Appendix

A The empirical consequences of involuntary job loss

I follow statistical framework of the program evaluation literature applied to the estimation of the earnings losses of displaced workers (Jacobson et al., 1993; Davis and von Wachter, 2011) to quantify the reduced form relationship between involuntary job loss and the labor market outcomes of displaced older workers. I estimate several regression models of the following form:

$$y_{it} = \alpha_i + \gamma_t + \mathbf{X_{it}}\beta + \sum_{k=-1}^{5} D_{it}^{k}\delta_k + \varepsilon_{it}. \tag{A.1}$$

In this equation, y_{it} is a labor market outcome of an individual i at time t that is affected by displacement, captured via a set of dummies and controls for fixed effects and time-varying characteristics. In most papers, the labor market outcome of interest is earnings. I follow Jarosch (2015), and estimate two additional specifications that take wage rate and employment status as the labor market outcomes. Each labor market outcome is regressed on individual fixed effects α_i that account for any permanent differences (observable or unobservable) between workers, time fixed effects γ_t, and an age quadratic $\mathbf{X_{it}}$. ε_{it} is an error term uncorrelated across individuals and time.

The labor market outcome of an individual i at time t in Eq. (A.1) depends on displacement through the set of displacement dummies D_{it}^{k}. Each displacement dummy takes a value of one if an individual i has been displaced k periods before time t, and zero otherwise. An individual coefficient δ_k measures the effect of displacement on worker's labor market outcome k periods after displacement. The cumulative impact of job loss over the period spanned by displacement dummies is estimated by the sum of coefficients δ_k.

Eq. (A.1) is estimated using a sample of the HRS males between ages 50 and 80. Following the established practice of the displacement literature, I restrict the estimation sample to workers with at least three years of tenure. Parameters of the three specifications that use employment status, earnings and wages as dependent variables are estimated by least squares.

The estimates are reported in Table A.1.

To estimate the employment consequences of involuntary job loss while taking into account the overall employment rates of older workers, I construct counterfactual employment rates for displaced workers by setting the values of all displacement dummies D_{it}^k for this group to zero. The counterfactual yields an estimated employment rate of displaced workers had the job loss not occurred. The ratio of the coefficient δ_k to the counterfactual employment rate k periods after displacement is the relative change of the employment rate due to involuntary job loss. These series are plotted in the left panel of Figure 1 in the paper.

The right panel of Figure 1 is constructed in a similar fashion using annual earnings and wage rates of displaced workers as the outcomes of interest. When computing the PDV of the earnings loss, I have to take into account that the HRS collects information on annual earnings biennially. I assume that both earnings and earnings losses between the waves are given by the arithmetic means of the corresponding values in the adjacent periods, and apply a discounting rate of 4%. The result is the difference between the PDV of actual realized earnings and the PDV of expected earnings had the job loss not occurred.

The dynamics of the costs of job loss shown by these estimates is consistent with other studies. Employment and earnings drop sharply in the period of separation, then go through a period of relatively steep recovery over the first two years. After that point the recovery slows down, and ten years after displacement there is still a 19% gap in earnings and 6% gap in wages (the latter is not statistically different from zero at 10% level). Employment rates therefore recover almost fully by the end of ten-year period. The main difference from the literature is substantial increase in the outcomes observed in pre-displacement period. Jacobson et al. (1993) find that earnings start dropping before displacement. Jarosch (2015) shows that in German data there is a small increase noticeable up to five years before the actual job loss. My results suggest that earnings go up 20% two years before displacement. This is likely related to the early retirement incentives which would be included in the total earnings of the HRS respondents, but irrelevant in other papers that avoid the issue by focusing on prime age workers.

The impact of displacement on the wage rate does not change substantially over the years, and on average reaches 9% of the counterfactual wage rate. Although jointly the displacement dummies are statistically significant at 5% level, the first three estimates of the displacement dummies in the wage regression are not statistically different from zero.

