Online Appendix for Search and the Sources of Life-Cycle Inequality*

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Abstract

I study how initial wealth affects lifetime earnings inequality when labor markets are frictional. To do this, I construct a model life-cycle model with search frictions, incomplete markets, and endogenous human capital accumulation. In the model incomplete markets prevent low-wealth workers from smoothing consumption, causing them to accept low pay jobs while unemployed. In anticipation, they build savings rather than human capital while employed. This amplifies the importance of initial wealth for life-cycle inequality. Using this model, I find that differences in initial wealth cause larger differences in lifetime earnings than either initial human capital or ability.
JEL Classification: E21, E24, J63, J64, D31, I32, J31
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A Online Appendix

A.1 Additional Tables and Figures

A.1.1 Empirical Evidence

	Job Losers		
	1st Quintile	2nd Quintile	>1st Quintile
Income and Wealth (2011$s)			
Net Liquid Wealth	-14853.7	4407.4	111708.2
Previous Income	25486.0	27112.6	36961.5
Demographics			
Age	35.26	36.31	37.89
Previous Tenure	25.12	26.35	39.44
Years of School	12.52	12.44	12.80
Married	0.198	0.298	0.463
White	0.299	0.347	0.480
Male	0.520	0.537	0.664
Observations	479	326	654

Table 1: Summary statistics for job losers. Columns 1 and 2 report the mean of several key variables for the first quintile, and second quintiles of the net liquid wealth distribution. Column 3 contains summary statistics for the higher than first quintile sample. Reported observations does not include those who did not lose a job.

	1st Quintile	2nd Quintile	>1st Quintile
Proxy			
Emp. Risk (pp)	0.0771	0.0473	-0.000532
Income and Wealth (2011$s)			
Net Liquid Wealth	-17028.1	5555.4	145468.8
Labor Income	36563.8	37379.2	55328.5
Demographics			
Age	34.23	34.62	36.86
Tenure	56.19	65.29	85.18
Years of School	13.07	12.69	13.20
Married	0.557	0.588	0.725
White	0.542	0.550	0.668
Observations	2650	2938	9656

Table 2: Summary statistics for job stayers. The first column reports the mean of several key variables for the first quintile. The second column does the same for the second quintile. The third column contains summary statistics for the higher than first quintile sample.

A.1.2 Unemployment Scarring in Learning by Doing

Here, I compare unemployment scarring by wealth in my baseline model and the LBD model. I repeat the same experiment that I describe in Section 4.4 in the model with only LBD

	Baseline + Fully Interacted		1st and 2nd Quintile		Male only Subsample		Differenced Earnings	
	Job Loss	X >1st Quintile	Job Loss	X 2nd Quintile	Job Loss	X >1st Quintile	Job Loss	X 2nd Quintile
1 Year	-0.2763***	0.0957*	-0.2731***	0.0746	-0.2656***	0.0921*	-0.4266***	0.1548***
	(0.0453)	(0.0492)	(0.0437)	(0.0499)	(0.0481)	(0.0543)	(0.0450)	(0.0506)
2 Years	-0.2277***	0.1091*	-0.2232***	0.1069*	-0.2076***	0.0976	-0.3695***	0.1763***
	(0.0560)	(0.0627)	(0.0514)	(0.0629)	(0.0644)	(0.0834)	(0.0587)	(0.0666)
3 Years	-0.2695***	0.1904***	-0.2525***	0.1756***	-0.2361***	0.1263**	-0.3782***	0.2012***
	(0.0464)	(0.0464)	(0.0470)	(0.0587)	(0.0558)	(0.0585)	(0.0479)	(0.0552)
4 Years	-0.2524***	0.2019***	-0.2365***	0.1976***	-0.1146*	0.0743	-0.3314***	0.1905***
	(0.0536)	(0.0631)	(0.0537)	(0.0713)	(0.0674)	(0.0834)	(0.0572)	(0.0676)
5 Years	-0.2004***	0.1290*	-0.2022***	0.1255	-0.1378	0.0388	-0.2613***	0.0894
	(0.0679)	(0.0735)	(0.0684)	(0.0786)	(0.0844)	(0.1081)	(0.0701)	(0.0792)
Observations	4442		3229		3461		4442	

Clustered standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Table 3: Unemployment scarring by wealth. The first column shows unemployment scarring for the pooled sample. The second and third column show the results with an interaction between wealth quintile and job loss.

