4.426	-3.912
	(3.461)	(4.068)	(3.993)	(3.625)
Dependent mean	14.991	14.784	14.168	13.535
Panel B.	**Married appellant total transfers ($1,000)**			
Allowed DI	9.110	6.499	5.008	5.395
	(4.000)	(4.423)	(3.703)	(3.628)
Dependent mean	16.621	17.356	17.919	18.508
Observations	7,844	7,740	7,648	7,548
Panel C.	**Unmarried appellant labor earnings ($1,000)**			
Allowed DI	-5.099	-10.939	-4.589	-6.475
	(7.402)	(6.932)	(7.018)	(5.686)
Dependent mean	13.279	13.646	13.34	12.883
Panel D.	**Unmarried appellant total transfers ($1,000)**			
Allowed DI	15.811	14.466	17.152	10.714
	(5.054)	(4.131)	(4.497)	(4.084)
Dependent mean	23.336	23.518	23.848	24.224
Observations	6,128	6,102	6,061	6,059

Standard errors (in parentheses) are clustered at the judge level.

Notes: This table reports the impact of DI allowance on earnings and total transfers among married (panel A and B) and unmarried appellants (panel C and D). Baseline estimation sample consists of unmarried DI applicants who appeal an initially denied DI claim during the period 1994-2005 (see Section II for further details). There are 75 unique judges. All regressions include fully interacted year and department dummies, dummy variables for month of appeal, county of residence, age at appeal, household size, gender, foreign born, marital status, children below age 18, education, and number of medical diagnoses. All control variables are measured prior to appeal.

Table A5—: **Specification Checks**

Dependent variable	**Died or migrated**	**Change in marital status**			**In restricted sample**
		Overall	Initially Unmarried	InitiallyMarried	
Judge leniency	0.017	-0.045	-0.023	-0.030	-0.015
	(0.048)	(0.058)	(0.074)	(0.071)	(0.020)
Dependent mean	0.092	0.141	0.166	0.109	0.981
Observations	14,359	14,092	6,031	8,061	14,092

Standard errors (in parentheses) are clustered at the judge level.

Notes: This table reports the impact of judge leniency on the probability of death or migration, the probability of a change in marital status, or membership in the restricted sample. Baseline estimation sample consists of individuals who appeal an initially denied DI claim during the period 1994-2005 (see Section II for further details). The second to fourth columns exclude those who die or migrate during the year of the appeal. The second column tests whether DI allowance affects the likelihood of a change in marital status (married to non-married or vice versa) for the baseline sample, and the third and fourth columns test whether DI allowance affected marriage entry and exit rates respectively. There are 75 unique judges. All regressions mirror the reduced form specification of Table 4.

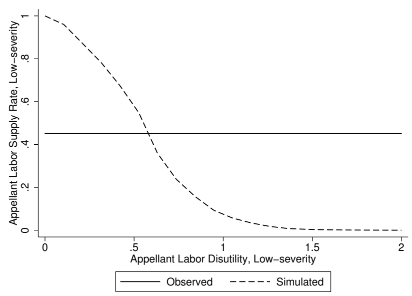
Table A6—: **Effect of DI Allowance on Types of Transfer Payments of the Appellant**

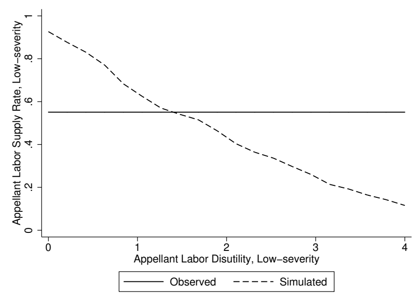
	Years after decision				
	1	**2**	**3**	**4**	**Average**
Panel A.			**DI benefits ($1,000)**		
Allowed DI	16.240	12.596	10.203	8.167	11.883
	(1.539)	(1.696)	(1.660)	(1.567)	(1.316)
Dependent mean	5.708	8.377	10.277	11.502	8.921
Panel B.			Total transfers ($1,000)		
Allowed DI	10.188	8.807	8.148	6.429	8.072
	(2.736)	(2.749)	(2.433)	(2.683)	(2.499)
Dependent mean	19.567	20.072	20.54	21.053	20.305
Panel C.			**Non-DI transfers ($1,000)**		
Allowed DI	-6.308	-3.744	-1.884	-1.611	-3.823
	(3.273)	(2.656)	(2.062)	(2.525)	(2.298)
Dependent mean	14.009	11.839	10.398	9.666	11.521
Panel D.			**Social assistance ($1,000)**		
Allowed DI	-1.524	-1.169	-1.315	-0.395	-0.964
	(1.123)	(1.031)	(0.783)	(0.677)	(0.778)
Dependent mean	2.852	2.182	1.78	1.464	2.103
Observations	13,972	13,842	13,709	13,607	13,972

Standard errors (in parentheses) are clustered at the judge level.

Notes: This table reports instrumental variables estimates of the causal effect of receiving a DI allowance at the appeal stage on DI participation (panel A), annual DI benefits (panel B), and annual labor earnings (panel C), annual total transfers inclusive of DI benefits (panel D), and annual transfers excluding DI benefits (panel E). Columns 1-4 report separate estimates for each year, whereas column 5 reports estimates for the average outcome over the four year period. The baseline sample consists of individuals who appeal an initially denied DI claim during the period 1994-2005 (see Section II for further details). There are 75 unique judges. All regressions include fully interacted year and department dummies, dummy variables for month of appeal, county of residence, age at appeal, household size, gender, foreign born, marital status, children below age 18, education, and a number of medical diagnoses. All control variables are measured prior to appeal.