Table A.1: Employment, earnings and wage losses of displaced workers

Explanatory variable	Dependent variable: Employment status	Earnings ($1,000)	Wage rate ($)
Age	-0.126	-9.841	1.597
	(0.022)	(1.035)	(1.061)
$0.01 \times \text{Age}^2$	0.090	7.627	-0.120
	(0.015)	(0.678)	(0.727)
Displacement dummies:			
displaced in the next survey wave	0.131	3.634	0.015
	(0.036)	(1.821)	(0.558)
displaced in this wave	-0.302	-10.391	-1.371
	(0.032)	(1.393)	(0.954)
displaced one wave ago	-0.097	-4.770	-1.675
	(0.031)	(1.154)	(1.095)
displaced two waves ago	-0.073	-4.194	-2.744
	(0.028)	(1.072)	(0.803)
displaced three waves ago	-0.055	-2.827	-2.098
	(0.025)	(0.927)	(0.797)
displaced four waves ago	-0.046	-1.888	-1.605
	(0.023)	(0.985)	(0.959)
displaced five waves ago	-0.019	-1.514	-1.247
	(0.023)	(0.886)	(1.280)
Number of observations	14,136	14,136	4,137
Wald test of model significance (p-value)	712 (0.000)	525 (0.000)	73 (0.000)
Wald test for joint significance of layoff variables (p-value)	139 (0.000)	77 (0.000)	16 (0.027)

Notes: Least squares estimates of Equation (A.1), including individual and year fixed effects. Robust standard errors are given in the parentheses. Estimation sample includes HRS males age fifty to eighty, with at least three years of tenure before involuntary separation. Earnings are measured in thousands, constant 2000 dollars.

B HRS data

B.1 The construction of monthly employment histories

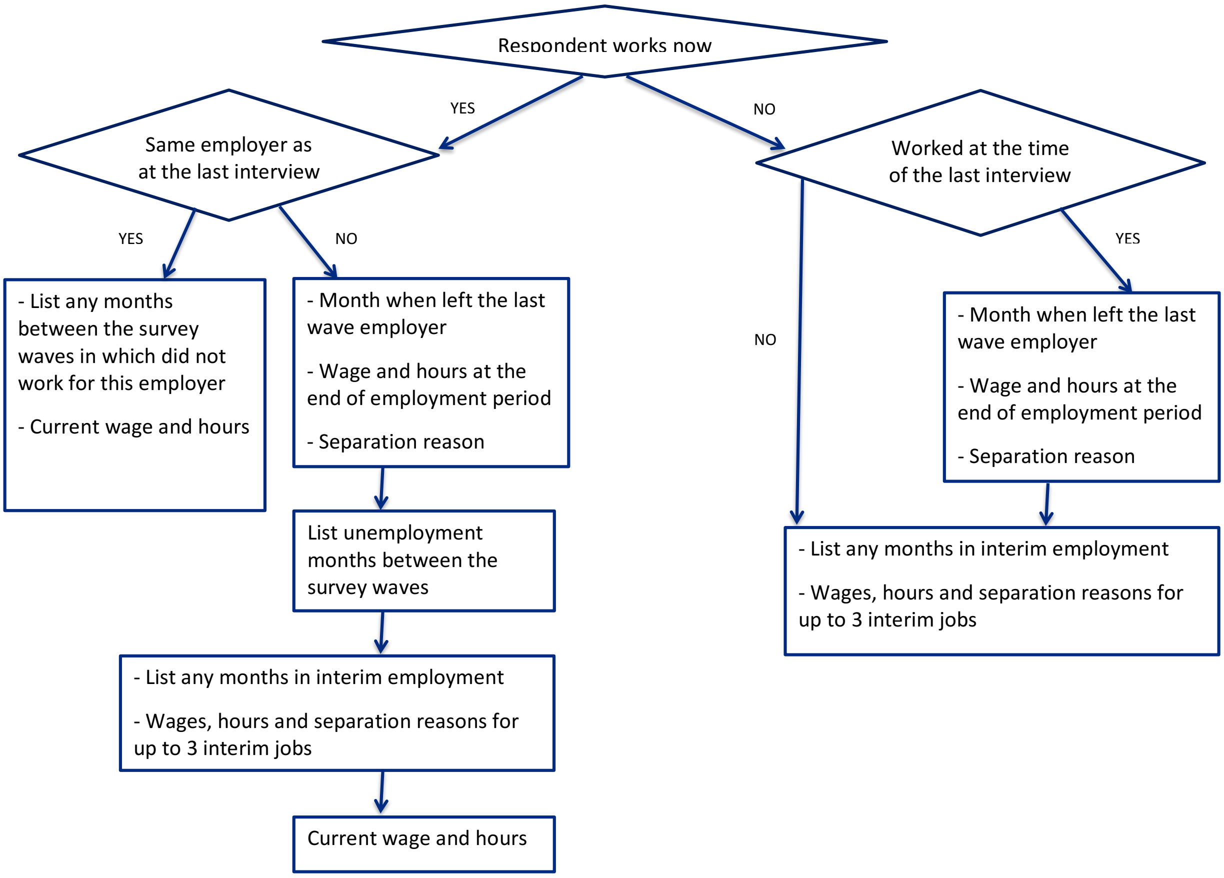
The Health and Retirement Study (HRS, http://hrsonline.isr.umich.edu/) is a biennial survey, which means that the data are collected from the respondents at two-year intervals. Because most of the labor force transitions take place at higher than biennial frequency, time aggregation would be a major problem for a project based solely on the labor force status data collected every two years. To address this problem, I turn to the HRS questions on individual labor market histories between survey waves.