	Baseline + Fully Interacted		Ordered Logit Wealth Quintiles		Job Stayers and Job Changers		Months of Tenure Proxy	
	Emp. Risk	X >1st Quintile	Emp. Risk	X >1st Quintile	Emp. Risk	X >1st Quintile	Tenure	X 2nd Quintile
1 Year	-0.0146***	0.0056	-0.0063**	0.0009	-0.0133***	0.0058	0.0013***	-0.0002
	(0.0052)	(0.0059)	(0.0025)	(0.0027)	(0.0051)	(0.0050)	(0.0001)	(0.0002)
2 Years	-0.0117	0.0096	-0.0089***	0.0059**	-0.0103	0.0092	0.0012***	-0.0007***
	(0.0078)	(0.0073)	(0.0030)	(0.0029)	(0.0063)	(0.0068)	(0.0002)	(0.0002)
3 Years	-0.0219**	0.0247***	-0.0076**	0.0068**	-0.0152*	0.0157*	0.0010***	-0.0004**
	(0.0093)	(0.0095)	(0.0032)	(0.0034)	(0.0088)	(0.0089)	(0.0002)	(0.0002)
4 Years	-0.0418***	0.0489***	-0.0119***	0.0105**	-0.0318***	0.0397***	0.0010***	-0.0003
	(0.0092)	(0.0085)	(0.0042)	(0.0046)	(0.0084)	(0.0075)	(0.0003)	(0.0004)
5 Years	-0.0233*	0.0327**	-0.0135***	0.0118**	-0.0104	0.0197**	0.0004	-0.0002
	(0.0133)	(0.0146)	(0.0042)	(0.0049)	(0.0089)	(0.0098)	(0.0004)	(0.0003)
Only Q1 or Q1:							X	
Observations	2740		18320		3355		993	

Clustered standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

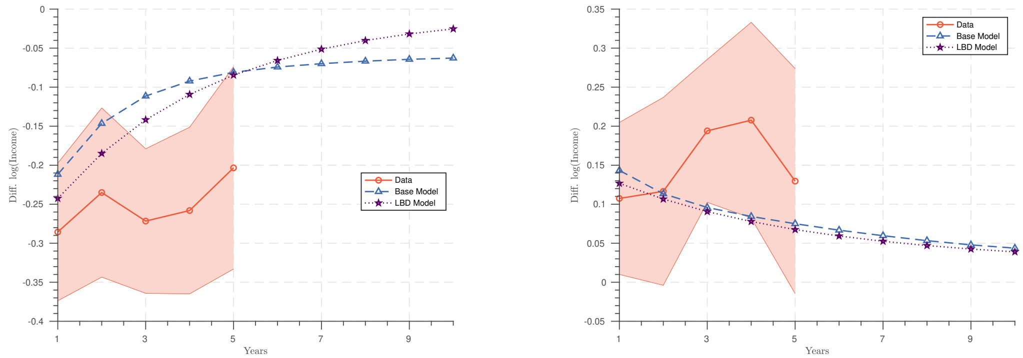
Table 4: Employment risk scarring by wealth. The first two columns for each proxy show results for first quintile vs. quintiles 2 through 5. The second two columns restrict the sample to first and second quintiles.

human capital accumulation. I then compare to my findings in the baseline model as well as the data. I present my findings in Figure 1.

A.2 Indirect Inference

A.2.1 Auxiliary Model

Here, I present the complete set of specifications for my auxiliary model. Outside of the wage and hazard elasticities, my sample selection follows the criteria from Huggett et al. (2011):



(a) Q1 unemployment scarring.

(b) Q2-Q5 unemployment scarring.

Figure 1: Unemployment scarring in the LBD model and my baseline model as well as the data. The shaded region in both figures correspond to the 95% confidence intervals in the data.

male, age 25 to 54, not in school, income $>$ 4750 and hours worked $>$ 260 if age $\leq$ 30, income $>$ 9500 and hours worked $>$ 520 if age $>$ 30.

