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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1 Introduction

How does an individual's wealth affect future earnings? Answering this question is crucial not only for understanding the sources of lifetime income inequality, but also for key recent policy debates. One common justification for transfer programs such at the Earned Income Tax Credit (EITC) or universal basic income is that, in addition to smoothing consumption, they may improve long-term outcomes by promoting human capital accumulation. Underlying such arguments is the implicit presumption that current wealth is in fact an important determinant of human capital and hence future earnings. A substantial existing literature has cast doubt on this assumption. For example, recent research by Huggett et al. (2011) reached the two-fold conclusion that initial conditions explain the bulk of lifetime earnings inequality and, furthermore, within these initial conditions, the role of wealth is negligible.

In this paper I show that accounting for search frictions in the labor market drastically increases the implied role of wealth for human capital accumulation and as a consequence, earnings inequality. The reason is that search frictions introduce an endogenous source of negatively skewed income risk that disproportionately affects low-wealth workers. In my model, an unemployed worker faces a trade-off between the accepted wage and the job-finding probability. Because poorer workers resolve this tradeoff in favor of low-paid jobs that are easier to find, they suffer more persistent earnings losses from unemployment. Crucially, anticipation of this risk affects the worker's portfolio decisions. Poorer workers choose to self-insure against this risk by accumulating precautionary savings rather than investing in human capital.

I document evidence of this channel using the Panel Study of Income Dynamics (PSID). I first show that poor workers are more responsive to increases in unemployment insurance than their wealthier peers. They respond both by searching for a longer period of time after which they find higher pay at their next job, while wealthier workers exhibit no change. Next, I show that low-wealth workers exhibit consistently higher job-to-job mobility throughout the life-cycle than higher wealth workers. Finally, I confirm that separations are more costly for poor workers. Should they separate, the scarring effects of unemployment are larger and persist longer for low-wealth workers once they regain employment.

I construct a life-cycle model that features search frictions, incomplete markets, and endogenous human capital accumulation to explain these regularities. I extend a life-cycle model of on-the-job directed search with wage posting (Menzio et al., 2016) to include risk-averse workers and endogenous human capital accumulation. When workers search for a job they face a trade-off between the wage and the employment probability. Poor workers apply for lower-wage jobs than their wealthier peers because these jobs offer a higher probability of employment. Once employed, workers make a portfolio allocation decision between spending productive time accumulating human capital (a risky asset) and building riskless precautionary savings. Human capital is risky both because it depreciates stochastically, and because it does not provide direct consumption insurance during unemployment.[2] This causes an interaction between wealth, search, and human capital because low-wealth workers anticipate that unemployment spells are more costly when they are poor and as a result prefer to build savings while they are employed. I augment these channels with heterogeneity in initial wealth, human capital, and the rate of return on human capital investment, which I call learning ability.

I use indirect inference to estimate the model. I specify an auxiliary model composed of targets that capture the joint dynamics of job search and life-cycle earnings. My auxiliary model includes specifications that capture the effect of wealth on search and discipline the sources of heterogeneity in the model. I use the elasticity of wages as well as the hazard rate with respect to unemployment insurance by wealth quintiles to identify income risk and search parameters of the model. I discipline the correlation between wealth and ability by using Mincer regressions stratified by initial wealth. I find that the model fits the data well, and is able to rationalize many of the features of the empirical regularities I observe about unemployment scarring by wealth.

Using the estimated model, I calculate how changing initial conditions affect income, human capital, and job placement. I first repeat a test from Huggett et al. (2011) and show that in a model with search frictions, the median worker is more sensitive to losses in wealth than losses in human capital. A standard deviation decrease in wealth causes a -6.4 percent change in life-cycle consumption, while human capital causes only a -3.8 percent change. This is the opposite finding from Huggett et al. (2011), who find that a standard deviation decrease in wealth causes the median worker to experience a -1.6 percent change in consumption, while the standard deviation decrease in human capital causes a -28.3 percent change in consumption. The reason is that job placement in my model is endogenous and determined by the precautionary effect on a worker's search behavior, while in Huggett et al. (2011) workers are paid their marginal product which increases the importance of human capital.

Next, I conduct two experiments in which I change the dispersion in initial conditions and calculate the effect on income, human capital, and job placement across the wealth distribution. First, a perform a 10 percent mean-preserving reduction in the variance of each initial condition, leaving the other two unchanged. What I find is that the reduction in

[2]A similar point is noted by Krebs et al. (2015) who explore the effects of human capital that is risky along similar dimensions on life-cycle consumption and economic growth.

wealth inequality leads to large improvements in lifetime income for the poorest workers in the economy (0.32 percent for initially first quintile workers) and that this increase is enough to cause an increase in income in the aggregate (0.19 percent). While learning ability has a larger effect overall for the poor (0.63 percent), I find that on average this effect is larger than the effect of reducing dispersion in human capital (0.16 percent) or learning ability (-0.20 percent) because reducing wealth inequality has a smaller negative effect for wealthier workers. I repeat this experiment instead eliminating differences in initial wealth and find larger increases in income both for the first quintile (5.79 percent) as well as on average (1.03 percent).

Then I place restrictions on my model as well as a Bewley (1986)-style model that features only idiosyncratic income risk to compute the degree to which wealth and search interact and affect human capital. In both my model and the Bewley (1986)-style model, I compare life-cycle human capital to restricted versions in which workers make human capital decisions as though they had the average level of wealth in the economy. I find that while the first quintile experiences precautionary effects on human capital in models with idiosyncratic income risk (3.29 percent), they are smaller than those in my model (6.01 percent). This means that employment risk plays a sizable role in the formation of human capital over the life-cycle for workers who are likely to suffer the largest consequences of job loss. I also provide additional evidence to validate this mechanism. I show that even in the absence of job loss, low-wealth workers experience persistent earnings losses as a result of employment risk, while their wealthier peers are unaffected. I demonstrate that my model is able to replicate this regularity, while alternate human capital specifications like learning-by-doing do not exhibit this precautionary response and are inconsistent with the data.

I build on a large array of literature both on search frictions and on inequality. The most closely related work from the search literature is Herkenhoff (2019), which uses a closely related model to understand the effect of credit on the labor market over the business cycle. Herkenhoff et al. (2016b) builds on this model to include exogenous human capital growth in order to understand the effects of credit constraints on aggregate output. Two more papers that incorporate risk aversion into a directed search framework are Chaumont and Shi (2017) and Eeckhout and Sepahsalari (2018). The former focuses on frictional inequality in a model without human capital, while the latter considers an environment with heterogeneous firm productivity, but neither on-the-job search nor human capital accumlation and focuses on determining optimal unemployment insurance. A number of other papers have considered random search frameworks without human capital (Lise (2013) and Burdett and Coles (2003), among others), with exogenous human capital growth (Bagger et al. (2014), Low et al. (2010) and Carillo-Tudela (2012), among other), or without risk aversion (Bowlus and Liu (2013), Jung and Kuhn (2019) and Herkenhoff et al. (2018), among others), each of which is important in my model. Braxton et al. (2019) and Herkenhoff et al. (2016a) provide related empirical evidence on the effect of credit constraints on earnings and job search behavior. The former shows that workers who become unemployed substantially increase their borrowing to replace lost income, while the latter shows that additional credit increases earnings and the incidence of self-employment.

The most closely related paper to my quantitative question is Huggett et al. (2011), which studies the effects of initial wealth, human capital, and learning on lifetime inequality in consumption and wealth. Similarly, Heathcote et al. (2014) use a model with heterogeneity in preferences and productivity to decompose sources of inequality. They reach a similar conclusion as Huggett et al. (2011): productivity is the primary driver of earnings inequality. Their work differs in that it assumes the labor market is competitive, which I show to be an important assumption when assessing the importance of initial wealth. These differences are quantitatively important, and suggest that times of high labor market risk like recessions may differentially affect the rich and the poor.

The paper is organized as follows. In Section 2, I show evidence in the data for the key mechanism in my model. In Section 3, I introduce the model and characterize worker behavior in response to risk. In Section 4, I explain how I estimate my model. In Section 5, I decompose life-cycle inequality among sources of uncertainty and initial conditions, and show the impact of employment risk and job ladders. In Section 6, I consider the lifetime effects of two unemployment insurance expansions. Lastly, in Section 7 I summarize my contributions and discuss routes for future work.

2 Empirical Evidence

In this section I provide evidence that search frictions have a disporportionate effect on low-wealth workers. First, I document that increasing unemployment insurance for low-wealth workers increases their duration of unemployment as well as earnings at their next job, but has no effect on wealthier workers. Next, I show that low-wealth workers climb the job ladder more quickly than their wealthier peers, although their wealthier peers start higher on the job ladder. Last, I show that the scarring effects of unemployment are both larger and more persistent for low-wealth workers. These three regularities motivate the construction of my model in Section 3.

2.1 Wealth and Job Search

I start by providing two pieces of evidence that a worker's wealth affects the resolution to their job search decisions. I first show that both a worker's hazard rate out of unemployment and their subsequent earnings are affected by their wealth. To do this, I exploit variation in unemployment insurance between states and over time, following Chetty (2008). I then assess how increasing unemployment insurance generosity affects these margins for different quintiles of the wealth distribution. I conclude this section by documenting evidence that low-wealth workers transition to new jobs more quickly than their wealthier peers once they regain employment.

2.1.1 Empirical Strategy

In the presence of search frictions, workers face a trade-off between wage and the probability of employment. When workers face borrowing constraints, low-wealth workers resolve this trade-off by accepting lower-pay jobs because this entails a shorter duration of unemployment in expectation. I explore both components of this trade-off by estimating the responsiveness of constrained (using liquid wealth as a proxy) individuals to changes in their unemployment insurance.

I fist use a proportional hazard model and focus on how unemployment insurance affects the hazard for different quintiles of the wealth distribution, largely following Chetty (2008). I include age, race, marital status, and education, as well as state and year fixed effects. I also include interaction terms between the wealth indicator and previous income, occupation and industry (both at 2-digit level). This yields the following specification:

$$ln\left(h_{i,j+1}\right) = \sum_{k=1}^{5} \beta_0^k ln\left(UI_{s,t}\right) \mathbb{1}_{a_{i,t} \in jthqtile} + \sum_{k=1}^{5} \beta_5^k ln(Y_{i,j}) \mathbb{1}_{a_{i,t} \in kthqtile} + \delta' X + \epsilon_{i,j+1} \tag{2.1}$$

where it's worth noting that the intercept is subsumed in a Cox proportional hazard model by the baseline hazard. In this specification, j refers to their job number, k their wealth quintile, and $a_{i,t}$ refers to the wealth of individual i, at time t, where t is the date on which separation occurs. If unemployment insurance affects the hazard more for the bottom quintile, β_0^1 should be significantly different than β_0^5. I restrict the sample to unemployed men who take-up unemployment insurance within one month of losing their job.

I estimate the effect of unemployment insurance by wealth on subsequent earnings using a specification in the same spirit as the hazard specification, with the addition of weeks of UI eligibility at the state level, interacted with the wealth quintile indicator. This specification is given by the following:

$$
\begin{aligned}
ln\left(Y_{i,j+1}\right) = \beta_0 + \sum_{k=2}^{5}\beta_1^k \mathbb{1}_{a_{i,t}\in kthqtile} + \beta_2 ln\left(UI_{s,t}\right) + \sum_{k=2}^{5}\beta_3^k ln\left(UI_{s,t}\right)\mathbb{1}_{a_{i,t}\in kthqtile} \\
+ \beta_4 ln(Y_{i,j}) + \sum_{j=2}^{5}\beta_5^k ln(Y_{i,j})\mathbb{1}_{a_{i,t}>1st\ qtile} + \delta' X + \epsilon_{i,j+1}
\end{aligned}
\tag{2.2}
$$

where j, k, and $a_{i,t}$ are the same definitions as in Equation 2.1. If unemployment insurance affects the subsequent wages, β_2 should be negative. If unemployment insurance only affects the hazard for low-wealth individuals, β_3^k should also be positive for each k. I restrict the sample to unemployed men 23 and older who take-up unemployment insurance within one month of losing their job.

I follow the previous literature (Browning and Crossley (2001), Bloemen and Stancanelli (2005), Sullivan (2008), and Chetty (2008), among others), and use liquid wealth as a proxy for the degree to which a worker is constrained.[3] In addition, I follow previous work to deal with unemployment benefit mismeasurement, which is a well-known problem in survey data, and use the average level of UI benefits in a state during the month a worker entered unemployment as a proxy for individual UI benefits. In my wage specification, I also include potential UI duration, defined as the average number of weeks a cohort of unemployed individuals could receive UI, at a state-by-quarter frequency to capture any correlation between replacement rates and duration generosity for a state unemployment insurance system. Effectively, I am exploiting within-state variation in benefit levels to identify the effect of unemployment insurance by wealth. I use Survey of Income and Program Participation (SIPP) panels from 1990-2008, as well as data from state unemployment insurance laws provided by the Employment and Training Administration.

2.1.2 Findings

I present the estimates from each specification in Table 1. The first column reports the estimated effect of an increase in unemployment insurance on re-employment earnings for the pooled sample. The second column reports the coefficients obtained by estimating Equation 2.2, my main specification. In the third column, I report the estimated effect of an increase in unemployment insurance on the hazard rate for the pooled sample. Finally, in the fourth column, I report the estimated effect on the hazard rate by wealth quintile.

Both elasticities provide evidence that wealth affects job search. First quintile workers exhibit a statistical significant shift towards lower job finding rates together and simultaneously a shift towards higher wages (upon hiring) when UI increases. For wealthier workers this pattern is weaker and statistically insignificant along both dimensions, except for the hazard

[3] These papers find that unemployment insurance is used as a substitute for income during unemployment spells among illiquid households, which motivates the use of net liquidity as a proxy for borrowing constraints.

	Wages		Hazard	
	(1) Pooled	(2) Main	(3) Pooled	(4) Main
log(State Ave. UI)	0.0881	0.474*	-0.506	
	(0.123)	(0.250)	(0.327)	
Q1 X log(State Ave. UI)				-0.881**
				(0.366)
Q2 X log(State Ave. UI)		-0.416*		-0.819**
		(0.209)		(0.384)
Q3 X log(State Ave. UI)		-0.626*		-0.157
		(0.313)		(0.451)
Q4 X log(State Ave. UI)		-0.409*		-0.469
		(0.216)		(0.334)
Q5 X log(State Ave. UI)		-0.444*		-0.103
		(0.238)		(0.380)
Observations	2334	2334	3882	3882

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

Table 1: The wage (columns 1 and 2) and hazard (columns 3 and 4) elasticity estimates. Columns 1 and 3 present the pooled estimates. 2 and 4 present the estimates with wealth quintile indicators.

elasticity for the second quintile. These results are consistent with those in Herkenhoff et al. (2016b) and Nekoei and Weber (2017), and provide additional evidence that the individuals affected are low-wealth. I conduct a t-test to determine whether I am able to statistically distinguish between the first and fifth hazard elasticities and find that I reject the null that they are the same (p-val of 0.0335).

2.1.3 Job Mobility by Wealth

I conclude this section by showing that despite suffering worse initial placement, low-wealth workers move up the job ladder more rapidly than their wealthier peers, regaining some of the ground lost out of unemployment. To do this, I use the National Longitudinal Survey of Youth, 1979, and track job-to-job movement over the life-cycle by wealth. I estimate the propensity to switch jobs among the employed using a logit specification given by the following:

$$P(J2J_{i,t} = 1|X) = \sum_{j=1}^{6} \sum_{q=1}^{5} \beta_0^j \mathbb{1}_{Age_{i,t} \in \, Bin_j} \mathbb{1}_{a_0^i \in a^q} + \delta' X + \epsilon_{i,t} \tag{2.3}$$

where q refers to the contemporaneous wealth quintile, and age bins are set to five-year intervals starting at age 25 (25-29, 30-34, etc.) and concluding with age 54.

I include controls for age, education, race, and marital status, as well as year and region fixed effects.[4] I restrict my sample to men, ages 25 to 54, who report that they are employed

[4]"Region" is the most granular level of geography included in the publicly available NLSY79.

and no longer in school. I also impose that workers ages 25-29 earn at least $4750 (2011$s) and work at least 260 hours annually, and those 30-54 earn at least $9500 (2011$s) and work more than 520 hours annually. I remove any workers who report more than 5820 hours during the year. These sample restrictions largely mirror those from Huggett et al. (2011), and are used for all my specifications that estimate life-cycle quantities.