At the time of the interview, respondents are asked a set of standard questions about their labor force status and employment details. In addition, the HRS retrospectively asks about employment changes that took place between the survey waves. Figure 1 summarizes the flow of questions on current and inter-wave employment. Using this information, I construct monthly employment histories that capture all unemployment spells and employment spells with up to three interim employers who are different from employers at the time of the interviews. These monthly histories include data on labor force status, wages, hours worked and separation reasons.

I use entry and exit interviews to complete the data for new and deceased respondents respectively. Depending on their labor force status, new survey entrants are asked about their tenure with the current employer or the month when they left their last job. Through these questions I obtain duration of initial employment and unemployment spells. The exit interviews ask similar questions about the job market history to the representatives of deceased respondents. As a result, I obtain a detailed picture of the labor force transitions in the HRS which is far superior to the biennial transitions that are straightforward to compute directly from the information on the current employment status. The displacement episodes and their dates in the paper are defined based on these monthly histories.

Other relevant variables with a clear link to calendar months are the dates of birth and death and the date of Social Security take up. Assets, health and medical expenses are only observed every two years at survey dates. I assume that asset values change pro rata between survey waves, health shocks are equally likely in each month, and medical expenses are distributed uniformly over the two-year period.

Figure 1: The HRS questions on the labor market history of respondents between survey waves



B.2 Pension data in the HRS

The HRS RAND wealth variables, used in the paper to measure the household assets, do not include the value of employer pensions. If pensions account for a substantial part of the retirement wealth, this omission could affect the results.

The employment section of the HRS contains questions on up to five of the respondent's pensions from the current and previous jobs. Based on this information, the HRS offers user contributed pension wealth data files for the period 1992-2010. These data contain the estimates of expected future benefits from defined benefits (DB) pensions and the current balances in the defined contributions (DC) accounts. The description of the dataset and the variable construction can be found in Gustman et al. (2010a) and the survey documentation.