1. Re-Employment Elasticities (SIPP):

- Wage Elasticity:

$$\begin{aligned} &ln\left(Y_{i,j+1}\right) = \beta_0 + \beta_1 \mathbb{1}_{a_{i,t}>1st\ qtile} + \beta_2 ln\left(UI_{s,t}\right) + \beta_3 ln\left(UI_{s,t}\right)\mathbb{1}_{a_{i,t}>1st\ qtile} \\ \text{(A.1)} \qquad &\qquad + \beta_4 ln(Y_{i,j}) + \beta_5 ln(Y_{i,j})\mathbb{1}_{a_{i,t}>1st\ qtile} + \beta_6 Age_{i,j+1} + \delta' X + \epsilon_{i,j+1} \end{aligned}$$

- Hazard Elasticity:

$$\begin{aligned} &ln\left(h_{i,j+1}\right) = \beta_7 + \beta_8 \mathbb{1}_{a_{i,t}>1st\ qtile} + \beta_9 ln\left(UI_{s,t}\right) + \beta_{10} ln\left(UI_{s,t}\right)\mathbb{1}_{a_{i,t}>1st\ qtile} \\ \text{(A.2)} \qquad &\qquad + \beta_{11} ln(Y_{i,j}) + \beta_{12} ln(Y_{i,j})\mathbb{1}_{a_{i,t}>1st\ qtile} + \beta_{13} Age_{i,j+1} + \delta' X + \epsilon_{i,j+1} \end{aligned}$$

- Controls: year, age, state, race, marriage, total wealth, qtile X education, qtile X prev. industry, qtile X prev. occupation, qtile X prev. ann. inc. (logs), and "on-seam" indicator.
- Sample: male, age 23 to 60, receiving UI within one month of layoff, not on temporary layoff (Chetty, 2008).

2. Unemployment Rate (PSID):

$$\text{(A.3)} \qquad Unemp_i = \beta_{14} \mathbb{1}_{Unemp_i} + \delta' X + \epsilon_i$$

- Controls: state, year, age, region, education, race, marriage, hours worked.

3. Job-to-Job Mobility by Wealth (NLSY):

$$J2J_{i,t} = \sum_{j=1}^{6}\sum_{q=1}^{5} \beta_0^j \mathbb{1}_{Age_{i,t} \in \, Bin_j} \mathbb{1}_{a_0^i \in a^q} + \delta' X + \epsilon_{i,t} \tag{A.4}$$

   - Age Bins: 25-29, 30-34, 35-39, 40-44, 45-49, 50-54.
   - Controls: year, age, region, education, race, marriage, hours worked.

4. Life-Cycle Profiles:
   - Earnings Profile (PSID):

$$ln\,(Y_{i,t}) = \sum_{j=25}^{54} \beta_0^j \mathbb{1}_{Age_{i,t}=j} + \delta' X + \epsilon_{i,t} \tag{A.5}$$

   - Variance Profile (PSID):

$$var(ln\,(Y_{i,t})) = \sum_{j=25}^{54} \beta_0^j \mathbb{1}_{Age_{i,t}=j} + \delta' X + \epsilon_{i,t} \tag{A.6}$$

   - Controls (both): year, age, state, education, race, marriage, hours worked.
   - Profiles generated by setting controls to sample means.

5. Age-Earnings Regressions by Initial Heterogeneity:
   - By Wealth Quintiles (PSID):

(A.7)

$$ln\,(Y_{i,t}) = \sum_{q=1}^{5} [\beta_0^q \mathbb{1}_{a_0^i \in a_0^q} + \beta_1^q \mathbb{1}_{a_0^i \in a_0^q} Age_{i,t} + \beta_2^q \mathbb{1}_{a_0^i \in a_0^q, Age_{i,t} \geq 40} + \beta_3^q \mathbb{1}_{a_0^i \in a_0^q, Age_i \geq 40} Age_{i,t}] + \delta' X + \epsilon_{i,t}$$

   - Controls: year, age, state, education, race, marriage, hours worked.
   - By AFQT Quintiles (NLSY):