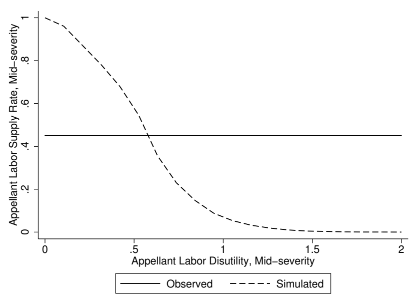
Figure A7. : **Local Identification of Disutility Parameters**

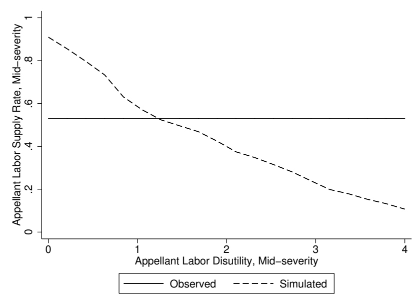




(a) Married: Labor disutility, low-severity

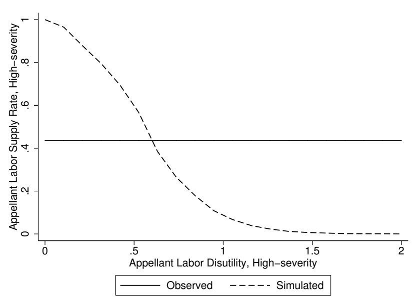
(b) Unmarried: Labor disutility, low-severity

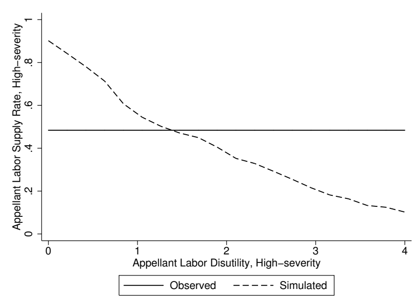




(c) Married: Labor disutility, mid-severity

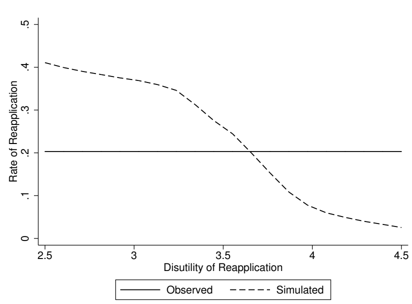
(d) Unmarried: Labor disutility, mid-severity

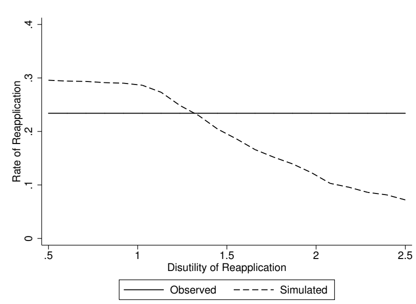




(e) Married: Labor disutility, high-severity

(f) Unmarried: Labor disutility, high-severity



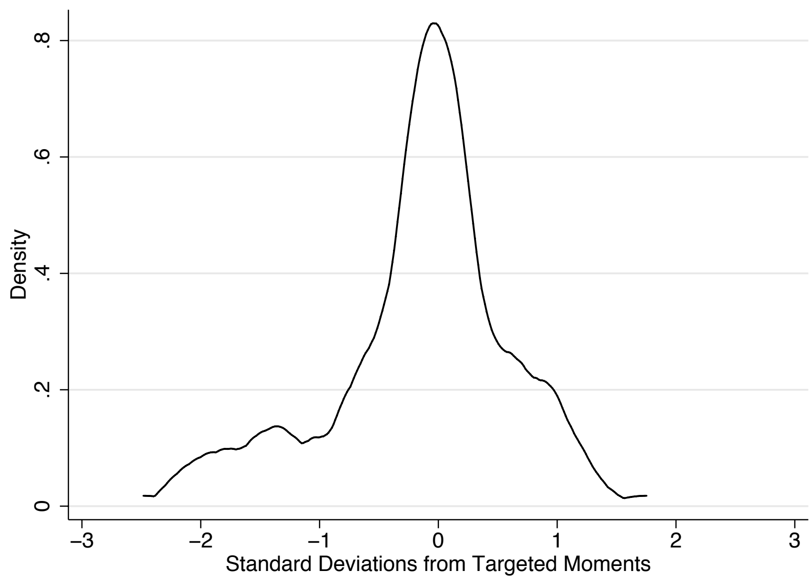


(g) Married: Reapplication disutility

(h) Unmarried: Reapplication disutility

Notes: These figures illustrate local identification of the six labor disutility parameters for appellants and two disutility parameters associated with reapplication. In each figure, the x-axis is the parameter representing the disutility. The y-axis is the corresponding moment, which is the average labor supply rate by severity type for labor disutility parameters and the average reapplication rate for

Figure A8. : **Distribution of Standardized Deviations from Targeted Moments**



Notes: This figure displays the distribution of standardized deviations of each simulated moment from its corresponding observed moment for the full set of targeted moments in the method of simulated moments model estimation.

Table A7—: **Model Parameters: Log Earnings Regressions**

	Main Estimation			Robustness to Control Function		
			Single and			**Single and**
	Married		**Unmarried**	**Married**		**Unmarried**
	Appellant	**Spouse**	**Appellant**	**Appellant**	**Spouse**	**Appellant**
Mid-severity of Disability	-0.015	-0.000	-0.021	-0.012	0.002	-0.021
	(0.008)	(0.005)	(0.002)	(0.011)	(0.006)	(0.005)
High-severity of Disability	-0.031	-0.032	-0.041	-0.045	-0.033	-0.027
	(0.008)	(0.005)	(0.002)	(0.012)	(0.006)	(0.010)
High School	0.096	0.072	0.145	0.180	0.086	0.100
	(0.007)	(0.005)	(0.002)	(0.040)	(0.008)	(0.030)
Some College	0.249	0.144	0.251	0.399	0.167	0.178
	(0.010)	(0.007)	(0.002)	(0.071)	(0.013)	(0.048)
Old Age	-0.064	-0.066	0.117	-0.193	-0.105	0.176
	(0.007)	(0.005)	(0.002)	(0.061)	(0.019)	(0.038)
Pre-App. Earnings	0.847	0.947	1.003	0.991	0.993	0.934
	(0.014)	(0.009)	(0.003)	(0.069)	(0.023)	(0.046)
Pre-App. Earnings, Squared	0.112	0.056	-0.017	-0.202	0.045	0.027
	(0.018)	(0.009)	(0.004)	(0.147)	(0.011)	(0.030)
Pre-App. Earnings, Cubed	0.016	0.068	-0.029	0.046	0.085	-0.004
	(0.029)	(0.013)	(0.006)	(0.038)	(0.015)	(0.023)
Constant	10.133	10.773	10.186	9.790	10.731	10.375
	(0.009)	(0.006)	(0.002)	(0.158)	(0.020)	(0.122)
Inverse Mills				0.547	0.152	-0.161
				(0.251)	(0.069)	(0.303)

Notes: This table presents estimated parameters from the post-application log earnings regression described in the text. "Pre-app. Earnings" refers to the average earnings constructed by forming the individual-specific average log earnings over the 10 years prior to application and residualizing on the other pre-application covariates.