Gustman et al. (2010b) estimate that the biggest asset of the early baby boomers cohort, born between 1948 and 1953, is Social Security, which accounts for 26.1 percent of the average wealth. Pensions account for further 23%, followed by 22% in housing. Financial assets comprise 9.8% of the total and IRA's are 6.8% (including 5.1% and 5% in direct stock holdings, respectively). The remaining amount is made of real estate, business assets and vehicles, each accounting for less than 6%.

Based on these estimates, the assets included in my model make up three quarters of the total wealth. I also account for 73% of stock investments through the IRA's and direct stock holdings. Although we have good estimates for the values of DB and DC pensions, proper modeling of pensions is complicated as it requires more information and additional assumptions on the details of multiple pension plans than is readily available in the data. I therefore decided against the inclusion of pensions into the model. Because other assets account for most of both the overall household wealth and stock holdings, I expect that the omission of pensions will have limited effect on results. However, the estimated effects of stock market dynamics on the retirement behavior of older workers should be seen as a lower bound due to the possible underestimation of the stock holdings.

C Estimating health, morality and wage transition probabilities

Individuals in the model face uncertainty about future survival, health and medical expenses, and future employment and income. I assume that beliefs about the likelihood of future events are fully rational, described by the Markov probability function $\Pr(S_{t+1}|S_t, D_t, \theta_p)$. In addition, I assume conditional independence that enables me to represent the state transition probabilities as products of the marginal conditional probabilities for individual state variables. Based on these assumptions, I estimate individual components of the state transition probability function between health, medical expenses, survival and wage states described as follows.

C.1 Health and mortality

I estimate biennial survival and health transition probabilities conditional on age, lagged health, and average lifetime income from a set of logit models. Table C.1 exhibits the estimated marginal effects. Based on these estimates, I predict conditional probabilities of health and survival transitions that are further supplied as an input in the simulations.

C.2 Health insurance and medical expenses

I assume that the health insurance status of employed individuals remains unaffected when they change jobs. A worker insured by employer automatically retains access to health insurance at a new job, while uninsured worker can not improve his status by switching jobs. This assumption holds for a large fraction of respondents in the data: over three fourths of workers who switched jobs between the HRS survey waves retained their health insurance status in a later wave. Loss of job leads to immediate termination of coverage for insured workers.[1] The consumption floor provided by the government accounts for the role of Medicaid. Employer provided health insurance becomes irrelevant after age sixty five when all workers in the model become eligible for Medicare.

Out-of-pocket medical expenses M_t follow an error components process with autoregressive

[1]Post-displacement jobs, on average, are less likely to offer health insurance than previously held career jobs. The model provides slightly better employment prospects for workers of insured type. I do not model COBRA or employer provided health insurance that can be retained after separation. Because individuals covered by COBRA typically pay higher premiums than insured by the employer, the process estimated for the group without employer provided health insurance gives a reasonable representation of their medical expenses.

error term:

$$\log M_t = \bar{M}_t + \zeta_t^m \tag{C.1}$$
$$\zeta_t^m = \rho^m \zeta_{t-1}^m + \varepsilon_t^m$$
$$\varepsilon_t^m \sim N(0, \sigma^2_{\varepsilon^m}),$$

where ζ_t^m is a persistent AR(1) component of medical expenses with autocorrelation ρ^m, and ε_t^m is white noise. The mean of log medical expenses $\bar{M}_t$ depends on age and health status. I estimate the parameters of Equation (C.1) using conditional maximum likelihood for each category of health insurance: employer provided, Medicare, and not insured by employer. To implement the estimation in logs, I drop reports of zero medical expenses.[2] The estimation results are shown in Table C.2. When simulating the model, I approximate the AR(1) process for the medical expense shock ζ^m with a first order three-node discrete Markov chain using Rouwenhorst method (Rouwenhorst, 1995; Kopecky and Suen, 2010).