I present the fitted probability of job-to-job movement by age and wealth in Table 2.

Age	Q1	Q2	Q3	Q4	Q5
25-29	0.323	0.2232	0.1907	0.1959	0.1875
30-34	0.2631	0.2167	0.1807	0.1434	0.1414
35-39	0.2923	0.2389	0.1788	0.1486	0.1259
40-44	0.2537	0.1839	0.1648	0.1575	0.1331
45-49	0.2207	0.2223	0.1948	0.1679	0.1447
50-54	0.1897	0.2451	0.1443	0.1753	0.1244
Observations	17934				

Table 2: Job mobility by wealth. Quintiles refer to contemporaneous quintiles at each age.

What I find may be surprising: throughout the life-cycle, low-wealth workers move job-to-job more rapidly than their wealthier peers. This is because low-wealth workers are not climbing the same rungs as high-wealth workers: they are climbing rungs that the wealthy jumped when first obtaining employment. Next, I show that despite higher mobility, unemployment scars low-wealth workers to a larger degree than their wealthier peers, which suggests that human capital plays a role.

2.2 Unemployment Scarring by Wealth

2.2.1 Empirical Strategy

My analysis in Section 2.1 shows that wealth affects job search while unemployed. Now I explore how long these effects persist. To do this, I explore the consequences of job loss and how they vary by wealth. I classify individuals by wealth quintile at time t and then calculate the scarring effect of job loss over horizons from 1 to 5 years, the limit of what I can reliably estimate in my sample. I do this by using the specification given by Equation 2.4.

$$\begin{aligned} ln(W_{i,t+n}) = \beta_0 + \beta_1 \mathbb{1}_{a>\tilde{a}^1} + \beta_2 \text{J2U}_{i,t} + \beta_3 \text{J2U}_{i,t} \times \mathbb{1}_{a>\tilde{a}^1} + \beta_4 ln(W_{i,t-1}) \\ + \delta_{Male} + \delta_{Male} \times \mathbb{1}_{a>\tilde{a}^1} + \delta_s + \delta_t + \beta_5' X_{i,t} + \epsilon_{i,t+n} \end{aligned} \tag{2.4}$$

where $W_{i,t+n}$ is earnings of individual i at time $t + n$ years in the future, $\mathbb{1}_{a>\tilde{a}^1}$ is an indicator for wealth in quintiles 2 through 5, and $\text{J2U}_{i,t}$ is an indicator for whether the individual lost a job during the year of the interview. I include state (δ_S) and year (δ_t) fixed effects, as well as terms for age, age squared, marriage, race, hours worked, education, and months of tenure as covariates in $X_{i,t}$. I also condition on log earnings during year $t-1$. I estimate my specification over the horizons n = 1,...,5 separately. This imposes less structure on my specifications because the effect need not be linked between years.

My main specification differs from the distributed lag framework commonly used in papers on unemployment scarring (e.g. Huckfeldt (2016), Jarosch (2015), and Davis and von Wachter (2011), among others). As an additional robustness check, I use a distributed lag framework following Jacobson et al. (1993) to estimate the scarring effects of unemployment by wealth quintile. I define two indicator variables to capture the effect of unemployment by wealth quintile. $D_{i,t}^k = 1$ if, in period t, worker i had been displaced k years before, and $D_{i,t}^{H,k} = 1$ if in addition the worker was in quintiles 2 through 5 of the liquid wealth distribution when they separated.

$$y_{i,t} = \alpha_i + \gamma_t + x_{it}\beta + \delta_H + \sum_{k\geq -1}^{10} D_{i,t}^k \delta_k + \sum_{k\geq -1}^{10} D_{i,t}^{H,k} \delta_k^H + \epsilon_{i,t} \tag{2.5}$$

where the dependent variable $y_{i,t}$ is log earnings of individual i at time t, respectively. I include individual (α_i) and time (γ_t) fixed effects as well as a vector of time-varying individual covariates x_{it}, and an indicator variable δ_H where $\delta_H = 1$ if the individual was in quintiles 2 through 5 of the wealth distribution when they separated during their current unemployment spell. The coefficients δ_k capture the effects of separation on earnings k periods before (or after if k is negative), while δ_k^H can be interpreted as how much smaller the earnings losses are when the individual is in quintiles 2 through 5 at the time of separation.

Although this specification relies on a stronger source of identification, I hesitate to make it my main specification because of data limitations. I restrict my sample to job losers in order to define wealth quintile at the time of separation. This means that I use within-individual variation in the values of x_{it} to identify β and within-individual between-spell variation in wealth quintiles to identify the effects of wealth on scarring, $D_{i,t}^k$ and $D_{i,t}^{H,k}$. I calculate the scarring effects for horizons of $k = -1, 0, \ldots, 10$.

2.2.2 Data

I use the Panel Study of Income Dynamics (PSID) for my analysis. The PSID is a yearly longitudinal dataset that offers observations on income, employment status, industry and occupation of employent, as well as a host of demographic covariates for repeated overlapping cohorts. In addition, the PSID began surveying several measures of wealth in 1984 and again in 1989, 1994, 1999, and for every subsequent panel. Because it contains both wealth and earnings in a panel setting, this is the best publicly available dataset for this analysis that uses US data.

There are two challenges to using the PSID. The first challenge is that the PSID changed industry coding to 2000 Census codes after the 2001 panel and many categories cannot be mapped one-to-one to previous years, all of which used industry codes from the 1970 Census. For this reason, I focus on the 12 major industry categories in the 1970 Census, all of which are comparable across classification systems. A second challenge is that the PSID switched from conducting surveys annually to biannually in 1997. For some applications this requires splitting the sample to pre-1997 (Huckfeldt, 2016), or post-1997 (Saporta-Eksten, 2014). Because my application does not employ variables that would be hard to measure over two-year frequencies (e.g. changes in occupation as in Huckfeldt (2016)), I include both periods in my sample. In addition, either restriction would yield too small a sample: either restriction yields roughly 200 observations in the bottom wealth quintile.

I impose the following sample restrictions, following standard conventions in the literature on scarring: I restrict the sample to heads of households between ages 23 and 50, who work at least 260 hours per year. I focus on workers who are no longer in school, but previously obtained a high school degree, some college, or a college degree. I am limited to fewer than 400 observations for whom I observe both wealth and a separation. As a result, I include female heads of households and interact wealth quintile with gender of the individual in my specification. The small sample also limits my ability to follow the previous literature and restrict the sample to mass layoffs, which are often used to address selection. My application focuses on the differences in unemployment scarring across the wealth distribution which means that this type of selection is a smaller concern than in other work on unemployment scarring. I give the summary statistics in Table 1 of the online appendix.

There are some potentially important differences across the wealth distribution. Wealthier individuals have longer tenure and higher income prior to separation, both of which may affect outcomes. In my robustness checks, I include interactions with these factors as well as others that may be associated with future income. In addition, the 2nd quintile makes up a large share of the wealthier individuals, and they differ less along these dimensions.

2.2.3 Findings

I find evidence that job loss has a larger and more persistent effect on low-wealth individuals than wealthier individuals. I present my regression results in Table 3 for a pooled specification and my main specification, and in Table 4 for the distributed lag specification.

The upper panel shows results for my main specification. The first row shows the average effect of job loss in my sample, while the second and third rows interact job loss with wealth quintile at the time of separation. The second row shows that the first quintile experiences

		Main Specification Results 1 Year	2 Years	3 Years	4 Years	5 Years
Pooled	Job Loss	-0.2295***	-0.1682***	-0.1536***	-0.1267***	-0.1194***
		(0.0232)	(0.0281)	(0.0335)	(0.0269)	(0.0411)
Wealth Interaction	Job Loss	-0.2854***	-0.2346***	-0.2717***	-0.2581***	-0.2035***
		(0.0440)	(0.0544)	(0.0465)	(0.0535)	(0.0647)
	X >1st Quintile	0.1027**	0.1159*	0.1925***	0.2061***	0.1333*
		(0.0469)	(0.0604)	(0.0460)	(0.0628)	(0.0726)
Observations		4441				

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

Table 3: Unemployment scarring by wealth for my pooled and main specifications.

	-1 Year	Job Loss	1 Year	2 Years	3 Years	4 Years	5 Years	6 Years	7 Years	8 Years	9 Years	10 Years
Earnings Loss	0.2650***	-1.0484***	-0.4274***	-0.2441***	-0.2726***	-0.1893**	-0.1387	-0.1345	-0.1302	-0.1393	-0.2175**	-0.2131*
	(0.0587)	(0.0988)	(0.0822)	(0.0767)	(0.0811)	(0.0848)	(0.0982)	(0.1135)	(0.1017)	(0.1083)	(0.1083)	(0.1180)
X >1st Quintile	-0.0977	0.1205	0.2288*	0.1921*	0.2758**	0.1946*	0.1175	0.1192	0.2093*	0.1606	0.1096	0.1744
	(0.0764)	(0.1261)	(0.1183)	(0.1140)	(0.1137)	(0.1093)	(0.1180)	(0.1292)	(0.1205)	(0.1297)	(0.1221)	(0.1318)
Observations	4647											

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

Table 4: Unemployment scarring by wealth for my distributed lag specification.

sizeable drops in earnings, ranging from 28.5 percent in the first year to 20.4 percent in year five. The third column indicates that wealthier workers experience both a smaller initial earnings penalty (18 percent) as a result of job loss and after five years they have recovered to near parity with those who did not separate (6 percent earnings loss).

My distributed lag specification (bottom panel) demonstrates the same conclusion. I find that first quintile workers suffer worse initial drops in earnings (42.7 percent vs. 19.9 percent for higher quintiles), and that these losses persist. This suggests that wealth plays a sizeable role in determining the extent to which job loss scars subsequent earnings. These estimates are roughly in-line with previous work using administrative datasets (Davis and von Wachter, 2011), but my main findings are somewhat smaller, consistent with other work (Stevens (1997), Birinci (2019)) that shows unemployment scarring appears smaller in the PSID.

I conduct additional robustness checks in Section A.1.1 of the online appendix. To address concerns about observables differences between the first quintile and higher quintiles, I first include a three-way interaction between wealth quintile, sex, and marital status, as well as interacting wealth quintile with education and race. Second, I re-run my baseline specification for only the first and second quintile of the wealth distribution because these quintiles are relatively balanced across observable covariates. Both checks (columns 1-2 and 3-4 in Table 3 of the online appendix, respectively) reach the same conclusions as my baseline specification.

To check whether including female heads of households affect my results, I restrict the sample to males and re-estimate my baseline specification. Last, I use earnings differenced between years $t-1$ and $t+n$ over $n = 1, \ldots, 5$ as the dependent variable in the final two columns. In all cases except for the males-only subsample, I reach a similar conclusion. For the males-only subsample, I reach qualitatively the same conclusions, but the findings are not significant over longer horizons (when I have fewer observations).[5]

These findings suggest that wealth affects an individual's ability to recover from an unemployment spell. In the next section, I explore whether latent employment risk has a different effect for employed workers by wealth. In conjunction with my previous results, these findings suggest that wealth affects job search, but also has an effect on earnings that may proceed through other channels like human capital. In the next section, I construct a model to rationalize this finding.

3 Model

3.1 Environment

Time is discrete and continues forever, while each agent participates in the labor market deterministically for $T \geq 2$ periods, before retiring. There is a continuum of both firms and workers, each of which discounts future value at the identical rate β. Each worker is born unemployed without unemployment insurance, and receives a draw from a correlated trivariate log-normal distribution $\Psi \sim LN(\psi, \Sigma)$ of wealth, human capital, and learning ability (a_0, h_0, ℓ). Over the life-cycle, a worker may be in one of three employment states: employed, unemployed with unemployment insurance, and unemployed without unemployment insurance. Workers in each employment state are allowed to direct their search to contracts posted by firms. Once a worker reaches age $T+1$, they receive exogenous retirement income and face a probability δ_D of dying in each subsequent period.

Workers are risk-averse, with utility $u'(c) \geq 0$, $u'(0) = \infty$, are allowed to borrow and save at rate r_F up to an age-specific natural borrowing constraint $\underline{a}_t$. Workers are not allowed to default on any debt obligations, nor enter retirement with negative asset holdings because they cannot credibly commit to repay. While employed, workers choose a fraction of productive time τ to spend accumulating human capital through a Ben-Porath (1967) production function, $H(h, \ell, \tau) = \ell(h\tau)^\alpha$, which is increasing in each argument. All workers face an *iid* human capital shock between periods, $\epsilon' \sim N(\mu_\epsilon, \sigma_\epsilon)$, that permanently alters

[5] One explanation is that the small sample size (around 100 first quintile and 300 wealthier separations by year five) prevents me from reaching concrete conclusions for most years.

human capital. This is modeled as $h' = e^{\epsilon'}(h + \ell(h\tau)^{\alpha})$ for employed workers and $h' = e^{\epsilon'}h$ for unemployed workers.

Employed workers may move up or drop down the job ladder. With probability $\lambda_E \leq 1$, they are allowed to search while employed for a new job, while with probability δ, they may instead receive a separation shock and enter unemployment. Employed workers receive $\mu(1-\tau)h$ as income each period, where μ is their piece-rate, $(1-\tau)$ is the time left over after human capital investment, and h is the linear production function. In the event of separation, workers are immediately allowed to search for new employment. Should they not find a new job, they receive unemployment benefits $b_{UI} = min\{b\mu(1-\tau)h, \bar{b}\}$, where b is the replacement rate, and $\bar{b}$ is a benefit cap. Agents stochastically lose benefits with probability γ, and receive $b_L \leq b_{UI}$, which reflects opportunities to earn money outside the labor force. Once a worker's age reaches $t = T + 1$, a worker retires with certainty and is entitled to retirement income b_{Ret}, which is identical for all workers.[6]

Firms post vacancies at cost κ. Vacancies are one-firm one-worker job offers that specify a piece-rate to which the firm can commit for the duration of the contract. Characteristics of searching workers are assumed to be observable, and thus firms open vacancies in submarkets that are indexed by the following tuple: $(\mu, a, h, \ell, t) \in \mathbb{R}_+ \times \mathbb{R} \times \mathbb{R}_+ \times \mathbb{R}_+ \times \mathbb{R}_+$. In equilibrium, each submarket has a known probability of employment. Once matched, a firm receives $(1-\mu)(1-\tau)h$ in profits each period. Any outside offers received by an employed worker are assumed to be private information and unverifiable by the firm. As a result, the firm does not respond to outside offers.

I refer to submarket tightness as $\theta_t(\mu, a, h, \ell) = \frac{v(\mu,a,h,\ell)}{s(\mu,a,h,\ell)}$. The number of matches in each submarket is characterized by a constant returns to scale matching function, $M(s, v)$, where s is the number of searchers (on and off-the-job) in the submarket and v is the number of firms posting vacancies in the submarket. I define job finding rate as $\frac{M(s,v)}{s} = p(\theta_t(\mu, a, h, \ell))$, and the contact rate as $\frac{M(s,v)}{v} = q(\theta_t(\mu, a, h, \ell))$. I assume that the free entry condition holds in any open submarket.

The aggregate state of the economy is summarized by aggregate productivity, measures of unemployment and employed workers, and the stochastic process that determines the measure of new workers each period, respectively. I suppress these states for ease of exposition because the equilibrium is stationary and block recursive (decision rules do not depend on the aggregate state).

[6] I require a period of retirement in the model for identification, which I discuss in Section 4.2.5. This specification is less computationally expensive than making retirement benefits proportional to lifetime income and unlikely to distort decision because most income is determined early in the life-cycle, when the present value of retirement benefits is small.

3.2 Worker's Problem

3.2.1 Job Search

While in the labor market, each period is divided into two subperiods. Agents start each period searching for a job and then enter the production and consumption subperiod. Unemployed agents in the job search period solve the problem given by Equation 3.1.

$$R_t^U(b_{UI}, a, h, \ell) = \max_{\mu'} P(\theta_t(\mu', a, h, \ell)) W_t(\mu', a, h, \ell) + (1 - P(\theta_t(\mu', a, h, \ell))) U_t(b_{UI}, a, h, \ell) \tag{3.1}$$

where b_{UI} denotes their current level of UI and μ' denotes the application strategy $\mu'(w, a, h, \ell, t)$. If they are offered a job, they enter employment with value $W_t(\mu', a, h, \ell)$; if not, they remain unemployed with value $U_t(b_{UI}, a, h, \ell)$. Unemployed searchers without unemployment insurance face an identical problem as Equation 3.1, but receive income b_L should they not find employment. Employed workers are allowed to search on the job, and solve the problem given by Equation 3.2.

$$R_t^E(\mu, a, h, \ell) = \max_{\mu'} \lambda_E P(\theta_t(\mu', a, h, \ell)) W_t(\mu', a, h, \ell) + (1 - \lambda_E P(\theta_t(\mu', a, h, \ell))) W_t(\mu, a, h, \ell) \tag{3.2}$$

where they return to employment with value $W_t(\mu, a, h, \ell)$ should they not find a new job.