(A.8)

$$ln\,(Y_t) = \sum_{q=1}^{5} [\beta_0^q \mathbb{1}_{\ell^i \in \ell^q} + \beta_1^q \mathbb{1}_{\ell^i \in \ell^q} Age_{i,t} + \beta_2^q \mathbb{1}_{\ell^i \in \ell^q, Age_{i,t} \geq 40} + \beta_3^q \mathbb{1}_{\ell^i \in \ell^q, Age_{i,t} \geq 40} Age_{i,t}] + \delta' X + \epsilon_{i,t}$$

   - Controls: year, age, region, education, race, marriage, hours worked.

6. Initial Distributions:
   - Wealth (PSID): Pre-labor market wealth deciles ($E[a_0 | a_0 \in a_0^d]$ for $d = 1, 2, \ldots, 10$).

- Earnings (PSID): First-job earnings deciles ($E[y_1|y_1 \in y_1^d]$ for $d = 1, 2, \ldots, 10$).

7. Late Career Earnings Growth:

   - Earnings Growth (PSID): $E\left[ln\left(y_n\right) - ln\left(y_0\right)\right]$ for $n = 1, \ldots, 3$ between ages 58 and 64.
   - Variance of Earnings Growth (PSID): $Var\left(ln\left(y_n\right) - ln\left(y_0\right)\right)$ for $n = 1, \ldots, 3$ between ages 58 and 64.
   - Covariance between Earnings Growth (PSID): $Cov\left(ln\left(y_n\right) - ln\left(y_0\right), ln\left(y_m\right) - ln\left(y_0\right)\right)$ for $n = 1, \ldots, 3$ between ages 58 and 64.
   - Controls: year, age, state, education, race, hours worked.
   - Sample: male, age $\geq$ 58, not in school, income $>$ 9500 and hours worked $>$ 520 (Huggett et al., 2011).

A.2.2 Implementation

I implement indirect inference as a generalized method of moments estimator, weighted by the inverse variance of the empirical targets. During each iteration, I average over 100 realizations of model, and impose identical sample restrictions and attrition as in the observed data. To deal with missing data in the PSID and NLSY, I drop observations randomly at the same frequency as in the data by age. I do this by wealth and AFQT quantiles so that the data generating process in the structural model is as close as possible to that in the data. I simulate separate sets of data for each dataset used in the auxiliary model. I start agents at age 23 with no labor market experience (i.e., unemployed without unemployment insurance) and a random draw from the joint distribution of initial conditions.

I use simulated annealing to estimate the model. This is a variant of the Metropolis-Hasting sampling algorithm that optimizes over the global parameter space by comparing objective function values. With some positive probability, it accepts a new point at which the objective function is higher than previous, and then searches nearby points. This allows the algorithm to search areas of the parameter space that other approaches would have ruled out. I draw 5000 sets of parameters using the simulated annealing algorithm and calculate standard errors over the final 4500, dropping the first 500 iterations.

A.3 Data Construction

A.3.1 Survey of Income and Program Participation (SIPP)

I use the SIPP to assess the effect that liquidity has on labor market outcomes. The SIPP is a panel dataset with separate surveys conducted annually from 1984 to 1993, and then during 1996, 2001, 2004, and 2008. Each survey follows a household for 16 to 36 months, with interviews every four months for each "wave" of respondents. Each interview includes detailed information on the employment, income, and unemployment insurance recipiency. Employment variables are coded down to a weekly frequency, which yields an extremely precise picture of a worker's unemployment spells for the duration of the panel. In addition, each wave includes detailed information on special topics in "topical modules." Although information on wealth is not available in the core questionnaire, it is included in some of the topical modules, averaging twice per panel.

My selection criteria is similar to the previous literature on the liquidity effects of unemployment insurance[2]. I pool SIPP panels from 1990 to 2008 and restrict my sample to unemployment spells for males age 23 and older with at least 3 months work experience, who took up UI within one month of job loss, and who are not on a temporary layoff. For each individual, I observe race, marital status, age, years of education, as well as tenure, industry, occupation, and wage at their previous job. I define liquid wealth following Chetty (2008) as total wealth minus housing wealth. In total, my SIPP sample contains 3915 spells.

