Borrowing Constraints, Search, and Life-Cycle Inequality

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Abstract

This paper quantifies the impact of borrowing constraints on life-cycle inequality through search frictions. I document a set of empirical regularities about the labor market behavior of borrowing constrained households using the Survey of Income and Program Participation (SIPP). Following unemployment spells, likely-constrained households match to jobs that pay 6 percent more per quarter when they receive a 10 percent increase in their unemployment insurance. I construct a life-cycle model of labor market search to assess the size and mechanisms through which borrowing constraints impact inequality. The model features risk averse workers who face borrowing constraints, accumulate human capital endogenously, and search both on and off the job. I use indirect inference to estimate the model, and show that borrowing constraints contribute to both placement into lower-paying jobs as well as slower human capital accumulation. Overall, I find that a standard deviation change in initial wealth is twice as important in determining life-cycle consumption and earnings inequality relative to a standard deviation change in initial human capital.

JEL Classification: E21, E24, J63, J64, D31, I32, J31
Keywords: Directed Search, Borrowing Constraints, Inequality, Human Capital

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1 Introduction

Households accumulate substantial amounts of debt by the time they enter the labor market. A worker at their first full-time job spends 18% of their income on debt payments, and of those workers more than 40% report denial of requested additional credit (Survey of Consumer Finances, 2013). This paper argues that borrowing constraints impact labor market outcomes, on-the-job human capital growth, and create persistent inequality among individuals with different levels of initial wealth. I show that borrowing constraints initially change the types of jobs constrained individuals acquire, and once employed cause them to substitute future wage growth in exchange for precautionary savings. Using the Survey of Income and Program Participation (SIPP), I find evidence that the job search of constrained households is affected by the replacement rate of their state’s unemployment insurance system. Constrained households in states with less generous benefits find lower-paying jobs at a faster rate than peers in states with more generous UI. Moreover, I find evidence that this effect persists. I assess the relationship between borrowing constraints, search frictions, and inequality by constructing a life-cycle model with search, incomplete asset markets, and human capital accumulation. I estimate the model and find that a standard deviation decrease in wealth at age 23 depresses income and consumption by more than a standard deviation decrease in human capital accumulation. This occurs in my model because constrained individuals apply for lower-paying, more easily obtainable jobs than their wealthier unconstrained peers, and then choose to substitute future human capital growth for precautionary savings.

To motivate the theory, I use the SIPP to show evidence that borrowing constraints alter employment outcomes following an unemployment spell. I exploit differences in replacement rates across states to estimate the differential effect that unemployment insurance generosity has on constrained and unconstrained households. My findings suggest that when households face constraints they change their search behavior: households from the first quintile of the liquid wealth distribution match to 7% higher paying jobs when given a 10% increase in unemployment insurance, despite nearly identical pre-spell earnings, tenure, and education. Like other recent studies on UI (Schmieder et al., 2016), I find that increases in potential UI duration negatively affect wages after exiting unemployment. However, I find that the effect is only significant for the wealthiest households. Over longer horizons, I find that the effects

\[ \text{Herkenhoff et al. (2016) find evidence that access to additional credit improves labor market outcomes following an unemployment spell.} \]
on wages appear to persist.

I construct a model to quantify the effect of borrowing constraints on post-schooling inequality in earnings and consumption. I start with a life-cycle model of on-the-job directed search with wage posting, building off the work done by Menzio et al. (2016) and Herkenhoff (2014). I consider risk averse households, a natural borrowing constraint, and Ben-Porath (1967) human capital accumulation. Risk aversion causes workers to strongly dislike periods of low consumption, and incomplete asset markets limit the ability of workers to directly substitute future into to younger ages in order to smooth consumption. Directed search allows workers to choose the degree of income (and consumption) risk that they face by directing their search to jobs who offer lower wages, but more likely employment. Ben-Porath human capital accumulation allows employed workers to allocate productive time between working and accumulating human capital without pay.\textsuperscript{4} This gives workers an alternative route to move income over the life-cycle: workers can substitute potential future income into the present by allocating more time to production instead of human capital accumulation. The model includes initial heterogeneity in wealth, human capital, and learning ability, each of which are important for understanding lifetime inequality.

To quantify the role of borrowing constraints, I estimate the model using indirect inference. I use findings from the SIPP as well as life-cycle growth rates from the Panel Study of Income Dynamics (PSID) and the National Longitudinal Study of Youth (NLSY79) to discipline key features that determine the behavior of agents in my model. The moments from the SIPP yield inference on borrowing constraints, as well as tradeoffs between earnings and unemployment duration. Moments from the PSID and NLSY provide inference on the correlations between wealth, human capital, and earnings throughout the life-cycle. The model is able to match these regularities as well as a number of non-targeted moments, giving credibility to my estimation strategy.

I find that constrained agents choose to decrease their consumption risk by applying to jobs that offer shorter expected unemployment durations, but lower wages. Wealthy workers are able to smooth consumption, and can experience extended unemployment spells while finding better employment. Though the estimation suggests that poor and wealthy individuals have similar productivities (initial productivity differences are less than 10%), their differences in wealth lead to large differences in earnings at their first jobs. I find that this

\textsuperscript{4}My paper is perhaps the first to incorporate Ben-Porath (1967) into an environment with risk aversion and incomplete markets, but not the first among search models. Bowlus and Liu (2013) do the same for a model with linear preferences and explore the contributions of search and human capital to wage growth.
effect extends beyond first employment, even among equally-able individuals: when faced with a decision to allocate time between working and acquiring human capital, wealthier employed individuals invest more time in human capital accumulation, knowing that the associated pay-cut will have little consequence on their ability to smooth consumption. Individuals with less wealth devote more time to production, slowing their human capital growth, but increasing their precautionary savings. In combination, this decouples the negative relationship between initial earnings and future earnings growth that is common among both search papers where employers contract on future growth (Burdett and Coles, 2010) and papers that employed Ben-Porath human capital production.

My findings suggest that borrowing constraints amplify inequality when workers face frictional labor markets. Differences in wealth among similarly productive individuals can lead to long-term differences in earnings and substantial lifetime consumption inequality. For the average individual, I find that a standard deviation decrease in initial wealth depresses lifetime consumption by more than a standard deviation decrease in initial human capital, −4.6% to −3.2%, and has a similar effect on lifetime earnings −4.6% to −3.2%. Wealth operates primarily by changing application strategies (XX%), but also changes lifetime human capital (XX%). I also find that the average individual at the 10th percentile of the wealth distribution experiences a lifetime earning increase of −4.6% when given the median wealth in the sample.

The paper is organized as follows: in Section 2 I review the literature and describe how previous work differs from mine. In Section 3 I document liquidity effects on re-employment wages for constrained groups. In Section 4, I construct a model that incorporates these findings, describe the equilibrium, and derive important analytical properties. In Section 5, I explain the functional form assumptions, my construction of moments for indirect inference, and examine the out of sample fit of the estimation. In Section 6, I decompose the implications for life-cycle inequality, and compare my findings to the existing literature. Finally, in Section 7 I summarize my contributions and discuss routes for future work.

2 Related Literature

This paper addresses a question that relates to the literatures on labor market search, human capital, and inequality. While an exhaustive review of all related work is not possible, I summarize many of the most closely related papers in this section.

Likely the most similar paper is Graber and Lise (2015), which investigates facts about
the age-profile of consumption and earnings variance within a model that features borrowing constraints, search, and human capital accumulation. They argue that such a model is required to match life-cycle facts about the variance in earnings and consumption (they increase roughly linearly) and the negative skewness of earnings changes. While both papers focus on inequality, I focus on inequality that results from initial conditions, while they focus on inequality in response to shocks over the life-cycle\(^5\). Our models also differ in that I endogenize human capital accumulation as well as the match rate between workers and firms. They employ a “learning-by-doing” human capital accumulation technology, which is essentially an exogenous positive drift while employed\(^6\). As my findings indicate, endogenous human capital accumulation plays an important role in lifetime inequality in models with borrowing constraints. Our findings are complementary in that they demonstrate that a model with similar features is needed to explain higher order life-cycle moments. Bowlus and Liu (2013) is the only other paper to include a model with both search and Ben-Porath (1967) human capital accumulation. Their main results focus on the decomposition of earnings growth between search frictions and human capital accumulation. Agents in their model are risk-neutral, the converse of which is the focus of my paper. Two more papers, Bagger et al. (2014) and Yamaguchi (2010) explore life-cycle wage dynamics in search models that feature human capital (through learning-by-doing). Both papers feature richer wage-setting environments (bargaining rather than piece-rate posted contracts), though neither features risk-averse agents nor borrowing constraints. In both cases, the papers primarily focus on decomposing the contributions of wage bargaining and human capital growth to wage growth.

One notable feature that distinguishes my model from much of the previous work is that my model allows both a distribution of human capital and a distribution of wealth that are determined endogenously. Burdett and Coles (2003) introduces risk averse agents into the Mortensen and Pissarides (1994) model, but restricts agents to face credit markets characterized by autarky in order to recover the structure of optimal contracts. They show that firms optimally backload contracts in order to retain workers, which generates the prediction that initially low-wage workers will achieve faster rates of earnings growth as they age. My estimation results suggest that such contracts would generate counterfactual wage profiles unless other heterogeneity was introduced into the model. Others who have introduced risk-aversion into the Mortensen and Pissarides (1994) model include Lentz and

\(^5\)Their work is a follow-up to Lise (2013), which was similar, but without human capital accumulation.

\(^6\)Recent evidence suggests that Ben-Porath (1967) human capital production accounts for life-cycle earnings growth 2-3 times better than learning-by-doing (Blandin, 2016). It’s unclear if these results would generalize to a frictional setting.
Tranaes (2005), Krusell et al. (2009), and Costain and Reiter (2008). These papers feature distributions of wealth, but do not include human capital. Building off of their previous work, Burdett and Coles (2010) introduces learning-by-doing and analyzes the structure of optimal contracts when workers accumulate general and firm-specific human capital. They again find that firms optimally backload contracts, generating faster rates of earnings growth among initially low-wage workers. In my model, this negative relationship between initial earnings and growth rates is decoupled as a result of low-wage workers substituting future earnings growth for precautionary savings.

My model also extends a recent literature on block recursive search models (Menzio and Shi, 2010) with risk aversion, first introduced by Herkenhoff (2012), to incorporate endogenous human capital. This class of models allows for substantial heterogeneity, while retaining computational tractability. A follow-up, Herkenhoff (2014), introduced directed search with risk aversion into a life-cycle version of the block recursive search model, first discussed by Menzio et al. (2016). Both Herkenhoff (2012) and Herkenhoff (2014) are focused on the effect that access to credit has on the business cycle. Another paper, Herkenhoff et al. (2016) introduces human capital accumulation into this framework, but does so through learning-by-doing, and again restrict their exploration to aggregate fluctuations. Chaumont and Shi (2017) uses a similar model of infinitely-lived agents to highlight the effects of unemployment risk on precautionary savings, noting that search frictions can substantially increase wealth inequality. Because they focus on cross-sectional dispersion, rather than life-cycle effects, they do not include human capital accumulation. They find that wealth effects alone play a small role in determining wage dispersion.

There is also a growing literature that focuses on debt and labor market outcomes. Rothstein and Rouse (2011), Luo and Mongey (2017), and Gervais and Ziebarth (2017) examine the role that student loans play in determining post-college outcomes. Gervais and Ziebarth uses the Baccalaureate and Beyond 1993 Longitudinal Study and exploit a kink in subsidized Stafford loan eligibility to show that an extra $1,000 in student loan debt at graduation decreases earnings by 2.5%. They also find that debt appears to alter occupational choice and search behavior. They don’t, however, find statistically significant persistence in these effects when they analyze outcomes in 1997 and 2003. I find similar levels of persistence among marginally constrained individuals, who constitute their primary source of identification. ? use more recent Baccalaureate and Beyond cross-sections (2000 and 2008), while Rothstein and Rouse use restricted data from a “highly selective university” (due to the nature of the data, they cannot disclose the name) to address related empirical questions. Both use varia-
tion in the ratio of grants to total loans across cohorts, but within institutions. Surprisingly, both papers find that debt increases earnings after graduation (1.21% in ? and $978 in Rothstein and Rouse). ? find that general job satisfaction as well as job fit measures decrease. While these results are quite interesting, they are challenging to interpret, as they focus on workers who obtained full-time employment immediately following graduation. Given that 2008 was the beginning of the Great Recession, it seems likely that there would be strong selection effects into who receives a full-time job following college. My paper also focuses on broader definitions of employment and debt because constrained individuals might be willing to take part-time employment to smooth consumption, and repayment of certain college loans only begins following employment. Ji (2017) studies the impact that student debt has on aggregate outcomes. He estimates a search model with borrowing constraints, risk-aversion, and a college entry decision, and analyzes the general equilibrium effects of two college debt repayment plans. To validate the mechanisms in his model, he employs the National Longitudinal Study of Youth 1997 (NLSY97) and estimates the impact that student debt has on unemployment wage income. Similar to my empirical regularities, he finds that unemployment duration and wage income both decrease when debt increase. Further, he finds that this is persistent for at least three years.

My paper also relates to the literature focused on identifying the causes of inequality. Broadly, the literature on life-cycle inequality focuses on assigning importance to initial conditions relative to shocks experienced in determining earnings or consumption variance. A small, but important distinction in my approach to inequality is that I address only the relative importance of three sources of initial heterogeneity rather than addressing whether shocks or initial heterogeneity shape earnings profiles. The most closely related, Huggett et al. (2011), studies both the relative importance of shocks and initial conditions, and the contribution of each initial condition (identical to the initial conditions in my model) to life-cycle inequality. They build a model with heterogeneity in wealth, human capital, and learning, and allow earnings to grow through a Ben-Porath production function. They find that initial conditions (age 23) determine more than 60 percent of variation in lifetime utility, but that the bulk of this results from human capital inequality. I find the opposite: that initial wealth plays a more important role in determining life-cycle inequality than heterogeneity in human capital. The difference results from my use of a frictional labor market, as opposed to competitively determined prices, which means that similarly productive individuals can receive very different earnings. Another related paper, Storesletten et al. (2004) find that transitory income risk over the life-cycle outweighs risk before entering the labor market. My
paper provides a mechanism through which transitory shocks can permanently alter long-term outcomes, which can reconcile some of the discussion about the importance of initial conditions and lifetime shocks. Two more papers, Keane and Wolpin (1997), and Heckman et al. (1998) development dynamic models of schooling, work and occupational choice, as well as human capital accumulation. They both focus on decisions prior to the period analyzed by this paper and are complementary in that they find that initial heterogeneity play substantial roles in determining long-term outcomes. Notably, the models in each of these papers include labor markets that are perfectly competitive, while my paper incorporates search frictions.

3 Empirical Regularities

I use the data to address three key empirical regularities that motivate the construction of my model. First, constrained individuals who receive more generous unemployment insurance replacement rates match to higher-paying jobs following an unemployment spell. Because unemployment insurance is a very small percentage of an individual’s lifetime income, unconstrained agents are unlikely to be affected by changes in the amount of UI they receive. Among high earners, this effect is even less-likely, as they hit unemployment insurance caps. For constrained households, however, additional unemployment insurance might afford them additional time to search and find a better job. Second, among the full-time employed, initially wealthy individuals consistently receive more training throughout the life-cycle. This suggests a link between initial wealth and human capital accumulation, which I explore further using my model. Last, I find that there are large, persistent differences in earnings among individuals with below median wealth and above median wealth. These findings are integral to my study on life-cycle inequality for two reasons: first, they show evidence that borrowing constraints affect labor market outcomes for constrained individuals, and suggest that there may be longer-term implications. Second, they form the basis for the set of moments I target when I estimate my model in Section 5.