C.3 Wage transition probabilities

The estimation of the wage process is similar to that of the medical expenses, except that I first impute the unobserved wages of nonworking individuals. I then model the wage transitions as an error components process with AR(1) disturbances:

$$\log W_t = \bar{W}_t + \zeta_t^w \tag{C.2}$$
$$\zeta_t^w = \rho^w \zeta_{t-1}^w + \varepsilon_t^w,$$
$$\varepsilon_t^w \sim N(0, \sigma^2_{\varepsilon^w}).$$

[2]Zero medical expenses are about 13% of the sample. There are no observable differences between respondents with zero expenses and the rest of the sample. I treat these observations as a result of measurement error, since very few people will literally spend zero on health and medications over a two year period.

The mean wage $\bar{W}_t$ depends on age, AIME and health. The estimates are reported in Table C.3. In simulations the autoregressive component is discretized into five nodes discrete Markov chain.

Table C.1: Logit estimates of survival and health transition probabilities

Explanatory variable	Income Type 1	Income Type 2	Income Type 3
		Survival probability:	
Age	-.006	-.006	-.006
	(.000)	(.000)	(.000)
Good health	.071	.086	.083
	(.008)	(.001)	(.012)
Number of observations	11,312	13,645	15,920
χ_2^2	1,082	1,047	809
		Probability of being in good health:	
Age	-.007	-.011	-.013
	(.001)	(.001)	(.001)
Good health	.559	.586	.698
	(.011)	(.015)	(.019)
Number of observations	9,701	12,115	14,836
χ_2^2	1,463	1,493	1,481

Notes: The estimation sample comprises HRS white non-Hispanic males 50 and older with at least ten years of non-government employment. It excludes early recipients of Social Security (before 62) and recipients of SSI/SSDI. The values reported are marginal effects of age and health on biennial transition probabilities from logit maximum likelihood estimation, computed at age 65 and lag health equal to 0. Standard errors are given in parentheses. Income types 1-3 correspond to the tertiles of the AIME distribution.

Table C.2: Estimates of the medical expenses process

Variable	Health insurance status: Insured by employer	No insurance	Medicare (Age 65+)
Mean of log medical expenses, estimated from biennial data			
Age	0.015	0.039	0.016
	(0.003)	(0.007)	(0.002)
Good health	-0.531	-0.419	-0.345
	(0.042)	(0.076)	(0.022)
Constant	3.162	1.775	2.902
	(0.206)	(0.426)	(0.129)
Autocorrelation of AR(1) disturbances	0.361	.354	0.396
	(0.012)	(0.033)	(0.009)
Innovation variance of AR(1) disturbances	1.827	2.043	1.779
	(0.028)	(0.056)	(0.022)
Number of observations	13,969	3,227	28,281
Parameters of monthly AR(1) error process			
Autocorrelation, ρ^m	0.958	0.958	0.962
Innovation variance, $\sigma^2_{\varepsilon^m}$	0.149	0.169	0.132

Notes: The estimation sample comprises HRS white non-Hispanic males 50 and older with at least ten years of non-government employment. It excludes early recipients of Social Security (before 62) and recipients of SSI/SSDI. Conditional maximum likelihood estimates of equation (C.1). Standard errors are given in parentheses. Zero medical expenses were omitted from estimation.

Table C.3: Estimates of the wage transition process

Variable	Estimate	Standard error
Mean of log wage rate, estimated from biennial data		
Age	-0.008	0.002
AIME, log	0.321	0.024
Good health indicator	0.070	0.019
Constant	0.649	0.215
Autocorrelation of AR(1) disturbances	0.688	0.028
Innovation variance of AR(1) disturbances	0.534	0.026
Number of observations	17,951	
Parameters of monthly AR(1) error process		
Autocorrelation, ρ^w	0.985	
Innovation variance, $\sigma^2_{\varepsilon^w}$	0.031	

Notes: The estimation sample comprises HRS white non-Hispanic males 50 and older with at least ten years of non-government employment. It excludes early recipients of Social Security (before 62) and recipients of SSI/SSDI. Conditional maximum likelihood estimates of equation (C.2). The estimation sample also excludes the top and bottom 1% of the wage rate values.

