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Three Essays on Market Imperfections and Inequality

A dissertation submitted in partial satisfaction
of the requirements for the degree

Doctor of Philosophy
in
Economics

by

Benjamin S. Griffy

Committee in charge:

Professor Peter Rupert, Chair
Professor Finn Kydland
Professor Peter Kuhn
Professor Javier Birchenall

June 2018

The Dissertation of Benjamin S. Griffy is approved.

Professor Finn Kydland

Professor Peter Kuhn

Professor Javier Birchenall

Professor Peter Rupert, Committee Chair

June 2018

Three Essays on Market Imperfections and Inequality

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by

Benjamin S. Griffy

To my family.

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Curriculum Vitæ
Benjamin S. Griffy

EDUCATION

University of California, Santa Barbara, Santa Barbara, CA

Ph.D., Economics, June 2018 (expected)

M.A., Economics, July 2013

University of Oregon, Eugene, OR

B.S., Economics and Mathematics with Honors, June, 2012

HONORS AND AWARDS

University of California, Santa Barbara:

- Andron Fellowship, 2012-2013
- Block Grant, 2012-2013
- Outstanding Teaching Assistant (PhD Macro I), Fall 2014
- Graduate Student Research and Travel Grant, Spring 2015, Fall 2015, Spring 2016, Fall 2016, Fall 2017
- Academic Senate Travel Grant, Spring 2018

WORKING PAPERS

"Borrowing Constraints, Search, and Life-Cycle Inequality," 2016
"Public Education Spending and Intergenerational Mobility in the United States," 2014
"Do Workers Direct their Search?" Joint with Christine Braun, Bryan Engelhardt, and Peter Rupert, 2015

WORKS IN PROGRESS

"Firm Bargaining Regimes and the Unemployment Volatility Puzzle," joint with Pedro Gomis-Porqueras, 2017
"Labor Market Frictions, Wealth Effects, and Portfolio Allocations," joint with Gaston Chaumont, 2017
"Student Debt and the College Premium," joint with Lancelot Henry de Frahan, 2017
"The Effects of Wealth on Search and Training," 2016

WORKS IN PROGRESS

2018: University at Albany, SUNY; University of South Carolina; University of Hawaii at Manoa; Federal Reserve Bank of Atlanta; Midwest Macroeconomics Spring (University of Wisconsin - Madison)

2017: Vienna Macro Workshop at NYU Abu Dhabi; Western Economic Association Annual Meetings (San Diego); University of Melbourne; UCSB Macroeconomics Workshop (hosted by Finn Kydland); UCSB Department Seminar; Midwest Macroeconomics Fall (University of Pittsburgh)

2016: Midwest Macro Fall (Kansas City Federal Reserve); West Coast Search and Matching (Simon Fraser University); Search and Matching Workshop (discussant, Konstanz University); Midwest Macro Spring Conference (Purdue University); UCSB Macroeconomics Workshop (hosted by Finn Kydland)

2015: Washington University, St. Louis Annual Economic Graduate Student Conference; University of Leicester Annual PhD Conference; UCSB Macroeconomics Workshop (hosted by Finn Kydland)

Refereeing

Journal of Labour Economics

Academic Experience

University of California, Santa Barbara, Santa Barbara, CA
Teaching Assistant **September 2013 - Present**

- ECON 204A: PhD Introductory Macroeconomics I, Fall 2014, Fall 2015
- ECON 204B: PhD Introductory Macroeconomics II, Winter 2015, Winter 2016
- ECON 204C: PhD Introductory Macroeconomics III, Spring 2015, Spring 2016
- ECON 101: Intermediate Macroeconomics, Fall 2013, Summer 2014, Fall 2016
- ECON 2: Introduction to Macroeconomics, Winter 2014, Spring 2014, Summer 2015, Summer 2016

Head Teaching Assistant **Winter 2017 - Present**

- ECON 2: Introduction to Macroeconomics, Winter 2017, Spring 2017

Abstract

Three Essays on Market Imperfections and Inequality

by

Benjamin S. Griffy

My dissertation focuses on margins that may disproportionally impact impoverished individuals. I primarily focus on two imperfections that I show contribute to inequality: frictional labor markets, and imperfect credit markets. Understanding the consequences of each, as well as how they interact, is central to better understanding the sources of inequality.

My first chapter quantifies the impact of borrowing constraints on consumption and earnings inequality using a life-cycle model. I first show that following an unemployment spell, likely-constrained workers in the Survey of Income and Program Participation match to jobs that pay more per quarter when they receive an increase in their unemployment insurance. I then construct a life-cycle model with 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 parameters, and show that wealth inequality causes both placement into lower-paying jobs as well as slower human capital accumulation when workers face borrowing constraints. Unemployment risk is partially responsible for this change in human capital accumulation. I compare changes in initial conditions and find that a standard deviation decrease in initial wealth causes a larger decline in life-cycle consumption than a standard deviation decrease in initial human capital.

My second chapter deals with the appropriate approach to modeling frictional labor markets, and is joint work with Christine Braun, Bryan Engelhardt, and Peter Rupert. In it, we address whether the arrival rate of a job independent of the wage that it pays. To do this we address how, and to what extent, unemployment insurance changes the hazard rate of leaving unemployment

across the wage distribution using a Mixed Proportional Hazard Competing Risk Model and data from the 1997 National Longitudinal Survey of Youth. Controlling for worker characteristics we reject that job arrival rates are independent of the wages offered. We apply the results to several prominent job-search models and interpret how our findings are key to determining the efficacy of unemployment insurance.

My final chapter addresses whether public education plays a role in decreasing intergenerational persistence of income. Intuitively, impoverished families face constraints when their children are young: either in moving to better school districts, or in buying adequate supplies for their children. I explore empirically the extent to which increases in public education spending can decrease the importance of a parent's income in determining their child's. I expand on the previous literature by using an instrument for government spending in order to assess the effect of public spending on public education in changing income persistence. I find that an increase in government spending on education significantly decreases persistence of income across generations.