Table A8—: **Model Parameters: Calibrations and Labor Disutility Estimates**

	Married	Single and Unmarried
Panel A.	**Externally set parameters**	
Interest rate:	0.016	0.016
Discount rate:	0.976	0.976
Coefficient of relative risk aversion:	1.5	1.5
Panel B.	**Estimated disutility parameters**	
Labor Disutility		
Low-severity:	0.702	0.485
	(0.014)	(0.010)
Mid-severity:	0.781	0.877
	(0.033)	(0.011)
High-severity:	0.829	1.076
	(0.007)	(0.013)
Spouse:	0.792	
	(0.008)	
Reapplication Disutility:	1.392	2.612
	(0.008)	(0.020)

Notes: This table summarizes the calibrated model parameters described in the text as well as the estimated model parameters representing disutility. Inference is based on reestimating the model on 20 block bootstrap replicates of the data (where the block corresponds to the individual).

Table A9—: **Simulated Labor Supply Elasticities**

	Main Estimation		Robustness to Control Function	
	Own-wage	**Cross-wage**	**Own-wage**	**Cross-wage**
Single Appellant:	0.201		0.184	
Married Appellant:	0.349	-0.331	0.324	-0.299
Spouse:	0.358	-0.345	0.309	-0.319

Notes: This table compares labor supply elasticities for married households and single and unmarried households by severity of disability. Because few appellants allowed DI are working, we consider in the immediately following year the subsample initially denied DI. These are Marshallian elasticities, that is, labor supply responses to permanent wage shocks. We compute the elasticity using the finite-difference evaluated at a one standard deviation permanent shock to the log wage.

Table A10—: **Robustness of Willingness to Pay**

	Married			Single and Unmarried		
	Control function:		**Test of equality:**	**Control function:**		**Test of equality:**
	With	**Without**	**P-value**	**With**	**Without**	**P-value**
Panel A.	**Baseline: Average Willingness to Pay**					
Average	2.327	2.300	0.750	10.816	11.316	0.999
Panel B.	**Counterfactuals: Average Willingness to Pay**					
Constraining Spousal Labor Supply:	10.036	9.852	0.100			
No Initial Savings Available:	3.349	3.319	0.750	13.247	13.740	0.999
No Reapplication Available:	15.589	15.506	0.200	19.085	19.490	0.999

Notes: This table shows estimates of the average welfare benefit ($1,000, per household member, annuitized over the four years after initial DI allowance) of DI allowance at appeal for married households and single and unmarried households. In the rows titled "Unconstrained", we use the estimated model to compute the welfare benefit of DI receipt. In the row titled, "Constrained spousal labor," we compute the willingness to pay for DI receipt while constraining the spousal labor supply to the observed labor supply during the year before DI allowance is announced. In the rows titled "No reapplication," we compute the willingness to pay for DI receipt while constraining denied appellants from reapplying for benefits by setting the probability of transitioning into DI equal to zero. The hypotheses tests correspond to testing equality in the average willingness with and without correcting for selectivity bias in the estimation of the earnings processes. P-values are based on reestimating the model on 20 block bootstrap replicates of the data (where the block corresponds to the individual).

Estimation and Computation Details

B1. Solving the Model, given a Discrete State Space

Here, we detail the algorithm used to compute the value function at each time period for each type of household, given a discrete state space. In particular, we present the algorithm for value functions after retirement (both single and married households), before retirement with DI (for single households only), and before retirement without DI (for single households only). The algorithms before retirement for married households are identical to those for single households, except that there is an additional choice (spousal labor supply) and an additional source of uncertainty that must be integrated out (spousal wage shocks), so we omit the algorithms for married households for brevity. The algorithms rely on a discretized state space in the continuous state variables, savings S_t and log wages $\log W_t$; denote the associated grids by $\mathcal{S}$ for savings and $\mathcal{W}$ for log wages.

Solution Algorithm after Retirement

We begin the solution method by solving for the value function at the years during retirement, which is simpler than the working age model because it does not involve labor supply (and the associated wage uncertain) or disability insurance (and the associated reapplication process).

1) Year of death ($t = T + 10$, where T is retirement year). In the final year of life, the household optimally consumes all remaining savings S_{T+10} plus retirement benefits b, so consumption is optimally given by $C_{T+10} = S_{T+10} + b$. The value function is then $V_{M,T+10}\left(S_{T+10}\right) = \frac{1}{1-\mu_M}\left(S_{T+10} + b\right)^{1-\mu_M}$, so given parameters (b, μ_M), $V_{M,T+10}$ is known for all S_{T+10}. We evaluate $V_{M,T+10}$ for all $S_{T+10} \in \mathcal{S}$.

2) Year prior to death ($t = T + 9$): The value function is simply, $V_{M,T+9}\left(S_{T+9}\right) = \max_{C_{T+9},S_{T+10}} \frac{1}{1-\mu_M}\left(C_{T+9}\right)^{1-\mu_M} + \zeta V_{T+10}\left(S_{T+10}\right)$ subject to the budget constraint $S_{T+10} \leq (1 + r)\left(S_{T+9} + b - C_{T+9}\right)$. Given (b, μ_M, r, ζ) and $V_{M,T+10}$ from 1., we find $S_{T+10} \in \mathcal{S}$ such that $V_{M,T+9}$ is maximized, ruling out those S_{T+10} that do not satisfy the budget constraint. This is done for each $S_{T+9} \in \mathcal{S}$.