3.2.2 Production, Saving, and Human Capital Accumulation

After the search subperiod resolves, workers enter the production and saving subperiod. In this subperiod all workers make consumption and savings allocations (c and a') and employed workers choose the share of time to spend accumulating human capital, τ. All agents are subject to a borrowing constraint $\underline{a}'_t$, which changes with age. Following these decisions, age advances. The problem faced by unemployed agents with UI is given by Equation 3.3.

$$U_t(b_{UI}, a, h, \ell) = \max_{c, a' \geq \underline{a}'_t} u(c) + \beta E\left[(1-\gamma) R_{t+1}^U(b_{UI}, a', h', \ell) + \gamma R_{t+1}^U(b_L, a', h', \ell)\right] \tag{3.3}$$

$$\text{s.t. } c + a' \leq (1 + r_F) a + b_{UI} \tag{3.4}$$

$$h' = e^{\epsilon'} h, \ \epsilon' \sim N(\mu_\epsilon, \sigma_\epsilon) \tag{3.5}$$

where R_{t+1}^U is the value of searching while unemployed. Unemployed agents stochastically lose their benefits with probability γ, and face shocks ϵ' to their human capital both realized at the beginning of the search period. Unemployed agents without unemployment insurance face an identical problem and receive subsistence benefits $b_L \leq b_{UI}$ and no probability of regaining unemployment insurance without first finding a job.

Employed workers solve the problem described in Equation 3.6.

$$W_t(\mu, a, h, \ell) = \max_{c, a' \geq \underline{a}'_t, \tau \in [0,1]} u(c) + \beta E\left[(1-\delta) R^E_{t+1}(\mu, a', h', \ell) + \delta R^U_{t+1}(b_{UI}, a', h', \ell)\right] \tag{3.6}$$

$$\text{s.t. } c + a' \leq (1 + r_F) a + \mu (1 - \tau) h \tag{3.7}$$

$$b_{UI} = min\{max\{b(1-\tau)\mu f(h), b_L\}, \bar{b}\} \tag{3.8}$$

$$h' = e^{\epsilon'}\left(h + \ell (h\tau)^{\alpha}\right), \ \epsilon' \sim N(\mu_\epsilon, \sigma_\epsilon) \tag{3.9}$$

where R^E_{t+1} and R^U_{t+1} are the values of searching while employed and unemployed, respectively. Any time allocated to human capital accumulation proportionally decreases income during the current period as well as unemployment benefits should the worker lose their job. Employed agents face a probability δ of separating exogenously from their current employer. Newly unemployed agents are allowed to search for a job immediately. Should they not find a job, they are assumed to have unemployment benefits equal to the minimum of the UI cap ($\bar{b}$) and the replacement rate times their previous income ($b(1-\tau)\mu h$) for at least one period. I assume that benefits cannot fall below subsistence level, $b_{UI} \geq b_L$.

Following period $T+1$, all agents enter retirement with value $W_{T+1}(\cdot) = U_{T+1}(\cdot) = U_R(a)$, where $U_R(a)$ is the value from a Bewley (1986)-style dynamic problem in Equation 3.10.

$$U_{T+1} = W_{T+1} = U_R(a) = \max_{a'} u(c) + \beta (1 - \delta_D) U_R(a') \tag{3.10}$$

$$\text{s.t. } c + a' = (1 + r) a + b_{Ret} \tag{3.11}$$

where δ_D is the probability of exiting the model each period after retirement.

3.3 Firm's Problem

Firms produce using a single worker as an input. Unmatched firms post contracts in submarkets characterized by (μ, a, h, ℓ, t), each of which is assumed to be observable. By posting a vacancy in a submarket, the firm commits to pay a piece-rate μ for the duration of the contract. Matched firms produce using technology $y = (1-\tau)h$, where τ is the time spent accumulating human capital by the worker that cannot be used in production. The firm retains a fraction $(1-\mu)$ of this output as profits and pays the rest out in wages. Outside offers are private information and unverifiable by the firm, and thus matches continue with probability $(1-\delta)(1-\lambda_E P((\theta_{t+1}(\mu', a', h', \ell)))$ until age $T+1$. The value function of a matched firm is given by Equation 3.12.

$$J_t(\mu, a, h, \ell) = (1-\mu)(1-\tau) h + \beta E\left[(1-\delta)\left(1 - \lambda_E P\left(\theta_{t+1}(\mu', a', h', \ell)\right)\right) J_{t+1}(\mu, a', h', \ell)\right] \tag{3.12}$$

$$h' = e^{\epsilon'}\left(h + \ell (h\tau)^{\alpha}\right), \ \epsilon' \sim N(\mu_\epsilon, \sigma_\epsilon) \tag{3.13}$$

where a' and τ are the worker policy decisions over wealth and human capital accumulation. μ' is the application strategy of the worker conditional upon their updated asset and human capital position. Jobs separate upon retirement and thus the value of a filled vacancy after retirement is zero, $J_{T+1}(\cdot) = 0$.

New firms have the option of posting a vacancy at cost κ in any submarket. Each submarket offers a probability of matching with a worker given by $q(\theta_t(\mu, a, h, \ell))$. In expectation, the value of opening a vacancy in submarket (μ, a, h, ℓ) is given by Equation 3.14.

$$V_t(\mu, a, h, \ell) = -\kappa + q(\theta_t(\mu, a, h, \ell)) J_t(\mu, a, h, \ell) \tag{3.14}$$

I assume that firms enter until the free entry condition holds for every open submarket, $V_t(\mu, a, h, \ell) = 0$. In equilibrium, this means that Equation 3.14 yields equilibrium contact rates (Equation 3.15).

$$q(\theta_t(\mu, a, h, \ell)) = \frac{\kappa}{J_t(\mu, a, h, \ell)} \tag{3.15}$$

Using the definition of the matching function, Equation 3.15 determines the job-finding rate in any open submarket.

3.4 Timing

The timing in the model for workers prior to retirement is as follows:

1. Firms open vacancies in submarkets (μ, a, h, ℓ, t).
2. Employed and unemployed workers search for vacancies in submarkets (μ, a, h, ℓ, t).
3. Agents who receive job offers transition employment states. Agents who are not offered a job remain unemployed.
4. All agents make consumption and savings decisions. Employed agents allocate time between production and human capital accumulation.
5. Age advances. Agents receive human capital shocks, benefit duration shocks, and unemployment shocks in that order.

In retirement, agents consume and save. Once age advances, they learn whether or not they exit the model.

3.5 Equilibrium

A *Block Recursive Equilibrium* (Shi (2009) and Menzio and Shi (2011)) in this model economy is a set of policy functions for workers, $\{c, \mu', a', \tau\}$, value functions for workers W_t, U_t, value functions for firms with filled jobs, J_t, and unfilled jobs, V_t, as well as a market tightness function $\theta_t(\mu, a, h, \ell)$.[7] These functions satisfy the following:

1. The policy functions $\{c, \mu', a', \tau\}$ solve the workers problems, W_t, U_t, R_t^E, R_t^U.
2. $\theta_t(\mu, a, h, \ell)$ satisfies the free entry condition for all submarkets (μ, a, h, ℓ, t).
3. The aggregate law of motion is consistent with all policy functions.

4 Estimation

To discipline the model, I use indirect inference. To begin, I preset function forms to common specifications in the literature and externally calibrate a subset of parameters, with further discussion in Section 4.1. In Section 4.2, I define the empirical specifications to be used as estimation targets for the remaining parameters and show how these moments provide identification of the underlying structural parameters. Section 4.3 shows the estimated structural parameters, and Section 4.4 shows the fit of the model.

4.1 Empirical Preliminaries

4.1.1 Functional Form and Distributional Assumptions

I set the functional forms to those commonly used in work on search and on inequality. Following the standard convention, I choose a power utility function of the form $u(c) = \frac{c^{1-\sigma}-1}{1-\sigma}$. Production is linear, $y = f(h) = h$. I use the matching function from den Haan et al. (2000), which is constant returns to scale and generates well-defined probabilities:

$$M(s, v) = \frac{sv}{(s^\eta + v^\eta)^{\frac{1}{\eta}}} \tag{4.1}$$

I assume that workers face an age-specific natural borrowing constraint equal to the

[7] A Block Recursive Equilibrium is one in which the first two "blocks" of the equilibrium, i.e. the individual decision rules, can be solved without conditioning upon the aggregate distribution of agents across states, i.e. the third block of the equilibrium. The aggregate state can then be recovered by simulation.

amount they can commit to repay before they retire:

$$\underline{a}_t' = \sum_{j=t}^{T} \frac{b_L}{(1+r_F)^j} \tag{4.2}$$

I assume that initial conditions (a_0, h_0, ℓ) are drawn from a multivariate log-normal distribution, $\Psi \sim LN(\psi, \Sigma)$, with mean ψ and variance-covariance Σ. I use a Gaussian copula with correlations $\rho_{AH}, \rho_{A\ell}, \rho_{H\ell}$ (the pairwise correlations between wealth, human capital, and learning, respectively) to generate initial conditions. The initial distribution of wealth is shifted by $-\underline{a}_0'$, the borrowing constraint in period 0, while the initial distributions of human capital and learning ability are shifted by h_{min} and ℓ_{min}, respectively. Finally, I assume that observed earnings are subject to measurement error $\xi \sim N(0, \sigma_\xi)$, to be estimated.

4.1.2 Preset Parameter Values

I externally calibrate parameters a subset of the remaining parameters. Agents in the model work for $T = 168$ quarters, covering the post-schooling and prime working ages, 23-65, before retiring. I follow the standard convention in macroeconomics and set $\sigma = 2$. I set the exogenous separation rate to match the average quarterly flows from employment to unemployment (Shimer, 2012), $\delta = 0.03$.[8] I calibrate the risk free rate to a quarterly $r_F = 0.012$, or roughly a 5 percent at annual average over the duration of my data (1968-2017), and set $\beta = \frac{1}{1+r_F}$. I use the quarterly earnings of an age-25 worker in the PSID ($\$4,277$) as a scale factor. I externally calibrate the UI system to match the US between 1968 and 2017. I set the replacement rate to $b = 0.42$, and set the UI cap to 2.74, or \$900 weekly which is comparable to the higher values in the US in 2016Q4. I set the probability of losing UI to $\gamma = 0.54$ (approximately 26.5 weeks). Once retired, workers receive social security income $b_{Ret} = 0.98$ quarterly ($\$4,200$ unscaled), 1/4th of the annual US average and they die after retirement with probability $\delta_D = 0.02$, the average after age 66 in the U.S. mortality tables. I show these as well as the remaining parameters remaining to be estimated in Table 5.

4.2 Indirect Inference and Auxiliary Model

I estimate the remaining parameters of the model using indirect inference (Gourieroux et al. (1993) and Smith (1993)). Indirect inference is a generalization of simulated method of moments that uses model generated data to match an auxiliary model made up of conditional

[8] I use the flows from employment to unemployment rather than 0.1, commonly assumed in search because my identification relies on worker take-up of unemployment insurance. A larger value is likely to amplify my findings.

moments that constitute an approximation to the equilibrium of the underlying structural model. This approach is less computationally expensive than alternatives like maximum likelihood and allows me to incorporate multiple datasets and handle other problems such as attrition in the data.

My approach focuses on using model-implied restrictions to identify the contribution of job mobility to earnings growth separately from human capital accumulation. In the following sections, I argue that this allows me to identify the structural parameters associated with each source of earnings growth and disciplines initial heterogeneity. Here I briefly outline my arguments. I use the elasticity of re-employment wages and the hazard with respect to unemployment insurance by wealth as an indirect measure of consumption risk faced by workers. This allows me to identify subsistence benefits from the wage elasticity and the matching function curvature from the hazard elasticity. I identify vacancy creation cost and on-the-job search efficiency using unemployment rates and the job-to-job transition rates. I use earnings over the life-cycle to identify correlations between initial conditions, learning ability, and human capital production. Because learning ability changes the slope of the human capital profile, while the production parameter α changes the curvature, I can separately identify them from these moments. I use life-cycle earnings by initial wealth to identify the correlations between initial wealth and initial human capital as well as initial wealth and learning ability. Similarly, I use life-cycle earnings by learning ability, which I proxy for using Armed Forces Qualifying Test (AFQT) scores, to identify the correlation between initial human capital and learning ability. I also show that near-retirement earnings identify measurement error and the depreciation distribution. I give additional details about the sample, data used, and specifications in Section A.2.1 of the online appendix.

My approach to identify the human capital parameters differs from Huggett et al. (2011) in important ways. While I also use the first and second moments of life-cycle earnings, I target these moments by observable sources of heterogeneity that I map into heterogeneity present in my model. This allows me to better discipline the correlation between sources of initial heterogeneity and subsequently differentiate between earnings growth caused by job search and human capital accumulation.

4.2.1 Identifying the Subsistence Benefits and Matching Parameters

In the model, workers trade-off finding a job quickly at low-pay with waiting for higher-pay employment. The resolution to this trade-off varies by wealth. I exploit this trade-off to separately identify b_L from the elasticity of the matching function and other search parameters. To do this, I target the elasticites of re-employment earnings and the hazard rate out of unemployment with respect to the unemployment insurance replacement rate generosity across the wealth distribution. In the following, I outline how the resolution to the trade-off between wages and the job-finding rate by wealth identifies both key parameters.

I start by describing how the elasticity of earnings with respect to UI by wealth identifies subsistence benefits, b_L. In the model, low-wealth workers resolve the trade-off between wages and job-finding rates by accepting lower pay jobs. Higher UI ameliorates or exacerbates this trade-off, depending on b_L. For low-wealth workers additional UI has a larger effect when b_L is smaller, because they are less able to insure their consumption if they lose benefits. If subsistence benefits are low, I would expect poor workers to exhibit a large increase in application strategies when UI increases because they are better able to insure against losing their unemployment benefits. Thus, observing the change in re-employment earnings that results from a change in unemployment insurance for different levels of wealth can identify b_L. Empirically, I target the moments in Section 2.1.1 and use the same specification and sample restrictions.

I use the elasticity of the unemployed hazard with respect to UI in concert with the elasticity of wages with respect to UI to separately identify the curvature of the matching function, η, from b_L as well as κ. I do this by exploiting information from resolution to the trade-off between wages and the job-finding rate across wealth quintiles to implicitly trace out the free entry condition of firms. The key insight is that η controls the shape of the matching function, and as a result the concavity of the job-finding rate with respect to wages. By contrast κ controls the scale of the matching function and thus primarily affects the *level* of employment. A larger value of η results in a more rapid decline in the hazard elasticity and vice-versa, which means I can identify η by comparing the slope for different values of μ. I again target the moments in Section 2.1.1 and use the same specification and sample restrictions.

I provide intuition for identifying subsistence benefits and the matching elasticity in Figure 4.2.1. The left panel depicts the relationship between application strategies and wealth for different values of subsistence benefits, b_L. If the elasticity is large (red line), b_L is a worse income state and causes the slope of application strategies to be steeper at average wealth in the first quintile. Holding wealth fixed, a higher level of b_L results in a smaller elasticity of earnings with respect to UI ($\epsilon_{Y,b}$), shown by the blue line. The right panel depicts the relationship between the elasticity of the hazard rate with respect to piece-rates ($\epsilon_{P,b}$) across the wealth distribution. If I observe similar elasticities, I would interpret η to be a small number. If the elasticities are different, it would suggest that η is a large number.