Contents

Chapter 1

Introduction

A father of the modern study of frictional labor markets, Dale Mortensen, begins his book on the topic by posing a question: "Why are Similar Workers Paid Differently?" The sources of economic inequality have been central to politics, conflict, and intellectual curiousity for generations. And while economics has made substantial progress in addressing the nature of inequality, many questions remain.

Inequality is a topic that is inherently difficult to study. We know that people are different, but determining how much of differences in outcomes is caused by skill, and how much is caused by luck is an empirically challenging question. Both are unobservable, and correlated with a host of other confounding factors. To better understand the mechanisms, economists often turn to theory to provide a structure in which to interpret inequality.

Nearly all theory in economics builds from the idea that individuals in the economy interact in markets that are perfectly competitive. This approach is appealing for many reasons, and provides an internally consistent view of the world that can be missing from other approaches to studying inequality. And in many circumstances, the assumption of perfectly competitive markets is innocuous, and yields clean analytic and computationally tractable results. However, realistic departures from perfect competition can imply radically different outcomes for impoverished households.

One of many ways to interpret the standard theory of asset markets is that individuals are able to use future income to insure against any idiosyncratic risk they may face in the present. An individual would like to maintain a roughly constant level of consumption throughout their life, so when presented with a negative income shock today, they are able to use future income or their accumulated wealth to smooth their consumption. For wealthy individuals, this is sensible: if there is no need to borrow, these individuals can easily draw down their savings until their income returns to its baseline. However, for poor individuals, a departure from this assumption has large consequences: if individuals are unable to borrow, they will change their decisions to mitigate consumption risk both now and in the future. Among others, these decisions could include the types of jobs they take, the amount of education that they receive, and the types of assets in which they invest. My work considers instances in which asset markets are imperfect, meaning that individuals can only borrow a limited fraction of their future lifetime income.

The standard approach to modeling the labor market is to assume that workers earn their marginal product. This means that for every hour worked, an individual is compensated for precisely what they produce. In accounting for inequality, this theory predicts that the bulk of income differences must be due to differences in human capital, or productivity, because workers are compensated solely on the basis of their output. Departing from this theory again yields very different predictions about inequality. When labor markets are frictional, meaning that it takes time and effort to find employment, workers are not paid their marginal product. Workers and firms share the rents created by their production; this share is of key importance for understanding inequality. If a worker receives a relatively small share of the surplus, they could be immensely productive and yet would appear to have minimal human capital if accounting for inequality in a model with perfectly competitive labor markets.

In isolation, these imperfections are important for inequality; together, they can play a consequential role in determining differences in earnings, welfare, and long-term outcomes.

Labor market frictions pose a very specific type of income and consumption risk: losing a job involves a discrete drop in earnings, which is highly persistent (though it may ultimately be transitory). When faced with borrowing constraints, labor market risk can amplify differences in earnings for poor individuals, further distorting their decisions and leading to larger degrees of inequality. Understanding the size of these effects, the consequences of these frictions, and the policies that can ameliorate these distortions are central to this dissertation.

Chapter 2

Borrowing Constraints, Search, and Life-Cycle Inequality

2.1 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 affect job placement, earnings, and on-the-job human capital growth. I construct a quantitative life-cycle model that considers risk-averse workers who face incomplete asset markets, must search for jobs, and can choose their rate of human capital accumulation. After estimating the model, I find that 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. The first effect is due to unemployment risk, while the second is due to both differences in permanent income and insurance against unemployment risk. Quantitatively, I show that a standard deviation decrease in wealth at age 23 decreases consumption and earnings growth by more than a standard deviation decrease in human capital.

I build a model to decompose the contribution of initial conditions to inequality when workers face borrowing constraints. 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. Incomplete asset markets limit the ability of workers to directly substitute future income 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 with an inverse relationship between wages and probability of employment in equilibrium. Human capital accumulation lets employed workers choose to allocate productive time between working and accumulating human capital.[1] The model considers initial heterogeneity in wealth, human capital, and learning, and quantifies the impact of each on life-cycle inequality.

To motivate the theory, I use the Survey of Income and Program Participation (SIPP) to show evidence that borrowing constraints alter earnings following an unemployment spell. I exploit differences in replacement rates across states to estimate the differential effect that unemployment insurance replacement rates have on constrained and unconstrained households. I find that workers from the first quintile of the liquid wealth (liquid assets net of unsecured debt) distribution match to 6.3% higher paying jobs when given a 10% increase in unemployment insurance, despite nearly identical pre-spell earnings, tenure, and education.[2] Over longer horizons, I find that the effects on wages appear to persist.

I estimate the model using indirect inference. Indirect inference creates a straightforward connection to the data by matching parameters from reduced-form specifications that approximate equilibrium outcomes of the model. I use findings from the SIPP as well as life-cycle

[1] To my knowledge, this is the first paper 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.

[2] Herkenhoff et al. (2016) find evidence that access to additional credit improves labor market outcomes following an unemployment spell.

earnings and job transition statistics from the Panel Study of Income Dynamics (PSID) and the National Longitudinal Study of Youth 1979 (NLSY) to discipline key features that determine the behavior of workers in my model. The moments from the SIPP yield inference on borrowing constraints, while moments from the PSID and NLSY provide inference on the correlations between wealth, human capital growth, and earnings over the life-cycle. I test the fit of the estimated model and find that the model fits the data well.

I find that constrained workers decrease their consumption risk by applying to jobs that offer shorter expected unemployment durations, but lower wages. Wealthy workers can smooth consumption and experience extended unemployment spells, while finding better employment. Though the estimation suggests that poor and wealthy individuals have similar productivities, wealth inequality causes large differences in first job placement. While the effect on initial job placement is transitory, differences in earnings persist. Unable to borrow against future income, constrained workers substitute intertemporally by allocating time to production, rather than human capital accumulation. They do this to smooth consumption, and to insure against potential unemployment spells. The placement effect causes earnings inequality for 5 years, while the human capital effect persists for the life-cycle.