D Parameters of the Social Security policy

The moments generated by the structural model are matched to the data moments for a sample of workers born between 1938 and 1943. The US Social Security policy differs slightly for these workers depending on the year of birth, and hence I take these differences into account when modeling the policy environment. Because the model is solved separately for each individual type who is partly described by the year of birth, these details do not contribute to additional computational burden. This appendix specifies the exact policy parameters that are used in the simulations.

D.1 The normal retirement age (NRA)

The NRA is the age at which workers are eligible to receive retirement benefits equal to the primary insurance amount (PIA). It is gradually increasing from 65 to 67 years of age depending on the year of birth. The NRA for the years of birth that were included in the estimation sample is shown in the first column of Table D.1.

D.2 The AIME bend points

The PIA is computed based on the worker's average indexed monthly earnings (AIME) using a set of bend points that depend on the year of birth. Following the Social Security Administration (SSA) approach, the PIA is calculated as a sum of 90% of the AIME under the first point, 32% of the AIME between the two points, and 15% of the AIME in excess of the second point. I use the SSA bend points that are set for each year of birth, as shown in the first two columns of Table D.2.

D.3 Minimum and maximum benefits

The minimum benefit is guaranteed to low wage earners who have contributed to the system for eleven years or longer. I set the minimum PIA to the SAA's year specific minimum for a worker with twenty years of contributions, as shown in the second column of Table D.1. The maximum benefit received by a family is computed with three threshold values. The formula is 150% of the PIA under the first threshold, plus 272% of the PIA between thresholds one and two, plus 134% of the PIA between thresholds two and three, and plus 75% of the PIA above threshold three. The threshold values are shown in the last three columns of Table D.2.

D.4 The early retirement penalty

The PIA determines the amount awarded to a worker who takes up the benefits at normal retirement age. This amount is reduced (or increased) proportionately to the time left until (or elapsed since) reaching the normal retirement age. I ignore the credit for delayed retirement and nonlinearity in the early retirement penalties after 36 months of early retirement. I only reduce the PIA for taking up benefits before the normal retirement age based on the pro-rated penalty for taking up benefits at age 62 instead of waiting to reach the NRA. These penalties are shown in the last column of Table D.1.

D.5 The Social Security Earnings Test

The Social Security benefits of early retirees may be taxed in accordance with the Social Security Earnings Test (SSET) when wages exceed retirement earnings exempt amounts. I use the lower exempt amount that applies in years before reaching the normal retirement age, and ignore the kink in the last few months before reaching the normal retirement age. Because the sample period only covers the years after 2000, SSET does not apply after the normal retirement age. The benefits are taxed at a rate of $1 for every $2 of earnings in excess of the lower exempt amount. I also ignore the refund of withheld benefits after the normal retirement age.

Table D.1: The NRA, PIA minimum and early retirement penalty

Year of birth	Normal retirement age	PIA minimum	Early retirement penalty for take up at age 62,%
1938	65 and 2 months	300.1	20.8
1939	65 and 4 months	307.9	21.7
1940	65 and 6 months	312.2	22.5
1941	65 and 8 months	318.7	23.3
1942	65 and 10 months	327.3	24.2
1943	66	340.7	25.0

Source: Normal retirement age - https://www.ssa.gov/OACT/ProgData/nra.html; minimum PIA for twenty years of coverage - http://www.socialsecurity.gov/OACT/ProgData/tableForm.html; early retirement penalty - https://www.ssa.gov/oact/ProgData/ar_drc.html.