I follow two standard approaches in the literature to identify λ_E and κ. Because η primarily changes the curvature of the matching function, I use the unemployment rate to identify κ. An increase in κ decreases the hazard rate to every piece-rate in the support and

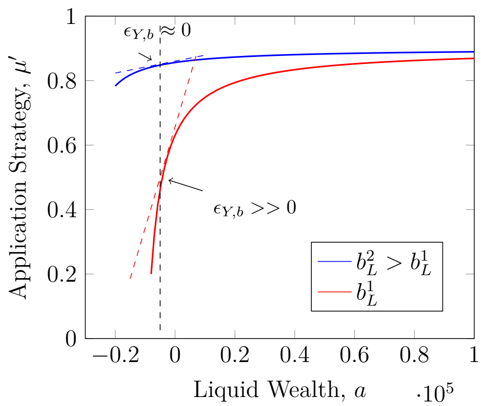


Figure 1: Identification of b_L.

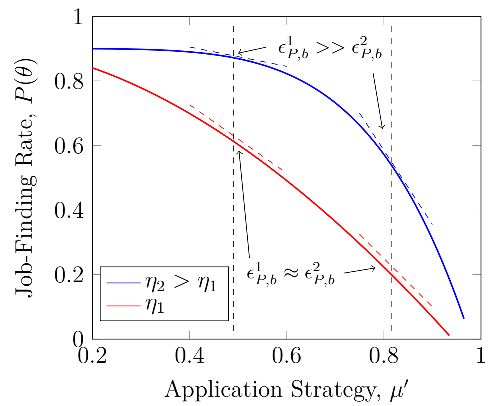


Figure 2: Identification of η.

equivalently causes an increase in the unemployment rate. I target the average unemployment rate over the life-cycle, given explicitly in the online appendix by Equation A.3. To identify λ_E, I match job-to-job mobility over the life-cycle by wealth. I do this because it is a standard approach in the literature and because I have used decisions by unemployed workers to identify the other key parameters in the search process above. Empirically, I match the average job-to-job rate for six equal-sized age-bins from 25 to 54 in the NLSY by contemporaneous wealth quintile and present the specification in the online appendix by A.4.

4.2.2 Identifying Human Capital Production and Learning Ability

Both the distribution of learning ability (μ_ℓ, σ_ℓ) and the production parameter (α) affect earnings dynamics. Two insights are important to understand how I separately identify these parameters. First, over long horizons initial human capital depreciates, leaving learning ability with increasing importance in determining human capital. Second, learning ability changes the slope of the human capital profile, while, α changes the curvature of the human capital profile.

Considering two extreme values of α provides clarity on identification. In the model, human capital growth for an employed worker is given by $h' = e^{\epsilon'}(h + \ell(\tau h)^\alpha)$. When $\alpha = 0$, this expression shows that growth is proportional to learning ability: $h' = e^{\epsilon'}(h + \ell)$ When $\alpha = 1$, the human capital profile will mirror the curvature of investment, τ: $h' = e^{\epsilon'}(h + \ell(\tau h))$. These expressions give insight into identifying μ_ℓ separately from α: μ_ℓ primarily determines the average growth rate of human capital and earnings, while α determines the curvature of the human capital profile. If earnings are grow in a nearly linear fashion over the life-cycle, α is likely to be close to zero. Earnings that grow rapidly early, but this growth falters subsequently, imply a higher value of α. I capture the curvature by targetting the life-cycle earnings profile that I make explicit in Equation A.5 using the PSID. I target age-earnings regressions that I describe in the online appendix in Section 4.2.4 to discipline the average growth. I include controls for year, age, state, education, race, marriage, hours worked, and restrict the sample to males age 25 to 54.

I identify the standard deviation of the learning distribution (σ_ℓ) by matching the variance profile. Similar to my previous argument, a change in σ_ℓ changes the average variance of earnings across all ages, while the curvature of the variance is determined by α. I target the variance profile using the PSID and estimate Equation A.6 given in the online appendix, subject to the same restrictions.

4.2.3 Identifying Initial Wealth and Human Capital

I use clear analogues to identify the marginal distributions of initial wealth and human capital. For human capital, I target the initial distribution of earnings, which I argue identifies μ_H, σ_H, and h_{min}. For initial wealth, I match the distribution of liquid wealth prior to entering the labor market. I then target initial earnings by wealth, which I argue identifies the correlation between human capital and wealth, ρ_{AH}.

Here, I outline how I identify the correlation between wealth and initial human capital. I start by taking the expectation of initial human capital conditional on initial wealth quintile.[9]

$$E\left[ln\left(h_0\right)|a_0 \in a_0^q\right] = \mu_H + \rho_{AH}\frac{\sigma_H}{\sigma_A}\left(E[a_0|a_0 \in a_0^q] - \mu_A\right) \tag{4.3}$$

where a_0^q denotes initial wealth quintile q. This yields initial earnings by quintile, subject to a proportionality factor determined by model decision rules. With estimates of μ_H, σ_H, σ_A, and μ_A that I argue are identified by the unconditional distributions of earnings and wealth, this expression only varies by ρ_{AH}. I formally target the slope and intercept of an age-earnings regression by wealth, which I discuss in Section 4.2.4.

Because earnings are proportional to human capital, targeting initial earnings provides a fairly clear source of identification for μ_H and σ_H. The intuition behind targeting observed wealth to identify μ_A and σ_A is similarly straightforward. In addition, I argue that the lowest level of earnings identifies the minimum level of human capital, h_{min}. I capture these sources of identification for human capital my targeting the deciles of initial (first-job) earnings in the PSID. I require that this first-job occur before age 25 and that I observe these individuals without a job during a previous survey. I match observed liquid wealth by decile to discipline the marginal distribution of wealth (μ_A, σ_A). I restrict my sample to workers for whom I observe wealth prior to entering the labor market in the PSID. I again limit this to male

[9]Generically, the conditional expectation of two jointly normal random variables X, Y with correlation ρ is given by $E[X|Y] = E[X] + \rho\frac{\sigma_X}{\sigma_Y}(Y - E[Y])$

workers younger than age 25 at which I observe wealth.

4.2.4 Identifying the Correlations with Learning Ability

To discipline the correlations between initial conditions, I target two age-earnings regressions. In the first, I interact the slope and intercept with an indicator variable for initial wealth quintile using the PSID. I do the same by quintiles of Armed Forces Qualifying Test (AFQT) scores using the NLSY, which I use as a proxy for learning ability.[10] Similar to my argument in Section 4.2.3, I argue that the intercepts identify the correlations between initial wealth and initial human capital as well as learning ability and initial human capital, while the slopes identify the correlations with learning ability.

I argue that the slope of the age-earnings regression by initial wealth and learning ability quintiles identifies the correlations with learning ability, $\rho_{A\ell}$ and $\rho_{H\ell}$. Given an initial quintile, the slope of the earnings profile is determined by the average learning ability. How these slopes vary across quintiles identifies the correlations. I show graphical intuition for identifying each parameter in Figure 4.2.4. The left panel shows that initial earnings by learning ability identify $\rho_{H\ell}$ (equivalently, ρ_{AH} from initial earnings by wealth). If $\rho_{H\ell}$, is approaching 1, initial earnings differences will mirror earnings differences throughout the life-cycle. If there is little correlation between learning ability and human capital ($\rho_{H\ell} \approx 0$) initial earnings will be similar across the learning ability distribution, and fan out over the lifecycle. The right panel shows the intuition for identification using the slope of earnings by wealth level for hypothesized values of $\rho_{A\ell}$. If $\rho_{A\ell}$ is approaching 1, dispersion between wealth quintiles will increase over the life-cycle, shown by the dashed top and bottom lines. If instead $\rho_{A\ell}$ is approaching 0, the slopes of wages will be approximately the same by wealth.

I implement these specifications in my auxiliary model using age-earnings regressions that exploit curvature in human capital profiles by allowing for both the slope and intercept to differ for ages 25-39 and ages 40-64. Formally, I target age-earnings regressions by initial wealth and learning quintiles using the PSID (wealth) and NLSY79 (learning) in which I include controls for year, age, geography (state in PSID, region in NLSY), education, race, marriage, and hours worked, and again restrict ages to be between 25 and 54. I give this specification in the online appendix Equation A.7.

I face two empirical challenges to this exercise. First, there are few individuals in the PSID who report both wealth at a young age and subsequently earnings at the concluding ages in my model. Second, learning ability cannot be observed directly. To handle the first challenge, I estimate initial wealth quintile for individuals without reported wealth prior

[10] The AFQT was a standardized test that nearly all participants in the NLSY took prior to entering the labor market. AFQT scores are commonly used to proxy for unobserved ability.

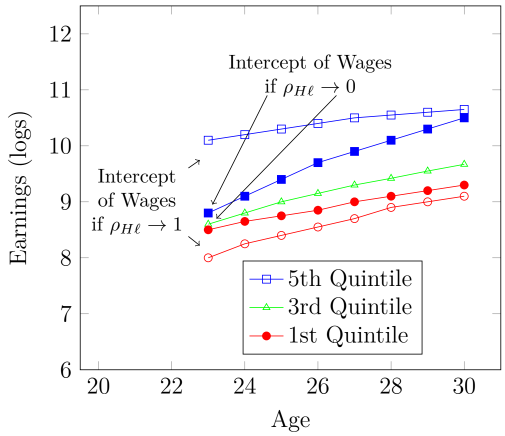


Figure 3: Identification of $\rho_{H\ell}$.

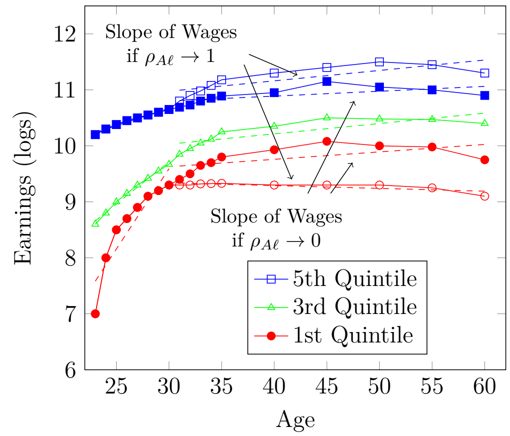


Figure 4: Identification of $\rho_{A\ell}$.

to entering the labor market. I do this by first estimating a conditional logit by wealth quintile, including controls for interest income, race, age, transfer income, housing status, family size, father's education, years of school, childhood economic status, state and year on the sample with wealth observations prior to entering the labor market. Individuals for whom I observe initial wealth are given their corresponding quintile; individuals for whom I do not are assigned the quintile with the highest probability. I report further specific details in the online appendix in Section A.3.3 and note that this is the **only** instance in which I use these estimated quintiles. To handle the second, I use AFQT scores in the NLSY79 as a proxy for learning ability.[11]

Finally, I argue that matching earnings by AFQT quintiles also allows me to identify the minimum level of learning ability, ℓ_{min}. Intuitively, given a μ_ℓ and σ_ℓ, I know the average learning ability of an individual in the first quintile with $\ell_{min} = 0$. This would imply a small earnings profile slope for the first quintile. The difference between this slope and the observed slope pins down the minimum learning ability, ℓ_{min}.

4.2.5 Identifying Human Capital Depreciation

I follow Huggett et al. (2011) and target changes in log-earnings near retirement to identify the human capital depreciation parameters $(\mu_\epsilon, \sigma_\epsilon)$, as well as measurement error (σ_ξ). As workers approach retirement they are less likely to invest in human capital, which means that observed changes in earnings among job-stayers are due to human capital depreciation.

[11] I assume that the AFQT score proxy imperfectly measures a workers learning ability, and thus is given by $\ell^{AFQT} = \ell + \omega$ where $\omega \sim N(0, \sigma_\omega)$ is classical measurement error. This means that measurement error in learning ability drops from any expectations and does not affect estimated correlations, because it is uncorrelated.

Consider growth in earnings between ages t and $t+n$ with $\mu_t = \mu \; \forall \; t$:

$$\Delta_n ln\left(y_n\right) = \Delta_n ln\left(h_n\right) + \Delta_n \xi_n$$
$$= \epsilon_n + \Delta_n \xi_n \tag{4.4}$$

where Δ_n denotes the difference between age - t and age - $t+n$. I use the expected value of earnings growth over this period to identify average depreciation (μ_ϵ), and higher-order moments to separately identify the variance of depreciation (σ_ϵ) and the variance of measurement error (σ_ξ). These are given by the following

$$E\left[\Delta_n ln\left(y_n\right)\right] = n\mu_\epsilon \tag{4.5}$$

$$Var\left(\Delta_n ln\left(y_n\right)\right) = n\sigma_\epsilon^2 + 2\sigma_\xi^2 \tag{4.6}$$

$$Cov\left(\Delta_n ln\left(y_n\right), \Delta_m ln\left(y_m\right)\right) = m\sigma_\epsilon^2 + \sigma_\xi^2, \; m \; < \; n \tag{4.7}$$

I use the PSID to estimate these moments. I restrict the sample to individuals who remain at the same job (i.e., $\mu_{58} = \mu_{59} = \ldots = \mu_{64}$) between ages 58 to 64, and use horizons of $n, \; m = 1, \ldots, 3, \; m \; < \; n$ years.

4.3 Estimation Results

The parameter estimates and standard errors are reported in Table 5. The standard errors around the estimates are small. Because of the differences in scale and frequency, some of the parameters are not directly comparable with the previous literature.

Table 5: Model parameters

(a) Preset parameter values

Parameter	Symbol	Value or Function	Source
Work-Life	T	168	Working Age 23-65
Risk Aversion	σ	2	Standard
Risk Free Rate	r_F	0.012	Annual rate of $\approx 5\%$
Discount Factor	β	0.9882	$\frac{1}{1+r_F}$
Separation Rate	δ	0.03	Shimer (2012)
Scale Factor		$4,277$	Average quarterly earnings (Age 25, PSID)
Social Security	b_{Ret}	0.98	US Average
Exit Prob.	δ_D	0.02	US Mortality Tables
UI Replacement Rate	b	0.42	U.S. Average
Max UI	$\bar{b}$	2.74	High UI cap
UI Loss Probability	γ	0.54	Potential UI Duration ($\approx$ 26.5 weeks)

(b) Estimated parameters

Category	Symbol	Model Value		
Model Parameters				
Subsistence Benefits	b_L	0.0204 [0.0199,0.0209]		
Elasticity of Matching Function	η	0.4325 [0.4225,0.4426]		
Vacancy Creation Cost	κ	1.7884 [1.7710,1.8058]		
On-the-job Search Efficiency	λ_E	0.5885 [0.5852,0.5918]		
Human Capital Curvature	α	0.5687 [0.5644,0.5731]		
Initial Conditions				
Initial Wealth	(μ_A, σ_A)	$\mu_A = 0.2311$ [0.2159,0.2462]	$\sigma_A = 0.9016$ [0.8910,0.9123]	
Initial Human Capital	(μ_H, σ_H)	$\mu_H = -0.5128$ [−0.5269,−0.4987]	$\sigma_H = 1.3504$ [1.3410,1.3598]	
Learning Ability	(μ_ℓ, σ_ℓ)	$\mu_\ell = 1.4900$ [1.4783,1.5017]	$\sigma_\ell = 0.5556$ [0.5462,0.5650]	
Correlations	$\rho_{AH}, \rho_{A\ell}, \rho_{H\ell}$	$\rho_{AH} = 0.3253$ [0.3176,0.3329]	$\rho_{A\ell} = 0.4642$ [0.4595,0.4690]	$\rho_{H\ell} = 0.6915$ [0.6854,0.6975]
Minimum h and ℓ	(h_{min}, ℓ_{min})	$h_{min} = 2.6050$ [2.5720,2.6381]	$\ell_{min} = 0.0875$ [0.0856,0.0895]	
Other Distributions				
Human Capital Depreciation	$(\mu_\epsilon, \sigma_\epsilon)$	$\mu_\epsilon = -0.0249$ [−0.0252,−0.0245]	$\sigma_\epsilon = 0.0621$ [0.0614,0.0627]	
Measurement Error	$(0, \sigma_\xi)$	$\sigma_\xi = 0.1288$ [0.1273,0.1304]		

Notes: The 95% confidence intervals of the estimates are shown in brackets beneath the structural parameters.