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, a standard deviation decrease in initial wealth depresses lifetime consumption by more than a standard deviation decrease in initial human capital. The difference in wealth causes consumption to decrease -10.5%, while the change in human capital causes consumption to change by -7.6%. Wealth operates primarily by changing the application strategy of workers (-2.2%), but also decreases earnings by changing average human capital (-1.1%). Of the change in human capital, I find that insurance against unemployment accounts for about 1/3rd of the total change. I also find that the average individual at the 10th percentile of the wealth distribution experiences a lifetime earnings increase of 3.5% when given the median wealth in the sample.

The paper is organized as follows: in section 2.2 I review the literature and describe how previous work differs from mine. In section 2.3 I document liquidity effects on re-employment wages for constrained groups. In section 2.4, I construct a model that incorporates these findings, and show the equilibrium. In section 2.5, I explain the functional form and parameter assumptions, and my construction of targets for indirect inference. In section 2.6, I decompose the implications for life-cycle inequality, and compare my findings to the existing literature. Lastly, in section 2.7 I summarize my contributions and discuss routes for future work.

2.2 Related Literature

This paper addresses a question that relates to the literatures on labor market search, human capital, and inequality. Here, I summarize many of the most closely related papers.

Graber and Lise (2015) 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.[3] 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[4], which allows for an exogenous productivity drift while employed, and assume that

[3] Their work is a follow-up to Lise (2013), which was similar, but without human capital accumulation.

[4] 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.

workers receive draws from a wage distribution at an exogenous rate, both for tractability. As my findings indicate, endogenous human capital accumulation plays an important role in lifetime inequality in models with borrowing constraints. To my knowledge, Bowlus and Liu (2013) is the only other paper to include a model with both search and Ben-Porath (1967) human capital accumulation. They focus on the decomposition of earnings growth between search frictions and human capital accumulation. Agents in their model are risk-neutral, while my paper shows that risk aversion has a consequential effect on both search and human capital. 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 primarily focus on decomposing the contributions of wage bargaining and human capital growth to wage growth, and neither feature risk aversion. Ji (2017) primarily studies the impact that student debt has on aggregate outcomes, but also considers the effect on life-cycle profiles. 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. He finds that individuals with student debt experience lower pay and shorter unemployment durations than non-borrowing peers for roughly 15 years. His model does not consider the dynamic effects through human capital accumulation.

There is also a growing literature primarily focused on identifying the short-term effects of student debt on labor market outcomes. Gervais and Ziebarth (2017) 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%. Luo and Mongey (2017) and Rothstein and Rouse (2011) use variation 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 Luo and Mongey and $\$978$ in Rothstein and Rouse). My paper 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 begin following employment.

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 (2010) introduces risk averse agents and learning-by-doing human capital accumulation 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. 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. Others who have introduced risk-aversion into the Mortensen and Pissarides (1994) model include Lentz and Tranaes (2005), Krusell et al. (2010), and Costain and Reiter (2008). These papers feature distributions of wealth, but do not include human capital.

My model extends the block recursive search frameworks Menzio and Shi (2010) and Menzio et al. (2016). These are search frameworks that allow for endogenously determined distributions of agents. Follow-up work by Herkenhoff (2014), introduced directed search with risk aversion into a life-cycle version of the block recursive search model, focused on the effects of credit access on the business cycle.[5] Another paper, Herkenhoff et al. (2016), introduced human capital accumulation into this framework, but did so through learning-by-doing, and again restrict their exploration to aggregate fluctuations. Chaumont and Shi (2017) uses a closely related model with infinitely-lived agents to highlight the effects of unemployment risk on precautionary savings. They focus on cross-sectional dispersion, rather than life-cycle effects, and do not include human capital accumulation. They find that wealth effects alone play a small role in determining wage dispersion.

[5] Herkenhoff (2012) was the first to consider risk averse workers facing borrowing constraints in this framework.

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. The most closely related, Huggett et al. (2011), studies both the relative importance of shocks and initial conditions, and decomposes the contribution of life-cycle inequality among initial conditions. Similary to my work, their model features heterogeneity in wealth, human capital, and learning, and allows 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. Similarly, Heathcote et al. (2014) use a model with heterogeneity in preferences and productivity to decompose sources of inequality. They reach a similar conclusion as Huggett et al.: productivity is the primary driver of earnings 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 is caused by my inclusion of frictional labor markets, which makes wealth have a first order effect on earnings.[6]

2.3 Empirical Regularities

Three key empirical regularities 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.[7] Second, among the full-time employed, initially wealthy individuals consistently receive more training throughout the life-cycle, sug-

[6] 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.

[7] 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 sparse.

gesting a link between initial wealth and human capital accumulation. Third, I find that there are large, persistent differences in earnings among individuals with below median wealth and above median wealth. I use these findings as motivation as well as estimation targets for my model in section 2.5.

2.3.1 Re-Employment Elasticities

To explore the effects of borrowing constraints on labor market outcomes, I estimate the responsiveness of constrained (using liquid wealth as a proxy) individuals to changes in their unemployment insurance replacement rates. I Find that the elasticity of the re-employment wage with respect to unemployment insurance amount is substantial 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 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 restrict my sample to 23 and older males who take up UI within one month of unemployment. More details on the construction of this data is available in subsection A.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 to quantify the effects of UI on labor market outcomes (Browning and Crossley (2001), Bloemen and Stancanelli (2005), Sullivan (2008), and Chetty (2008), among others). These papers find that unemployment insurance is used as a substitute for income during unemployment spells among illiquid households, which motivates the use of net liquidity as a proxy for borrowing constraints.