3) We then repeat the procedure in 2. for $t = T + 8, t = T + 7, \ldots, t = T + 1$. Note also that the terminal condition is always satisfied, since all remaining savings are consumed at $t = T + 10$ and $S_{T+11} = 0$. Lifetime utility would be infinitely negative if $C_{T+10} = S_{T+10} + b$ were negative with positive probability, so households will use precautionary savings across the lifecycle to ensure that $S_{T+10} \geq -b$.

This procedure yields $V_{M,t}\left(S_t\right)$ for each $t = T + 1, \ldots, T + 10$, for each S_t in the grid of possible values, given only the parameters (b, μ_M, r, ζ).

Solution Algorithm before Retirement for a Single Household with Disability Insurance

A single household ($M = 1$) with DI ($D_t = 1$) chooses appellant labor supply ($P_{A,t}$) and savings, which also determines consumption through the budget constraint. This is only more complicated than the retired household's problem due to the need to account for the labor supply decision and associated wage uncertainty, as well as the tax-transfer system that maps earnings, DI status, and household characteristics into disposable income.

1) One year prior to retirement ($t = T$): The household's problem is, $V_{1,T}(D_t = 1, \log W_{A,T}, S_T; O_1)$ $= \max_{P_{A,T},C_T,S_{T+1}} \frac{1}{1-\mu_1}(C_T \exp(-\phi_{1,A,H}P_{A,T}))^{1-\mu_1} + \zeta V_{T+1}(S_{T+1})$ subject to the budget constraint $S_{T+1} \leq (1+r)(S_T + I_T - C_T)$. Note that we express the value function in terms of the observed log wage $\log W_{A,t}$ rather than the shock $\tau_{A,t}$, as each is known from the other given O_1 and t (see the wage equation in the main text). Furthermore, disposable income is determined by $I_T = (1 - \Lambda_{1,1,K,T})(E_{A,t})^{(1-\Psi_{1,1,K,T})}$ if $P_{A,t} = 1$ and $I_T = \Phi_{1,1,K,T}$ if $P_{A,T} = 0$, where $E_T = W_{A,T}P_{A,T}$ is earnings. Recall that $V_{M,T+1}$ is known from the retirement solution. Given $V_{1,T+1}(S_{T+1})$, we evaluate the objective $\frac{1}{1-\mu_1}(C_T \exp(-\phi_{1,A,H}P_{A,T}))^{1-\mu_1} + \zeta V_{T+1}(S_{T+1})$ for each $P_{A,T} \in \{0, 1\}$, $S_{T+1} \in \mathcal{S}$, choosing the objective-maximizing combination as the optimal household solution, which yields $V_{1,T}(D_t = 1, \log W_{A,T}, S_T; O_1)$, given each state space combination $S_T \in \mathcal{S}$, $\log W_T \in \mathcal{W}$, O_1.

2) Two years prior to retirement ($t = T - 1$): The household's problem is $V_{1,T-1}(D_{T-1} = 1, \log W_{A,T-1}, S_{T-1}; O_1)$ $= \max_{P_{A,T-1},C_{T-1},S_T} \frac{1}{1-\mu_1}(C_{T-1} \exp(-\phi_{1,A,H}P_{A,T-1}))^{1-\mu_1}$ $+\zeta \mathbb{E}V_{1,T}(D_T = 1, \cdot, S_T; O_1)$. Since we know from 1. how to compute $V_{1,T}(D_t = 1, \log W_{A,t}, S_T; O_1)$ for each $\log W_{A,T} \in \mathcal{W}$, we can integrate across the distribution of $\log W_{A,T}$ to compute the expectation $\mathbb{E}V_{1,T}(D_T = 1, \cdot, S_T; O_1)$. In particular, since we have assumed $\log W_{A,t}$ follows a random walk process, then $\log W_{A,T}$ is Normally distributed with mean $\log W_{A,T-1}$, so we can use Gaussian quadrature to approximate the integral numerically. Given $\mathbb{E}V_{1,T}(D_T = 1, \cdot, S_T; O_1)$, we evaluate the objective $\frac{1}{1-\mu_1}(C_{T-1} \exp(-\phi_{1,A,H}P_{A,T-1}))^{1-\mu_1} + \zeta \mathbb{E}V_{1,T}(D_T = 1, \cdot, S_T; O_1)$ for each $P_{A,T-1} \in \{0, 1\}$, $S_T \in \mathcal{S}$, choosing the objective-maximizing combination as the optimal household solution, which yields $V_{1,T-1}(D_{T-1} = 1, \log W_{A,T-1}, S_{T-1}; O_1)$, given each state space combination $S_{T-1} \in \mathcal{S}$, $\log W_{T-1} \in \mathcal{W}$, O_1.

3) We then repeat the procedure in 2. for $t = T - 2, t = T - 3, \ldots, t = 1$. Recall that $T = 27$ for single households that are young at the time of

appeal and $T = 11$ for households that are old at the time of appeal, so we must compute the algorithm separately for young and old households.

This procedure yields $V_{1,t}(D_t = 1, \tau_{A,t}, S_t; O_1)$ for each $t = 1, \ldots, T$, for each discretized $(S_t, \log W_{A,t}, O_1)$ combination, given the model parameters.

Solution Algorithm before Retirement for a Single Household without Disability Insurance

A single household without DI chooses appellant labor supply, reapplication (R_t), and savings, which also determines consumption through the budget constraint. This is only more complicated than the solution algorithm with DI because the household must choose DI reapplication and we must account for the probability of receiving DI approval in the next period.