3.1 Re-Employment Elasticities

To demonstrate the effects of borrowing constraints in the data, I show that the elasticity of the re-employment wage with respect to unemployment insurance amount is substantial.

While there is previous evidence for the effect of borrowing constraints (also known as liquidity effects in the literature) on unemployment outcomes, (Herkenhoff et al. (2016) on earnings, Chetty (2008) on durations, among others) the effects on re-employment earnings is not well-established in the literature.
for constrained individuals, but has no effect for unconstrained individuals. As a robustness check, I perform a similar exercise on employment-to-employment job transitions and find no effect. I use the 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. I detail the construction of this data in Section C.1.

3.1.1 Empirical Strategy

I do not have a direct measure of the degree to which each household is constrained, so I compare the labor market outcomes of individuals by quintiles of net liquid wealth (defined as liquid assets net of unsecured debt) in response to changes in unemployment insurance. This proxy has been used extensively in the literature (Browning and Crossley (2001), Bloemen and Stancanelli (2005), Sullivan (2008), and Chetty (2008), among others), and captures the notion that individuals with less liquid wealth are more likely to need to borrow in order to smooth consumption during an unemployment spell. The results from these previous papers suggest that unemployment insurance is used as a substitute for employment income during unemployment spells among illiquid households, suggesting that these households are indeed borrowing constrained.

Individuals frequently misreport their level of unemployment benefits; therefore, I proxy for unemployment insurance by using the state-month average weekly benefit over an unemployment spell. This provides a credible source of exogenous variation that has been used extensively in the literature: unemployment insurance replacement rates vary within a state over time as a result of changes in legislation. Because UI is only a small fraction of lifetime income, it seems unlikely that individuals would locate to a state on the basis of UI generosity. Further, among key labor market characteristics (previous wage, tenure, etc.), ?? shows that households do not appear to sort between states on the basis of UI replacement rates. I 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 UI replacement rates and UI duration generosity. I also use a linear spline of the previous annual wage to control for changes in behavior across the income distribution as well as for endogeneity with respect to ability, to the extent possible. I also include state fixed effects to control for endogeneity with respect to location choice. In other words, I exploit variation in unemployment insurance over time that is not the result of previous income, UI duration, or choice of location. Similar identification strategies are employed by
Engen and Gruber (2001), Chetty (2008), among others.

?? summarizes key employment and demographic characteristics by liquidity quintile and UI generosity. The table shows that individuals vary across the liquid wealth distribution, but do not vary by state UI generosity for characteristics that would be potential sources of concern. The first quintile shows no difference in previous wage, previous tenure, education or age, which would be areas of concern for the validity of the comparison. As noted, selecting on unemployment insurance recipients may cause bias in my estimates; however, the rates of UI takeup do not vary across wealth quintiles, which suggest that endogenous takeup is not driving the following results that I find for individuals from the first quintile. Additionally, first quintile takeup in below median UI states is lower than in states above the median, counter to what we would expect if the recipients selected along liquidity needs. Finally, the first quintile below median group is more likely to be married than the above median group, which means they are more likely to have additional sources of income during an unemployment spell.

My approach to measure the effect of unemployment insurance on re-employment wages is to use a standard Mincer equation and bin the sample of unemployed individuals into quintiles of liquid wealth. In each of the following equations, the vector of covariates includes age, race, marital status, education, tenure, as well as state and year fixed effects. It also includes interactions between net liquidity quantiles and each of industry, occupation and the log-wage spline. My main test uses the following specification:

\[
\ln(Y_{i,j+1,s,t}) = \alpha_0 + \sum_{q=1}^{5} \delta_0^q \times \ln(UI_{s,t}) + \sum_{q=1}^{5} \delta_1^q \times UIDur_{s,t} + \delta_s + \delta_t + X_{i,j,t}\beta + \epsilon_{i,j+1,s,t} \tag{3.1}
\]

where \(j\) is the previous job and \(j + 1\), the next job, reported by individual \(i\) at time \(t\) in net liquidity quintile \(q\). \(\delta_0^q\) and \(\delta_1^q\) are coefficients on the effect of UI replacement rates and duration for an individual in net liquid wealth quintile \(q\) at the start of a spell. A positive \(\delta_0^q\) indicates that more generous unemployment insurance is associated with better employment outcomes for quintile \(q\). A negative \(\delta_1^q\) indicates that longer unemployment insurance durations result in worse re-employment outcomes. Note that the vector of covariates, \(X_{i,j,t}\) includes the set of controls detailed above, meaning that a significant result will not be driven by previous wage, state of residence, previous industry or occupation, year of spell, or any
combination. The results in column 1 of Table 3.1 show that a 10% increase in UI generosity increases re-employment wages by 7%. Column 2 shows that this effect persists even when wages are averaged over the following quarter as well.

### 3.1.2 Findings

My results show that constrained workers alter their search behavior when presented with additional unemployment insurance. Likely constrained individuals are willing to trade a 6.3% increase in their next wage for a 10% increase in UI while unemployed, shown in column (1) of Table 3.1. The estimate is significant at the 5-percent level, using Taylor Linearized standard errors, the suggested variance estimator for the SIPP’s complex survey design. I also find that longer potential UI is associated with a decline in wages, though only for the wealthiest population. This is at least partially consistent with Schmieder et al. (2016), who find that increases in UI duration and hence unemployment duration have a significant negative effect on future earnings. Column (2) reports the same regression using wages from the full quarter following unemployment, and shows results of a similar magnitude. This suggests that there may be persistence in these placement effects.

Given that jobs last an average of 2.5 years (Shimer, 2005), while the average unemployment spell in my sample is less than 25 weeks, an elasticity of 0.63 strongly suggests that individuals alter their job search behavior when they are constrained and unemployed. Going into an unemployment spell, Table B.1 shows that households in states with low UI generosity look almost identical to households from states with high UI generosity from the same wealth strata. My results show that upon exiting, these households experience very different labor market outcomes.

Results clustered at the state level yield similar significance levels, and are reported in Table B.2. As a check on the credibility of my findings, I explore whether unemployment insurance generosity has any predictive ability on job-to-job (J2J) wage changes. If there were some underlying state trend over time driving my results, it would be reasonable to expect to find a similar pattern among job-to-job wage changes. Running the same regression as Equation 3.1, with wages at their new employer on the right hand side yields insignificant results for all coefficients of interest (Table B.3).
## Re-Employment Labor Income Regressions (by Net Liquidity)

<table>
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<th>VARIABLES</th>
<th>Log of Next Weekly Earnings</th>
<th>Log of Next Quarterly Earnings</th>
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<tr>
<td>Net Liq. Quintile 1 X Log of Avg. UI</td>
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<td>0.628**</td>
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<tr>
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<td>0.381</td>
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State FE X X
Year FE X X
Qtile FE + Qtile X Wage Spline X X
Ind + Ind X Qtile FE X X
Occ + Occ X Qtile FE X X

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.1: Elasticities by net liquidity quintile. Column 1 reports employment outcomes during the first month following an unemployment spell. Column 2 reports employment outcomes for wages over the first quarter following an unemployment spell. Liquid wealth quintile refers to liquid assets net of unsecured credit.

### 3.2 Life-Cycle Profiles by Wealth

To examine the correlation between initial wealth and lifetime earnings, I use the Panel Study of Income Dynamics (PSID) and National Longitudinal Survey of Youth 1979 (NLSY79), and partition individuals into their wealth quantiles before entering the labor force. I detail the sample selection as well as the construction of these profiles in ?. I first use the NLSY79 to explore the correlation between initial wealth and training hours over the life-cycle. Then
I use the PSID to explore differences in earnings. For both results, I use the following specification:

\[ Y_{i,a,s,t} = \alpha_0 + \sum_{q=1}^{5} (\delta_q^a \times \delta_a) + \delta_s + \delta_t + X_{i,a,t} \beta + \epsilon_{i,a,s,t} \]  

(3.3)

where \( Y_{i,a,s,t} \) is the outcome of interest (either training hours or log-earnings) for individual \( i \), at age \( a \), in state \( s \), in year \( t \). In each regression, I include indicator variables for education level, race, marital status, state (or region in the NLSY), year, as well as the hours worked by individual. In each case, I weight the results by the provided sample weights.

### 3.2.1 Human Capital Accumulation

I use the NLSY79 to show a correlation between initial wealth (prior to entering the labor market), and training over the duration of this study (ages 25-54). The sample is restricted to individuals employed full-time, and wealth quintiles are permanent and defined before entering the labor market. The profiles show a clear correlation between initial wealth and time training (Figure 3.1).

These measures include training outside of work as well as training sponsored by employers.

### 3.2.2 Earnings

Figure 3.2 shows the average profiles of high school and college educated individuals by their liquid wealth prior to entering the labor market.

Both figures demonstrate that individuals who enter the labor market with less wealth do not catch up to their wealthier peers, regardless of their education level.
Figure 3.1: Average hours per week spent training for individuals from across the wealth spectrum. Wealth quintiles are defined before first employment.

Figure 3.2: Earnings Profiles by initial wealth and education groupings. The left panel is high school educated individuals and the right panel is college educated individuals. For both education levels, there is a large degree of separation between laborers at age 25 that expands over the life-cycle.
4 The Model

4.1 Environment

Time is discrete and continues forever, while each agent lives deterministically for $T \geq 2$ periods. A time period in the model is one quarter. There is a continuum of both firms and workers, each of which discounts future value at the identical rate $\beta$. Workers are risk-averse, and face “natural” borrowing constraints that equal the present value of the worst series of income shocks over the lifecycle (i.e., they never bind). Workers may be in one of three employment states: employed, unemployed with unemployment benefits, and unemployed without unemployment benefits. All three types are allowed to direct their search for new contracts posted by firms.

Each worker is born unemployed without benefits, and receives a draw from a correlated trivariate log-normal distribution $\Omega \sim LN(M, \Sigma)$ of wealth, human capital, and learning ability. Each worker is endowed with one indivisible unit of labor that they can enjoy as leisure during unemployment or supply inelastically after having found a job. Leisure utility $\nu$ is assumed to be linear, $u(c) + \nu$. Employed workers transition employment states through one of two ways: with probability $\delta$, they receive a separation shock and enter unemployment, and with probability $\lambda_E \leq 1$, they are allowed to search for new employment. After receiving an unemployment shock, workers receive unemployment benefits $b_U(\mu, h) = b \times \mu \times \phi(h_t)$, where $b$ is the replacement rate, $\mu$ is their wage at the time of unemployment, and $h$ is their human capital. To match the empirical regularities, I assume that unemployment benefits are drawn from a distribution $b \sim N(\mu_b, \sigma_b)$. This enables variation across similar individuals in the amount of unemployment insurance that they receive. They stochastically lose benefits with probability $\gamma$. Agents without benefits receive $b_L \leq b_U \forall(\mu, h)$, which reflects opportunities to earn money outside the labor force. Employed workers can receive up to $\mu \phi(h)$ as income each period, where $\mu$ is their piece-rate wage and $\phi(h)$ is their productivity given their current human capital. Contracts are assumed to be renegotiation-proof, and firms are not allowed to respond to outside offers.

Workers are risk-averse, with utility $u'(c) \geq 0$, $u'(0) = \infty$, and are allowed to smooth consumption over the life-cycle by borrowing and saving at rate $r_F$. They face a borrowing limit at each age, $a_t = \sum_{j=t}^{T} \frac{b_L}{(1+r_f)^j}$. Workers are not allowed to default on any debt obligations, nor can they exit the model while holding debt. While employed, workers are allowed to devote productive time $\tau$ to accumulating human capital through a Ben-Porath production
function, $H(h, \tau, l)$, which is increasing in each of its arguments. When a worker devotes time to accumulating human capital, earnings decrease proportionally, $w = (1 - \tau)\mu \phi(h)$. All workers face an iid human capital shock each period, $z \sim N(\mu_z, \sigma_z)$, that permanently alters human capital. That is, workers choose time investment to decide the deterministic component of human capital, and are hit with a shock, making their human capital evolution $h_{t+1} = e^z(h_t + H(h_t, \tau_t, l))$. Unemployed workers cannot invest in human capital.

Firms post vacancies at cost $\kappa$ into specific submarkets that are indexed by the “type” of worker that is required for the job. These vacancies are one-firm-one worker contracts that specify the piece-rate of output paid as earnings, $\mu$, and the likelihood of receiving a job offer, $p$, which is determined in equilibrium. Submarkets are identified by the following tuple: $(\mu, a, h, l, t) \in \mathbb{R}_+ \times \mathbb{R} \times \mathbb{R}_+ \times \mathbb{R}_+$. For simplicity, I assume that the current state of the worker is observable by the firm. Following Pissarides (1985), I refer to submarket tightness as $\theta(t(\mu, a, h, l))$. Once matched, a firm receives $(1 - \tau)(1 - \mu)\phi(h)$ in profits each period. They continue until the match dissolves, either through exogenous separation or on-the-job search.

The rate at which firms and workers match in each submarket is characterized by a constant returns to scale matching function, $M(u, v)$, where $u$ is the number of unemployed searchers in the submarket and $v$ is the number of firms posting vacancies in the submarket. I define the probability at which firms meet workers as $\frac{M(u, v)}{v} = q(\theta)$, and the rate at which workers meet firms as $\frac{M(u, v)}{u} = p(\theta)$, both of which I assume to be invertible. I assume that within each submarket the free entry condition holds, meaning that firms compete away any expected profits from a vacancy.