Individuals frequently misreport their level of unemployment benefits; therefore, I proxy for unemployment insurance by using the average weekly benefit over an unemployment spell at the state-month level and frequency. 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. 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 level and frequency to capture any correlation between replacement rates and duration generosity for a state unemployment insurance system. Table A.2.1 summarizes key employment and demographic characterics 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.[8]

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. 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. In each of the following equations, I include age, race, marital status, education, tenure, as well as

[8]Selecting on unemployment insurance recipients may cause bias in my estimates; however, per Table A.2.1, 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. Within the 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.

state and year fixed effects. I also include interactions between net liquidity quantiles and each of industry, occupation (2-digit) and the log-wage spline. My main test uses the following specification:

$$ln(Y_{i,j+1,s,t}) = \alpha_0 + \sum_{q=1}^{5} \delta_0^q \times ln(UI_{s,t}) + \sum_{q=1}^{5} \delta_1^q \times \text{UIDur}_{s,t} \tag{2.3.1}$$

$$+ \delta_s + \delta_t + X_{i,j,t}\beta + \epsilon_{i,j+1,s,t} \tag{2.3.2}$$

where j is the previous job and $j+1$, the next job, reported by individual i at time t in net liquidity quintile q. δ_0^q and δ_1^q are the effect of UI replacement rates and potential UI duration for an individual in net liquid wealth quintile q at the start of a spell. A positive δ_0^q indicates that more generous unemployment insurance is associated with better employment outcomes for quintile q. A negative δ_1^q indicates that longer unemployment insurance durations result in worse re-employment outcomes.

Findings

My results show that constrained workers alter their search behavior when presented with additional unemployment insurance. Individuals from the first quintile of liquid wealth find jobs offering 6.34% higher pay the month after unemployment when they receive a 10% increase in UI (column 1 of Table 2.3.1). Column 2 shows that the effect is the same magnitude (6.28%) during the quarter following unemployment. 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) but only for the first quintile. I also find that longer potential UI is associated with a decline in wages, though only for the wealthiest population.

Given that employment is highly persistent, while the average unemployment spell in my sample is less than 25 weeks, an elasticity of 0.63 suggests that an additional source of income

Re-Employment Labor Income Regressions (by Net Liquidity)

VARIABLES	(1) Log of Next Weekly Earnings	(2) Log of Next Quarterly Earnings
Net Liq. Quintile 1 X Log of Avg. UI	0.634**	0.628**
	(0.262)	(0.260)
Net Liq. Quintile 2 X Log of Avg. UI	0.223	0.303
	(0.258)	(0.273)
Net Liq. Quintile 3 X Log of Avg. UI	0.00351	-0.0310
	(0.351)	(0.279)
Net Liq. Quintile 4 X Log of Avg. UI	0.132	0.0194
	(0.205)	(0.214)
Net Liq. Quintile 5 X Log of Avg. UI	0.174	0.109
	(0.256)	(0.272)
Net Liq. Quintile 1 X Potential UI Weeks	-0.00102	0.0160
	(0.00985)	(0.0112)
Net Liq. Quintile 2 X Potential UI Weeks	-0.00946	-0.00847
	(0.00836)	(0.00701)
Net Liq. Quintile 3 X Potential UI Weeks	0.0155	0.0113
	(0.0174)	(0.0172)
Net Liq. Quintile 4 X Potential UI Weeks	0.0117	0.00507
	(0.0112)	(0.00983)
Net Liq. Quintile 5 X Potential UI Weeks	-0.0225**	-0.0217***
	(0.00977)	(0.00777)
Observations	2172	2311
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

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

Table 2.3.1: 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.

alters job search behavior. Prior to separation, these individuals had nearly identical labor market characteristics (Table A.2.1). Results clustered at the state level yield similar significance levels, and are reported in the online appendix. As a check on the credibility of my findings, I explore whether unemployment insurance generosity is predictive of 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. I use the same specification as Equation 2.3.1, and include UI interacted with liquid wealth quintiles. This yields insignificant results for all coefficients of interest, and is reported in the online appendix.

2.3.2 Life-Cycle Profiles

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 (NLSY), 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 section A.1. I first use the NLSY 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 individuals from different wealth quantiles. For both results, I use the following specification:

$$Y_{i,a,s,t} = \alpha_0 + \sum_{q=1}^{5}(\delta_0^q \times \text{Age}) + \delta_s + \delta_t + X_{i,a,t}\beta + \epsilon_{i,a,s,t} \tag{2.3.3}$$

where $Y_{i,a,s,t}$ is the outcome of interest (either training hours or log-earnings) for individual i, at age a, in area s, in year t. Both regressions control 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.

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. Details of the sample selection are available in subsection A.1.3. The profiles show a clear correlation between initial wealth and time training (Figure 2.3.1). These

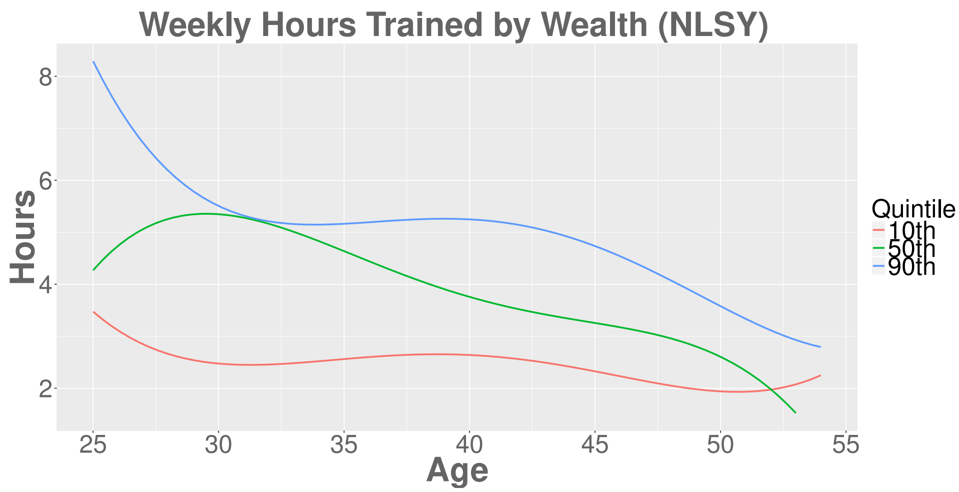


Figure 2.3.1: Training Hours Per Week by Wealth Quintile.

measures include training outside of work as well as training sponsored by employers. These profiles suggest that there is a correlation between wealth and human capital accumulation while working.