1) Year prior to retirement $(t = T)$: The household's problem is,
$V_{1,T}(D_t = 0, \log W_{A,T}, S_T; O_1)$
$= \max_{P_{A,T}, C_T, R_T, S_{T+1}} \frac{1}{1-\mu_1}(C_T \exp(-\phi_{1,A,H} P_{A,T}) - R_T \exp(\omega_1))^{1-\mu_1}$
$+\zeta V_{T+1}(S_{T+1})$ subject to the budget constraint
$S_{T+1} \leq (1+r)(S_T + I_T - C_T)$, where earnings and disposable income are determined analogously to the case with DI. Recall that $V_{M,T+1}$ is known from the retirement solution, so for each O_1, we can directly compute the objective $\frac{1}{1-\mu_1}(C_T \exp(-\phi_{1,A,H} P_{A,T}))^{1-\mu_1} + \zeta V_{T+1}(S_{T+1})$ for each combination of $P_{A,T} \in \{0,1\}$, $R_T \in \{0,1\}$, $S_{T+1} \in \mathcal{S}$, $\log W_T \in \mathcal{W}$, choosing the maximizing combination as the optimal household solution, which yields $V_{1,T}(D_t = 1, \log W_{A,T}, S_T; O_1)$, given each state space combination $S_{T-1} \in \mathcal{S}$, $\log W_{T-1} \in \mathcal{W}$, O_1. Note that $R_T = 0$ is always optimal, since reapplication incurs a cost but no benefits are received due to retirement in the next period.

2) One year earlier $(t = T-1)$: The household's problem is
$V_{1,T-1}(D_{T-1} = 0, \log W_{A,T-1}, S_{T-1}; O_1) = \max_{P_{A,T-1}, R_{T-1}, C_{T-1}, S_T}$
$\frac{1}{1-\mu_1}(C_{T-1} \exp(-\phi_{1,A,H} P_{A,T-1}) - R_{T-1} \exp(\omega_1))^{1-\mu_1} + \zeta \mathbb{E} V_{1,T}(\cdot, \cdot, S_T; O_1)$.
Note that we can write,
$\mathbb{E} V_{1,T}(\cdot, \cdot, S_T; O_1) = (1 - \pi_{1,H,T-1}) \mathbb{E} V_{1,T}(D_T = 0, \cdot, S_T; O_1)$
$+\pi_{1,H,T-1} \mathbb{E} V_{1,T}(D_T = 1, \cdot, S_T; O_1)$ using the DI approval rate $\pi_{1,H,T-1}$. Since we know from 1. how to compute $V_{1,T}(D_t = 0, \log W_{A,t}, S_T; O_1)$ for each $\log W_{A,T} \in \mathcal{W}$, we can integrate across the distribution of $\log W_{A,T}$ to compute the expectation $\mathbb{E} V_{1,T}(D_T = 0, \cdot, S_T; O_1)$. Given
$\mathbb{E} V_{1,T}(D_T = 1, \cdot, S_T; O_1)$ and $\mathbb{E} V_{1,T}(D_T = 0, \cdot, S_T; O_1)$, we evaluate the objective of $V_{1,T-1}(D_{T-1} = 1, \log W_{A,T-1}, S_{T-1}; O_1)$ at each combination of $P_{A,T-1} \in \{0,1\}$, $R_{T-1} \in \{0,1\}$, $S_T \in \mathcal{S}$, choosing the objective-maximizing combination as the optimal household solution, which yields
$V_{1,T-1}(D_t = 1, \log W_{A,T-1}, S_{T-1}; O_1)$, given each state space combination $S_{T-1} \in \mathcal{S}$, $\log W_{T-1} \in \mathcal{W}$, O_1.

3) We then repeat the procedure in 2. for $t = T-2, t = T-3, \ldots, t = 1$. Again, we must compute the algorithm separately for young and old households.

This procedure yields $V_{1,t}(D_t = 0, \tau_{A,t}, S_t; O_1)$ for each $t = 1, \ldots, T$, for each discretized $(S_t, \log W_{A,t}, O_1)$ combination, given the model parameters.

Feasible Discretization of the State Space

The algorithms described above rely on the discretized state spaces $\mathcal{S}$ and $\mathcal{W}$. We construct a grid in each using equally spaced quantiles of the observed marginal distributions of savings and wages, respectively. In practice, we use ten points to represent the state space for S_t and ten points to represent the state space for $\log W_t$. We investigate the robustness of the model results to this approximation for single households by allowing for 100 points in the state space for S_t and 100 points in the state space for $\log W_{A,t}$, so that there are 100 times as many grid points and the model requires approximately 100 times longer to compute. We find that the model fit is similar, suggesting that the model solution is not very sensitive to additional fineness of the grid. When integrating across the distribution of $\log W_{A,t}$, we construct the 10×10 transition matrix representing the probability of transitioning to any point on the grid from any other point on the grid using the conditional Normal probability distribution function evaluated at each point.

The implied computational burden is substantial. For single households before retirement without DI that are young at the time of appeal, one simulation of the model requires millions of distinct numerical evaluations, with even more for married households.[1] We must then also perform these evaluations for young single and married households with DI, old single and married households without DI, and old single and married households with DI, as well as compute the single and married household value functions after retirement. As discussed below, estimating the unknown model parameters will require that we repeat these solution algorithms thousands of times, while bootstrapping the estimates requires thousands more times.

One other point to note: This approach does not simulate or approximate the initial distribution of the state space. Instead, it uses the exact observed values. That is, for each household, our approach computes its predicted optimal choice variables conditional on its observed characteristics, preserving the exact initial distribution of observed characteristics.

[1] This is because we must evaluate the value function objective at (10 current savings state points) $\times$ (10 next period savings choice points) $\times$ (10 current appellant wage state points) $\times$ (2 appellant labor supply choice points) $\times$ (2 DI reapplication choice points) $\times$ (12 static household types) $\times$ (27 time periods), for a total of over a million distinct numerical evaluations. For married households, there are also 10 current spouse wage states and 2 spousal labor supply choice points to consider, for a total of over 20 million distinct numerical evaluations.