A.3.2 Panel Study of Income Dynamics (PSID)

The PSID is a panel that follows a group of households from the United States yearly from 1968 to 1997, and in alternating years through the present. The PSID began recording information on household wealth holdings in their "wealth supplements," in 1984 repeated these questions in 1989, 1994, and 1999, and then in each subsequent interview. In the United States, this is the only publicly available dataset that contains multiple cohorts, long-term observations on earnings, and measures of household wealth at ages close to or before labor market entry[3]. In addition to these variables, the PSID includes rich observations on demographics, labor market experience, as well as family history and behavioral characteristics.

I employ sample restrictions similar to Huggett et al. (2011). First, I require that each individual be head of their household, male, and between the ages of 25 and 54. For constructing the distribution of wealth and earnings at first employment (moments 1 and 4), I require that the individual either be observed *before* entering employment, or that they

[2] See Chetty (2008) and Meyer (1990) for two examples using the same selection criteria.

[3] The NLSY79 contains information on wealth, but for few individuals before labor market entry.

report they entered employment during the previous year and the job is their first. I also require that these individuals be no younger than 23 and no older than 27. Over the life-cycle, I require that the individuals in my sample be strongly attached to the labor market: any individual in my sample must work at least 520 hours during the year and earn at least $\$9,500$ in 2011 dollars if they are 31 or older. If they are younger than 30, I lower this requirement to $\$4,750$, and 260 hours, to capture individuals who might choose part-time employment in order to have a steady income stream. I use the same sample restrictions when constructing profiles by initial liquid wealth quantile, where I define liquid wealth to be any liquid assets, including checking, savings, stocks, bonds, etc. net of any unsecured obligations, including credit cards and student debt. I observe the wealth of 2815 individuals prior to entering the labor market, but have relatively few observations late in the life-cycle. For this reason, I use an ordered logit to predict wealth quintile by individual, which I discuss in the next section.

A.3.3 Wealth Quantile Construction

To assign individuals to **initial** quintiles in the wealth distribution, I exclude observations who do not meet the following characteristics: first, agents must be the head of their household when I observe their assets; second, they must be age 30 or younger during a year in which I observe their assets. This subsample faces limitations, as few individuals have both observations on their assets at an age younger than 30 and simultaneously have observations on earnings at later ages. I also scale wealth before entering the labor market by the number of individuals in the household. I pool all individuals for whom I observe assets and adjust for growth over time.

Because the wealth data contains few observations on earnings for individuals, while simultaneously observing their wealth before age 30, I employ a strategy similar to a synthetic control method. I classify individuals into five quintiles as described above, and then using these generated quintiles, I run an ordered logit to classify individuals for whom I do not have observations on wealth, based on their observables. Qualitatively, this technique generates earnings profiles that exhibit the same correlations in earnings for the ages for which I have wealth observations, but allows me to match my model to earnings at ages greater than 50. This expands my PSID sample to at least 2500 at each age in my analysis (25 to 54) and to 120,553 observations, though many are the same individuals (I observe each individual on average 10 times each).

$$P(a_{i,t} = k|X) = \beta' X + \epsilon_{i,t} \tag{A.9}$$

A.3.4 National Longitudinal Survey of Youth, 1979 (NLSY)

The National Longitudinal Survey of Youth follows cohorts who were ages 14-22 in 1979 through the present. It was conducted annually from 1979-1994 and bi-annually from 1994 until present, and includes detailed information on labor market status, including current employer, weeks employed, unemployed, and out of the labor force, as well as any training received by the individual since the last interview. Earnings are recorded annually as well as hours worked. In addition, the NLSY includes scores from a standardized test, the Armed Forces Qualification Test (AFQT), for many individuals in the sample. This allows me to link individuals by their AFQT scores to their outcomes late in the life-cycle. I use identical sample restrictions as Section A.3.2. Ultimately, I observe 3205 individuals an average of 10 times (33,439 total observations).