Earnings

There appear to be permanent earnings differences between individuals from different wealth strata. Figure 2.3.2 shows the average earnings profiles individuals by their liquid wealth prior to entering the labor market. The left panel shows high school educated individuals, and the right panel shows college educated individuals. Both show that individuals from the bottom of the wealth distribution experience persistently different earnings profiles from their wealthier peers. Details of the sample selection are available in subsection A.1.2.

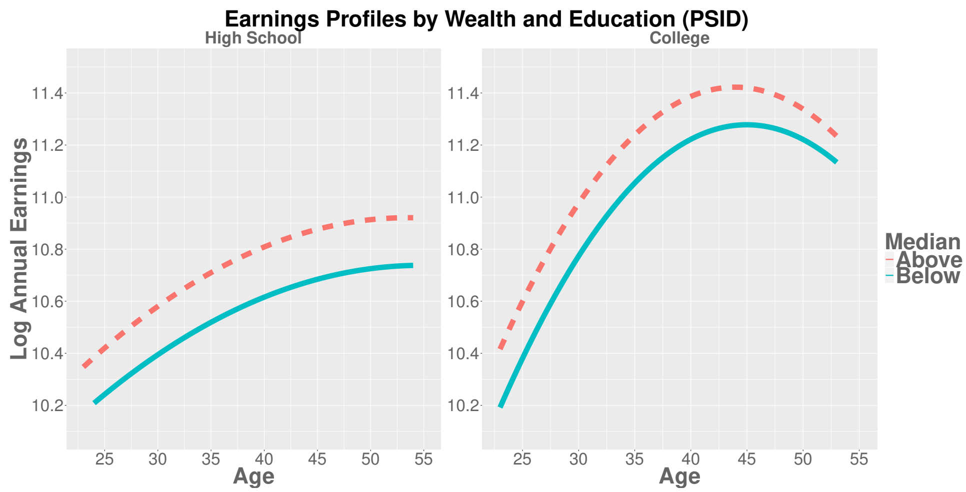


Figure 2.3.2: Earnings Profiles by Initial Wealth and Education.

2.4 The Model

2.4.1 Environment

Time is discrete and continues forever, while each agent lives deterministically for $T \geq 2$ periods. There is a continuum of both firms and workers, each of which discounts future value at the identical rate β. Each worker is born unemployed without benefits, and receives a draw from a correlated trivariate log-normal distribution $\Psi \sim LN(\psi, \Sigma)$ of wealth, human capital, and learning ability (a_0, h_0, ℓ). Over the life-cycle, a worker may be in one of three employment states: employed, unemployed with unemployment insurance, and unemployed without unemployment insurance. Workers in each employment state are allowed to direct their search to contracts posted by firms.

Each worker is endowed with one indivisible unit of labor that they can enjoy as leisure during unemployment or supply inelastically while employed. Leisure utility ν is assumed to be additively separable, $u(c) + (1 - e)\nu$, where e denotes employment status. 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,

$\underline{a}'$, and are not allowed to default on any debt obligations, nor exit the terminal period T with negative asset holdings. While employed, workers are allowed to devote productive time τ to accumulating human capital through a Ben-Porath production function, $H(h, \ell, \tau, L)$, which is increasing in its first 3 arguments. L denotes the labor market status E or U. All workers face an iid human capital shock between periods, $\epsilon' \sim N(\mu_\epsilon, \sigma_\epsilon)$, that permanently alters human capital. This is modeled as $h' = e^{\epsilon'}(h + H(h, \ell, \tau, E))$.

Workers transition from employment to unemployment in one of two ways: with probability δ, they receive a separation shock and enter unemployment, and with probability $\lambda_E \leq 1$, they are allowed to search while employed for a new job. Employed workers receive $\mu(1-\tau)f(h)$ as income each period, where μ is their piecerate wage, $(1-\tau)$ the time left over after human capital decisions, and $f(h)$ is their productivity given their current human capital. If they receive an unemployment shock, workers receive unemployment benefits $b_{UI} = min\{b\mu(1-\tau)f(h), \bar{b}\}$, where b is the replacement rate, and $\bar{b}$ is the maximum benefit allowed per quarter. I assume that unemployment benefits are drawn from a distribution $b \sim N(\mu_b, \sigma_b)$. Both the distribution of replacement rates and benefit cap are important for my identification strategy. Agents stochastically lose benefits with probability γ, and receive $b_L \leq b_{UI}$, which reflects opportunities to earn money outside the labor force.

Firms post vacancies at cost κ. These vacancies are one-firm-one worker contracts that specify the piecerate of output paid as earnings, μ. These contracts are assumed to be renegotiation-proof, and firms are not allowed to respond to outside offers, thus μ is fixed for the duration of the contract. Worker characteristics are assumed to be observable, and thus firms open vacancies into specific submarkets that are indexed by the observables of the worker. Thus, submarkets are identified by the following tuple: $(\mu, a, h, \ell, t) \in \mathbb{R}_+ \times \mathbb{R} \times \mathbb{R}_+ \times \mathbb{R}_+ \times \mathbb{R}_+$. In equilibrium, each submarket has a known probability of employment. Once matched, a firm receives $(1-\mu)(1-\tau)f(h)$ in profits each period. They continue until the match dissolves, either through exogenous separation or on-the-job search.

Following Pissarides (1985), I refer to submarket tightness as $\theta_t(\mu, a, h, \ell) = \frac{v(\mu,a,h,\ell)}{u(\mu,a,h,\ell)}$. 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 $\frac{M(u,v)}{v} = q(\theta_t(\mu, a, h, \ell))$, and the rate at which workers meet firms as $\frac{M(u,v)}{u} = p(\theta_t(\mu, a, h, \ell))$, 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 within a submarket by opening additional vacancies.