B2. Interpolating the Discretized Model to a Continuous State Space and Simulating Sample Moments

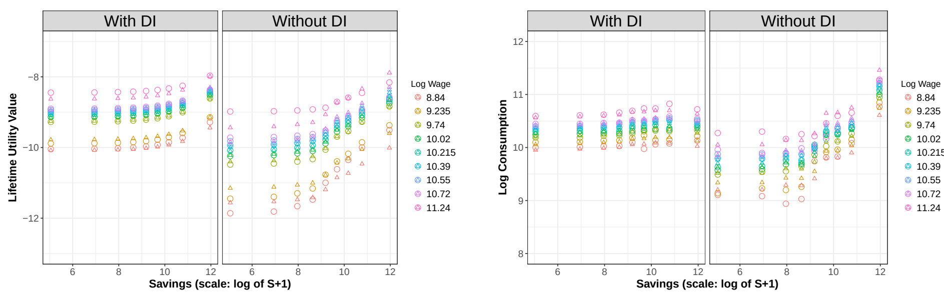
Our aim is to use the value functions to infer optimal choices of consumption, labor supply, and DI reapplication for the households in our sample, given the model parameters. The computational algorithms described above provide an approximate mapping from the state space to the value function for a discrete grid of points in the state space. For example, for single households, it provides a numerical solution to the value function, $V_{1,t}$, when given a time period t, the vector of static household characteristics O_1, and the current values of savings in $\mathcal{S}$ and log wages in $\mathcal{W}$. However, it does not provide the value function $V_{1,t}$ or associated optimal choices for $S_t \notin \mathcal{S}$ or $\log W_t \notin \mathcal{W}$, which is nearly the entire sample of households.

In order to approximate optimal household choices (i.e., consumption, labor supply, and DI reapplication) for all $(S_t, W_{A,t})$ pairs in the observed sample, we use interpolation. In particular, for each of the choice outcomes, interpolation uses the state space points for which we know the optimal choices, $\mathcal{S} \times \mathcal{W}$, to approximate the optimal choices for other state spaces. Our chosen interpolation method is cubic spline interpolation in the consumption choice and cubic spline interpolation of the underlying index functions for labor supply and DI reapplication choices. This is implemented using the "gam" function from the published R package *mgcv*, version 1.8-12. To allow full flexibility in the discrete components of the state space, we interpolate separately for each (observed time period $t = 1, 2, 3, 4$) $\times$ (current DI state 0 or 1) $\times$ (household static characteristic O_M) $\times$ (marital status M). This way, the interpolation method only requires smoothing approximations on the continuous components of the state space $(S_t, W_{A,t})$, but is unrestricted across discrete components of the state space.

For each individual in our sample at each time period, the interpolation fit on the discretized model provides a prediction of consumption, labor supply, and DI reapplication at times $t = 1, 2, 3, 4$. Using these predictions, we then construct the simulated moments from these predictions. For example, average spousal labor supply is simulated as the mean predicted labor supply of spouses provided by the interpolation.

Figure 1 (of this appendix) demonstrates the performance of the interpolation in out-of-grid prediction for the value function as well as the optimal choice of consumption. In particular, we first compute $V_{1,t}(D_t, \log W_{A,t}, S_t; O_1)$ for $t = 1$ on the grid $\mathcal{G} = \mathcal{S} \times \mathcal{W}$, separately for each of the 12 O_1 types. Second, we also compute $V_{1,t}(D_t, \log W_{A,t}, S_t; O_1)$ for an alternate grid $\mathcal{H}$, where $\mathcal{G} \cap \mathcal{H} = \emptyset$. We then interpolate $V_{1,t}(D_t, \log W_{A,t}, S_t; O_1)$ computed on $\mathcal{G}$ onto the points $\mathcal{H}$, which is an out-of-grid prediction. We choose the points in $\mathcal{H}$ to be particularly difficult to match by selecting the midpoints between any two grid points in $\mathcal{G}$ (midpoints maximize the distance between $\mathcal{H}$ points and $\mathcal{G}$ points within the same interval).

The figure shows the out-of-grid prediction of $\mathcal{H}$ as triangles, and the in-grid prediction of $\mathcal{H}$ from directly-computing $V_{1,t}\left(D_t, \log W_{A,t}, S_t; O_1\right)$ on $\mathcal{H}$ as circles, where each is formed from averaging across the 12 O_1 types. Visually, the goal of the interpolation is to approximate the circles with the triangles. This allows us to approximate the value function and optimal choices at thousands of out-of-grid points in the sample using only a small grid. We see that the out-of-grid interpolation predictions track the in-grid directly-computed circles. It performs especially well across the savings grid and at interior values of the log wage grid. The approximation is less precise at the end points of the log wages grid, but these points represent only a small sample of outlier observations in the data.



(a) Value Function

(b) Consumption

Figure B1. : Interpolation Fit for Out-of-Grid State Space Values

Notes: This figure demonstrates the performance of the interpolation in out-of-grid prediction for the value function as well as the optimal choice of consumption. In particular, we first compute $V_{1,t}\left(D_t, \log W_{A,t}, S_t; O_1\right)$ for $t = 1$ on the grid $\mathcal{G} = \mathcal{S} \times \mathcal{W}$, separately for each of the 12 O_1 types. Second, we also compute $V_{1,t}\left(D_t, \log W_{A,t}, S_t; O_1\right)$ for an alternate grid $\mathcal{H}$, where $\mathcal{G} \cap \mathcal{H} = \emptyset$. We then interpolate $V_{1,t}\left(D_t, \log W_{A,t}, S_t; O_1\right)$ computed on $\mathcal{G}$ onto the points $\mathcal{H}$, which is an out-of-grid prediction. We choose the points in $\mathcal{H}$ to be particularly difficult to match by selecting the midpoints between any two grid points in $\mathcal{G}$ (midpoints maximize the distance between $\mathcal{H}$ points and $\mathcal{G}$ points within the same interval). The figure shows the out-of-grid prediction of $\mathcal{H}$ as triangles, and the in-grid prediction of $\mathcal{H}$ from directly-computing $V_{1,t}\left(D_t, \log W_{A,t}, S_t; O_1\right)$ on $\mathcal{H}$ as circles, where each is formed from averaging across the 12 O_1 types.

B3. Solving for the Optimal Parameters

We choose two sets of moments to match. The first set consists of raw data moments, chosen based on the identification arguments in the text. These moments are mean log disposable income and expected log disposable income conditional on log earnings among households that supply labor, mean disposable income among households that do not supply labor, and employment rates and reapplication rates among those not receiving DI. Each of these moments is matched conditional on observable types over which the parameters vary in order to pin down all of the type-specific model parameters. The second set of moments is the IV results for consumption, disposable income, and earnings among appellants and spouses, included to discipline the model to recover our estimates of the causal effects of DI allowance.