The aggregate state of the economy is summarized by the following tuple: $\psi = (z, u, e, \rho)$. The first component is the current level of output in terms of the numeraire for each job in the economy. The second component is a function that tracks the measure of workers with assets $a$, human capital $h$, at age $t$, $u(a, h, t)$. The third determines the measure of employment for each of these same types. The last component is the stochastic process that determines newly born workers in each period. By restricting the equilibrium to be block recursive, I can redefine the aggregate state to be $\psi = z$, because neither the decision rules of the workers nor the vacancy posting decisions of the firm depend upon the distribution of workers across employment states, or the distribution of assets. I demonstrate this in Section A.1. Because the aggregate state is stationary in this model, it is suppressed in all value functions for notational simplicity.
4.2 Worker’s Problem

4.2.1 Job Search Subperiod

Each period is divided into two subperiods: job search, and production. All shocks are realized following the production period. Unemployed agents with benefits in the job search period face the following problem:

\[
R^U_t(\mu, a, h, l) = \max_{\mu'} P(\theta_t(\mu', a, h, l))W_t(\mu', a, h, l)
+ (1 - P(\theta_t(\mu', a, h, l)))U_t(\mu, a, h, l)
\]

(4.1)

where \( \mu \) denotes their piece-rate wage in their previous employment and \( \mu' \) denotes the application strategy \( \mu'(\mu, a, h, l, t) \). Unemployed searchers without benefits solve the following:

\[
R^U_t(b_L, a, h, l) = \max_{\mu'} P(\theta_t(\mu', a, h, l))W_t(\mu', a, h, l)
+ (1 - P(\theta_t(\mu', a, h, l)))U_t(b_L, a, h, l)
\]

(4.2)

where \( b_L \leq b_H \forall (\mu, h) \). Employed workers are allowed to search on the job, and maximize the following program:

\[
R^E_t(\mu, a, h, l) = \max_{\mu'} \lambda_E P(\theta_t(\mu', a, h, l))W_t(\mu', a, h, l)
+ (1 - \lambda_E P(\theta_t(\mu', a, h, l)))W_t(\mu, a, h, l)
\]

(4.3)

4.2.2 Production, Savings, and Human Capital Accumulation Subperiod

Following search decisions, all workers enter the production subperiod. Unemployed agents choose consumption and savings to enter the following search subperiod with, and face shocks to their benefits (if they have any) and human capital after these decisions. Unemployed agents with unemployment benefits in the economy face the following problem:

\[
U_t(\mu, a, h, l) = \max_{c, a'} u(c) + \nu + \beta E[(1 - \gamma)R^U_{t+1}(\mu, a', h', l) + \gamma R^U_{t+1}(b_L, a', h', l)]
\]

(4.4)
\[ \text{s.t. } c + a' \leq (1 + r_F)a + b\mu(h) \]  
\[ a' \geq a \]  
\[ h' = H(h, U) \]  

Where \( a \) is their current net assets, and \( h \) is their current human capital level, and \( l \) their fixed learning ability. Unemployed agents face shocks to both their benefits, which they lose with probability \( \gamma \), and their human capital, which depreciates stochastically with probability given by \( H(h, U) \). They make choices over consumption, \( c \), assets to save or borrow, \( a' \), at risk-free rate, \( r_F \), subject to the natural borrowing limit \( a_t \). Following these decisions, they age and receive benefits and human capital shocks. Unemployed agents without UI face the following problem:

\[ U_t(b_L, a, h, l) = \max_{c, a'} u(c) + \nu + \beta E[R_{t+1}(b_L, a', h', l)] \]  
\[ \text{s.t. } c + a' \leq (1 + r_F)a + b_L \]  
\[ a' \geq a \]  
\[ h' = H(h, U) \]  

Where \( b_L < b_H \). Without benefits, these workers have no probability of receiving benefits again without first becoming employed. Unemployed agents of both types die in \( T \) periods with certainty and thus their utility in period \( T + 1 \) of being unemployed is zero:

\[ U_{T+1} = 0 \]  

Employed agents face a probability \( \delta \) of separating from their employer. They are further allowed to search for jobs while employed, denoted by \( \mu' \), and search when they lose their job, denoted by \( \tilde{\mu}' \). Employed agents in the economy face the following problem:

\[ W_t(\mu, a, h, l) = \max_{c, a', \tau} u(c) + \beta E[(1 - \delta)R_{t+1}^E(\mu, a, h', l) + \delta R_{t+1}^U(b_H, a', h', l)] \]
\[
s.t. \quad c + a' \leq (1 + r_F) a + \mu (1 - \tau) \phi(h) \quad (4.14)
\]
\[
a' \geq a \quad (4.15)
\]
\[
h' = H(h, E, \tau, l) \quad (4.16)
\]
\[
b_H = b'(1 - \tau) \mu \phi(h) \quad (4.17)
\]
\[
b' \sim N(\mu_b, \sigma_b) \quad (4.18)
\]
\[
\tau \in [0, 1] \quad (4.19)
\]

The function \( H \) determines the evolution of human capital, and affects workers remaining in employment and entering an unemployment spell differentially. Here, it is an increasing function of time spent accumulating human capital \( \tau \), \( H_3 \geq 0, H_{33} \leq 0 \). Human capital shocks are assumed to be realized before separation shocks, so any time spent accumulating human capital during employment is carried into unemployment. In addition, newly unemployed agents are assumed to have unemployment benefits for at least one period.

\[
W_{T+1} = 0 \quad (4.20)
\]

4.3 Firm’s Problem

Production in this economy is similar to \( ? \), while wage contracts are assumed to be renegotiation-proof, and offered as a piece-rate of total output. Firms post piece-rate wage contracts in submarkets characterized by age and human capital, and learning ability, which dictate the share of revenue to be received by each side in the match, as well as the probability a worker who applies will receive a job offer. A firm with a filled vacancy produces using technology \( y = (1 - \tau) \phi(h) \), where \( \tau \) 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 revenue as profits and pays the rest out in wages. At the beginning of each production period, the firm knows that they face an exogenous probability of the match continuing, \( (1 - \delta) \), as well as the possibility that a worker is unable to find a job while employed, given by that \( (1 - P((\theta_{t+1}(\mu', a', h', z))) \). They discount at the same rate as workers, \( \beta \). Thus, profits of a firm in expectation can be given by
\[ J_t(\mu, a, h, l) = (1 - \mu)(1 - \tau)\Phi(h) \]
\[ + \beta E[(1 - \delta)(1 - P(\theta_{t+1}(\mu', a', h', l)))J_{t+1}(\mu, a', h', l)] \]  
\[ 4.21 \]

\[ h'_E = H(h, E, \tau, l) \]  
\[ \tau = g_r(\mu, a, h, l) \]  
\[ a' = g_a(\mu, a, h, l) \]  
\[ \mu' = g_\mu(\mu, a', h', l) \]  
\[ 4.22 \]
\[ 4.23 \]
\[ 4.24 \]
\[ 4.25 \]

Where \( a' = g_a(\mu, a, h, l) \) is the policy rule of the worker for assets, and \( \mu' = g_\mu(\mu, a', h', l) \) is the application strategy of the worker condition on his assets. Profits from a filled vacancy at \( T + 1 \) are zero:

\[ J_{T+1} = 0 \]  
\[ 4.26 \]

Each prospective firm must calculate the expected profits from opening a vacancy. They have the option of posting a vacancy at cost \( \kappa \) in any submarket; each submarket offers a probability of matching with a worker given by \( q(\theta_t(\mu, a, h, l)) \). In expectation, the value of opening a vacancy in submarket \( (\mu, a, h, z) \) is

\[ V_t(\mu, a, h, l) = -\kappa + q(\theta_t(\mu, a, h, l))J_t(\mu, a, h, l) \]  
\[ 4.27 \]

The free entry condition implies that the profit from opening a vacancy must be competed away to zero. This allows us to rewrite the previous expression in such a way that \( \theta_t(\mu, a, h, l) \) is uniquely defined for each submarket by the cost of posting a vacancy \( \kappa \), and the discounted profits to the firm, \( J_t(\mu, a, h, l) \).

\[ \kappa = q(\theta_t(\mu, a, h, l))J_t(\mu, a, h, l) \]  
\[ 4.28 \]

We can rearrange this previous equation to get the following:

\[ q(\theta_t(\mu, a, h, l)) = \frac{\kappa}{J_t(\mu, a, h, l)} \]  
\[ 4.29 \]
Using the fact that \( \frac{M(u,v)}{a} = P(\theta_t(\mu, a, h, l)) \) and \( \frac{M(u,v)}{a} = q(\theta_t(\mu, a, h, l)) \), we can write \( P(\theta_t(\mu, a, h, l)) = \theta q(\theta_t(\mu, a, h, l)) \), which defines the probability offered in each submarket to workers as a function of the cost of opening a vacancy as well as the discounted profits to a firm of employing a worker of human capital \( h \) at wage \( \mu \). This relationship is key for defining the firm’s decision rules in such a way that they are not functions of the distributions of workers across states.

### 4.4 Timing

The timing in the model is as follows:

1. Firms choose to open jobs in each submarket \((\mu, a, h, l, t)\) until the free entry condition binds.
2. Employed and unemployed workers apply for jobs in submarkets \((\mu, a, h, l, t)\).
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 choose to allocate time between production and human capital accumulation.
5. Age advances. Agents receive human capital shocks, benefits shocks, and unemployment shocks in that order. Employed agents who separate retain human capital accumulated during the previous period.

### 4.5 Equilibrium

A Block Recursive Equilibrium (BRE) in this model economy is a set of policy functions for workers, \( \{c, \mu', a', \tau\} \), value functions for workers \( W_t, U_t \), policy function for a firm with a filled job, \( x \), value functions for firms with filled jobs, \( J_t \), and unfilled jobs, \( V_t \), as well as a market tightness function \( \theta_t(\mu, a, h, l) \). 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. \( \theta_t(\mu, a, h, l) \) satisfies the free entry condition for all submarkets \((\mu, a, h, l)\forall t\).
3. The aggregate law of motion is consistent with all policy functions.

---

\*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. For an extended discussion see Section A.2.

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20
5 Estimation

I use indirect inference to estimate the model. Indirect inference is a moment-matching approach based on targeting parameters from reduced-form models that capture key aspects of the underlying structural model. This approach has gained recent popularity among both papers seeking to estimate household response to risk (Guvenen and Smith, 2014), and those seeking to estimate search behavior over the life-cycle (Bowlus and Liu (2013)). This approach allows me to select moments that can be closely associated with key features of the model (borrowing constraints, initial heterogeneity, etc.), without linearizing and estimating my model using full-information methods. I expand on this methodology in Section 5.2.4.

To implement indirect inference, I first select functional forms that are ubiquitous throughout the related literature. I then preset a subset of parameters from related models that are widely used in the literature to ease the computational burden of the estimation procedure. These choices are detailed in Section 5.1. The remaining parameters are estimated by indirect inference, matching the auxiliary model in Section 5.2.

5.1 Empirical Preliminaries

5.1.1 Functional Form and Distributional Assumptions

I first assume a set of standard functional forms that are common in both the literature on search and the literature on inequality. These include the utility, matching, and production functions. For the utility function, I choose a power utility function of the following form:

$$u(c) = \begin{cases} \frac{c^{1-\sigma-1}}{1-\sigma} & \text{if } \sigma > 0, \sigma \neq 1 \\ \ln(c) & \text{if } \sigma = 1 \end{cases}$$ (5.1)

When agents are unemployed, I assume that they receive linear leisure utility, $u(c) + \nu$. I use the matching function from Schaal (2011), which exhibits constant returns to scale and well-defined probabilities:

$$M(u, v) = \frac{uv}{(u^n + v^n)^{\frac{1}{n}}}$$ (5.2)

Like Graber and Lise (2015) and Bowlus and Liu (2013), I assume production is linear in human capital:
\[ y = \phi(h) \]  
\[ \phi(h) = h \]  

(5.3)  
(5.4)

I assume that all workers face shocks to their human capital each period, given by \( \epsilon_t \sim N(\mu, \sigma) \). Employed workers accumulate human capital using Ben-Porath (1967) technology:

\[ h_{t+1} = e^{\epsilon_{t+1}} (h_t + H(h, E, \tau, \ell)) \]  
\[ H(h, E, \tau, \ell) = \ell (h_t \tau)^{\alpha \ell} \]  

(5.5)  
(5.6)

where \( \ell \) is the learning ability of an individual endowed at the beginning of the life-cycle and can be thought of as a fixed effect (it is constant). \( \tau_t \) is the fraction of productive time that an employed worker spends accumulating human capital. The fractional exponent reflects the fact that my model is quarterly, while previous work incorporating human capital is generally at an annual frequency.

Ben-Porath human capital accumulation is a departure from much of the previous work in the search literature that incorporates human capital. With the exception of Bowlus and Liu (2013), models of search with human capital have assumed that human capital is accumulated through “learning-by-doing,” which means that human capital grows exogenously while employed. Any difference in human capital growth rates while employed between individuals is imposed exogenously, not an outcome of the equilibrium. The learning-by-doing approach yields tractability, which papers like Bagger et al. (2014) and Carillo-Tudela (n.d.) exploit in order to decompose the variance of wage growth over the life-cycle.

Thus far, empirical evidence from the human capital literature is divided on which approach best fits the data. Recent evidence from ??, who nests both approaches within a single model and tests their predictions finds that Ben-Porath fits the data roughly 4 times better than learning-by-doing. It’s unclear if those results generalize to a model with labor market frictions. Within the context of my model, Ben-Porath generates earnings, variance, and skewness profiles that are roughly consistent with the data as equilibrium outcomes, whereas learning-by-doing would need additional assumptions to match, for example, the decline in earnings at the end of the life-cycle. Additionally, Ben-Porath is widely employed among papers on human capital and inequality, which allows for more straightforward comparisons.
between my findings and the findings of other papers on inequality.

For unemployed workers, I assume that they are unable to invest in human capital and face only the i.i.d. human capital depreciation process.

\[
\begin{align*}
    h_{t+1} &= H(h, U) \\
    &= e^{\epsilon_{t+1}} h_t
\end{align*}
\]  

(5.7)  

(5.8)

I allow unemployed workers to invest in human capital as an extension in ???. Finally, I assume that agents are subject to the natural borrowing constraint each period:

\[
a_t = \sum_{j=t}^{T} \frac{b_L}{(1 + r_F)^j}
\]  

(5.9)

In each period \( t \), \( a_t \) is the amount that any agent could repay if he or she were in the worst income state (\( b_L \)) until the terminal date. Modeling borrowing constraints in this way is appealing because it never fully binds and prevents periods of zero consumption. While natural borrowing constraints are common in the heterogeneous agent literature (Huggett (1993), and Aiyagari (1994) among many others), two alternative approaches that endogenize credit limits are Herkenhoff (2014), and Kehoe and Levine (1993). Both of these papers assume that debt contracts are not fully enforceable, but that agents can be excluded from subsequent credit market usage upon default. In most cases, adopting an alternate approach like these would yield tighter borrowing constraints in my model. Agents who need to borrow would also be the most likely to default, causing either higher borrowing costs or lower borrowing limits.

Lastly, I assume that initial conditions \((a_0, h_0, \ell)\) are drawn from a multivariate log-normal distribution, \( \Psi \sim LN(\psi, \Sigma) \). The preset functional forms and initial conditions are summarized in Table 5.1.

5.1.2 Preset Parameter Values

I select a subset of the parameters to be set to common values from the relevant literature. Agents in the model live for \( T = 128 \) quarters, covering the post-schooling and prime working ages, 25-54. I follow Shimer (2005) and select a quarterly separation rate of \( \delta = 0.1 \), meaning
<table>
<thead>
<tr>
<th>Category</th>
<th>Symbol</th>
<th>Value or Function</th>
<th>Source</th>
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</thead>
<tbody>
<tr>
<td>Preferences and Technology</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Utility Function</td>
<td>U(c)</td>
<td>$\frac{1-\sigma-1}{1-\sigma} z h$</td>
<td>Power Utility</td>
</tr>
<tr>
<td>Production Function</td>
<td>f(h)</td>
<td>$\ell(h_t \tau)^{\alpha h}$</td>
<td></td>
</tr>
<tr>
<td>Human Capital Technology</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Production Function</td>
<td>H(h, l, τ)</td>
<td>$\ell(h_t \tau)^{\alpha h}$</td>
<td>Ben-Porath (1967)</td>
</tr>
<tr>
<td>Human Capital Evolution</td>
<td>$h_{t+1}$</td>
<td>$e^{\epsilon_{t+1}}(h_t + H(h, l, \tau))$</td>
<td></td>
</tr>
<tr>
<td>Depreciation</td>
<td>$\epsilon_t$</td>
<td>$\epsilon_t \sim N(\mu, \sigma)$</td>
<td></td>
</tr>
<tr>
<td>Labor and Asset Markets</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Matching Function</td>
<td>M(u, v)</td>
<td>$\sum_{j=t}^{N} \frac{u^{j}}{(u^{j}+v^{j})^{\frac{n}{2}}}$</td>
<td>Schaal (2012)</td>
</tr>
<tr>
<td>Borrowing Constraint</td>
<td>a_t</td>
<td>$\sum_{j=t}^{T} \frac{b_{L}}{(1+r)^{j}}$</td>
<td>Natural Borrowing Limit</td>
</tr>
<tr>
<td>Initial Conditions</td>
<td></td>
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<td></td>
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<tr>
<td>Distribution</td>
<td>$\Psi$</td>
<td>$\Psi \sim LN(\theta, \Sigma)$</td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>$\psi$</td>
<td>$[\mu_A, \mu_H, \mu_L]'$</td>
<td></td>
</tr>
<tr>
<td>Variance</td>
<td>diag(\Sigma)</td>
<td>$(\sigma_A, \sigma_H, \sigma_L)$</td>
<td></td>
</tr>
<tr>
<td>Correlation</td>
<td></td>
<td>$(\rho_{AH}, \rho_{AL}, \rho_{HL})$</td>
<td></td>
</tr>
</tbody>
</table>

Table 5.1: Functional form assumptions and distributional assumptions for the initial conditions.

that an average worker experiences an unemployment spell once every 2.5 years. I allow employed agents to be 73\% as efficient at search as their unemployed peers ($\lambda_E = 0.73$), following the estimate from Herkenhoff (2014). The risk-free rate is set to a quarterly $r_F = 0.0125$, which generates an annual risk-free rate of about 5\%. As noted, an exogenous interest rate is required for the equilibrium concept. I set $\beta = \frac{1}{1+r_F}$, so that agents smooth consumption in expectation. Because this is a life-cycle model, a group of agents will still choose to borrow. Additionally, I set $\gamma = 0.5$, which means that unemployed agents average two quarters of unemployment benefits after an unemployment shock\(^9\).