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 a job in the economy, independent of human capital. The second component is a function that tracks the measure of workers with assets a, human capital h, learning ability ℓ, at age t, $u(a, h, \ell, t)$. 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, decision rules do not depend on the distribution of workers or firms. I demonstrate this in subsection A.3.1. The aggregate state z is suppressed because the model is stationary.

2.4.2 Worker's Problem

Production, Savings, and Human Capital Accumulation

Each period is divided into two subperiods: job search, and production. During the production subperiod agents choose consumption and savings allocations (c and a'), and the employed workers choose the proportion of time to spend accumulating human capital, τ. All agents are subject to a borrowing constraint $\underline{a}'$, which changes with age. Following these decisions, age advances. Employed workers solve the problem given in Equation 2.4.1.

$$W_t(\mu, a, h, \ell) = \max_{c, a' \geq \underline{a}', \tau \in [0,1]} u(c) + \beta E[(1-\delta) R^E_{t+1}(\mu, a', h', \ell) + \delta R^U_{t+1}(b_{UI}, a', h', \ell)] \tag{2.4.1}$$

$$\text{s.t. } c + a' \leq (1 + r_F)a + \mu(1-\tau)f(h) \tag{2.4.2}$$

$$h' = e^{\epsilon'}(h + H(h, \ell, \tau, E)) \tag{2.4.3}$$

$$\epsilon' \sim N(\mu_\epsilon, \sigma_\epsilon) \tag{2.4.4}$$

$$b_{UI} = min\{b(1-\tau)\mu f(h), \bar{b}\} \tag{2.4.5}$$

$$b \sim N(\mu_b, \sigma_b) \tag{2.4.6}$$

Human capital evolves according to $e^{\epsilon'}(h + H(h, \ell, \tau, E))$, where ϵ' is the human capital depreciation shock experienced at the start of the following period. The function H determines the accumulation of human capital and is a non-decreasing function of τ, $H(h, \ell, \tau, E)\tau \geq 0$, $H^2(h, \ell, \tau, E)\tau^2 \leq 0$. Human capital accumulation is realized before separation shocks, so any time spent accumulating human capital affects b_{UI}. Employed agents face a probability δ of separating from their current employer. Newly unemployed agents are assumed to have unemployment benefits for at least one period. Following period $T + 1$, employed utility is zero:

$$W_{T+1}(\mu, a, h, \ell) = 0 \tag{2.4.7}$$

Unemployed agents choose consumption and savings and receive benefit and human capital shocks ϵ' once age advances. Their problem is given in Equation 2.4.8.

$$U_t(b_{UI}, a, h, \ell) = \max_{c, a' \geq \underline{a}'} u(c) + \nu + \beta E[(1-\gamma) R^U_{t+1}(b_{UI}, a', h', \ell) + \gamma R^U_{t+1}(b_L, a', h', \ell)] \tag{2.4.8}$$

$$\text{s.t. } c + a' \leq (1 + r_F)a + b_{UI} \tag{2.4.9}$$

$$h' = e^{\epsilon'}(h + H(h, \ell, \tau, U)) \tag{2.4.10}$$

$$\epsilon' \sim N(\mu_\epsilon, \sigma_\epsilon) \tag{2.4.11}$$

where b_{UI} is their unemployment benefit. Unemployed agents face shocks to their benefits, which they lose with probability γ, and their human capital, which evolves according to $e^{\epsilon'}(h + H(h, \ell, \tau, U))$. Note that $H(h, \ell, \tau, U)$ is assumed to be zero for all unemployed agents. Following these decisions, age advances and unemployed workers receive benefits and human capital shocks. Unemployed agents without UI face a problem described by Equation 2.4.12.

$$U_t(b_L, a, h, \ell) = \max_{c, a' \geq \underline{a}'} u(c) + \nu + \beta E[R^U_{t+1}(b_L, a', h', \ell)] \tag{2.4.12}$$

$$\text{s.t. } c + a' \leq (1 + r_F)a + b_L \tag{2.4.13}$$

$$h' = e^{\epsilon'}(h + H(h, \ell, \tau, U)) \tag{2.4.14}$$

$$\epsilon' \sim N(\mu_\epsilon, \sigma_\epsilon) \tag{2.4.15}$$

where $b_L \leq b_{UI}$. Without benefits, these workers have no probability of receiving benefits again without first becoming employed. Unemployed agents of both types die after T periods with certainty and thus their unemployment utility in period $T + 1$ is zero:

$$U_{T+1}(\text{UI}, a, h, \ell) = 0 \; \forall \; \text{UI} \in \{b_{UI}, b_L\} \tag{2.4.16}$$

Job Search

Age advances and shocks are realized following the production period. Unemployed agents in the job search period solve the problem given by Equation 2.4.17.

$$\begin{aligned} R_t^U(b_{UI}, a, h, \ell) = \max_{\mu'} & P(\theta_t(\mu', a, h, \ell))W_t(\mu', a, h, \ell) \\ & + (1 - P(\theta_t(\mu', a, h, \ell)))U_t(b_{UI}, a, h, \ell) \end{aligned} \tag{2.4.17}$$

where b_{UI} denotes their current level of UI and μ' denotes the application strategy $\mu'(w, a, h, \ell, t)$. For agents without unemployment insurance, $b_{UI} = b_L$. Employed workers are allowed to search on the job, and solve the problem given by Equation 2.4.18.

$$\begin{aligned} R_t^E(\mu, a, h, \ell) = \max_{\mu'} & \lambda_E P(\theta_t(\mu', a, h, \ell))W_t(\mu', a, h, \ell) \\ & + (1 - \lambda_E P(\theta_t(\mu', a, h, \ell)))W_t(\mu, a, h, \ell) \end{aligned} \tag{2.4.18}$$