To simulate the moments, we solve the value function, estimate the interpolation splines and predict the choice of each household, then compute the moment on the predicted household choices. We compare each simulated moment to the same moment computed on the observed household choices from the data. We form the objective function by forming the difference between the observed and simulated moment, and divide by the standard deviation corresponding to the observed moment. This weighting is equivalent to using the diagonal weighting matrix to form the objective function, as in Equation (13) of Blundell, et al. (2016) and motivated by the finding of Altonji and Segal (1996) that the asymptotically efficient weighting matrix has poor small-sample properties. We weight up the IV moments so that the sum of their weights is equal to that of the raw data moments.

We solve numerically for the parameters that minimize this objective function. For each vector of candidate parameters, we compute the value function on the discrete state space conditional on these parameters, interpolate to form the model prediction of optimal choices for each household, then evaluate the objective function for the simulated moments. To minimize the objective function, we apply two approaches. First, we use a particle swarm optimization algorithm to search for the globally optimal parameter vector, utilizing the "psoptim" function from the published R package *psoptim*, version 1.0. Second, we use the standard BFGS optimization algorithm, initialized at the optimal parameters found by psoptim, to verify that psoptim has found the locally optimal parameters. Together, these optimization algorithms require over a thousand complete evaluations of the model. We perform inference using the block bootstrap, where each bootstrap also requires estimation using these optimization algorithms. In particular, we randomly draw block replicates of the sample, where each "block" is a household's four-year history, then repeat the approach described above to find the optimal parameter vector for this replication sample. The distribution of each parameter across replication samples is then used to compute block bootstrap p-values for inference.

B4. Extracting Willingness to Pay

Once the optimal parameter estimates are obtained, we can use the estimated model to perform counterfactual exercises. The counterfactual exercise of interest is to solve for the amount of income a household would be willing to give up each year across the remainder of the working life in order to be initially approved for DI. In particular, for single households, we parameterize this by modifying the budget constraint to include a *Cost* parameter: $S_{t+1} \leq$

$(1+r)(S_t + I_t - Cost - C_t)$. Denote the value function with this budget constraint by $V_{1,t}(D_t, \log W_{A,t}, S_t; O_1, Cost)$. Then, the willingness to pay from time $t = 1$, denoted WTP, solves this equation:

$$\begin{aligned} &V_{1,1}(D_1 = 0, \log W_{A,t}, S_t; O_1, Cost = 0) \\ &\qquad\qquad = V_{1,1}(D_1 = 1, \log W_{A,t}, S_t; O_1, Cost = WTP) \end{aligned}$$

In words, WTP is the value of $Cost$ that makes the household indifferent between being initially denied DI ($D_1 = 0$) but paying $Cost = 0$, and being initially approved DI ($D_1 = 1$) but paying $Cost = WTP$ annually.

In practice, we cannot solve the above equation exactly because we do not have a closed-form representation for $V_{1,1}$, so we instead use numerical optimization. For each household in our sample, we express WTP as the solution to a one-dimensional optimization problem in which we search for the value of $Cost$ that minimizes the squared deviation from the above equality:

$$\begin{aligned} WTP = \arg\min_c \Big\{ &V_{1,1}(D_1 = 0, \log W_{A,t}, S_t; O_1, Cost = 0) \\ &- V_{1,1}(D_1 = 1, \log W_{A,t}, S_t; O_1, Cost = c) \Big\}^2 \end{aligned}$$

We then report the average WTP across the sample of single households, and perform the analogous procedure for married households.

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REFERENCES

Administration, U.S. Social Security. 2017. "Annual Report of the Supplemental Security Income Program." U.S. Government Printing Office.

Aguiar, Mark, and Erik Hurst. 2013. "Deconstructing Life Cycle Expenditure." *Journal of Political Economy*, 121(3): 437 – 492.

Altonji, Joseph G, and Lewis M Segal. 1996. "Small-sample bias in GMM estimation of covariance structures." *Journal of Business & Economic Statistics*, 14(3): 353–366.

Atkinson, Anthony B., Lee Rainwater, and Timothy M. Smeeding. 1995. "Income Distributions in OECD Countries: Evidence from the Luxembourg Income Study." *OECD Publications and Information Center.*

Autor, David H. 2011. "The Unsustainable Rise of the Disability Rolls in the United States: Causes, Consequences, and Policy Options." *NBER Working Paper.*

Autor, David H., and Mark G. Duggan. 2003. "The Rise in the Disability Rolls and the Decline in Unemployment." *Quarterly Journal of Economics*, 118(1): 157–205.

Autor, David H., and Mark G. Duggan. 2006. "The Growth in the Social Security Disability Rolls: A Fiscal Crisis Unfolding." *Journal of Economic Perspectives*, 20(3): 71–96.

Autor, David H., Mark G. Duggan, and Jonathan Gruber. 2014. "Moral Hazard and Claims Deterrence in Private Disability Insurance." *American Economic Journal: Applied Economics*, 6(4): 110–141.

Autor, David, Nicole Maestas, Kathleen J. Mullen, and Alexander Strand. 2017. "Does Delay Cause Decay? The Effect of Administrative Decision Time on the Labor Force Participation and Earnings of Disability." *NBER Working Paper No. 23466.*

Baicker, Katherine, Amy Finkelstein, Jae Song, and Sarah Taubman. 2014. "The Impact of Medicaid on Labor Market Activity and Program Participation: Evidence from the Oregon Health Insurance Experiment." *American Economic Review*, 104(5): 322–328.

Blundell, Richard, Luigi Pistaferri, and Ian Preston. 2008. "Consumption Inequality and Partial Insurance." *American Economic Review*, 98(5): pp. 1887–1921.

Blundell, Richard, Luigi Pistaferri, and Itay Saporta-Eksten. 2016. "Consumption inequality and family labor supply." *American Economic Review*, 106(2): 387–435.

Blundell, Richard, Martin Browning, and Costas Meghir. 1994. "Consumer Demand and the Life-Cycle Allocation of Household Expenditures." *The Review of Economic Studies*, 61(1): pp. 57–80.