I assume that the unemployment insurance replacement rate distribution has mean $\mu_b = 0.42$, and $\sigma_b = 0.053$, which is a normal distributed approximation to the distribution of replacement rates allowed under most state UI systems in my data. I restrict draws from this distribution to be two standard deviations or less to ensure that negative replacement rates are not possible, meaning that the range of possible replacement rates is [34\%, 53\%]. I also cap unemployment insurance at a weekly maximum of $\$450$, which is the weighted average of the maximum benefits in my data. I assume that unemployment insurance does not fluctuate with human capital depreciation, but can be lost with probability $\gamma$. I scale

\(^9\)This has not been true for the entire duration of my data, but for the sake of simplicity, I assume it is constant.
the curvature of the human capital production function, $\alpha_H$, to 0.7, which is around the midpoint of the values surveyed by Browning et al. (1999), and the same value used by Huggett et al. (2011). I allow agents to live for $T = 120$ quarters (ages 25-54), capturing the period in which most agents have finished their schooling and remain in the workforce. The remaining parameters to be estimated are $b_L, \nu, \mu_A, \mu_H, \mu_L, \sigma_A, \sigma_H, \sigma_L, \sigma_{AH}, \sigma_{AL}, \sigma_{HL}, \mu_e, \sigma_e$.

The preset parameters are summarized in Table 5.2.

<table>
<thead>
<tr>
<th>Category</th>
<th>Symbol</th>
<th>Value or Function</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Preferences and Technology</td>
<td>$\beta$</td>
<td>0.9882</td>
<td>$\frac{1}{1+r_F}$</td>
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<tr>
<td>Risk Aversion</td>
<td>$\sigma$</td>
<td>2</td>
<td>Standard</td>
</tr>
<tr>
<td>UI System</td>
<td>$\eta$</td>
<td>0.5</td>
<td>Shi (2016)</td>
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<tr>
<td>Elasticity of Matching Function</td>
<td>$(\mu_b, \sigma_b)$</td>
<td>(0.4, 0.1)</td>
<td>Distribution</td>
</tr>
<tr>
<td>UI Replacement Rate Distribution</td>
<td>$\gamma$</td>
<td>0.5</td>
<td>Average UI duration $\approx$ 26 weeks</td>
</tr>
<tr>
<td>Separation Rate</td>
<td>$\delta$</td>
<td>0.0</td>
<td>Annual average 1968-2013</td>
</tr>
<tr>
<td>Asset Market</td>
<td>$r_F$</td>
<td>0.0120</td>
<td>Annual rate of $\approx$ 5%</td>
</tr>
</tbody>
</table>

Table 5.2: Preset parameter values. Where appropriate, I estimate these parameters directly from the data.

### 5.2 Indirect Inference and Auxiliary Model

I estimate the remaining structural parameters of the model using indirect inference (Gourieroux et al., 1993). Indirect inference is a generalized method of moments (GMM) estimation technique in which the user selects a set of coefficients from a parsimonious “auxiliary model” composed of one or many reduced-form equations. Rather than matching unconditional moments, indirect inference minimizes the distance between parameters from the auxiliary model and identical reduced-form estimations run on simulated data. This technique has both empirical and computational advantages over alternative approaches. It has also been widely applied in papers that analyze inequality through the lens of search models (Bowlus and Liu (2013), Lise (2013), Graber and Lise (2015), among others).

Empirically, the primary advantage for my application is that I can select a set of reduced-form equations as an auxiliary model, whose relation to the data is clear, and then provide a structural interpretation using my model. If the auxiliary model yields inference on a mechanism in the data, then the structural parameters that result from the estimation are consistent with that mechanism, provided that the auxiliary models identify all the structural
parameters. In addition, the technique allows me to easily deal with flaws in my estimation sample by inserting the same flaws into the model generated data. This allows me to deal with missing observations and measurement error with minimal assumptions imposed on the estimation.

Computationally, this technique has ample advantages over competing approaches. While there are ways of estimating search models using maximum likelihood, the degree of heterogeneity in my model would require substantial computing power to estimate accurately\(^{10}\). Alternatively, I could linearize the model and use one of a host of tools available for estimation\(^{11}\). This approach would be faster, but would hamper the accuracy of my model. Linearizing the model would change the way that agents respond to unemployment risk, specifically by making periods of low consumption much less costly. For a study in which the primary focus is average individuals, linearizing and estimating would be a very reasonable approach, but here my focus is primarily on households that do not respond linearly to changes in risk.

I have initial heterogeneity coming from three sources: differences in wealth, differences in initial human capital, and differences in learning ability, which are jointly distributed at the beginning of the life-cycle. I pick a set of reduced-form moments and estimate auxiliary models in order to discipline this initial heterogeneity. The set of moments for which I calibrate the model is broken down into three categories: borrowing constraints, marginal distributions of initial conditions, and correlations between initial conditions. In each auxiliary model, I denote the set of parameters to be matched through indirect inference with \(\beta_j\), where \(j\) indexes the parameter or set of parameters. In my empirical specifications, I use an extensive set of controls that have no analog in my model. I denote these “nuisance” parameters \(\delta_i\), where \(i\) indicates the data feature for which they control.

### 5.2.1 Model Parameters

To discipline the borrowing constraints in my model, I match the re-employment wage elasticities with respect to changes in unemployment insurance for individuals from each of the liquid wealth quintiles. This regression largely follows my approach in Section 3, with two modifications to limit the number of auxiliary parameters to estimate. First, I drop potential

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\(^{10}\) estimates a model with (fixed) worker productivity heterogeneity using maximum likelihood. To make this possible, the paper restricts the number of initial productivity nodes to 3. Here, worker productivity is allowed to be continuous and evolve over the life-cycle.

\(^{11}\)See DeJong and Dave (2011) for a discussion of these techniques.
UI duration from the specification. This is because in my model all agents face the same expected UI duration, and in the data there is relatively little variation. Second, rather than condition on a piecewise linear spline over the worker’s previous wage, I condition directly on their previous wage. The specification that I use in both the SIPP and the simulated data is given in Equation 5.10.

\[
\ln(W_{j+1}) = \beta_0 + \sum_{q=1}^{5} \beta_1^q \times \ln(UI) + \sum_{q=1}^{5} \beta_2^q \times \ln(W_j) + \beta_3 \times \text{Age} \\
+ \delta_s + \delta_t + X_2 \delta + \epsilon_{iqst}
\]  

(5.10)

(5.11)

I match the set of auxiliary parameters \(\beta_0, \beta_1^q, \beta_2^q, \beta_3\), and treat the set of data controls \(\delta_s, \delta_t, \delta\) as nuisance parameters. Note that these nuisance parameters are controls in my empirical specification and have no analog in my model.

These moments directly connect the degree to which an individual is capable of smoothing consumption during an unemployment spell to their subsequent employment outcome, which yields inference on the degree to which a borrowing constraint is binding for individuals across the asset distribution, as demonstrated for a simpler model in Appendix E.

For inference on the human capital production function curvature parameter, \(\alpha_h\), I use six age bins of five years each (25-29, 30-34, 35-39, 40-44, 45-49, 50-54), and match within job earnings growth from the NLSY.

\[
\Delta \ln(W_{i,j}) = \sum_{a=1}^{6} \beta_4^a + \Delta X_2 \delta + \Delta \epsilon_{ij}
\]  

(5.12)

In my model, human capital accumulation is the only source of earnings growth for individuals who stay with the same job, making this the appropriate analog. I use a similar strategy to estimate the on-the-job search efficiency parameter, \(\lambda_E\). I use the same age bins and look at the probability that an individual will remain with the same job the following year, estimating an equation of the form Equation 5.16.

\[
\text{SameJob}_{ija} = \sum_{a=1}^{6} \beta_5^a + \delta_s + \delta_t + X_2 \delta + \epsilon_{ija}
\]  

(5.13)
The likelihood that an individual remains with the same job is composed of two components in my model: the exogenous separation rate, the probability a worker leaves through on-the-job search. The exogenous separation rate is preset to the average over the duration of the NLSY sample (1979-2014). While the second component is a function of the application strategy and the search efficiency, $\lambda_E$ has a first order effect on the outcome, satisfying the requirement for ex ante identification.

Finally, to identify leisure, I match the sample unemployment rate in the PSID. I use the worker’s employment status at the time of interview to estimate the unemployment rate. This takes the following form:

$$URate = \frac{1}{NT} \sum_{t=1}^{54} \sum_{t=25}^{54} j_{Unemp.} + \epsilon$$

where $N$ is the number of individuals in the PSID and $T$ is the number of years for which I record their observations (30). As noted, the panel is not balanced, so observations for individuals are missing at some ages.

### 5.2.2 Marginal Distribution Parameters

With information on the borrowing constraint, the marginal distribution of wealth can be directly estimated from the data. I use the distribution of liquid wealth in the Panel Study of Income Dynamics (PSID) for men prior to first entering the labor market, but after exiting school. As with the SIPP, I define liquid wealth to be liquid assets net of unsecured credit. I detail the construction in Section C.3.

For the marginal distribution of human capital, I use the distribution of earnings at the first job reported in the PSID. I use the same sample restrictions as in construction the liquid wealth deciles, and match deciles of the initial earnings distribution.

Lastly, in order to obtain the marginal distribution of learning ability, I use the following specification to estimate the average growth rate of earnings over the life-cycle:

$$ln(Y_{ist}) = \delta_0 + \beta_6 Age_i + \delta_t + \delta_s + X\delta + \epsilon_{ist}$$

I match $\beta_5$, the slope of the average earnings profile over the life-cycle. I do not include the intercept among my auxiliary parameters because I have already included the distribution
of initial earnings from the same dataset. Like Guvenen and Smith (2014) and Huggett et al. (2011), I add noise to the income observations in order to reduce the singularity of the data matrix, distributed \( N(0, 0.15) \). The average growth rate of earnings is directly related to the average learning ability in the economy. As Huggett et al. (2011) note, initial human capital can be thought of as the intercept of earnings over the life-cycle, while the average learning ability can be thought of as the slope of earnings over the life-cycle. As before, \( \delta \) is a set of nuissance parameters: features in the data that are not present in the model. To obtain the variance of learning ability, I match the average residual earnings variance in my sample. This auxiliary model is given by

\[
\sigma^2_\epsilon = \frac{1}{NT} \sum_{t=1}^{T} \sum_{i=1}^{N} (\ln(Y_{ist}) - \ln(\hat{Y}_{ist}))^2
\]  

(5.16)

### 5.2.3 Correlations

The final three parameters to estimate are the correlations between initial wealth, human capital, and learning ability. To discipline the correlation between wealth and human capital as well as learning ability, \( \sigma_{AH} \) and \( \sigma_{AL} \), I connect individuals in the PSID for whom I observe wealth prior to entering the labor market to their age 25 earnings and the slope of their earnings profiles, following the same steps to sample the data as described in Section C.3. I use the following auxiliary model:

\[
\ln(Y_{ist}) = \sum_{q=1}^{5} \beta_{q}^{I} + \sum_{q=1}^{5} \beta_{q}^{S} \times \text{Age}_{ist} + \delta_s + \delta_t + X\delta + \epsilon_{ist}
\]  

(5.17)

where I again add \( N(0, 0.15) \) measurement error in my model-generated analog to avoid singularity. I estimate separate intercepts for individuals from each of the five liquid wealth quintiles in the PSID, as well as separate slopes for I treat \( \delta, \delta_s, \delta_t \). This, in conjunction with the liquidity effects estimated from the re-employment elasticities, allows me to extract the correlation between initial wealth and intial human capital. Intuitively, liquidity effects serve to depress initial earnings for low-wealth individuals, meaning that the variance in human capital is likely to be lower than previously estimated. The slope for individuals from different liquid wealth quantiles allow me to discipline the correlation between initial wealth and learning ability.
Finally, to estimate the correlation between initial human capital and learning ability, $\sigma_{HL}$, I use life-cycle moments from the 1979 panel of the National Longitudinal Survey of Youth (NLSY79). The NLSY79 records Armed Force Qualifying Test (AFQT) scores, which serve as a rough proxy for initial human capital. I then stratify individuals by their percentile scores using the national distribution and assess the average growth rate of their earnings. I discuss my sample restrictions and data construction in Section C.2. I choose an auxiliary model that allows for different earnings growth rates by AFQT scores:

$$ln(Y_{ist}) = \sum_{q=1}^{5} \beta^q_l + \sum_{q=1}^{5} \beta^q_s \times Age_{ist} + \delta_s + \delta_t + X_\delta + \epsilon_{ist} \quad (5.18)$$

where $q$ here corresponds to the AFQT quintile. While not a perfect proxy, these test scores give insight into the differences in human capital at the start of the life-cycle, and how these translate into wage growth. Because learning ability acts as the “slope” for life-cycle profiles, this yields inference on the correlation between human capital and learning ability, $\sigma_{HL}$.

### 5.2.4 Implementation

Indirect inference can be implemented as either maximum likelihood, by minimizing a Gaussian objective function, or generalized method of moments. Because my sample size varies across auxiliary models, generalized method of moments provides a more natural fit to my estimation. Specifically, the method that I employ is closely related to seemingly unrelated regressions (SUR) estimation, as I use multiple datasets for my analysis. Indirect inference proceeds by first specifying a set of auxiliary models (here: Section 5.2.1, Section 5.2.2, Section 5.2.3), and minimizing the distance between auxiliary parameters from the data and model simulations. Let $M$ denote the number of auxiliary models, and note that the sample size $n_m$ need not be constant across auxiliary models. I largely follow the notation from DeJong and Dave (2011) in the following explanation of the procedure. In the first stage I solve
\[ \beta(Z) = \arg \max_{\delta} \Delta(Z, \delta) \] (5.19)

\[ \beta(Y, \theta) = \arg \max_{\delta} \Delta(Y, \delta) \] (5.20)

Where \( Z = [z_1, ..., z_M] \) and \( Y = [y_1, ..., y_M] \) are observed data and model generated data for auxiliary models 1,...,M, respectively. Note that the sample size for each \( y_1, ..., y_M \) is the same as its empirical counterpart. \( \Delta \) are the set of auxiliary models, \( \theta \) are the structural parameters of the model, and \( \beta \) the auxiliary parameters estimated from the auxiliary model. For the model generated data, I average over \( S = 100 \) simulations for each auxiliary model.

\[ \beta_S(Y, \theta) = \frac{1}{S} \sum_{j=1}^{S} \beta(Y^j, \theta) \] (5.21)

where \( j \) is the \( j \)th simulation of the model. The goal is to minimize the distance between the model generated auxiliary parameters and their empirical counterparts. I follow DeJong and Dave (2011) and minimize the following objective function:

\[ \min_{\theta} \Gamma(\theta) = g(Z, \theta)' \times \Omega g(Z, \theta) \] (5.22)

\[ g(Z, \theta) = \beta(Z) - \beta_S(Y, \delta) \] (5.23)

where \( \Omega \) is a positive-definite weighting matrix and \( g(Z, \theta) \) the moments constructed from the binding functions. For the weighting matrix, I choose the variance of the sample moments \( \text{var}(\beta(Z)) \), because it is a consistent though not efficient estimator of the variance-covariance matrix.