2.4.3 Firm's Problem

Firms produce using a single worker as an input. New firms post piece-rate wage contracts in submarkets characterized by (μ, a, h, ℓ, t), each of which is assumed to be observable to the firm. Contracts dictate the share of revenue to be received by each side in the match. Wage contracts are assumed to be renegotiation-proof. A firm with a filled vacancy produces using technology $y = (1 - \tau)f(h)$, where τ is the time spent accumulating human capital by the worker that cannot be used in production. The firm retains a fraction $(1-\mu)$ of this output as profits and pays the rest out in wages. Matches continue with probability $(1 - \delta)(1 - \lambda_E P((\theta_{t+1}(\mu', a', h', \ell)))$, the probability that the match does not separate exogenously and the worker does not find a new employer. Firms discount at the same rate as workers, β. The value function of a firm matched with a worker is given in Equation 2.4.19.

$$J_t(\mu, a, h, \ell) = (1-\mu)(1-\tau)f(h) + \beta E[(1-\delta)(1-\lambda_E P((\theta_{t+1}(\mu', a', h', \ell)))J_{t+1}(\mu, a', h', \ell)] \tag{2.4.19}$$

$$h' = e^{\epsilon'}(h + H(h, \ell, \tau, E)) \tag{2.4.20}$$

where $a' = g_a(\mu, a, h, \ell)$ and $\tau = g_\tau(\mu, a, h, \ell)$ are the worker policy decisions over wealth and human capital accumulation. $\mu' = g_\mu(\mu, a', h', \ell)$ is the application strategy of the worker conditional upon his asset and human capital policy rule. Profits from a filled vacancy at age $T+1$ are zero:

$$J_{T+1}(\mu, a, h, \ell) = 0 \tag{2.4.21}$$

New firms have the option of posting a vacancy at cost κ in any submarket. Each submarket offers a probability of matching with a worker given by $q(\theta_t(\mu, a, h, \ell))$. In expectation, the value of opening a vacancy in submarket (μ, a, h, ℓ) is given by Equation 2.4.22.

$$V_t(\mu, a, h, \ell) = -\kappa + q(\theta_t(\mu, a, h, \ell))J_t(\mu, a, h, \ell) \tag{2.4.22}$$

I assume that the free entry condition holds for every open submarket. Firms enter until the expected profits of a vacancy, $V_t(\mu, a, h, \ell) = 0$. This means that Equation 2.4.22 can be rewritten as Equation 2.4.23.

$$\kappa = q(\theta_t(\mu, a, h, \ell))J_t(\mu, a, h, \ell) \tag{2.4.23}$$

In equilibrium, this yields the following:

$$q(\theta_t(\mu, a, h, \ell)) = \frac{\kappa}{J_t(\mu, a, h, \ell)} \tag{2.4.24}$$

$$\theta_t(\mu, a, h, \ell) = q^{-1}(\frac{\kappa}{J_t(\mu, a, h, \ell)}) \tag{2.4.25}$$

Using the definition of the matching function, $\frac{M(u,v)}{u} = p(\theta_t(\mu, a, h, \ell))$ and $\frac{M(u,v)}{v} = q(\theta_t(\mu, a, h, \ell))$, the equilibrium job-finding rate for workers and firms in a submarket can be expressed as $p(\theta_t(\mu, a, h, \ell)) = \theta q(\theta_t(\mu, a, h, \ell))$.

2.4.4 Timing

The timing in the model is as follows:

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

2.4.5 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, value functions for firms with filled jobs, J_t, and unfilled jobs, V_t, as well as a market tightness function $\theta_t(\mu, a, h, \ell)$.[9] These functions satisfy the following:

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

2.5 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 make up an "auxiliary model" and capture important aspects of the underlying structural model. I select reduced-form equations in my auxiliary model to identify borrowing constraints and heterogeneity in earnings growth, the key mechanisms in my structural model. This approach is popular among papers estimating household response to risk (Guvenen and Smith, 2014), as well as those estimating search behavior over the life-cycle (Lise (2013), Bowlus and Liu (2013)). I discuss this methodology further in section 2.5.2. In subsection 2.5.5, I use decision rules from the estimated model to demonstrate the sources of identification.

To implement indirect inference, I preset functional forms and parameters that are ubiquitous throughout the related literature. These choices are detailed in subsection 2.5.1. The remaining parameters are estimated by indirect inference by matching moments from the auxiliary model presented in subsection 2.5.2.

[9] 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 subsection A.3.2.

2.5.1 Empirical Preliminaries

Functional Form and Distributional Assumptions

I set the functional forms to those commonly used in the literatures on search and on inequality. I choose a power utility function of the following form:

$$u(c) = \begin{cases} \frac{c^{1-\sigma}-1}{1-\sigma} & \text{if } \sigma > 0, \sigma \neq 1 \\ \ln(c) & \text{if } \sigma = 1 \end{cases} \tag{2.5.1}$$

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

$$M(u,v) = \frac{uv}{(u^\eta + v^\eta)^{\frac{1}{\eta}}} \tag{2.5.2}$$

I assume the following functional form for production:

$$y = f(h) \tag{2.5.3}$$

$$f(h) = zh \tag{2.5.4}$$

where z is a scale factor. Linear production is a common restriction in the search literature when models do not consider physical capital. I assume that all workers face shocks to their human capital each period, $e^{\epsilon'}$ with $\epsilon' \sim N(\mu_\epsilon, \sigma_\epsilon)$. Employed workers accumulate human capital using Ben-Porath (1967) technology:

$$h' = e^{\epsilon'}(h + H(h, \ell, \tau, E)) \tag{2.5.5}$$

$$H(h, \ell, \tau, E) = \ell(h\tau)^{\alpha_H} \tag{2.5.6}$$

where ℓ 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). τ 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 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. However, this assumption 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. The learning-by-doing approach yields tractability, which papers like Bagger et al. (2014) and Carillo-Tudela (2012) exploit in order to decompose the variance of wage growth over the life-cycle. The empirical evidence is divided on which approach best fits the data. Recent evidence from Blandin (2016), who nests learning-by-doing and Ben-Porath within a single model and tests their predictions about life-cycle earnings finds that Ben-Porath fits the data roughly 4 times better than learning-by-doing. It is unclear if those results generalize to a model with labor market frictions. Within the context of my model, learning-by-doing causes trouble matching the downturn in earnings growth without other assumptions.