4.4 Fit and Non-Targeted Moments

In this section, I show the fit of the auxiliary model as well as the ability of the estimated model to match my empirical evidence from Section 2. I report the estimation results of the auxiliary model in Table 6 and Table 7. Despite having more than 200 auxiliary parameters, difference-in-means tests show that the model replicates the data along many dimensions. My estimated coefficients in the wage and hazard elasticities are not significantly different from the data, indicating that the estimation captures the wage-hazard trade-off by wealth reasonably well. The model comes reasonably close to replicating the average earnings profile (Figure 5a), but overestimates the variance profile, despite capturing the overall shape (Figure 5b). The model also matches the initial distribution of earnings (Figure 5c) as well as the initial distribution of wealth (Figure 5d). The model struggles to match the slope and intercepts of both the wealth and AFQT age-earnings regressions, but does better for the first and second quintiles. Missing the slope coefficients in both specifications suggests that the correlations of wealth and human capital with learning ability might be overstated, which would cause me to understate the importance of wealth in my quantitative findings with the model or that measurement error for learning ability is not classical, which has less clear implications. It does a good job matching all late career earnings growth moments. It also matches the unemployment rate and does a reasonable job matching the pattern of job mobility (Table 7) by wealth after age 30, which suggests that the vacancy creation cost and on-the-job search efficiency parameters are reasonable estimates, although it tends to overstate mobility between ages 25 and 29

Table 6: Estimated auxiliary parameters from elasticity and age-regression moments

Slopes and Intercepts by Wealth (PSID)			
Var.	Data	Model	P-Val
Age	0.0388	0.0446	0.0401
	(0.003)	(0.0014)	
Q2 x Age	-0.0049	0	0.1996
	(0.0054)	(0.0023)	
Q3 x Age	-0.0099	-0.0012	0.0157
	(0.0036)	(0.0017)	
Q4 x Age	-0.0113	-0.0011	0.0062
	(0.0038)	(0.0016)	
Q5 x Age	-0.0147	-0.0018	0.0063
	(0.0048)	(0.0021)	
Q2	0.1729	-0.0015	0.1622
	(0.1602)	(0.0754)	
Q3	0.3997	0.0382	0.0016
	(0.1089)	(0.0562)	
Q4	0.5452	0.0322	0
	(0.1092)	(0.0514)	
Q5	0.7568	0.0573	0
	(0.1482)	(0.0693)	
Cons.	8.907	9.3082	0.0003
	(0.1067)	(0.044)	
Q1 x Age x (Age >= 40)	-0.0389	-0.0372	0.3802
	(0.0051)	(0.0025)	
Q2 x Age x (Age >= 40)	-0.0364	-0.037	0.4763
	(0.0085)	(0.0035)	
Q3 x Age x (Age >= 40)	-0.0216	-0.036	0.0005
	(0.004)	(0.0018)	
Q4 x Age x (Age >= 40)	-0.0239	-0.036	0.0004
	(0.0033)	(0.0014)	
Q5 x Age x (Age >= 40)	-0.0137	-0.0351	0.0018
	(0.0069)	(0.0027)	
Q1 x (Age >= 40)	1.5245	1.3938	0.2946
	(0.2178)	(0.1056)	
Q2 x (Age >= 40)	1.457	1.3823	0.4238
	(0.3581)	(0.1505)	
Q3 x (Age >= 40)	0.8002	1.3559	0.0014
	(0.1682)	(0.0781)	
Q4 x (Age >= 40)	0.9369	1.3557	0.0027
	(0.1385)	(0.0584)	
Q5 x (Age >= 40)	0.4745	1.3221	0.0039
	(0.2964)	(0.1167)	
Unemp. Rate (PSID)	0.0392	0.0399	0.499
	(0.194)	(0.1956)	

Slopes and Intercepts by AFQT (NLSY)			
Var.	Data	Model	P-Val
Age	0.0349	0.0331	0.3924
	(0.0065)	(0.0016)	
Q2 x Age	0.0007	-0.0056	0.0236
	(0.0024)	(0.0021)	
Q3 x Age	0.0013	0.0031	0.2508
	(0.0015)	(0.0021)	
Q4 x Age	0.0059	0.0374	0
	(0.0028)	(0.0021)	
Q5 x Age	0.0255	0.0301	0.1484
	(0.0039)	(0.002)	
Q2	0.0742	0.2098	0.0658
	(0.0606)	(0.0664)	
Q3	0.1581	0.0178	0.0725
	(0.0698)	(0.0663)	
Q4	0.0021	-0.7661	0
	(0.0911)	(0.0642)	
Q5	-0.5819	0.0759	0
	(0.1381)	(0.0633)	
Cons.	9.1016	9.3457	0.1392
	(0.22)	(0.0481)	
Q1 x Age x (Age >= 40)	-0.017	-0.0314	0.0313
	(0.0047)	(0.0062)	
Q2 x Age x (Age >= 40)	-0.0349	-0.0258	0.2402
	(0.0123)	(0.0038)	
Q3 x Age x (Age >= 40)	-0.0226	-0.0189	0.3554
	(0.0092)	(0.0034)	
Q4 x Age x (Age >= 40)	-0.0262	-0.0539	0
	(0.0035)	(0.0029)	
Q5 x Age x (Age >= 40)	-0.046	-0.0613	0.0108
	(0.0061)	(0.0028)	
Q1 x (Age >= 40)	0.5849	1.1175	0.0592
	(0.2081)	(0.2701)	
Q2 x (Age >= 40)	1.4009	0.9228	0.1911
	(0.5216)	(0.1653)	
Q3 x (Age >= 40)	0.8461	0.6847	0.353
	(0.401)	(0.1491)	
Q4 x (Age >= 40)	1.0469	2.0765	0
	(0.165)	(0.1273)	
Q5 x (Age >= 40)	1.8269	2.2637	0.0603
	(0.2539)	(0.1214)	
$cov(\Delta\, log(y_{t+2}), \Delta\, log(y_{t+3}))$	0.0624	0.0674	0.4923
	(0.0057)	(0.2596)	

Wage-UI Elasticity (SIPP)			
Var.	Data	Model	P-Val
log(UI)	0.4652	0.2918	0.1955
	(0.2001)	(0.0296)	
> Q1 x log(UI)	-0.4425	-0.2731	0.1632
	(0.1698)	(0.0308)	
Age	0.0009	0.0025	0.1613
	(0.0014)	(0.0008)	
log(Prev. Inc.)	0.35	0.3909	0.3014
	(0.0629)	(0.0473)	
Q1 x log(Prev. Inc.)	0.0773	0.2731	0.0076
	(0.0636)	(0.0497)	
Cons.	1.2626	-3.0874	0.0004
	(1.2101)	(0.4768)	
> Q1	2.0471	4.9384	0.0194
	(1.3244)	(0.4493)	

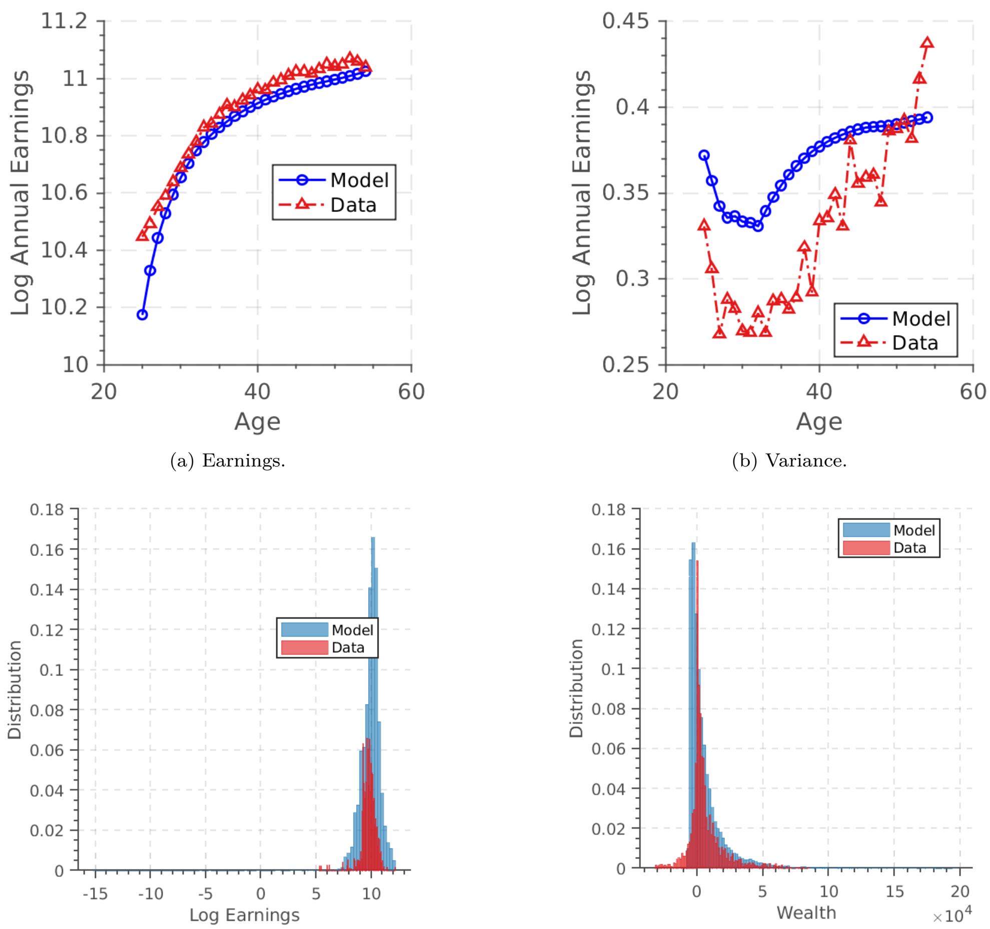
Hazard-UI Elasticity (SIPP)			
Var.	Data	Model	P-Val
Q1 x log(UI)	-0.8664	-0.932	0.4291
	(0.3553)	(0.0929)	
> Q1 x log(UI)	-0.4542	-0.3336	0.3662
	(0.3417)	(0.0885)	
Age	-0.0156	-0.0425	0
	(0.0026)	(0.0019)	
log(Prev. Inc.)	0.0825	0.1279	0.2831
	(0.0443)	(0.0657)	

Late Career Earnings Growth (PSID)			
Var.	Data	Model	P-Val
$\Delta\, log(y_{t+1})$	-0.0255	-0.0466	0.4703
	(0.005)	(0.2823)	
$\Delta\, log(y_{t+2})$	-0.0697	-0.0747	0.4945
	(0.0086)	(0.362)	
$\Delta\, log(y_{t+3})$	-0.1141	-0.0942	0.4802
	(0.0123)	(0.3995)	
$var(\Delta\, log(y_{t+1}))$	0.096	0.0677	0.4567
	(0.0061)	(0.2602)	
$cov(\Delta\, log(y_{t+1}), \Delta\, log(y_{t+2}))$	0.0433	0.0444	0.4981
	(0.004)	(0.2106)	
$cov(\Delta\, log(y_{t+1}), \Delta\, log(y_{t+3}))$	0.0459	0.0307	0.4655
	(0.0058)	(0.1751)	
$var(\Delta\, log(y_{t+2}))$	0.1357	0.1119	0.4716
	(0.0083)	(0.3344)	
$var(\Delta\, log(y_{t+3}))$	0.1772	0.1436	0.4646
	(0.0132)	(0.3789)	

The estimated model is also able to replicate my findings in Section 2 on unemployment scarring. I start by calculating the scarring effects of unemployment in my model by wealth quintile, which I compare to my estimates in Table 3. I do this by simulating a control and treatment group that are identical until age - t when the treatment group is subject to an unemployment shock, while the control group remains employed. Both groups are employed at age - $t-1$ at firms that offer the average piece-rate for their age. After this separation, both groups receive an identical series of shocks. I treat cohorts at ages 23 to 50, following my

Table 7: Estimated auxiliary parameters from job-to-job mobility by wealth

	J2J Rate Q1 (NLSY)			J2J Rate Q2 (NLSY)			J2J Rate Q3 (NLSY)			J2J Rate Q4 (NLSY)			J2J Rate Q5 (NLSY)		
Age Group	Data	Model	P-Val	Data	Model	P-Val	Data	Model	P-Val	Data	Model	P-Val	Data	Model	P-Val
25 - 29	0.323	0.3735	0.0087	0.2232	0.2983	0	0.1907	0.2485	0	0.1959	0.2099	0.3168	0.1875	0.1877	0.4946
	(0.0173)	(0.0123)		(0.0153)	(0.0108)		(0.0052)	(0.0101)		(0.0278)	(0.0095)		(0.0113)	(0.0091)	
30 - 34	0.2631	0.2834	0.0772	0.2167	0.212	0.3869	0.1807	0.1673	0.1345	0.1434	0.141	0.4101	0.1414	0.1583	0.0983
	(0.0072)	(0.0123)		(0.0126)	(0.0107)		(0.0072)	(0.0098)		(0.0053)	(0.0091)		(0.0094)	(0.009)	
35 - 39	0.2923	0.2492	0.0521	0.2389	0.1767	0.001	0.1788	0.1452	0.0202	0.1486	0.1356	0.2213	0.1259	0.1569	0.0577
	(0.0219)	(0.015)		(0.0154)	(0.013)		(0.0111)	(0.0121)		(0.0125)	(0.0115)		(0.0163)	(0.011)	
40 - 44	0.2537	0.2336	0.2931	0.1839	0.1648	0.1591	0.1648	0.1381	0.1449	0.1575	0.1566	0.4891	0.1331	0.1499	0.1056
	(0.033)	(0.0167)		(0.0124)	(0.0147)		(0.0213)	(0.0136)		(0.0279)	(0.013)		(0.0073)	(0.0114)	
45 - 49	0.2207	0.2245	0.4548	0.2223	0.1622	0.024	0.1948	0.1493	0.1662	0.1679	0.1782	0.3074	0.1447	0.1412	0.4261
	(0.0268)	(0.0194)		(0.0246)	(0.0178)		(0.0437)	(0.0171)		(0.0142)	(0.0147)		(0.0145)	(0.0119)	
50 - 54	0.1897	0.213	0.3016	0.2451	0.1629	0.0106	0.1443	0.1534	0.4062	0.1753	0.1879	0.3361	0.1244	0.1366	0.3567
	(0.0343)	(0.0288)		(0.0228)	(0.0274)		(0.0284)	(0.0257)		(0.0205)	(0.0215)		(0.0286)	(0.0171)	



(a) Earnings.

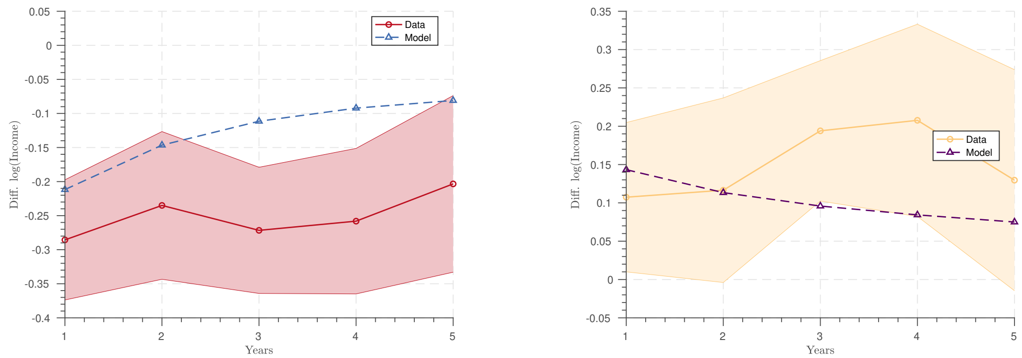
(b) Variance.

(c) Initial earnings.

(d) Liquid wealth.

Figure 5: Model fit.

restriction in Section 2.2.2 and estimate the treatment effect of job separation on my model generated data using my specification in Equation 2.4. I plot the coefficients for my results in Figure 6 and compare them to the data. The left panel shows the estimated coefficients for the first quintile (coefficient on job loss) in the model (blue dashed line) and in the data (red solid line). The right panel shows my model estimates (purple dashed line) and data (yellow solid line) for the interaction term between job loss and being in quintiles 2 through 5 at the time of separation.



(a) Q1 unemployment scarring.

(b) Q2-Q5 unemployment scarring.

Figure 6: Unemployment scarring comparison. The shaded region in both figures correspond to the 95% confidence intervals in the data.

The model underestimates the size of unemployment scarring for the first quintile, but generates smaller scarring effects for higher quintiles that are roughly in line with what I observe in the data. This suggests that while there may be additional factors that cause large average scarring effects, the model captures important elements of the mechanism that drives the difference in unemployment scarring between the first and higher quintiles.