During each iteration of the estimation, I simulate 100 cohorts whose size correspond to the number of observations for each of my empirical moments. I treat simulated data precisely the same as in my empirical analysis: I impose identical sample restrictions (where applicable) in my simulations, and force each sample to contain an identical number of observations as its empirical counterpart. To deal with missing data in the PSID and NLSY, I drop observations randomly at the same frequency as in the data. I do this by wealth and AFQT quantiles so that I can match aggregated moments from my datasets.

I start agents at age 23 with no labor market experience and a random draw from the joint distribution of initial conditions. This assumption is because I ultimately test the degree to
which initial wealth alters labor market outcomes, and need a date at which all agents start unemployed. Starting agents at age 23 rather than age 25 allows a distribution of agents across employment states when I calculate the growth rate by age, which is necessary to replicate the data.

5.3 Estimation Results

I use simulated annealing to estimate the model. This allows me to solve for a global minimum by sampling randomly from the parameter space and comparing objective function values. This solution method is commonly used in search papers that are estimated using indirect inference, like Lise (2013) and Bowlus and Liu (2013). This results in the following estimated parameters:

<table>
<thead>
<tr>
<th>Category</th>
<th>Symbol</th>
<th>Value or Function</th>
<th>Scaled Qtrly Value (2011 Dollars)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Preferences and Technology</td>
<td>$\nu$</td>
<td>0.0005</td>
<td></td>
</tr>
<tr>
<td>Scale Factor</td>
<td>z</td>
<td>18164.95</td>
<td>$4096</td>
</tr>
<tr>
<td>Asset Market</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Subsistence Benefits</td>
<td>$b_L$</td>
<td>0.02</td>
<td>$84</td>
</tr>
<tr>
<td>Borrowing Constraint</td>
<td>$\omega$</td>
<td>$\sum_{j=t}^{T} \frac{b_L}{(1+rF)^j}$</td>
<td>$84,65129$</td>
</tr>
<tr>
<td>Initial Heterogeneity</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Marginal Distribution of Wealth</td>
<td>$(\mu_A, \sigma_A)$</td>
<td>(1.335, 0.994)</td>
<td>$16999$</td>
</tr>
<tr>
<td>Marginal Distribution of Human Capital</td>
<td>$(\mu_H, \sigma_H)$</td>
<td>(−0.644, 0.380)</td>
<td></td>
</tr>
<tr>
<td>Marginal Distribution of Learning Ability</td>
<td>$(\mu_L, \sigma_L)$</td>
<td>(−2.905, 0.990)</td>
<td></td>
</tr>
<tr>
<td>Correlations</td>
<td>$(\sigma_{AH}, \sigma_{AL}, \sigma_{HL})$</td>
<td>(0.663, 0.613, 0.555)</td>
<td></td>
</tr>
</tbody>
</table>

5.4 Fit

The model is overidentified, so should not be expected to perfectly fit each of the moments specified. However, it still does a reasonable job matching each of the auxiliary parameters from the auxiliary models. Table B.5 shows that the model closely matches the elasticity moments from the SIPP, indicating that the model is able to capture that borrowing constraints have on labor market outcomes following an unemployment spell. The model also does a reasonable job matching the life-cycle growth moments in Table B.4. It is better able to match the moments from the PSID than the moments from the NLSY, the results of which suggest that it is attributing too much growth to human capital. The model matches the initial distributions well, Table B.6. In addition, the model is able to match non-targeted moments, shown in Figure 5.1.
Figure 5.1: Life-cycle earnings profiles for the average individual in the PSID. The profile is adjusted for covariates.
6 Findings

I now use the estimated model to address the central question posed in this paper: how do borrowing constraints interact with search frictions and human capital to alter life-cycle inequality? I start by exploring the key mechanisms in the model: worker application strategies and time allocations. I do this in ???. Then I show how each of these mechanisms contribute to earnings growth and dispersion over the life-cycle in Section 6.2.

In Section 6.3, I quantify how changes in initial wealth, human capital, and learning ability impact inequality. I do this by comparing the baseline simulation of the model from Section 6.2 to simulations in which one of the initial conditions is either increased or decreased in isolation by a standard deviation. I then compare these outcomes to simulations in which two of the initial conditions are altered by one standard deviation, in either the same or opposite directions. The interaction shows how the impact of changes in one initial condition can be magnified or mollified by changes in the others.

Last, in Section 6.3.2, I explore outcomes for individuals from bottom quintile of each marginal distribution. With this as the baseline, I give each a “helicopter drop” of wealth, human capital, or learning ability, and compare outcomes. I also compare these outcomes against an individual who started with median values of each of the initial conditions.

6.1 Mechanisms

6.1.1 Wealth Effects and Application Strategies

6.1.2 Substitution Effects and Human Capital Growth

6.2 Sources of Life-Cycle Earnings Growth

Agents in the economy experience substantial earnings growth during the first ten years of their working career, before remaining relatively flat until retirement (Figure 6.1a). Consistent with previous work on inequality, earnings profiles begin to decline as agents approach retirement. Consumption and wealth profiles roughly follow the same pattern, though agents decumulate and consumption their savings rapidly at the end of the life-cycle (Figure 6.1b and Figure 6.1c, respectively).

Over the life-cycle, the model predicts that growth comes from two sources in two distinct time periods. When agents first join the labor force, a combination of search frictions and borrowing constraints contribute to wages well below the rest of the life-cycle for the average
agent in the economy. Agents experience substantial growth in their piece rate pay through about age 35 (Figure 6.2a), and subsequently grow their earnings by increasing their human capital (Figure 6.2b). As agents approach retirement, wages growth turns negative and the average profile declines. Previous work, like Huggett et al. (2011) attribute this solely to a decline in human capital, but here it is largely the result of less generous contract terms offered by firms, knowing that agents are approaching retirement.

Agents initially use the job ladder to increase their earnings, Figure 6.3a, but soon scale their career prospects without increasing their human capital. They devote substantial time during the middle of their careers to accumulating human capital, Figure 6.3b, but eventually use just enough time to maintain their current human capital.

Thus far, the profiles fall roughly in line with previous work on inequality, though the magnitudes may be different. However, agents respond in substantively different ways based on their employment status. ?? shows that unemployed agents apply for low-paying jobs
Figure 6.2: Much of the growth in earnings comes from moving up the job ladder early in the life-cycle, and then increases in human capital later in the life-cycle.

(relative to those employed), while their peers without unemployment insurance apply for even lower paying jobs. It would be easy to conclude that this is the result of differences in human capital, and indeed ?? shows substantial differences in human capital among each of these groups. But, unemployed agents without UI simultaneously apply for jobs that offer the highest likelihood of employment, despite the lower human capital. (??).
6.3 Initial Conditions and Life-Cycle Inequality

To assess the effect that borrowing constraints have on life-cycle inequality, I first compare my results to Huggett et al. (2011), in Table 6.2. Notably, my model attributes smaller upside to an increase in initial wealth, but substantial downside risk, as individuals approach the borrowing constraint. The largest divergence is in the equivalent variation that results from changes in human capital. I attribute an increase of only 4.2 to a one standard deviation increase in human capital, while Huggett et al. (2011) attribute nearly equivalent variation of nearly 40% to a standard deviation increase. Finally, learning ability is substantially more important in my framework than it is in theirs, with large downside risk. I also find that learning ability is much more important, with a substantial life-time consumption cost associated with a standard deviation decrease. The following table Table 6.1 lists the initial conditions and the conditions after a standard deviation change in each of the initial conditions.

6.3.1 Average Household

For the average household a standard deviation change in any of the initial conditions is important. Unlike previous work, I find that a standard deviation decrease in initial wealth plays a larger role in determining both lifetime consumption and lifetime wealth than a standard deviation change in human capital. The reason is that here wealth and human capital have similar effects: both human capital and wealth improve initial placement and
Table 6.1: The table presents the initial conditions associated with the baseline individual as well as the comparison group.

lead to faster human capital growth. The relatively tight distribution of human capital needed to match the data makes a change in human capital relatively unimportant compared with changes in wealth. I also find that learning ability is the primary driver of inequality: a decrease in learning ability leads to little or no human capital growth throughout the life-cycle. This is because earnings growth is driven by both human capital accumulation and search frictions, making the average learning ability in the economy lower than in previous papers.\textsuperscript{12}

Wealth plays a role through two channels: first, agents who start poor are rushed to find a job, consistent with the regularities that I found in the SIPP (Section 3). Then, they accumulate less human capital while employed. Figure 6.4 shows this effect for the average individual in the economy. An increase in wealth plays a small role early in the life-cycle, but has little dynamic effect as the average individual in the economy is not constrained. However, moving closer to the borrowing constraint has a tangible and dynamic effect on earnings. Until late in the life-cycle, these individuals have lower earnings than their wealthier counterparts. Human capital has a relatively small effect in both directions, and learning

\textsuperscript{12}In Huggett et al. (2011), they find that average learning ability is 0.321. They need such a large value to match earnings profiles, but here earnings growth is driven by search frictions. A model without search frictions would not be consistent with the empirical regularities from the SIPP.
<table>
<thead>
<tr>
<th>Variable</th>
<th>Change</th>
<th>Δ Consumption</th>
<th>Δ Wealth</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>EV (%)</td>
<td>HYG 2011 (%)</td>
</tr>
<tr>
<td>Initial Wealth</td>
<td>+1 St. Deviation</td>
<td>+8.4</td>
<td>+7.1</td>
</tr>
<tr>
<td></td>
<td>-1 St. Deviation</td>
<td>-4.6</td>
<td>-1.6</td>
</tr>
<tr>
<td>Human Capital</td>
<td>+1 St. Deviation</td>
<td>+4.2</td>
<td>+39.3</td>
</tr>
<tr>
<td></td>
<td>-1 St. Deviation</td>
<td>-3.2</td>
<td>-28.3</td>
</tr>
<tr>
<td>Learning Ability</td>
<td>+1 St. Deviation</td>
<td>+81.2</td>
<td>+5.7</td>
</tr>
<tr>
<td></td>
<td>-1 St. Deviation</td>
<td>-51.4</td>
<td>-2.6</td>
</tr>
</tbody>
</table>

Table 6.2: The table presents the change in lifetime utility (equivalent variation) for a one standard deviation change in each of the listed variables. When a variable is changed, the other initial conditions are set to their mean values. This is for comparability with Huggett et al. (2011).

ability plays a big role in both directions (?? and ?? respectively).

While the initial wealth effect is important, wealth continues to have an effect by dynamically altering the accumulation of human capital. A single standard deviation change in wealth alters the accumulation of human capital drastically over the first 20 quarters of work, as shown in Figure 6.4. A change in human capital does little to alter acquisition over the lifetime, as shown in Figure 6.5. The interaction between wealth and human capital accumulation is substantial, causing a continued difference even late into the life-cycle.

6.3.2 10th Percentile Household
Figure 6.4: A decrease in wealth plays a substantial role in the time allocated to learning by individuals in the economy. Low-wealth individuals now allocate less time to future earnings growth and more to accumulating precautionary savings.
Figure 6.5: The application strategy of unemployed individuals changes substantially after a change in wealth, but shows relatively small changes for either changes in human capital or change in learning ability.
7 Conclusion

This paper demonstrates that borrowing constraints are an important determinant of life-cycle inequality. I first show that constrained individuals in the SIPP exhibit large liquidity effects. Constrained individuals are highly responsive to increases in unemployment insurance generosity, both in terms of re-employment earnings and unemployment duration. I also find evidence that this effect persists. Then I construct a model that incorporates all these features and allows me to explore the effects of borrowing constraints over the life-cycle.

My model solves and simulates a worker’s life-cycle for individuals with three dimensions of heterogeneity: liquid wealth, human capital, and learning ability. It incorporates each of these dimensions into a life-cycle model of on-the-job directed search, which allows me to match the empirical regularities that I find in the SIPP. The model demonstrates two channels through which borrowing constraints increase inequality: first, wealth changes the manner in which agents search for jobs when they are faced with liquidity constraints; in particular, low-wealth agents search for jobs in submarkets that offer low pay, but a high probability of employment. Second, workers with less wealth choose to spend more of their productive time acquiring income to increase their savings, and less of their time accumulating human capital. This is not inconsequential, and nearly of the same magnitude as the initial differences in earnings caused by wealth.

I match the model to the data using indirect inference. This provides credible estimates of borrowing constraints over the life-cycle as well as the distribution of initial heterogeneity by requiring the model be consistent with reduced-form estimates with credible sources of exogenous variation. I match the moments from my exploration of the SIPP as well as life-cycle moments from the PSID. Despite substantially more moments than estimated parameters, the model does a good job matching both the moments in my estimation and several non-targeted moments.

I find that the impact of wealth on life-cycle inequality is more than an order of magnitude larger than differences in initial human capital. A standard deviation decrease in initial wealth causes a −4.6 percent change in lifetime consumption, relative to an individual who starts with average levels of wealth. Learning ability is the primary driver changing consumption by, −51.4 percent; however, the same test for human capital produces a change of only −3.2 percent in lifetime consumption, substantially smaller in importance relative to either wealth or human capital.

I perform another counterfactual experiment by endowing households with the charac-
teristics of a 10th percentile (of the wealth distribution) household and then change wealth, human capital, and learning ability to the median value, keeping the other two variables constant. I find that changing wealth to the median level yields consumption and income levels roughly in line with the median household. However, changes in either human capital or learning ability are not as effective. I interpret this to mean that for liquidity constrained households, distance from the constraint has a larger effect on lifetime inequality than either their productivity or ability to learn, both of which are endogenously impacted by their degree of constraint even while employed.
References


Carillo-Tudela, Carlos, “Job Search, Human Capital and Wage Inequality.”


A Proofs

A.1 Existence of a Block Recursive Equilibrium

The existence proof of a block recursive equilibrium follows closely to previous models of life-cycle directed search with wage posting, namely ?, and Herkenhoff (2014). This is shown by using backwards induction and at each stage of the life-cycle showing that agents decisions are not conditional on the distribution of workers across states. Throughout, I include aggregate productivity $z$ in the aggregate state, though this is stationary in the model.