A.4 Restricted Models

A.4.1 Bewley Model

I determine the precautionary effects in a standard model of idiosyncratic income risk. I start with a Bewley (1986)-style model that includes Ben-Porath human capital accumulation. This model is closely related to the model in Huggett et al. (2011), lacking only a labor-leisure choice and an endogenous interest rate. I assume that workers receive their marginal product ($(1-\tau)h$), and are subject to shocks, δ that prevent them from investing during the period (parallel to the separation shocks in my baseline model). This yields a dynamic program solved by the following:

$$W_t(a,h,\ell) = \max_{c,a'\geq\underline{a}',\tau} u(c) + \beta E[(1-\delta)W_{t+1}(a',h',\ell) + \delta U_{t+1}(a',h',\ell)] \tag{A.10}$$

$$\text{s.t. } c + a' \leq (1+r_F)a + (1-\tau)h \tag{A.11}$$

$$h' = e^{\epsilon'}(h + \ell(h\tau)^{\alpha}),\ \epsilon' \sim N(\mu_\epsilon, \sigma_\epsilon) \tag{A.12}$$

$$U_t(b_{UI},a,h,\ell) = \max_{c,a'\geq\underline{a}'} u(c) + \beta E[(1-\delta)W_{t+1}(a',h',\ell) + \delta U_{t+1}(a',h',\ell)] \tag{A.13}$$

$$\text{s.t. } c + a' \leq (1+r_F)a + h \tag{A.14}$$

$$h' = e^{\epsilon'}h,\ \epsilon' \sim N(\mu_\epsilon, \sigma_\epsilon) \tag{A.15}$$

I impose an identical sequence of δ and ϵ shocks and impose that workers receive the same draw of initial conditions as in the baseline model. I leave the calibration identical to that in Section 4 for the remaining parameters. I refer to this as "Bewley" in Table 12. I apply the same restriction that I imposed on my baseline model on this model by imposing that workers make human capital accumulation decisions as though they have the average level of wealth in the simulation. I refer to this as R2 (restiction 2) in Table 12.

After the terminal period, workers enter retirement given as before by Equation 3.10.

A.4.2 Learning-By-Doing Model

I adapt my model of Section 3 to feature learning-by-doing human capital accumulation rather than Ben-Porath (1967) human capital. Employed workers now solve the problem described in Equation A.16.

$$W_t\left(\mu,a,h,\ell\right)=\max_{c,a'\geq \underline{a}'_t} u\left(c\right)+\beta E\left[\left(1-\delta\right)R^E_{t+1}\left(\mu,a',h',\ell\right)+\delta R^U_{t+1}\left(b_{UI},a',h',\ell\right)\right] \tag{A.16}$$

$$\text{s.t. } c+a'\leq\left(1+r_F\right)a+\mu\left(1-\bar{\tau}\right)h \tag{A.17}$$

$$b_{UI}=min\{max\{b\left(1-\bar{\tau}_t\right)\mu f\left(h\right),b_L\},\bar{b}\} \tag{A.18}$$

$$h'=e^{\epsilon'}\left(h+\ell\left(h\bar{\tau}_t\right)^{\alpha}\right),\ \epsilon'\sim N\left(\mu_\epsilon,\sigma_\epsilon\right) \tag{A.19}$$

where R^E_{t+1} and R^U_{t+1} are identical to Equation 3.2 and Equation 3.1, the values of searching while employed and unemployed, respectively. Time is allocated deterministically at each age-t as $\bar{\tau}_t=E[\tau_t]$, but the problem is otherwise identical to Equation 3.6. The problem of a firm matched with a worker is similarly affected:

$$J_t\left(\mu,a,h,\ell\right)=\left(1-\mu\right)\left(1-\tau\right)h+\beta E\left[\left(1-\delta\right)\left(1-\lambda_E P\left(\theta_{t+1}\left(\mu',a',h',\ell\right)\right)\right)J_{t+1}\left(\mu,a',h',\ell\right)\right] \tag{A.20}$$

$$h'=e^{\epsilon'}\left(h+\ell\left(h\bar{\tau}_t\right)^{\alpha}\right),\ \epsilon'\sim N\left(\mu_\epsilon,\sigma_\epsilon\right) \tag{A.21}$$

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