5 Findings

I now use the estimated model to address the central question posed in this paper: how do wealth, search, and human capital interact and what are the consequences for lifetime earnings? I first show how search and investment decisions differ by wealth and show that this contributes to differences in income over the life-cycle (Section 5.1). Then I explore how counterfactual initial conditions affect income and human capital in Section 5.2. Next, I show how the interaction between wealth, search, and human capital influences my findings. Last, I show additional evidence for my mechanism and that "learning-by-doing" human capital growth is inconsistent with these findings.

5.1 Understanding the Dynamics of the Model

5.1.1 Search Decisions

In the labor market, low wealth agents exhibit a precautionary motive. Figure 7 shows application rules by employment status for workers with average human capital and learning ability of an age-24 worker. The left panel depicts the application strategy of an age-24 unemployed agent without unemployment insurance across the wealth distribution. The dashed lines correspond to the average level of wealth within the 1st and 5th quintiles for an age-24 worker and shows that a 5th quintile individual applies for jobs that pay 35 percentage points more on average, for equal human capital and learning ability. The right panel plots employed application strategies across the wealth distribution for two different piece-rates at their current employment. The blue line depicts application strategies conditional on an age-24 worker gaining employment at a firm that offers the 5th quintile piece-rate in the left panel. The red line shows application strategies for workers conditional on current employment at a firm that offers the 1st quintile piece-rate in the left panel.

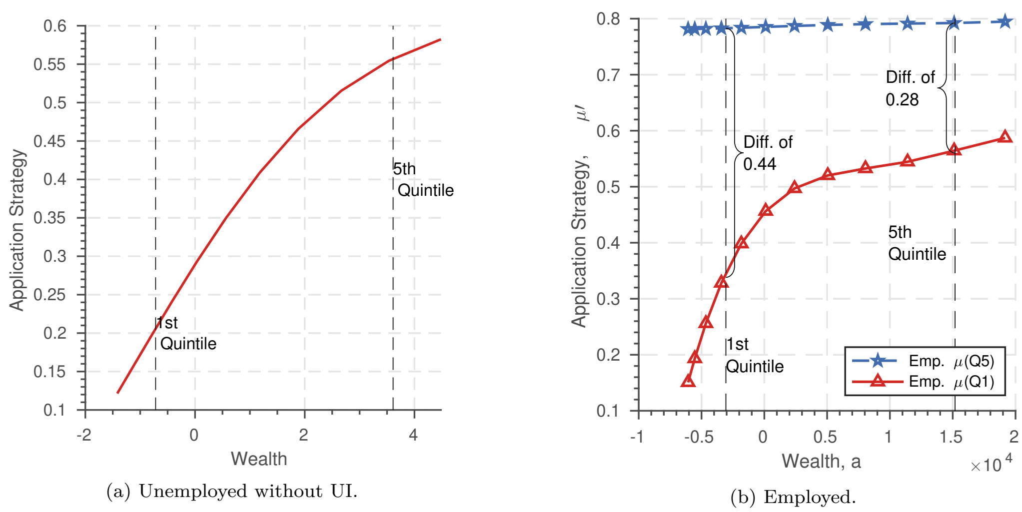


Figure 7: Application strategies by employment status for age 24 workers.

Taken together, these figures show one channel through which low-wealth can dynamically affect earnings. Even with identical levels of human capital and learning ability, poor workers search for lower-pay jobs (left panel). Once they obtain these jobs, they select into lower paying jobs as they move up the ladder (right panel).

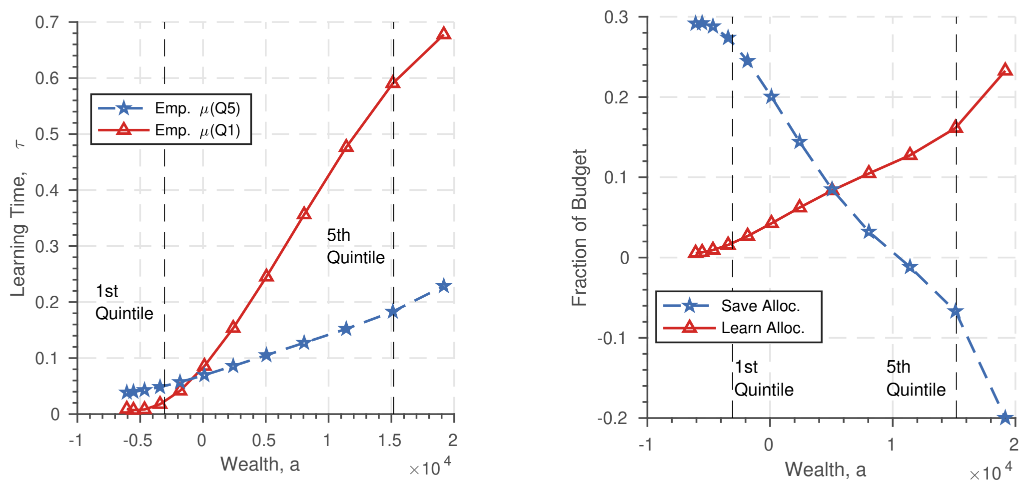
5.1.2 Portfolio Allocation Decisions

The next figure (Figure 8) shows contour sets that characterize the portfolio allocation decisions of workers across the wealth distribution. The left panel shows human capital investment decisions of employed age-24 workers across the wealth distribution for different piece-rates. The red line depicts the investment decisions of a worker currently employed at the 1st wealth quintile piece-rate and the blue line plots the investment decisions for workers at the 5th quintile piece-rate. When a wealthy individual is employed at a low piece-rate (the red line), they spend a large share of their time investing, because the opportunity cost is low. If they are employed at a high piece-rate (the blue line), they spend less time on human capital. By contrast, wealth effects dominate for the 1st quintile. When they have a low piece-rate, they prefer to build their savings and allocate *less* time to human capital.

The right panel shows the portfolio allocation decisions of workers across the wealth distribution. The blue line plots the fraction of an average age-24 worker's budget that they allocate toward precautionary savings, while the red line plots their income forgone while investing in human capital as a fraction of their overall budget. Their budget is given by

$$c + a' + \tau\mu h = \mu h + (1+r)a \tag{5.1}$$

which means their saving allocation is given by $\frac{a'}{\mu h+(1+r)a}$ and their learning allocation is given by $\frac{\tau\mu h}{\mu h+(1+r)a}$. Low-wealth workers allocate very little of their budget toward human capital accumulation, preferring to build their stock of savings. By contrast, their wealthy peers may prefer to dissave in order to build their stock of human capital.

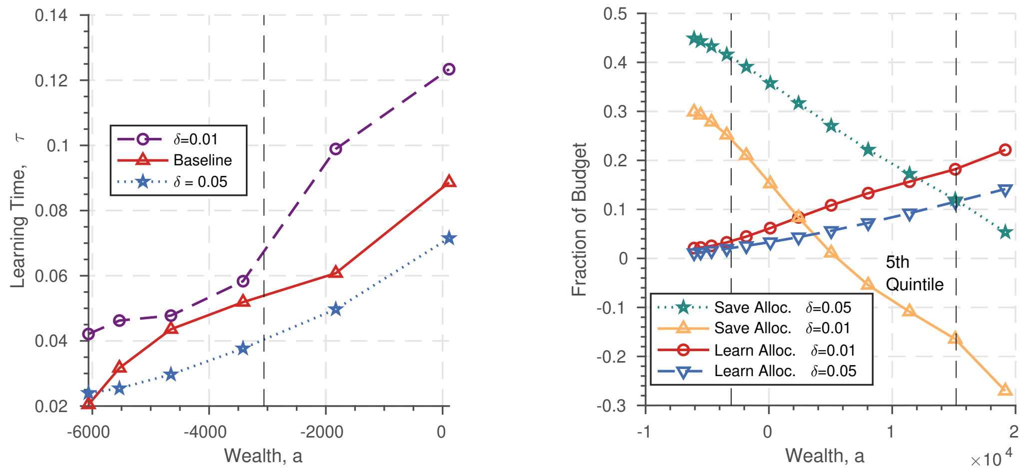


(a) Human capital investment.

(b) Portfolio allocation.

Figure 8: Portfolio allocation decisions.

In Figure 9, I vary separation risk of an age-24 worker by changing δ from $\delta = 0.03$ in the baseline to $\delta = 0.01$ and $\delta = 0.05$ and plot the decision rules. The figure in the left panel plots learning time, τ, for an average age-24 worker near the average wealth level in the first quintile. This shows that the effect of unemployment risk on human capital investment varies across the wealth distribution. For a low-wealth worker, decreasing unemployment risk causes a sizeable increase in human capital investment. The right panel plots portfolio allocation in the low separation risk and high separation risk economies. In the model with $\delta = 0.01$, learning time makes up a larger share of an individuals budget across the entire wealth distribution compared with the $\delta = 0.05$ economy (red line vs. blue line). A similar pattern is evident in the household's allocation of their budget to savings as well, though lower separation risk produces a reduction in precauiontary savings across the entire wealth distribution.



(a) Human capital investment by separation risk.

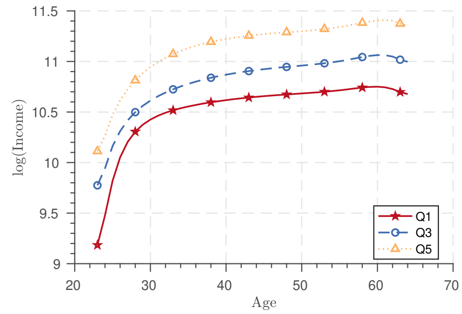
(b) Portfolio allocation by separation risk.

Figure 9: Portfolio allocation decisions under different degrees of separation risk.

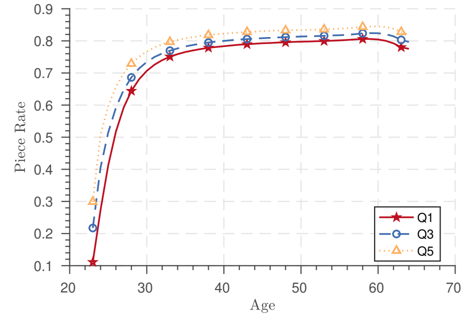
5.1.3 Earnings Dynamics

Next, I explore the dynamics of the model and how they vary across initial wealth quintiles. The average earnings profile is similar to many papers on life-cycle inequality. The mean earnings profile is hump shaped, increasing rapidly at the beginning of the life-cycle and declining slightly as individuals approach retirement age (Figure 10a). Agents spend a large fraction of their time accumulating human capital early in the life-cycle, which slows as they enter prime working age, and then tapers off as they approach retirement (Figure 10d). They initially experience sizeable earnings growth from increases in piece-rates (Figure 10b), but this slows by age 30 and plateaus around age 35 before declining near retirement. After age 30, human capital is the primary source of earnings growth, growing until late in the life-cycle.

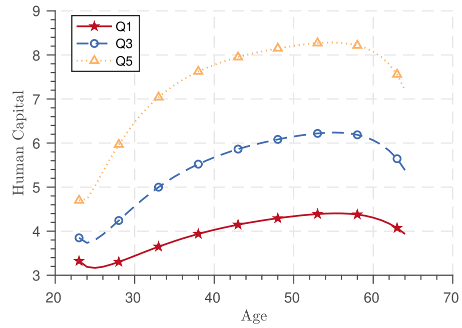
These figures show clear differences in earnings dynamics across the wealth distribution. Earnings are initially higher for wealthy individuals and this gap grows throughout the life-cycle (Figure 10a). Early in the life-cycle, high wealth workers obtain better jobs, but this difference falls as workers age (Figure 10b). The majority of the differences in earnings result from differences in human capital rather than piece-rates. While 5th quintile workers start with about 1.4 times the human capital of 1st quintile workers, this gap increases to nearly 2 times as much by the late 40s (Figure 10c). Driving this change is a higher rate of investment in human capital (Figure 10d) as well as the positive correlation between wealth



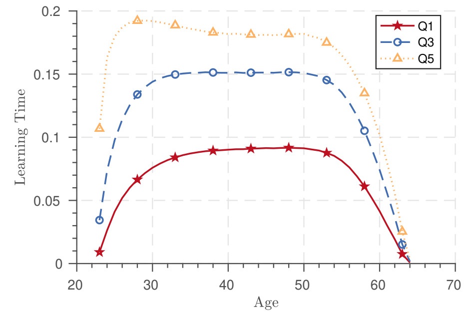
(a) Earnings profiles by wealth.



(b) Piece rate by wealth.



(c) Human capital by wealth.



(d) Time allocation by wealth.

Figure 10: Profiles of income and income determinants.

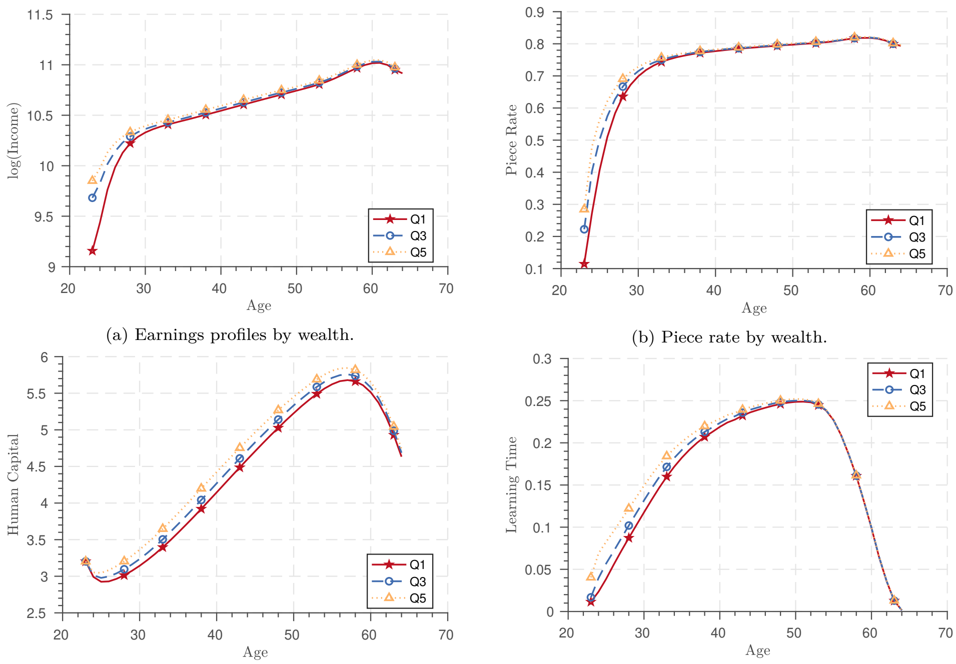
and learning ability, leading to a higher rate of return on human capital investment. Some of these differences can be attributed to differences in human capital and learning ability while some are caused by the dynamic effect that wealth and search have on human capital and earnings. I devote the next sections to addressing this question.

5.2 Initial Wealth and Life-Cycle Inequality

The profiles in Section 5.1.3 show that income and its determinants vary greatly over the life-cycle across initial wealth. In this section, I explore how consumption, human capital, and income are affected when workers start with different initial conditions. I do this in two ways. First, I experiment with changing the dispersion in initial conditions. I consider both a large and small reduction in initial inequality and assess the effect on lifetime outcomes. Second, I conduct the same experiment as Huggett et al. (2011) by setting agents to the median values of the initial distribution and then decreasing each initial condition by a standard deviation, leaving the other two unchanged.

5.2.1 Test 1: The Median Worker

I start by assessing the effect that differences in initial wealth has on the median worker. I use the initial distribution from the baseline model, but assign each worker the median value of initial human capital and learning ability, allowing initial wealth to continue to vary. I plot the same time series as in Figure 10 in Figure 11. Although life-cycle differences fall for all plots compared to Figure 10, there are still persistent differences for initially high and low-wealth individuals. This suggests that although differences in human capital and learning ability play a large role in differences, wealth contributes as well.



(a) Earnings profiles by wealth.
(b) Piece rate by wealth.
(c) Human capital by wealth.
(d) Time allocation by wealth.

Figure 11: Profiles of income and income determinants holding initial human capital and learning fixed at median.

These profiles give insight into the effect of wealth. While the effect of wealth is smaller than in Figure 10 and dissipates over the life-cycle, it remains an important driver of differences in human capital. This also shows that careful estimation of the correlation between initial conditions are important when estimating earnings dynamics.