Because the value in $T+1$ for all agents is 0, the three worker value functions Equation 4.4, Equation 4.8, and Equation 4.13 respectively, satisfy the following in period $T$.

\[ U_T(\mu, a, h, l; \psi) = u((1 + r_F)a + b\mu \phi(h_T)) \]  \hspace{1cm} (A.1)

\[ U_T(b_L, a, h, l; \psi) = u((1 + r_F)a + b_L) \]  \hspace{1cm} (A.2)

\[ W_T(\mu, a, h, l; \psi) = u(\mu \phi(h_T) + (1 + r_F)a) \]  \hspace{1cm} (A.3)

The optimal policy policy for the terminal period is known: agents will use all accumulated savings to purchase consumption, and spend no time accumulating human capital, because the gains would not be realized until the following period. Because the interest rate is assumed to be the world interest rate and taken as given, each of the value functions do not depend on the distribution of workers across states. Therefore, the distributions, $\psi$ can be dropped from the state space and the value functions rewritten as $U_T(\mu, a, h, l; \psi) = U_T(\mu, a, h, l; z)$, $U_T(b, a, h, l; \psi) = U_T(\mu, a, h, l; z)$, and $W_T(\mu, a, h, l; \psi) = W_T(\mu, h, a, l; z)$. Since there is no new employment activity for workers of age $T$, the decision rules of these agents do not depend upon the distribution of agents in the economy. Now, consider the market tightness function for firms posting vacancies for workers who will be age $T$ when they are first employed (i.e., are currently in the search subperiod of age $T$). Since the continuation value to the firm in period $T + 1$ is zero, the period $T$ value of a vacancy is given by

\[ J_T(\mu, a, h, l; \psi) = (1 - \mu)\Phi(h) \]  \hspace{1cm} (A.4)

Where again, I impose the optimal learning time of age $T$ agents. The vacancy creation
conditions can then be solved explicity for every worker state:

\[ V(\mu, a, h, l; \psi) = -\kappa + q(\theta_T(\mu, a, h, l; \psi))(1 - \mu)\phi(h) \]  

(A.5)

Free entry of firms yields the following:

\[ \kappa = q(\theta_T(\mu, a, h, l; \psi))(1 - \mu)\phi(h) \]  

(A.6)

By assumption, q is invertible, and this is imposed in the calibration. Therefore, sub-market tightness can be solved for any worker state:

\[ \theta_T(\mu, a, h, l; \psi) = \begin{cases} 
q^{-1}\left(\frac{\kappa}{(1 - \mu)\phi(h)}\right) & : \text{if } (1 - \mu)\phi(h) \geq \kappa \\
0 & : \text{else}
\end{cases} \]

This again does not depend upon the distribution of workers; thus, \( \theta_T(\mu, a, h, l; \psi) = \theta_T(\mu, a, h, l; z) \). This means that the vacancy creation condition is known to workers without knowing the distribution of workers across the state space in the rest of the economy. Now, consider the search and matching decision of unemployed workers of age \( T \):

\[ R^U_T(\mu, a, h, l; \psi) = \max_{\mu'} P(\theta_T(\mu', a, h, l; \psi))W_T(\mu', a, h, l; \psi) \]
\[ + (1 - P(\theta_T(\mu', a, h, l; \psi)))U_T(\mu, a, h, l; \psi) \]  

(A.7)

\[ R^U_T(b_L, a, h, l; \psi) = \max_{\mu'} P(\theta_T(\mu', a, h, l; \psi))W_T(\mu', a, h, l; \psi) \]
\[ + (1 - P(\theta_T(\mu', a, h, l; \psi)))[\gamma U_T(b_L, a, h, l; \psi)] \]  

(A.8)

Imposing the conditions for \( \theta_T \), as well as the value functions in the terminal production and consumption period yields the following

\[ R^U_T(\mu, a, h, l; \psi) = \max_{\mu''} P(\theta_T(\mu'', a, h, l; z))W_T(\mu', a, h, l; z) \]
\[ + (1 - P(\theta_T(\mu', a, h, l; z)))U_T(\mu, a, h, l; z) \]  

(A.9)
Note that neither the probabilities within each submarket, nor the continuation value depend on the distribution of workers across states. Therefore, the job search value functions are independent of the aggregate state and can be written

\[ R^U_T(b_L, a, h, l; \psi) = \max_{\mu'} P(\theta_T(\mu', a, h, l; z)) W_T(\mu', a, h, l; z) + (1 - P(\theta_T(\mu', a, h, l; z))) [\gamma U_T(b_L, a, h, l; z) \] (A.10)

which again shows that the employed job searcher’s value function does not depend on the aggregate distribution nor does the optimal application strategy, meaning

\[ R^E_T(\mu, a, h, l; \psi) = \max_{\mu'} P(\theta_T(\mu', a, h, l; \psi)) W_T(\mu', a, h, l; \psi) + (1 - P(\theta_T(\mu', a, h, l; \psi))) W_T(\mu, a, h, l; \psi) \] (A.11)

which again shows that the employed job searcher’s value function does not depend on the aggregate distribution nor does the optimal application strategy, meaning

\[ R^E_T(\mu, a, h, l; \psi) = \max_{\mu'} P(\theta_T(\mu', a, h, l; z)) W_T(\mu', a, h, l; z) + (1 - P(\theta_T(\mu', a, h, l; z))) W_T(\mu, a, h, l; z) \] (A.12)
\[
\text{s.t. } c + a' \leq (1 + r_F)a + b\mu \phi(h) \quad (A.14)
\]
\[
d' \geq a \quad (A.15)
\]
\[
h' = H(h, U) \quad (A.16)
\]

\[
U_{T-1}(b_L, a, h, l; \psi) = \max_{c, a'} u(c) + \nu + \beta E[R_T^U(b_L, a', h', l; \psi)]
\]
\[
\text{s.t. } c + a' \leq (1 + r_F)a + b_L \quad (A.18)
\]
\[
da' \geq a \quad (A.19)
\]
\[
h' = H(h, U) \quad (A.20)
\]

Substituting in the age \(T\) value functions yields the following:

\[
U_{T-1}(\mu, a, h, l; \psi) = \max_{c, a'} u(c) + \nu + \beta E[(1 - \gamma)R_T^U(\mu, a', h', l; z) + \gamma R_T^U(b_L, a', h', l; \psi)]
\]
\[
\text{s.t. } c + a' \leq (1 + r_F)a + b\mu \phi(h) \quad (A.22)
\]
\[
da' \geq a \quad (A.23)
\]
\[
h' = H(h, U) \quad (A.24)
\]

\[
U_{T-1}(b_L, a, h, l; \psi) = \max_{c, a'} u(c) + \nu + \beta E[R_T^U(b_L, a', h', l; z)]
\]
\[
\text{s.t. } c + a' \leq (1 + r_F)a + b_L \quad (A.26)
\]
\[
da' \geq a \quad (A.27)
\]
\[
h' = H(h, U) \quad (A.28)
\]

Note that the neither the continuation values nor the prices depend on the aggregate distribution of workers, as debt is priced individually (in this case, with one price). This
means that the consumption and savings rules of unemployed workers are independent of
the distribution of workers, and the value functions can be written

\[ U_{T-1}(\mu, a, h, l; \psi) = U_{T-1}(b_L, a, h, l; \psi) = U_{T-1}(b_L, a, h, l; z) \]

By essentially the same argument, the value function during the consumptiono and savings period of an employed worker can be written as

\[
W_{T-1}(\mu, a, h, l; \psi) = \max_{c, a', \tau} u(c) + \beta E[(1 - \delta)R^E_T(\mu, a, h', l; \psi') + \delta R^U_T(\mu, a', h', l; \psi)]
\]

s.t. \( c + a' \leq (1 + r_F)a + \mu(1 - \tau)\phi(h) \)  \hspace{1cm} (A.30)
\[ a' \geq a \]  \hspace{1cm} (A.31)
\[ h' = H(h, E, \tau, l; \psi) \]  \hspace{1cm} (A.32)
\[ \tau \in [0, 1] \]  \hspace{1cm} (A.33)

\[
W_{T-1}(\mu, a, h, l; \psi) = \max_{c, a', \tau} u(c) + \beta E[(1 - \delta)R^E_T(\mu, a, h', l; z) + \delta R^U_T(\mu, a', h', l; z)]
\]

s.t. \( c + a' \leq (1 + r_F)a + \mu(1 - \tau)\phi(h) \)  \hspace{1cm} (A.35)
\[ a' \geq a \]  \hspace{1cm} (A.36)
\[ h' = H(h, E, \tau, l; \psi) \]  \hspace{1cm} (A.37)
\[ \tau \in [0, 1] \]  \hspace{1cm} (A.38)

Again, neither the consumption, nor savings decisions depend on the distribution of workers across states. Furthermore, because human capital and learning are assumed to be observable, each worker state vector maps to a wage offer by the firm, independent of the distribution of human capital, learning, or wealth and wage. Thus, the human capital accumulation decision is independent of the distribution of workers, and the value function can be written \( W_{T-1}(\mu, a, h, l; \psi) = W_{T-1}(\mu, a, h, l; z) \), and each of the decision rules are independent of the distribution of workers across states.

It’s similarly easy to show that the value of a filled vacancy of a worker age \( T - 1 \) does not depend on the distribution of workers across states. The value function of the firm may
be written

\[
J_{T-1}(\mu, a, h, l; \psi) = (1 - \mu)(1 - \tau)\Phi(h) \\
+ \beta E[(1 - \delta)(1 - P((\theta_T(a', h', l; \psi'))))J_T(\mu, a', h', l; \psi')] 
\]  
(A.39)

\[
h'_E = H(h, E, \tau, l; \psi) 
\]  
(A.40)

\[
\tau = g_r(\mu, a, h, l; \psi) 
\]  
(A.41)

\[
a' = g_a(\mu, a, h, l; \psi) 
\]  
(A.42)

\[
\mu' = g_\mu(\mu, a', h', l; \psi) 
\]  
(A.43)

Each of the employed worker decision rules do not depend on the distribution of workers across states. In addition, \(\Theta_T\), and \(J_T\) do not depend on the distribution as shown earlier. Thus,

\[
J_{T-1}(\mu, a, h, l; \psi) = (1 - \mu)(1 - \tau)\Phi(h) \\
+ \beta E[(1 - \delta)(1 - P((\theta_T(a', h', l; z)))J_T(\mu, a', h', l; z)] 
\]  
(A.44)

\[
h'_E = H(h, E, \tau, l; z) 
\]  
(A.45)

\[
\tau = g_r(\mu, a, h, l; z) 
\]  
(A.46)

\[
a' = g_a(\mu, a, h, l; z) 
\]  
(A.47)

\[
\mu' = g_\mu(\mu, a', h', l; z) 
\]  
(A.48)

Therefore, the value function of a filled vacancy for a worker age \(T - 1\) does not depend on the distribution of workers across states, \(J_{T-1}(\mu, a, h, l; \psi) = J_{T-1}(\mu, a, h, l; z)\). From the free entry condition and the invertibility of \(q(\theta)\), this yields

\[
\theta_{T-1}(\mu, a, h, l; \psi) = \begin{cases} 
q^{-1}(\frac{\kappa}{J_{T-1}(\mu, a, h, l; \psi})) & \text{if } J_{T-1}(\mu, a, h, l; \psi) \geq \kappa \\
0 & \text{else} 
\end{cases}
\]

and furthermore, \(\theta_{T-1}(\mu, a, h, l; \psi) = \theta_{T-1}(\mu, a, h, l; z)\).

Finally, it remains to be shown that a worker who is searching during age \(T - 1\) does
not make decisions conditional on the distribution of workers. Similar to before, the value functions of unemployed searchers can be written

\[ R_{T-1}^U(\mu, a, h, l; \psi) = \max_{\mu'} P(\theta_{T-1}(\mu', a, h, l; \psi))W_{T-1}(\mu', a, h, l; \psi) \]

\[ + (1 - P(\theta_{T-1}(\mu', a, h, l; \psi)))U_{T-1}(\mu, a, h, l; \psi) \quad (A.49) \]

\[ R_{T-1}^U(b_L, a, h, l; \psi) = \max_{\mu'} P(\theta_{T-1}(\mu', a, h, l; \psi))W_{T-1}(\mu', a, h, l; \psi) \]

\[ + (1 - P(\theta_{T-1}(\mu', a, h, l; \psi)))U_{T-1}(b_L, a, h, l; \psi) \quad (A.50) \]

Again, because the continuation values as well as the set of submarket tightnesses do not depend on the distribution, this can be written

\[ R_{T-1}^U(\mu, a, h, l; \psi) = \max_{\mu'} P(\theta_{T-1}(\mu', a, h, l; z))W_{T-1}(\mu', a, h, l; z) \]

\[ + (1 - P(\theta_{T-1}(\mu', a, h, l; z)))U_{T-1}(\mu, a, h, l; z) \quad (A.51) \]

\[ R_{T-1}^U(b_L, a, h, l; \psi) = \max_{\mu'} P(\theta_{T-1}(\mu', a, h, l; z))W_{T-1}(\mu', a, h, l; z) \]

\[ + (1 - P(\theta_{T-1}(\mu', a, h, l; z)))U_{T-1}(b_L, a, h, l; z) \quad (A.52) \]

where once again, the application strategy is independent of the distribution of workers across states, and therefore \( R_{T-1}^U(b_L, a, h, l; \psi) = R_{T-1}^U(b_L, a, h, l; z) \). Lastly, the same can be shown of employed searchers of age \( T - 1 \):

\[ R_{T-1}^E(\mu, a, h, l; \psi) = \max_{\mu'} P(\theta_{T-1}(\mu', a, h, l; \psi))W_{T-1}(\mu', a, h, l; \psi) \]

\[ + (1 - P(\theta_{T-1}(\mu', a, h, l; \psi)))W_{T-1}(\mu, a, h, l; \psi) \quad (A.53) \]
\[ R^E_{T-1}(\mu, a, h, l; \psi) = \max_{\mu'} P(\theta_{T-1}(\mu', a, h, l; z))W_{T-1}(\mu', a, h, l; z) \]
\[ + (1 - P(\theta_{T-1}(\mu', a, h, l; z)))W_{T-1}(\mu, a, h, l; z) \]  

(A.54)

where again, \( R^E_{T-1}(\mu, a, h, l; \psi) = R^E_{T-1}(\mu, a, h, l; z) \); thus, all decision rules for actors in the model in period \( T - 1 \) do not depend on distributions. The proof can be repeated for ages \( \{T - 2, ..., 1\} \), and by the same logic as above, these value and policy functions will not depend upon the aggregate distribution of agents across states. Thus, the model exhibits a block recursive equilibrium.

### A.2 BRE Discussion

A block recursive equilibrium in this economy is possible because of a few assumptions: first, the interest rate cannot depend on the distribution of assets. With this, firms and workers do not have to condition on the distribution of assets in their policy functions. Second, workers must be able to direct their search to submarkets, and in these submarket workers characteristics must either be observable, or be implied by sorting. This assumption allows firms to know the expected profits from opening a vacancy within a submarket, causing policy functions to no longer have to depend upon the distribution of workers across types. Third, the matching function must be constant returns to scale. This implies that the probability of a firm matching with a worker is a function only of the ratio of vacancies to unemployed searchers, which causes policy functions to no longer depend upon the distribution of workers within types. Finally, the probability that firms meet with workers must be invertible, which allows the recovery of the probability a worker meets with a firm in a submarket. With this, workers can select a submarket and know the wage offered and probability of employment.