Blundell, Richard, Monica Costa Dias, Costas Meghir, and Jonathan Shaw. 2016. "Female Labor Supply, Human Capital, and Welfare Reform." *Econometrica*, 84(5): 1705–1753.

Board, Social Security Advisory. 2015. "Technical Panel on Assumptions and Methods."

Borghans, Lex, Anne C. Gielen, and Erzo F. P. Luttmer. 2014. "Social Support Substitution and the Earnings Rebound: Evidence from a Regression Discontinuity in Disability Insurance Reform." *American Economic Journal: Economic Policy*, 6(4): 34–70.

Bound, John. 1989. "The Health and Earnings of Rejected Disability Insurance Applicants." *American Economic Review*, 79(3): 482–503.

Browning, Martin, and Costas Meghir. 1991. "The Effects of Male and Female Labor Supply on Commodity Demands." *Econometrica*, 59(4): pp. 925–951.

Browning, Martin, and Soren Leth-Petersen. 2003. "Imputing consumption from income and wealth information." *The Economic Journal*, 113(488): F282–F301.

Chen, Susan, and Wilbert van der Klaauw. 2008. "The work disincentive effects of the disability insurance program in the 1990s." *Journal of Econometrics*, 142(2): 757–784.

Chetty, Raj, and Adam Szeidl. 2007. "Consumption commitments and risk preferences." *Quarterly Journal of Economics*, 122(2): 831–877.

Cullen, Julie B., and Jonathan Gruber. 2000. "Does Unemployment Insurance Crowd out Spousal Labor Supply?" *Journal of Labor Economics*, 18(3): pp. 546–572.

Dahl, Gordon, Andreas Kostøl, and Magne Mogstad. 2014. "Family Welfare Cultures." *Quarterly Journal of Economics*, 129(4): 1711–1752.

Eika, Lasse, Magne Mogstad, and Ola Vestad. 2017. "What can we learn about household consumption from information on income and wealth?" *Mimeo.*

Fadlon, Itzik, and Torben Heien Nielsen. 2019. "Household labor supply and the gains from social insurance." *Journal of Public Economics.*

Finkelstein, Amy, Nathaniel Hendren, and Erzo F.P. Luttmer. 2019. "The Value of Medicaid: Interpreting Results from the Oregon Health Insurance Experiment." *Journal of Political Economy.*

French, Eric, and Jae Song. 2014. "The Effect of Disability Insurance Receipt on Labor Supply." *American Economic Journal: Economic Policy*, 6(2): 291–337.

Gruber, Jonathan. 2000. "Disability insurance benefits and labor supply." *Journal of Political Economy*, 108(6): 1162–1183.

Heathcote, Jonathan, Kjetil Storesletten, and Giovanni L Violante. 2014. "Consumption and labor supply with partial insurance: An analytical framework." *American Economic Review*, 104(7): 2075–2126.

Imbens, Guido W., and Donald B. Rubin. 1997. "Estimating Outcome Distributions for Compliers in Instrumental Variables Models." *The Review of Economic Studies*, 64(4): 555–574.

Keane, Michael P. 2011. "Labor Supply and Taxes: A Survey." *Journal of Economic Literature*, 49(4): 961–1075.

Kostøl, Andreas, and Magne Mogstad. 2014. "How Financial Incentives Induce Disability Insurance Recipients to Return to Work." *American Economic Review*, 104(2): 624–55.

Kostøl, Andreas, and Magne Mogstad. 2015. "Earnings, Disposable Income, and Consumption of Allowed and Rejected Disability Insurance Applicants." *American Economic Review*, 105(5): 137–41.

Liebman, Jeffrey B. 2015. "Understanding the Increase in Disability Insurance Benefit Receipt in the United States." *Journal of Economic Perspectives*, 29(2).

Low, Hamish, and Luigi Pistaferri. 2015. "Disability Insurance and the Dynamics of the Incentive Insurance Trade-Off." *American Economic Review*, 105(10): 2986–3029.

Lundberg, Shelly. 1985. "The added worker effect." *Journal of Labor Economics*, 11–37.

Maestas, Nicole, Kathleen J. Mullen, and Alexander Strand. 2013. "Does Disability Insurance Receipt Discourage Work? Using Examiner Assignment to Estimate Causal Effects of SSDI Receipt." *American Economic Review*, 103(5): 1797–1829.

Meghir, Costas, and Luigi Pistaferri. 2011. "Earnings, Consumption and Life Cycle Choices." In . Vol. 4, Part B of *Handbook of Labor Economics*, , ed. David Card and Orley Ashenfelter, 773 – 854. Elsevier.

Meyer, Bruce D., and Wallace K.C. Mok. 2018. "Disability, earnings, income and consumption." *Journal of Public Economics.*

Milligan, Kevin S., and David A. Wise. 2011. "Social Security and Retirement around the World: Mortality, Health, Employment and Disability Insurance Participation and Reforms." *Harvard Kennedy School Working paper.*

OECD. 2010. *Sickness, Disability and Work: Breaking the Barriers. A synthesis of findings across OECD countries.* OECD Publishing.

OECD. 2015. "OECD Social Expenditure Database (SOCX)."

of Trustees of the Federal Hospital Insurance, Board, and Federal Suplememntary Medical Insurance Trust Funds. 2017. "2017 Medicare Trustees Report." U.S. Government Printing Office.

of Trustees of the Federal OASDI Trust Funds, Board. 2017. "The 2017 Annual Report of the Board of Trustees of the Federal Old-Age and Survivors Insurance and Federal Disability Insurance Trust Funds." U.S. Social Security Administration, U.S. Government Printing Office.

Parsons, Donald O. 1980. "The Decline in Male Labor Force Participation." *Journal of Political Economy*, 88(1): 117–134.

Persson, Petra. 2019. "Social insurance and the marriage market." *Journal of Political Economy.*

Pistaferri, Luigi. 2015. "Household consumption: Research questions, measurement issues, and data collection strategies." *Journal of Economic and Social Measurement*, 40(1-4): 123–149.

U.S. Social Security Administration. 2017. *Annual Statistical Report on the Social Security Disability Insurance Program, 2016.* Office of Retirement and Disability Policy.