Next, I repeat a test from Huggett et al. (2011). I start workers in the model at the median values of each initial condition and then decrease each by a standard deviation. Huggett et al. (2011) features a model that is similar in many respects to mine, but assumes that labor markets are competitive. In that sense, this experiment shows the effect that the interaction between search frictions and wealth have on earnings and human capital. I report my findings in Table 8.

Wealth has a sizeable effect on outcomes, and is more important than initial human capital. The decrease in wealth causes declines in earnings (−5.75 percent) and job placement (−4.79 percent) that exceed the effect of human capital (−3.60 percent and −0.38 percent for income and human capital, respectively) and cause similar sized changes in human capital

Table 8: Effects of changing initial conditions on median worker

Change	Δ Consumption (%)	HVY (%)	Δ Earnings (%)	Δ h (%)	Δ τ (%)	Δ μ' (%)
Wealth -1 St. Dev.	-6.4	-1.6	-5.8	-2.5	-5.7	-4.8
Human Capital -1 St. Dev.	-3.8	-28.3	-3.6	-4.8	-5.9	-0.4
Learning Ability -1 St. Dev.	-15.5	-2.6	-16.8	-29.1	-96.3	0.3

Notes: The table presents the change in key variables for a one standard deviation change in each of the initial conditions. When a variable is changed, the other variables are left unchanged. HVY refers to Huggett et al. (2011).

(-2.53 percent vs. -4.78 percent for the decrease in wealth and human capital, respectively) and investment (-5.68 percent vs. -5.94 percent for the decrease in wealth and human capital, respectively). Changing learning ability causes the largest change in each of the variables in the table except for piece-rates.

Of particular note is that a standard deviation decrease in wealth causes a -6.44 percent change in consumption, while a standard deviation decrease in human capital only causes a -3.79 percent change. This is a notable difference between my findings and Huggett et al. (2011), who find that human capital drives nearly all of the lifetime differences in consumption. The reason is that search frictions result in income risk that has a larger effect on poor individuals, whereas idiosyncratic income risk has more symmetric effects across the wealth distribution. I explore this further in the next two sections.

5.2.2 Test 2: Eliminating Initial Inequality

Next, I consider how reductions in initial inequality affect income and its determinants across the wealth distribution. I first reduce the dispersion of each initial condition by 10 percent, while leaving the other initial conditions unchanged. I assess the effect that this reduction in inequality has on average earnings, human capital, and job placement (piece-rates) across the wealth distribution. I report my findings in Table 9.

The first surprise that this experiment reveals is that an increase in initial wealth is equally as important for poor workers as an increase in human capital or learning ability. First quintile workers experience a 0.32 percent increase in income when initial wealth dispersion is reduced by 10 percent, while they experience 0.22 percent and 0.63 percent increases when dispersion in initial human capital and learning ability are reduced by 10 percent, respectively. This increase for first quintile workers when wealth dispersion is reduced is driven by both increases in human capital (0.13 percent), and improvements in job placement (0.21 percent). While higher human capital and learning ability improve outcomes among the poor, the

Table 9: Effects of 10% reduction in initial inequality

Counterfactual	Δ Income (%) 1st	3rd	5th	Ave	Δh (%) 1st	3rd	5th	Ave	Δμ (%) 1st	3rd	5th	Ave
$\widehat{\sigma_a^2} = 0.9\sigma_a^2$	0.32	0.26	−0.11	0.19	0.13	0.09	−0.09	0.05	0.26	0.22	−0.09	0.21
$\widehat{\sigma_h^2} = 0.9\sigma_h^2$	0.22	0.22	0.03	0.16	0.33	0.34	0.15	0.28	0.05	0.03	0.02	0.04
$\widehat{\sigma_\ell^2} = 0.9\sigma_\ell^2$	0.63	0.02	−0.98	−0.20	1.26	0.93	0.08	0.72	0.03	−0.08	−0.13	−0.07

Notes: I calculate each change using the present discounted value of each variable from the perspective of an age-23 entrant. I define quintile by wealth (1st, 3rd, and 5th) in the baseline model for each worker, and subject them to the same series of shocks.

larger effect of wealth indicates that income risk heavily affects the decisions of the poor

In the aggregate, a 10 percent reduction in initial wealth inequality leads to a 0.19 percent increase in income, while equal sized reductions in human capital and learning ability inequality lead to smaller improvements (0.16 percent and -0.20 percent for human capital and learning ability, respectively). Notably, the reduction in wealth inequality leads to the largest gains of all three counterfactuals. This differs from my findings in Section 5.2.1, where the loss of learning ability caused the largest decrease in earnings.

This shows a clear pattern: reducing wealth inequality leads to increases in income for the initially wealth-poor, but has a negative effect on initially wealthy individuals. The reason is that the reduction in wealth exposes previously wealthy individuals to consumption risk, leading to a precautionary response that affects the determinants of income. Simultaneously, the increased level of consumption insurance caused by higher wealth among the poor causes the opposite effect. Wealthy individuals earn more and have higher human capital and learning ability on average, so the negative effects have the potential to dwarf the positive effects felt by the bottom of the distribution. However, the improvement in outcomes among the poor is large enough to outweigh the negative effects on the wealthy and lead to an increase on average. To understand whether the negative effect on the wealthy ultimately outweighs the positive effect on the poor, I explore how a larger change in initial inequality affects these outcomes. I completely eliminate dispersion in each initial condition while leaving the other two unchanged. I subject workers to an identical series of shocks as in the baseline model and calculate the change in the present discount value of income, human capital, and job placement (piece-rates) by initial wealth quintile. I report my findings in Table 10.

As with my first experiment, decreasing wealth dispersion leads to an improvement in outcomes that vary by wealth. Eliminating initial wealth inequality leads to an 1.03 percent increase in income, driven by both higher average piece-rates (1.42 percent) and human

Table 10: Effects of eliminating dispersion in initial inequality

	Δ Income (%)				Δh (%)				$\Delta\mu$ (%)			
Counterfactual	1st	3rd	5th	Ave	1st	3rd	5th	Ave	1st	3rd	5th	Ave
$a_0 = E[a_0]$	5.79	1.09	-2.06	1.03	1.50	0.44	-1.33	0.12	5.44	0.89	-1.84	1.42
$h_0 = E[h_0]$	1.74	-0.65	-3.40	-1.10	3.16	0.69	-2.14	0.23	0.69	-0.16	-0.52	-0.01
$\ell = E[\ell]$	24.85	1.24	-17.97	-1.07	37.75	11.32	-8.37	9.65	1.26	-0.51	-1.35	-0.29

Notes: "1st", "3rd", and "5th" refer to the first, third, and fifth quintiles of the age-23 wealth distribution, while "Ave" denotes the outcomes of the average individual. Each entry denotes the change in income, human capital, or piece-rate for the group in the column, relative to the same group in the baseline. I calculate each change using the present discounted value of each variable from the perspective of an age-23 entrant. I define quintile by wealth (1st, 3rd, and 5th) in the baseline model for each worker, and subject them to the same series of shocks.

capital (0.12 percent). Once again, reducing wealth dispersion causes a larger increase in income than identical reductions in human capital dispersion (-1.10 percent), but this time also has a larger effect than reducing learning ability inequality (-1.07 percent)

The improvements are larger than the test in Table 9, indicating that the loss of insurance among the wealthy is again smaller than the benefits of additional consumption insurance among the poor. Starting instead with average wealth produces *slightly* worse outcomes for individuals who are in the top quintile in the baseline model. This is because some previously wealthy workers experience sequences of negative employment and income shocks and are less able to insure against them than in the baseline. The source of importance for learning ability is also clear from the top quintile of the wealth distribution.

5.3 The Interaction between Wealth, Search, and Human Capital

In this section I demonstrate that an interaction between wealth, search, and human capital is key for explaining my quantitative findings in Table 10 and Table 8. In Section 5.3.1, I conduct an experiment to compare the precautionary effects on human capital in my baseline model to the precautionary effects on human capital in a canonical heterogeneous agent (Bewley (1986)-style) model to show how wealth and search interact and affect life-cycle human capital and income.

5.3.1 Decomposing the Interaction

I start by showing that the interaction between search, wealth, and human capital is an important determinant of the effect that wealth has on lifetime inequality. Search frictions amplify income risk for poor workers which leads to lower human capital accumulation and as a result, worse lifetime outcomes. I first restrict my baseline model so that the precautionary motive no longer affects a worker's decision to accumulate human capital. I compare this counterfactual to my baseline model to determine the effect that insuring against unemployment has on human capital in my baseline model. Then I remove search as a source of income risk by constructing a Bewley (1986)-style model with the same human capital environment as in my baseline model. I further restrict this Bewley (1986)-style model to determine how much of the precautionary effect on human capital is due to search frictions.

I define the precautionary motive on human capital to be the human capital forgone in order to insure against income risk. This occurs in my model because wealth and search affect the portfolio allocation decision as I describe in Section 5.1.2. Poor workers have a higher marginal utility of consumption, which causes the solution to this portfolio allocation decision to bind at lower values of τ, which leads to a slower rate of human capital accumulation. The goal of comparing my counterfactual models is to (i) quantify the size of the precautionary motive, (ii) determine how much of the precautionary motive is caused by search frictions, by assessing how much each affects the outcome of this portfolio allocation decision.

My first counterfactual restricts this precautionary motive in my baseline model. I do this by using decision rules from my baseline model, but imposing that workers decide on their portfolio allocation as though they have the average level of wealth for their age in my simulations. This yields investment and savings decisions given by $\tilde{\tau}_t(\mu, a, h, \ell) = \tau_t(\mu, \bar{a}_t, h, \ell) \forall\ t$ and $\tilde{a'}_t(\mu, a, h, \ell) = a_t(\mu, \bar{a}_t, h, \ell) \forall\ t$, respectively, which I rescale to respect the individual budget constraint. I compare human capital accumulation in this environment (which I refer to as R1) to my baseline model to quantify the size of the precautionary motive on human capital by initial wealth quintile and present my findings in Table 11.

Table 11: Income risk and human capital in baseline model

	$\Delta\tau$ (%)				Δh (%)			
Counterfactual	1st	3rd	5th	Ave	1st	3rd	5th	Ave
%Δ(Base→R1)	33.18	17.84	6.42	16.51	6.01	4.90	1.36	4.09

Notes: I calculate each change using the present discounted value of each variable from the perspective of an age-23 entrant in both the baseline and R1 restricted model. 1st, 3rd and 5th refer to the first, third, and fifth age-23 wealth quintile.

This shows that the effect of income risk is sizable in my baseline model and varies by wealth. If a first quintile worker allocated their portfolio as though they had the average level of wealth, their learning time would increase 33.18 percent, causing an increase of 6.01 percent in human capital over the life-cycle. For an average worker, a 16.51 percent increase in learning time leads to an 4.09 percent increase in human capital. I even find a positive effect for the fifth quintile because initially wealthy workers who experience a sequence of negative shocks invest more than in the baseline model.

Next, I determine how much of these findings can be explained by search frictions. I do this by comparing my findings in Table 11 to an identical experiment performed in a heterogeneous agent model. I start with a Bewley (1986)-style model that includes Ben-Porath human capital accumulation.[12] 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). I present this model in the online appendix in Section A.4.1. I subject workers in this model to an identical sequence of shocks (δ and ϵ) and impose the same 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.

To determine the effect of income risk in my Bewley model, I conduct the same experiment as I do in my baseline model. I use decision rules from the Bewley model, but impose 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 (Restriction 2) in Table 12. Differences between the Bewley-model and its restricted version quantify the size of the precautionary effects caused by the idiosyncratic income risk present in the Bewley model. Taking the difference between my results for the baseline model from Table 11 and these results yields the percentage point change in human capital and τ caused by the interaction between wealth and search.

Table 12: Impact of wealth and search on human capital

	$\Delta\tau$				Δh			
Counterfactual	1st	3rd	5th	Ave	1st	3rd	5th	Ave
%Δ(Bewley$\rightarrow$R2)	15.15%	12.49%	6.80%	11.16%	3.29%	3.75%	2.16%	3.19%
Effect of Wealth x Search	18.03pp	5.35pp	-0.37pp	5.35pp	2.72pp	1.16pp	-0.80pp	0.90pp

Notes: The "Effect of Wealth x Search" row is calculated by subtracting $\%\Delta(Base \rightarrow R1)$ in Table 11 from $\%\Delta(Bewley \rightarrow R2)$ in this table. I define quintile by wealth (1st, 3rd and 5th) at age-23 in the baseline model for each worker and calculate the change by taking the discounted present value of each variable from the perspective of an age-23 entrant.

These findings indicate that the interaction between wealth, search constitutes a sizable impact on human capital. Eliminating the precautionary motive caused by the interaction between wealth and search causes a 0.90 percentage point increase in human capital on average and 2.72 percentage point for the first quintille. This also shows that the idiosyncratic income risk in the Bewley model also induces a precautionary motive on human capital (3.19

[12] This model is closely related to the model in Huggett et al. (2011), and differs in that it does not contain a labor-leisure choice or an endogenous interest rate.

percent on average, 3.29 percent for the first quintile) and is more important than search for higher quintiles.

Now I take use these findings to show that the interaction between wealth, search, and human capital contributes to differences in income. I do this by first calculating the percent difference in lifetime income (discounted to the present) for quintiles of the wealth distribution and comparing them to the average individual. Then I calculate the percent that is explained by the effect of wealth and search on human capital that I calculated in Table 12. This measures the impact that the interaction between wealth, search, and human capital has on income across the wealth distribution, relative to an average individual. I present my findings in Table 13.

Table 13: Impact of interaction (wealth, search and human capital) on income

Counterfactual	1st	3rd	5th
%ΔIncome (Base→R1)	41.11%	3.24%	−26.87%
% Explained by Interaction	6.61%	35.69%	2.98%

Notes: The "Explained by Interaction" is calculated by dividing the "$\%\Delta Income(Base \rightarrow R1)$" with "Effect of Wealth x Search" in Table 12, where interaction refers to the interaction between wealth, search, and human capital. I calculate each change using the present discounted value of each variable from the perspective of an age-23 entrant. I define quintile by wealth (1st, 3rd, and 5th) at age-23 in the baseline model for each worker.

The interaction is important for each quintile of the wealth distribution. Over the life-cycle, both the first and third quintiles receive lower than average income (the first line in the table), while the fifth receives substantially more. For the first quintile, the interaction between wealth, search, and human capital explains 6.61 percent of the overall precautionary effect of wealth on income. For the third quintile, the interaction explains a larger 35.69 percent, caused by the right-skewness of the wealth distribution relative to the learning ability distribution, which indicates that workers with higher learning ability can be heavily affected by the interaction between wealth, search, and human capital. Although much of the difference for the fifth quintile is caused by their higher levels of initial human capital and learning ability, the interaction still causes 2.98 percent.

These findings show that the interaction between wealth, search and human capital is important for lifetime income. Wealth and search interact and depress the human capital accumulation of workers throughout the life-cycle. This leads to a persistent reduction in income for these workers that varies across the wealth distribution.

5.4 Direct Evidence of the Mechanism

In this section, I provide additional evidence to corroborate the mechanism in my model. I show that the data suggests that low-wealth employed workers respond differently than their wealthier peers when exposed to employment risk and that this response negatively affects earnings. I conclude by showing that a model with learning-by-doing human capital accumulation that is otherwise identical cannot rationalize these regularities.

5.4.1 The Scarring Effects of Employment Risk by Wealth

My findings in Section 2.2 indicate that job separation is more costly and persistent for low-wealth workers. How does this affect employed workers? If workers are forward-looking, it would be reasonable to expect poor workers to take precautionary measures to insure against the the consumption risk associated with job loss. While a precautionary response could take many forms, I focus on whether employment risk has an effect on future earnings that varies by wealth, which I interpret as an effect on human capital. I define employment risk as the probability of being unemployed at the time of an interview after being employed at the time of the previous interview, meaning that employment risk encompases both separation risk and job-finding risk, and more closely measures the degree of consumption risk caused by the spectre of unemployment.

Because I cannot directly observe the degree of exposure to employment risk for an employed worker, I proxy for employment risk with deviations in the employment rate by industry from the previous trend. While in some settings this might provide a plausibly exogenous source of variation in employment risk, it is unlikely to be true in general and I only rely on it as an additional regularity to understand through the lens of the model.[13] I calculate this proxy by using information on separation rates in previous years to predict the likelihood of separation in the current year by estimating Equation 5.2.

$$E2U_{i,t} = \beta_0 \times Ind_{i,t} + \beta_1 \times Ind_{i,t} \times t + \epsilon_{i,t},\ t < j \tag{5.2}$$

where j is the current year, meaning that I use only information from prior years to predict future employment risk. This can be interpreted as a best linear prediction by a worker of their future employment risk. I scale this variable by 100 to yield the percentage point deviation from trend.