### B Tables and Figures
<table>
<thead>
<tr>
<th>Summary Statistics for Estimation Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Avg. State UI</strong></td>
</tr>
<tr>
<td>&lt; Med</td>
</tr>
<tr>
<td>White</td>
</tr>
<tr>
<td>Q1 0.700</td>
</tr>
<tr>
<td>Q2 0.552</td>
</tr>
<tr>
<td>Q3 0.589</td>
</tr>
<tr>
<td>Q4 0.810</td>
</tr>
<tr>
<td>Q5 0.896</td>
</tr>
<tr>
<td>HS Degree</td>
</tr>
<tr>
<td>Q1 0.353</td>
</tr>
<tr>
<td>Q2 0.332</td>
</tr>
<tr>
<td>Q3 0.405</td>
</tr>
<tr>
<td>Q4 0.314</td>
</tr>
<tr>
<td>Q5 0.332</td>
</tr>
<tr>
<td>Coll. Degree</td>
</tr>
<tr>
<td>Q1 0.112</td>
</tr>
<tr>
<td>Q2 0.0317</td>
</tr>
<tr>
<td>Q3 0.0536</td>
</tr>
<tr>
<td>Q4 0.170</td>
</tr>
<tr>
<td>Q5 0.154</td>
</tr>
<tr>
<td>Age</td>
</tr>
<tr>
<td>Q1 36.62</td>
</tr>
<tr>
<td>Q2 37.26</td>
</tr>
<tr>
<td>Q3 37.37</td>
</tr>
<tr>
<td>Q4 40.54</td>
</tr>
<tr>
<td>Q5 43.92</td>
</tr>
<tr>
<td>Observations</td>
</tr>
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<table>
<thead>
<tr>
<th>Avg. State UI</th>
<th>&lt; Med</th>
<th>&gt; Med</th>
<th>P-Val</th>
</tr>
</thead>
<tbody>
<tr>
<td>Duration</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Q1 17.27</td>
<td>19.59</td>
<td>0.0939</td>
<td></td>
</tr>
<tr>
<td>Q2 18.66</td>
<td>20.16</td>
<td>0.215</td>
<td></td>
</tr>
<tr>
<td>Q3 17.52</td>
<td>19.90</td>
<td>0.146</td>
<td></td>
</tr>
<tr>
<td>Q4 18.48</td>
<td>19.78</td>
<td>0.385</td>
<td></td>
</tr>
<tr>
<td>Q5 17.66</td>
<td>19.31</td>
<td>0.285</td>
<td></td>
</tr>
<tr>
<td>UI Reported</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Q1 250.3</td>
<td>329.5</td>
<td>1.62e-90</td>
<td></td>
</tr>
<tr>
<td>Q2 246.7</td>
<td>324.1</td>
<td>3.20e-95</td>
<td></td>
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<td>Q3 249.6</td>
<td>327.5</td>
<td>4.33e-72</td>
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</tr>
<tr>
<td>Q4 253.1</td>
<td>332.2</td>
<td>5.47e-83</td>
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</tr>
<tr>
<td>Q5 251.7</td>
<td>336.0</td>
<td>7.81e-95</td>
<td></td>
</tr>
<tr>
<td>Q1 36391.3</td>
<td>36471.7</td>
<td>0.967</td>
<td></td>
</tr>
<tr>
<td>Q2 28051.0</td>
<td>31679.2</td>
<td>0.0357</td>
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</tr>
<tr>
<td>Q3 31155.4</td>
<td>33229.5</td>
<td>0.323</td>
<td></td>
</tr>
<tr>
<td>Q4 44891.5</td>
<td>46128.4</td>
<td>0.701</td>
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</tr>
<tr>
<td>Q5 62213.4</td>
<td>55497.1</td>
<td>0.197</td>
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</tr>
<tr>
<td>Prev. Tenure (wks)</td>
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<td></td>
<td></td>
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<tr>
<td>Q1 44.08</td>
<td>43.94</td>
<td>0.969</td>
<td></td>
</tr>
<tr>
<td>Q2 36.82</td>
<td>43.52</td>
<td>0.0338</td>
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<tr>
<td>Q3 41.80</td>
<td>48.97</td>
<td>0.0955</td>
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<td>Q4 48.73</td>
<td>41.02</td>
<td>0.0329</td>
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<td>Q5 47.67</td>
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<tr>
<td>Observations</td>
<td>1210</td>
<td>1144</td>
<td>2354</td>
</tr>
</tbody>
</table>

Table B.1: Summary statistics by liquidity quintile, stratified above and below median state weekly average UI. Means are weighted and variance is corrected for the survey design. Number of observations is unweighted.
## Re-Employment Labor Income Regressions (by Net Liquidity), State Cluster SEs

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Net Liq. Quintile 1 X Log of Avg. UI</td>
<td>0.634**</td>
<td>0.628***</td>
</tr>
<tr>
<td></td>
<td>(0.265)</td>
<td>(0.199)</td>
</tr>
<tr>
<td>Net Liq. Quintile 2 X Log of Avg. UI</td>
<td>0.223</td>
<td>0.303</td>
</tr>
<tr>
<td></td>
<td>(0.240)</td>
<td>(0.258)</td>
</tr>
<tr>
<td>Net Liq. Quintile 3 X Log of Avg. UI</td>
<td>0.00351</td>
<td>-0.0310</td>
</tr>
<tr>
<td></td>
<td>(0.313)</td>
<td>(0.267)</td>
</tr>
<tr>
<td>Net Liq. Quintile 4 X Log of Avg. UI</td>
<td>0.132</td>
<td>0.0194</td>
</tr>
<tr>
<td></td>
<td>(0.215)</td>
<td>(0.168)</td>
</tr>
<tr>
<td>Net Liq. Quintile 5 X Log of Avg. UI</td>
<td>0.174</td>
<td>0.109</td>
</tr>
<tr>
<td></td>
<td>(0.219)</td>
<td>(0.271)</td>
</tr>
<tr>
<td>Net Liq. Quintile 1 X Potential UI Weeks</td>
<td>-0.00102</td>
<td>0.0160</td>
</tr>
<tr>
<td></td>
<td>(0.0101)</td>
<td>(0.0118)</td>
</tr>
<tr>
<td>Net Liq. Quintile 2 X Potential UI Weeks</td>
<td>-0.00946</td>
<td>-0.00847</td>
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<tr>
<td></td>
<td>(0.0111)</td>
<td>(0.00637)</td>
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<tr>
<td>Net Liq. Quintile 3 X Potential UI Weeks</td>
<td>0.0155</td>
<td>0.0113</td>
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<td>(0.0172)</td>
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<td>Net Liq. Quintile 4 X Potential UI Weeks</td>
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<td>(0.00954)</td>
<td>(0.00902)</td>
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<tr>
<td>Net Liq. Quintile 5 X Potential UI Weeks</td>
<td>-0.0225</td>
<td>-0.0217**</td>
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<tr>
<td></td>
<td>(0.0137)</td>
<td>(0.0102)</td>
</tr>
</tbody>
</table>

$R^2$ 0.359 0.381

State FE X X
Year FE X X
Qtile FE + Qtile X Wage Spline X X
Ind + Ind X Qtile FEs X X
Occ + Occ X Qtile FEs X X

**Robust standard errors in parentheses**

*** p<0.01, ** p<0.05, * p<0.1

Table B.2: Elasticities of re-employment wages by net liquidity quintile. Column 1 reports wages in the month following re-employment, and column 2 reports wages during the first quarter following re-employment. Standard errors are clustered at the state level.
Employment Labor Income Regressions (by Net Liquidity)

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>Log of Initial Wage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Net Liq. Quartile 1 X Log of Avg. UI</td>
<td>-0.916 (1.241)</td>
</tr>
<tr>
<td>Net Liq. Quartile 1 X Tenure</td>
<td>0.0810 (0.0649)</td>
</tr>
<tr>
<td>Net Liq. Quartile 2 X Log of Avg. UI</td>
<td>-0.768 (1.613)</td>
</tr>
<tr>
<td>Net Liq. Quartile 2 X Tenure</td>
<td>-0.0808** (0.0405)</td>
</tr>
<tr>
<td>Net Liq. Quartile 3 X Log of Avg. UI</td>
<td>0.275 (1.359)</td>
</tr>
<tr>
<td>Net Liq. Quartile 3 X Tenure</td>
<td>-0.0329 (0.0540)</td>
</tr>
<tr>
<td>Net Liq. Quartile 4 X Log of Avg. UI</td>
<td>0.240 (1.586)</td>
</tr>
<tr>
<td>Net Liq. Quartile 4 X Tenure</td>
<td>-0.0316 (0.119)</td>
</tr>
<tr>
<td>Net Liq. Quartile 5 X Log of Avg. UI</td>
<td>2.188 (1.581)</td>
</tr>
<tr>
<td>Net Liq. Quartile 5 X Tenure</td>
<td>0.0983 (0.100)</td>
</tr>
</tbody>
</table>

Observations 22,939
\( R^2 \) 0.694
State FE Y
Year FE Y
Qtile FE + Qtile X Wage Spline Y
Ind + Ind X Qtile FE s Y
Occ + Occ X Qtile FE s Y
Taylor Linearized SE s Y
Clustered SE s N

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B.3: Elasticities of Job-to-Job moves by implied unemployment insurance. Unlike the re-employment elasticities, there are no significant results.
Table B.4: Earnings Profiles by Initial Wealth and Education

<table>
<thead>
<tr>
<th>Var.</th>
<th>PSID Var. Data</th>
<th>PSID Model</th>
<th>NLSY Var. Data</th>
<th>NLSY Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>0.0219</td>
<td>0.017240403</td>
<td>0.0206</td>
<td>0.025818289</td>
</tr>
<tr>
<td>Wilth Q2 x Age</td>
<td>0.0002</td>
<td>0.002614653</td>
<td>AFQT Q2 x Age</td>
<td>0.0003</td>
</tr>
<tr>
<td>Wilth Q3 x Age</td>
<td>-0.0069</td>
<td>0.003680533</td>
<td>AFQT Q3 x Age</td>
<td>0.0013</td>
</tr>
<tr>
<td>Wilth Q4 x Age</td>
<td>-0.0079</td>
<td>0.003972341</td>
<td>AFQT Q4 x Age</td>
<td>0.0054</td>
</tr>
<tr>
<td>Wilth Q5 x Age</td>
<td>-0.0082</td>
<td>0.001369083</td>
<td>AFQT Q5 x Age</td>
<td>0.0118</td>
</tr>
<tr>
<td>Wilth Q2</td>
<td>0.0072</td>
<td>0.13995567</td>
<td>AFQT Q2</td>
<td>0.0649</td>
</tr>
<tr>
<td>Wilth Q3</td>
<td>0.2564</td>
<td>0.31346933</td>
<td>AFQT Q3</td>
<td>0.1354</td>
</tr>
<tr>
<td>Wilth Q4</td>
<td>0.3759</td>
<td>0.56622501</td>
<td>AFQT Q4</td>
<td>-0.0016</td>
</tr>
<tr>
<td>Wilth Q5</td>
<td>0.4578</td>
<td>1.180341</td>
<td>AFQT Q5</td>
<td>-0.1798</td>
</tr>
<tr>
<td>Cons.</td>
<td>9.6977</td>
<td>9.7870251</td>
<td>Cons.</td>
<td>9.5107</td>
</tr>
</tbody>
</table>

Variance

| Earnings Residual LC Avg. | 0.2517 | 0.2798 |

Table B.4: SIPP Re-Employment Elasticity Comparisons

Table B.5: Re-Employment Elasticities by Liquid Wealth Quintile

<table>
<thead>
<tr>
<th>Var.</th>
<th>Data</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Q1 x Ln(UI)</td>
<td>0.7304</td>
<td>0.50423998</td>
</tr>
<tr>
<td>Q2 x Ln(UI)</td>
<td>0.3005</td>
<td>0.18792296</td>
</tr>
<tr>
<td>Q3 x Ln(UI)</td>
<td>-0.1621</td>
<td>0.06668889</td>
</tr>
<tr>
<td>Q4 x Ln(UI)</td>
<td>0.0718</td>
<td>0.04498655</td>
</tr>
<tr>
<td>Q5 x Ln(UI)</td>
<td>0.0229</td>
<td>0.02924884</td>
</tr>
<tr>
<td>Q2</td>
<td>0.0229</td>
<td>-0.58095917</td>
</tr>
<tr>
<td>Q3</td>
<td>0.0229</td>
<td>-1.5253957</td>
</tr>
<tr>
<td>Q4</td>
<td>0.0229</td>
<td>-3.0384027</td>
</tr>
<tr>
<td>Q5</td>
<td>0.0229</td>
<td>-4.7999015</td>
</tr>
<tr>
<td>Age</td>
<td>0.7304</td>
<td>0.50423998</td>
</tr>
<tr>
<td>Q1 x Ln(LstWg)</td>
<td>0.3005</td>
<td>0.18792296</td>
</tr>
<tr>
<td>Q2 x Ln(LstWg)</td>
<td>-0.1621</td>
<td>0.06668889</td>
</tr>
<tr>
<td>Q3 x Ln(LstWg)</td>
<td>0.0718</td>
<td>0.04498655</td>
</tr>
<tr>
<td>Q4 x Ln(LstWg)</td>
<td>0.0229</td>
<td>0.02924884</td>
</tr>
<tr>
<td>Q5 x Ln(LstWg)</td>
<td>0.0229</td>
<td>0.02924884</td>
</tr>
</tbody>
</table>

Table B.5: SIPP Re-Employment Elasticity Comparisons
Table B.6: Initial Distributions of Earnings and Wealth

<table>
<thead>
<tr>
<th>Decile</th>
<th>Initial Earnings (logs)</th>
<th>Initial Liquid Wealth</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Data</td>
<td>Model</td>
</tr>
<tr>
<td>1st</td>
<td>8.61088.7222311</td>
<td>-11779–1597.7503</td>
</tr>
<tr>
<td>2nd</td>
<td>9.31659.1321323</td>
<td>-234.649.33201</td>
</tr>
<tr>
<td>3rd</td>
<td>9.49269.3768199</td>
<td>-115.59330.7049</td>
</tr>
<tr>
<td>4th</td>
<td>9.63529.5790553</td>
<td>753.64 6129.977</td>
</tr>
<tr>
<td>5th</td>
<td>9.75599.7577245</td>
<td>2082.3 9380.4309</td>
</tr>
<tr>
<td>6th</td>
<td>9.893 9.9368699</td>
<td>3787.7 13412.543</td>
</tr>
<tr>
<td>7th</td>
<td>10.03110.129897</td>
<td>6073.6 18525.572</td>
</tr>
<tr>
<td>8th</td>
<td>10.17510.343724</td>
<td>10168 25678.061</td>
</tr>
<tr>
<td>9th</td>
<td>10.38310.611623</td>
<td>17388 37049.007</td>
</tr>
<tr>
<td>10th</td>
<td>10.78511.00902</td>
<td>40651 59817.866</td>
</tr>
</tbody>
</table>