Table D.2: Dollar amounts in PIA and maximum family benefit formulae

	PIA bend points		Maximum family benefit bend points		
Year of birth	1st	2nd	1st	2nd	3rd
1938	531	3,202	679	980	1,278
1939	561	3,381	717	1,034	1,349
1940	592	3,567	756	1,092	1,424
1941	606	3,653	774	1,118	1,458
1942	612	3,689	782	1,129	1,472
1943	627	3,779	801	1,156	1,508

Source: https://www.ssa.gov/OACT/COLA/bendpoints.html.

E Estimating the structural parameters

The structural parameters of the model are estimated with the method of simulated moments (MSM) which minimizes the distance between the sample moments $\hat{\mathbf{M}}_{l\times 1}$ and their equivalents in the simulated dataset $\mathbf{M}_{l\times 1}(\theta, \hat{\theta}_p)$, where l is the number of moment conditions.

The simulated moments are computed from a dataset that is generated by the model. Setting up the simulation, I first randomly draw the joint values of variables that form initial conditions from the estimation dataset. Each data point is selected into initial state with a probability inversely proportional to the individual HRS weight of an observation. Second, I generate a matrix of random shocks that determine the realization of the exogenous processes. These two inputs remain fixed across the simulations. The two value functions of the model can then be solved numerically by backward induction, yielding decision rules for any feasible choice of the structural model parameters $\theta_s \in \Theta$. I discretize the state space and use linear interpolation methods to evaluate the value functions between the grid points. Decisions that are ruled out by the model constraints are assigned large negative values. Finally, I put together the initial conditions, shocks and decision rules to simulate a dataset that contains a life path for each of the $n = 10,000$ modeled individuals.

For the vector of sample moment conditions $\bar{\mathbf{m}}_n(\hat{\mathbf{M}}, \theta_s, \hat{\theta}_p) = \hat{\mathbf{M}} - \mathbf{M}(\theta_s, \hat{\theta}_p)$, the estimate $\hat{\theta}_s \in \Theta$ minimizes the MSM criterion,

$$\hat{\theta}_s = \underset{\theta_s \in \Theta}{\operatorname{argmin}} \; \bar{\mathbf{m}}_n(\hat{\mathbf{M}}, \theta_s, \hat{\theta}_p)' \mathbf{W}_n \bar{\mathbf{m}}_n(\hat{\mathbf{M}}, \theta_s, \hat{\theta}_p), \tag{E.1}$$

where $\mathbf{W}_n$ is a symmetric positive definite weight matrix of size l. The optimal weight matrix that returns asymptotically efficient estimates is the inverse of the variance-covariance matrix of the population moments. Its method of moments estimator is the inverse of the variance-covariance matrix of the sample moments, which however may generate bias in small samples (Pischke, 1995). To avoid this problem, I use a diagonal weight matrix with non-zero elements given by the reciprocals of the sample moment variances, as suggested by Altonji and Segal (1996). This choice of weights implies that the moments estimated more precisely receive higher weight in the MSM criterion, while dependence among the moments is ruled out. In this way, I solve Eq. (E.1) numerically, using a simplex algorithm to search over the parameter space on a 64-node cluster.

Pakes and Pollard (1989) show that under certain regularity conditions optimization estimator $\hat{\theta}_s$ is consistent and asymptotically normally distributed with variance-covariance matrix given by

$$\mathbf{V}_{\theta_s} = (\mathbf{J}'\mathbf{W}_n\mathbf{J})^{-1}\mathbf{J}'\mathbf{W}_n\Omega\mathbf{W}_n\mathbf{J}(\mathbf{J}'\mathbf{W}_n\mathbf{J})^{-1}, \tag{E.2}$$

where $\mathbf{J} = \mathbb{E}\frac{\partial}{\partial \theta_s'}\mathbf{m}_i(\theta_s)$ is the Jacobian matrix of the moment conditions and $\Omega = \mathbb{E}(\mathbf{m}_i\mathbf{m}_i')$ is their variance-covariance matrix. I use the method of moments estimators of these matrices to compute the standard errors.

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