For my main analysis, I interact my proxy with an indicator for whether an individual is in

[13] I assume that workers can predict trends in separations by using available data on each industry, but cannot predict fluctuations around this trend. This means that although a worker may select into an industry based on its job security, these fluctuations are plausibly unanticipated.

the second through fifth quintiles of the wealth distribution. I then estimate how employment risk affects earnings over horizons that range from 1 to 5 years. To do this, I estimate the specification given by Equation 5.3.

$$\begin{aligned}(5.3)\quad ln(W_{i,t+n}) = \beta_0 + \beta_1 \mathbb{1}_{a>\tilde{a}^1} + \beta_2 \widehat{EmpRisk}_{i,t} + \beta_3 \mathbb{1}_{a>\tilde{a}^1} \times \widehat{EmpRisk}_{i,t} + \beta_4 ln(W_{i,t-1}) \\ + \delta_s + \delta_t + \beta_5' X_{i,t} + \epsilon_{i,t+n}\end{aligned}$$

where $\widehat{EmpRisk}_{i,t}$ is the proxy for employment risk and the set $X_{i,t}$ is identical to the set specified in Section 2.2.1.

I follow largely the same sample restrictions as in Section 2.2.2. The main difference is that a larger pool of employment spells allows me to restrict the sample I use for my main specification (Equation 5.3) to male heads of households. In addition, I restrict my sample to individuals who remain with their current employer (neither experience a job loss, nor a change in employers) during the year in which they are surveyed. In Table 2 of the online appendix, I report summary statistics of my sample for the first and second quintiles of the wealth distribution as well as for quintiles 2 through 5 pooled together. Although the first quintile differs from higher quintiles in possibly important ways (shorter tenure, lower previous income, etc.), they face similar degrees of employment risk (a difference of less than 0.08 percentage points). In addition, the first and second quintile appear similar along nearly all dimensions. The most sizeable difference is in wealth: the second quintile is more than $20,000 richer than the first quintile.

5.4.2 Empirical Findings

I find evidence of an interaction between wealth and employment risk, and that this interaction depresses the earnings growth of low-wealth workers. Table 14 reports my findings.

The first two columns show the results for the sample that includes all wealth quintiles. The last two columns restrict the sample to only the first and second quintiles of the wealth distribution. Both show evidence that employment risk has a larger effect on low-wealth workers than wealthier workers and that this effect is tends to be negative. The last two columns suggest that even among relatively-poor first and second quintile workers, wealth continues to play a role even among observably similar workers.

In Section A.1.1 of the online appendix, I show that this finding is robust to alternate specifications and sample selection criteria. I first interact wealth quintile with other variables that may be plausibly related to future earnings, including race, education, marital status, previous income, and months of tenure to address concerns about selection (columns 1 and 2). Seond, I include job changers in my baseline sample to show that these effects persist even

	Unanticipated Employment Risk Proxy			
	Emp. Risk	X >1st Quintile	Emp. Risk	X 2nd Quintile
1 Year	-0.0148***	0.0062	-0.0147**	0.0083
	(0.0054)	(0.0058)	(0.0060)	(0.0084)
2 Years	-0.0122	0.0109	-0.0151*	0.0087
	(0.0075)	(0.0070)	(0.0089)	(0.0074)
3 Years	-0.0217**	0.0248**	-0.0290**	0.0206*
	(0.0096)	(0.0099)	(0.0113)	(0.0122)
4 Years	-0.0417***	0.0495***	-0.0481***	0.0583***
	(0.0097)	(0.0087)	(0.0119)	(0.0129)
5 Years	-0.0223*	0.0325**	-0.0295**	0.0381**
	(0.0127)	(0.0143)	(0.0149)	(0.0161)
Observations	2740		989	

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

Table 14: Main Findings. 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. Clustered standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

among workers who change jobs, and I present these results in columns (3)-(4) of Table 4 of the online appendix. I also repeat the same analysis using months of tenure with a current employer as a proxy for employment risk (columns 5 and 6). In each robustness check, I find results that coincide with my main findings, though the findings are muted over longer horizons for the tenure proxy.

It is worth noting that although this supports my mechanism, it is not the perfect evidence. My findings in Section 2.1 provides evidence that wealth affects job search. Neither the findings presented in this section, nor my findings on unemployment scarring by wealth (Section 2.2) show direct evidence that my model is the correct one for explaining these phenomena. Ideally, I would be able to provide two additional pieces of evidence: that with the appropriate set of controls, low-wealth workers have shorter unemployment spells and that relative to high wealth workers, the poor experience higher wages early in the life-cycle. The former is suggested by my findings on job-to-job mobility, while the latter is implied by my age-earnings regressions by wealth quintiles. Unfortunately, isolating the effect of wealth on these findings separately from ability presents a serious empirical challenge. The available datasets either have sparse data on proxies for ability or wealth. As I showed in Section 4.4 my model is able to qualitatively match both sets of moments. I also show in the next section that the evidence presented here cannot be rationalized in models with exogenous human capital accumulation, but is consistent with my model.

5.4.3 Model Comparison

Now, I demonstrate that allowing workers to choose human capital accumulation on the job is important for explaining my findings in the previous section and that this is the source of the interaction between wealth, search, and human capital. I first consider a similar environment in which human capital accumulation is "Learning-by-Doing" (LBD), which does not allow for this interaction. Then, I show that while my model can qualitatively replicate my findings in Section 5.4.2, the LBD model is unable.

First, I introduce the LBD model and discuss the key differences between it and my model. I select LBD human capital accumulation, where human capital grows while employed and depreciates when unemployed, because it is far more common in search models of the labor market.[14] These two approaches differ in two important ways. First, Ben-Porath (1967) technology assumes that accumulation is a choice made each period by the worker, while the rate of accumulation is exogenous in LBD, although it may vary exogenously over time. Second, human capital accumulation is rival with income with Ben-Porath (1967) technology, but is nonrival under LBD.[15]

The differences between these two approaches affect their predictions about the response of wealthy and poor workers to employment risk. With either LBD or Ben-Porath (1967) technology, poor workers experience large unemployment scarring effects if they are risk averse and face incomplete markets. How workers prepare for possible future unemployment spells is vital: In my model, poor workers anticipate that unemployment is costly when poor and reduce their human capital accumulation to build consumption insurance through precautionary savings. This causes different rates of human capital accumulation in my model for wealthy and poor, all else equal. This margin is not present in a model with LBD accumulation. As a result, my model is able to rationalize the different responses to employment risk by wealth that I observe in the data.

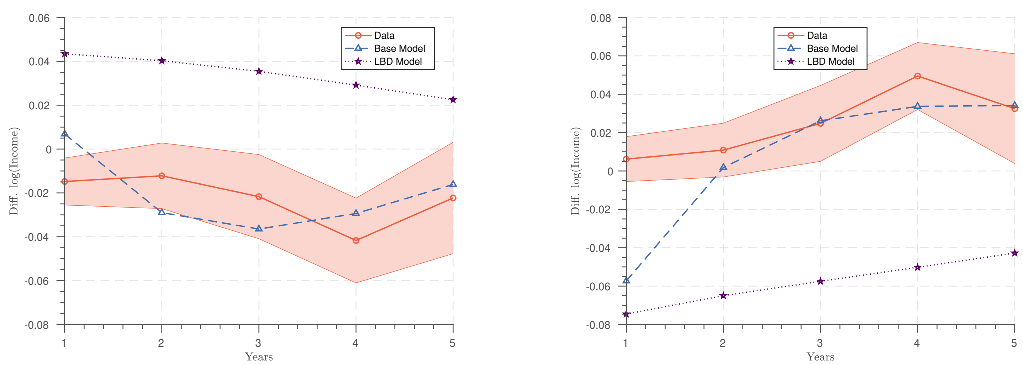
To implement LBD in my baseline model, I adjust the problem of the employed worker (Equation 3.6) so that human capital accumulates at a rate $h' = e^{\epsilon'}\left(h + \ell\left(h\bar{\tau}\right)^{\alpha}\right)$, where $\bar{\tau}$ equals the average τ over the life-cycle. I leave the model otherwise identical and present the changes to the worker and firm problems in online appendix Equation A.4.2. This allows workers to have individual differences in human capital growth based on their learning ability or current human capital, but cannot adjust their accumulation in response to changes in employment risk.

[14] To my knowledge, the only other paper that uses Ben-Porath (1967) is Bowlus and Liu (2013).

[15] While allowing for complete flexibility in adjusting training may seem unappealing, it is worth noting that when jobs have a limited scope for intensive margin adjustment of training, workers may select over jobs as bundles of training and production and endogenously generate a similar outcome (Heckman et al., 2002).

I now describe how I implement varying exposure to employment risk in my baseline model as well as the LBD model. I start agents with a draw from the age - t distribution of wealth, human capital, and learning ability and employment at a firm that offers the average piece-rate for their age. At age - t, these agents are unexpectedly subject to a change in their separation risk. They receive a new separation probability between $\delta = 0.01$ and $\delta = 0.05$ and subsequently make decisions knowing that this is a permanent shock. I then calculate employment risk as the probability that an individual separates times the probability that they are unable to find a job during the next year, identical to my definition of employment risk in Section 5.4.1.

I focus my comparison between models on employment risk because this allows me to show that the LBD model which includes an interaction between wealth and search, but lacks an interation between wealth, search, and human capital, is not able to explain the responses to employment risk by wealth.[16] I present the results for in Figure 12. I show the effect of employment risk for the first quintile in the left panel and compare the data (orange, solid with circles) to my baseline model (blue, dashed with triangles), and the LBD model (purple, dotted with stars). In the right panel I show how the degree to which being in wealth quintiles two through five reduces the response to employment risk (the interaction term in my regression specification) varies between models.



(a) Q1 employment risk effect.

(b) Q2-Q5 employment risk effect.

Figure 12: Employment risk comparison. The shaded region in both figures correspond to the 95% confidence intervals in the data.

Outside of the first year for quintiles 2 through 5, my baseline model again does a good job replicating my findings in the data. While the effect of an increase in employment risk is initially negative for higher quintiles (right panel), they experience a much smaller decline than the first quintile (left panel). The model initially predicts a negative effect on earnings for wealthier quintiles as they reduce the time spent accumulating human capital less than

[16]In Section A.1.2 of the online appendix, I show that both models exhibit differences in unemployment scarring effects by wealth, but the effect does not persist in the LBD model, unlike my baseline model.

their first quintile peers. Over longer horizons, the effect of this reduction in learning begins to take hold for the first quintile, who experience a negative effect on their earnings, while wealthier quintiles are unaffected.

By contrast, the LBD model makes counterfactual predictions for both wealth groups. For the first quintile, the LBD model predicts a far less severe response to employment risk than either the data or my baseline model. For higher quintiles, the effect of employment risk is counterfactually negative in the LBD model, indicating that employment risk is far worse for wealthy individuals relative to the first quintile. As the figure shows this prediction is entirely inconsistent with the data.

6 Policy Experiment

My findings show that separation and employment risk plays an important role labor market outcomes and the formation of human capital. Can policies enacted to limit consumption risk during unemployment ameliorate these effects? In this section, I explore this question by considering an expansion of unemployment insurance. I do this by implementing an increase in unemployment insurance generosity and eligibility that mirrors a proposed expansion during the Covid-19 crisis. I find that a lump-sum UI policy has large positive effects both for lifetime incomes and human capital.

6.1 Expanded Unemployment Insurance

I implement an expansion in unemployment insurance that mirrors a proposal by Senate Republicans during the Covid-19 crisis. I do this not as an endorsement of this particular policy, but because it is a specific proposal that spells out expansions along four key dimensions of standard unemployment insurance: it proposed to increased each state's UI cap by $500, extend eligibility by 13 weeks, and it would have initially allowed a lump-sum $200 per week payment that would eventually shift to a 70 percent replacement rate. I consider this proposal as two policies: one in which generosity is expanded by a lump-sum $200 payment, and another in which the replacement rate is increased to 70 percent, both following the proscribed changes to eligibility and the cap.

I compare each counterfactual to my baseline economy in Table 15. I focus on the impact of each policy on lifetime income, human capital, and employment. I do this for each quintile of the initial wealth distribution.

My findings show a clear advantage for the lump-sum payments. Under the lump-sum plan, lifetime income increases by 1.84 percent, while the increases in replacement rates cause

Table 15: Unemployment Insurance Policy Comparison

	Δ *Labor Income* (%)				Δ *Employment* (%)				Δ h (%)			
Counterfactual	1st	3rd	5th	Ave	1st	3rd	5th	Ave	1st	3rd	5th	Ave
$200 Lump-Sum	2.78	1.45	1.30	1.84	0.30	0.30	0.09	0.21	4.20	4.04	2.35	3.58
70% Rep. Rate	0.50	−0.44	0.02	−0.08	−0.24	−0.15	−0.18	−0.19	−0.26	−0.58	−0.30	−0.43

Notes: I calculate each change using the present discounted value of each variable from the perspective of an age-23 entrant in the baseline and in under each alternative UI policy. 1st, 3rd and 5th refer to the first, third, and fifth age-23 wealth quintile of each individual in the baseline model. Ave refers to the present value of the average individual at each age.

a small decrease of 0.08 percent. Behind this dichotomy is a stark difference in their effects on human capital: the lump-sum payment scheme causes a 3.58 percent increase in human capital, while the higher replacement rate yields a decrease of 0.19 percent. Underlying this change is a sizable difference in the effects on human capital investment: for the lump-sum plan, investment increases by 13.8 percent, but falls by 2.05 percent when replacement rates are increased. Along each of these dimensions, the bottom quintile experiences the largest gains in the lump-sum plan and smallest losses under the replacement rate plan.

The reason for this difference is that increases in replacement rates have competing effects on investment that dampen their effectiveness in my model, while the lump-sum payments unambiguously increase investment. While an increase in replacement rates provides additional consumption insurance, it requires workers to forgo more unemployment insurance to invest in human capital at the margin. These effects partially offset, limiting the scope for improvement. Under the lump-sum plan, there is no such disincentive, causing a sizable increase in human capital. Both plans initially cause longer unemployment durations, leading the replacement rate plan to an overall decline in human capital, while this effect is eventually overcome under the lump-sum plan through higher job-finding rates that result from higher human capital.

Last, I calculate the net benefit of each policy, subtracting the present value of the increased UI payments from the increased income. I find that the replacement rate policy produces a return of -$0.06 per dollar spent, while the lump-sum policy produces a return of $1.49 per dollar spent, both in present value terms. This indicates that in addition to producing better outcomes, the lump-sum policy is more cost-efficient, and provides suggestive evidence that other lump-sum income replacement policies may be even more effective.

7 Conclusion

A fundamental question in economics is whether lifetime differences are determined by innate productivity and ability, or whether different market imperfections also play a role. In this paper, I show that search frictions negatively affect the subsequent earnings and human capital of workers who are initially wealth-poor and that these effects are large and persistent.

I do this by constructing and estimating a life-cycle model of inequality and human capital accumulation. In the model, risk averse workers must search for employment and make a portfolio allocation decision between precautionary savings and human capital accumulation. Poor workers resolve their search decisions by accepting lower-pay jobs, which lead to subsequently lower earnings. In anticipation, low-wealth workers work extra hours to build savings, instead of using that time to build their human capital like their wealthier peers. This leads to persistently lower human capital in addition to worse job placement.

I show that unlike previous work on inequality, differences in wealth can cause sizable differences in consumption, income, and human capital over the life-cycle. Importantly, I find that these effects can be as large or larger than those of both differences in initial human capital and learning ability depending on the counterfactual. This differs from previous work that concluded that the effect of wealth was negligible and paled in comparison to that of human capital, because my model features an important interaction between wealth and search that affects human capital. This interaction is absent in competitive models of the labor market.

My findings suggests many avenues for future work. Labor market risk plays a substantial role in human capital formation in my model, which suggests that recessions may differentially affect poor and wealthy individuals and could affect aggregates if enough workers lack the savings to insure their consumption. The model may also provide justification for government programs aimed at increasing consumption insurance, like the earned income tax credit and universal basic income, because it is likely that these policies would permanently increase human capital in my model.

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