Table B.6: This table shows model estimates of components 2 through 4 of the auxiliary model from Section 5.2, and compares them with the data.
<table>
<thead>
<tr>
<th>Category</th>
<th>Symbol</th>
<th>Value or Function</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Preferences and Technology</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Utility Function</td>
<td>$U(c)$</td>
<td>$\frac{c^{1-\sigma}}{1-\sigma}$</td>
<td>Power Utility</td>
</tr>
<tr>
<td>Discount Factor</td>
<td>$\beta$</td>
<td>0.9882</td>
<td></td>
</tr>
<tr>
<td>Risk Aversion</td>
<td>$\sigma$</td>
<td>2</td>
<td>Macro Standard</td>
</tr>
<tr>
<td>Production Function</td>
<td>$f(h)$</td>
<td>$zh$</td>
<td>Standard</td>
</tr>
<tr>
<td><strong>Human Capital</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Accumulation Function</td>
<td>$H_E(h, l, \tau)$</td>
<td>$l(h_1 \tau \frac{1}{\tau})^{\alpha_h}$</td>
<td>Ben-Porath (1967)</td>
</tr>
<tr>
<td>Depreciation</td>
<td>$H_U(h, l, \tau)$</td>
<td>$e^{\alpha_h}h_t$</td>
<td>Huggett, Ventura, Yaron (2011)</td>
</tr>
<tr>
<td>Returns to learning time</td>
<td>$\alpha_h$</td>
<td>0.5</td>
<td>Browning, Hansen, Heckman (1999)</td>
</tr>
<tr>
<td>Human Capital Evolution</td>
<td>$h_{t+1}$</td>
<td>$(h_t + H(h, l, \tau))$</td>
<td>Ben-Porath (1967)</td>
</tr>
<tr>
<td><strong>Labor Market</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Matching Function</td>
<td>$M(u, v)$</td>
<td>$uv(\omega + \eta)^\gamma$</td>
<td>Schaal (2012)</td>
</tr>
<tr>
<td>On-the-job Search Intensity</td>
<td>$\lambda_E$</td>
<td>0.73</td>
<td>Herkenhoff (2016)</td>
</tr>
<tr>
<td>Elasticity of Matching Function</td>
<td>$\eta$</td>
<td>0.5</td>
<td>Shi (2016)</td>
</tr>
<tr>
<td>UI Replacement Rate Distribution</td>
<td>$\left(\mu_b, \sigma_b\right)$</td>
<td>(0.4, 0.1)</td>
<td>Avg. from data</td>
</tr>
<tr>
<td>UI Loss Probability</td>
<td>$\gamma$</td>
<td>0.5</td>
<td>2 quarter average</td>
</tr>
<tr>
<td>Separation Rate</td>
<td>$\delta$</td>
<td>0.0</td>
<td>Shiner (2005)</td>
</tr>
<tr>
<td><strong>Asset Market</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Borrowing Constraint</td>
<td>$\alpha_t$</td>
<td>$\sum_{j=t}^{j=T} \frac{b_j}{1+r_F^j}$</td>
<td>Natural Borrowing Constraint</td>
</tr>
<tr>
<td>Risk Free Rate</td>
<td>$r_F$</td>
<td>0.0120</td>
<td>Annual rate of $\approx 5%$</td>
</tr>
<tr>
<td><strong>Initial Conditions</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Distribution</td>
<td>$\Psi$</td>
<td>$\Psi \sim LN(\psi, \Sigma)$</td>
<td>HVY (2011)</td>
</tr>
<tr>
<td>Mean</td>
<td>$\psi$</td>
<td>$[\mu_A \mu_H \mu_L]^T$</td>
<td></td>
</tr>
<tr>
<td>Variance-Covariance</td>
<td>$\Sigma$</td>
<td>$\begin{bmatrix} \sigma_A &amp; \sigma_{AH} &amp; \sigma_{AL} \ \sigma_{AH} &amp; \sigma_H &amp; \sigma_{HL} \ \sigma_{AL} &amp; \sigma_{HL} &amp; \sigma_L \end{bmatrix}$</td>
<td></td>
</tr>
<tr>
<td>Human Capital Depreciation</td>
<td>$\epsilon_t$</td>
<td>$\epsilon_t \sim N(\mu_h, \sigma_h)$</td>
<td></td>
</tr>
</tbody>
</table>

Table B.7: Functional form and parameter assumptions. I preset these quantities to commonly
accepted values from related literature to decrease the computational requirements of estimating
the model.
C Data Construction

C.1 Survey of Income and Program Participation (SIPP)

I use the SIPP to assess the effect that liquidity has on labor market outcomes. The SIPP is a panel dataset with separate surveys conducted annually from 1984 to 1993, and then during 1996, 2001, 2004, and 2008. Each survey follows a household for 16 to 36 months, with interviews every four months for each “wave” of respondents. Each interview includes detailed information on the employment, income, and unemployment insurance recipiency. Employment variables are coded down to a weekly frequency, which yields an extremely precise picture of a worker’s unemployment spells for the duration of the panel. In addition, each wave includes detailed information on special topics in “topical modules.” Although information on wealth is not available in the core questionnaire, it is included in some of the topical modules, averaging twice per panel. This allows me to link 2,442 unemployment spells to a variety of measures of their wealth upon entering an unemployment spell. The selection of individuals who experience unemployment spells but do not report wealth is random, because questions on wealth are only asked during some waves of the panel. The high frequency of the data, as well as the availability of detailed information on wealth makes the SIPP the best publicly available source to explore liquidity effects for the United States.

My selection criteria is similar to the previous literature on the liquidity effects of unemployment insurance\textsuperscript{13}. I first pool SIPP panels from 1990 to 2008. From these panels, I restrict my sample to unemployment spells for males age 21 and older with at least 3 months work experience, who took up UI within one month of job loss, and who are not on a temporary layoff\textsuperscript{14}. This leaves me with 2,442 spells for which I have some measure of wealth during unemployment. For each individual, I observe race, marital status, age, years of education, as well as tenure, industry, occupation, and wage at their previous job. Demographic characteristics are shown in Table B.1.

The SIPP employs a stratified sample design whose primary sampling units changed in 1992, 1996, and 2004. I make use of this complex survey structure to obtain accurate estimates of subsample variance, while accounting for design change by specifying the primary sampling units during each design regime (1990-1991,1992-1993,etc.) with a unique identifier. That is, an individual from the first PSU in 1990 would not be assigned to the same

\textsuperscript{13}See Chetty (2008) and Meyer (1990) for two examples using the same selection criteria.

\textsuperscript{14}Selecting on an endogenous variable, like unemployment insurance, may lead to biased estimates (Anderson and Meyer, 1997). I discuss this in Section 3.1.1
variance strata as an individual from the first PSU in 2001. I weight all of my results using person weights for individuals at the start of their unemployment spells. This allows me to effectively increase the size of my sample, while simultaneously retaining a very precise and accurate estimate of the variance. For robustness, I include results for standard errors clustered at the state level.

I incorporate data on UI laws by state from the Employment and Training Administration. This includes the average benefit received by individuals at a state by month frequency, as well as the potential number of weeks recipients could continue with unemployment insurance, at a state by quarter frequency, both from 1990 to 2014. Because surveyed unemployment insurance amounts are subject to a great deal of measurement error, I use this data as a proxy for unemployment insurance received. I repeat the results using reported unemployment insurance amounts as well.

C.2 National Longitudinal Survey of Youth, 1979 (NLSY79)

The National Longitudinal Survey of Youth follows cohorts who were ages 14-22 in 1979 through the present. It was conducted annually from 1979-1994 and bi-annually from 1994 until now, and includes detailed information on labor market status, including current employer, weeks employed, unemployed, and out of the labor force, as well as any training received by the individual since the last interview. Earnings are recorded annually as well as hours worked. In addition, the NLSY recorded a standardized test score, the Armed Forces Qualification Test (AFQT) for every individual in the sample. This allows me to link individuals by their AFQT scores to their outcomes late in the life-cycle, which I use to discipline correlations between human capital and growth rates in my model. In 1985, the NLSY began recording information on the wealth of individuals. Unfortunately, a large fraction of the sample had already become employed, making its usage challenging in my analysis.

I employ sample restrictions similar to Huggett et al. (2011). First, I require that each individual be head of their household, male, and between the ages of 25 and 54. For constructing the distribution of wealth and earnings at first employment (moments 1 and 4), I require that the individual either be observed before entering employment, or that they report they entered employment during the previous year and the job is their first. I also require that these individuals be no younger than 23 and no older than 27. Over the life-cycle, I require that the individuals in my sample be strongly attached to the labor market: any in-
individual in my sample must work at least 520 hours during the year and earn at least $9,500 in 2011 dollars if they are 31 or older. If they are younger than 30, I lower this requirement to $4,750, and 260 hours, to capture individuals who might choose part-time employment in order to have a steady income stream. I use the same sample restrictions when constructing profiles by initial liquid wealth quintile. My variables are defined as closely as possible to their analogues in Section 3, but at an annual frequency.

C.3 Panel Study of Income Dynamics (PSID)

I use the Panel Study of Income Dynamics (PSID) to estimate and match moments 1, 4, 5, 6, 7, and 8. The PSID is a panel that follows a group of households from the United States that ran yearly from 1968 to 1997, and in alternating years through the present. Because the PSID spans nearly 50 years, it has been frequently employed for researchers interested in exploring life-cycle effects within the United States (Storesletten et al. (2004) and Rupert and Zanella (2015), among others), as well as researchers interested in inequality (Huggett et al. (2011), Guvenen (2009), among others). In addition to this, the PSID began recording information on household wealth holdings in their “wealth supplements,” in 1984 repeated these questions in 1989, 1994, and 1999, and then in each subsequent panel. In the United States, this is the only publicly available dataset that contains multiple cohorts, long-term observations on earnings, and measures of household wealth at ages close to or before labor market entry. In addition to these variables, the PSID includes rich observations on demographics, labor market experience, as well as family history and behavioral characteristics. The sample restrictions that I use are identical to those used for the NLSY79 sample in Section C.2.

C.3.1 Wealth Quantile Construction

I use net liquid wealth as a measure of liquidity in the PSID. I define this to be any liquid assets, including checking, savings, stocks, bonds, etc. net of any unsecured obligations, including credit cards and student debt. I define earnings to be exclusively labor earnings at an annual frequency, and always in 2011 dollars, identical to the definition that I use in my exploration of the SIPP. Unfortunately, prior to 2011, the PSID did not report the specific composition of the debt held by households other than a few aggregated categories.

To assign individuals to initial quintiles in the wealth distribution, I first exclude observations who do not meet the following characteristics: first, agents must be the head of their

---

15The NLSY79 contains information on wealth, but only long after labor market entry.
household when I observe their assets; second, they must be age 30 or younger during a year in which I observe their assets; third, they must have no labor market experience, having earned no more than $9,750 dollars (2011 dollars) or worked more than 520 hours (one standard deviation less than the sample average) during the previous year.\(^{16}\) This subsample faces limitations, as few individuals have both observations on their assets at an age younger than 30 and simultaneously have observations on earnings at later ages. I also scale wealth before entering the labor market by the number of individuals in the household. I pool all individuals for whom I observe assets and adjust for growth over time.

Having run this regression, I assign individuals to quantiles within the distribution based on their observed liquid wealth. I assign individuals to the nearest quintile (in terms of their rank) within the distribution. Because the wealth data contains few observations on earnings for individuals, while simultaneously observing their wealth before age 30, I employ a strategy similar to a synthetic control method. I classify individuals into five quintiles as described above, and then using these generated quintiles, I run an ordered logit to classify individuals for whom I do not have observations on wealth, based on their observables. Qualitatively, this technique generates earnings profiles that exhibit the same correlations in earnings for the ages for which I have wealth observations, but allows me to match my model to earnings at ages greater than 50.

### C.3.2 Earnings and Wealth Life-Cycle Moment Construction

I use the Panel Study of Income Dynamics (PSID) to estimate and match moments 1, 4, 5, 6, 7, and 8. The PSID is a panel that follows a group of households from the United States that ran yearly from 1968 to 1997, and in alternating years through the present. Because the PSID spans nearly 50 years, it has been frequently employed for researchers interested in exploring life-cycle effects within the United States (Storesletten et al. (2004) and Rupert and Zanella (2015), among others), as well as researchers interested in inequality (Huggett et al. (2011), Guvenen (2009), among others). In addition to this, the PSID began recording information on household wealth holdings in their “wealth supplements,” in 1984 repeated these questions in 1989, 1994, and 1999, and then in each subsequent panel. In the United States, this is the only publicly available dataset that contains multiple cohorts, long-term observations on earnings, and measures of household wealth at ages close to or before labor market entry.\(^{17}\) In addition to these variables, the PSID includes rich observations on demographics, labor

---

\(^{16}\)Huggett et al. (2011) use a similar sample selection method.

\(^{17}\)The NLSY79 contains information on wealth, but only long after labor market entry.
market experience, as well as family history and behavioral characteristics.

I employ sample restrictions similar to Huggett et al. (2011). First, I require that each individual be head of their household, male, and between the ages of 25 and 54. For constructing the distribution of wealth and earnings at first employment (moments 1 and 4), I require that the individual either be observed before entering employment, or that they report they entered employment during the previous year and the job is their first. I also require that these individuals be no younger than 23 and no older than 27. Over the life-cycle, I require that the individuals in my sample be strongly attached to the labor market: any individual in my sample must work at least 520 hours during the year and earn at least $9,500 in 2011 dollars if they are 31 or older. If they are younger than 30, I lower this requirement to $4,750, and 260 hours, to capture individuals who might choose part-time employment in order to have a steady income stream. I use the same sample restrictions when constructing profiles by initial liquid wealth quintile. My variables are defined as closely as possible to their analogues in Section 3, but at an annual frequency. I define liquid wealth to be any liquid assets, including checking, savings, stocks, bonds, etc. net of any unsecured obligations, including credit cards and student debt. I define earnings to be exclusively labor earnings at an annual frequency, and always in 2011 dollars.

D Estimation

Following DeJong and Dave (2011), indirect inference is defined as follows: let \( \delta(z_t) \) be a set of reduced-form empirical moments generated from the data \( z_t \), and let \( \delta(y_t, \theta) \) be the set of reduced-form moments from model-generated data \( y_t \) with structural parameters \( \theta \). The set of moments is then given by \( g(z_t, \theta) = \delta(z_t) - \delta(y_t, \theta) \), and the objective function can be written as

\[
\min_{\theta} [g(z_t, \theta)' \Omega^* g(z_t, \theta)]
\] (D.1)

where \( \Omega^* \) is a positive semi-definite weighting matrix. Gourieroux et al. (1993) show that the indirect inference estimator for \( \theta \) is asymptotically normal with mean 0 and variance \( W \). I follow Bowlus and Liu (2013) and use \( \text{var}(\delta(z_t))^{-1} \), the efficient weighting matrix, for \( \Omega^* \).
E Simple Model of Borrowing Constraints

I show the connection between the re-employment elasticities in Table 3.1 and borrowing constraints in a simple 2-period consumption-savings model. In the model, agents start unemployed with a random level of wealth $a_1$ and unemployment insurance $b$. During the second period, they find a job with probability 1, and receive an income of $w_2$. During period 1, agents may choose to save or borrow up to $a_1$, both at interest rate $r$.

In addition, agents can choose to receive part of their future income during period 1. To do this, they forgo income in the second period at rate $\rho > r$, meaning that for unconstrained agents this borrowing vessel is rate of return dominated by borrowing assets. Intuitively, this proxies the decision faced by a poor agent, to start receiving income sooner, but receive lower incomes in the future. The problem faced by an agent is given by the following:

$$U_1(a_1, b) = \max_{c_1, a_2, w_1} \frac{c_1^{1-\sigma} - 1}{1 - \sigma} + \beta U_2(a_1, w_1)$$ \hspace{1cm} (E.1)

s.t. $c_1 + a_2 \leq (1 + r)a_1 + b + w_1$ \hspace{1cm} (E.2)

$$a_2 \geq a$$ \hspace{1cm} (E.3)

$$U_2(a_2, w_1) = u(c_2)$$ \hspace{1cm} (E.4)

s.t. $c_2 = (1 + r)a_1 + w_2 - (1 + \rho)w_1$ \hspace{1cm} (E.5)

For simplicity, assume that $\beta = \frac{1}{1+r}$. For an unconstrained agent, the optimal allocation is given by the following:

$$a_2^* = \frac{(1 + r)a_1 + b - w_2}{1 + r}$$ \hspace{1cm} (E.6)

$$w_1^* = 0$$ \hspace{1cm} (E.7)

When an agent is constrained, however, they borrow up to the limit and then forgo future income in order to satisfy their Euler Equation. The optimal allocation for these agents becomes
\[ a_2^* = a \]  
\[ w_1^* = \frac{(1 + r)a + w_2 - (1 + r)a_1 - b}{2 + \rho} \]  

Now, consider how both types of agents change their income allocations in response to a change in unemployment insurance. First, an unconstrained agent:

\[ \frac{\partial w_1^*}{\partial b} = 0 \]  

Like the wealthy individuals in the SIPP, these unconstrained agents show no response to a change in their unemployment insurance. However, for constrained agents:

\[ \frac{\partial w_1^*}{\partial b} = -\frac{1}{2 + \rho} \]  

An increase in unemployment insurance decreases the income that they are willing to forgo in the future by relaxing their borrowing constraints. This is a simplified version of the tradeoff faced by constrained agents during the job search process, but illustrates the connection between unemployment insurance, borrowing constraints, and future earnings. The model that I build incorporates these features, as well as moral hazard, and persistence from differences in human capital accumulation. I use the empirical results from this section to discipline borrowing constraints in my model.