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.

$$\begin{aligned} h' &= e^{\epsilon'}(h + H(h, \ell, \tau, U)) && (2.5.7) \\ &= e^{\epsilon'} h && (2.5.8) \end{aligned}$$

I assume that agents are subject to a natural borrowing constraint each period:

$$\underline{a}' = \sum_{j=t}^{T} \frac{b_L}{(1+r_F)^j} \tag{2.5.9}$$

In each period t, $\underline{a}'$ is the amount that any agent could repay if he were in the worst income state (b_L) in every period until the terminal date. Modeling borrowing constraints in this way is appealing because it never fully binds and is the least restrictive borrowing constraint in a model without the option to default. While natural borrowing constraints are common in the heterogeneous agent literature (Huggett (1993), and Aiyagari (1994) among many others), it is not ubiquitous. One commonly used alternative is Kehoe and Levine (1993), which allows default under penalty of future autarky. In most cases, adopting an alternate approach like these would yield tighter borrowing constraints in my model. Specifically, for agents approaching the borrowing constraint, this would yield larger borrowing premiums and a tighter debt limit.

Lastly, I assume that initial conditions (a_0, h_0, ℓ) are drawn from a multivariate log-normal distribution, $\Psi \sim LN(\psi, \Sigma)$, with mean ψ and variance-covariance Σ, so that human capital and learning ability are both positive and each marginal distribution can be characterized by a shape and scale parameter. The initial distribution of wealth is shifted by $-\underline{a}'(t = 0)$, the borrowing constraint in period 0. These are common assumptions when modeling inequality. I use a Gaussian copula with correlations $\rho_{AH}, \rho_{AL}, \rho_{HL}$ (the pairwise correlations between wealth, human capital, and learning, respectively) to generate correlated draws from this initial distribution. The preset functional forms and initial conditions are summarized in Table 2.5.1.

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 set the exogenous separation rate to match the average quarterly flows from

Table 2.5.1: Preset Functional Forms and Distributions

Category	Symbol	Value or Function	Source
Model Parameters			
Utility Function	U(c)	$\frac{c^{1-\sigma}-1}{1-\sigma} + (1-e)\nu$	Power Utility
Production Function	$f(h)$	zh	
Human Capital Production	$H(h, \ell, \tau, E)$	$\ell(h\tau)^{\alpha_H}$	Ben-Porath (1967)
Human Capital Evolution	h'	$e^{\epsilon'}(h + H(h, l, \tau, E))$	
Matching Function	$M(u, v)$	$\frac{uv}{(u^\eta + v^\eta)^{\frac{1}{\eta}}}$	Schaal (2012)
Borrowing Constraint	$\underline{a}'$	$\sum_{j=t}^{j=T} \frac{b_L}{(1+r_F)^j}$	Natural Borrowing Limit at time t
Distributional Parameters			
Depreciation	ϵ'	$\epsilon' \sim N(\mu_\epsilon, \sigma_\epsilon)$	
Initial Conditions	Ψ	$\Psi \sim LN(\psi, \Sigma)$	
Mean	ψ	$\begin{bmatrix}\mu_A & \mu_H & \mu_L\end{bmatrix}'$	
Variance	diag(Σ)	$(\sigma_A, \sigma_H, \sigma_L)$	
Correlation		$(\rho_{AH}, \rho_{AL}, \rho_{HL})$	

employment to unemployment (Shimer, 2012), $\delta = 0.030$. An exogenous interest rate is required to for the equilibrium concept used to solve the model, so I set the risk-free rate to a quarterly $r_F = 0.012$, which generates an annual risk-free rate of about 5%. I set $\beta = \frac{1}{1+r_F}$, so that agents smooth consumption in expectation. The elasticity parameter of the matching function, η is set so that the elasticity of the job-finding probability of unemployed workers with respect to submarket tightness is on average 0.5, consistent with the empirical exploration in Shi (2016). The cost of opening a vacancy, κ, is also set at 0.2 using the results from Shi (2016). I use a scale factor, z, equal to the average quarterly income in the PSID at age 25.

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 discretize this distribution and restrict draws 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 $[32\%, 53\%]$. I also cap unemployment insurance at a weekly maximum of $\$450$, which is the average cap in my data. Both of these considerations are required for identification in my estimation procedure. I assume that unemployment insurance does not fluctuate with human capital depreciation, but can be lost with probability γ. I set $\gamma = 0.54$, which matches the expected max duration of UI in my data (≈ 24.1 weeks).

There are 15 parameters remaining to be estimated (shown in Table 2.5.3). The preset parameters are summarized in Table 2.5.2.

Table 2.5.2: Preset Parameter Values

Category	Symbol	Value or Function	Source
Model Parameters			
Discount Factor	β	0.9882	$\frac{1}{1+r_F}$
Risk Aversion	σ	2.0	Standard
Quarters	T	128	Standard
Elasticity of Matching Function	η	0.5	Shi (2016)
Vacancy Creation Cost	κ	0.2	Shi (2016)
Separation Rate	δ	0.030	Quarterly average 1968-2013
Scale Factor	z	18 165	Mean quarterly earnings (Age 25, PSID)
Quarterly Max UI (unscaled)	γ	1.29	Average UI cap
UI Loss Probability	γ	0.54	Sample max UI duration average
Risk Free Rate	r_F	0.0120	Annual rate of $\approx 5\%$
Distributional Parameters			
UI Replacement Rate Distribution	(μ_b, σ_b)	$(0.42, 0.053)$	Approx. sample distribution

2.5.2 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. 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).

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 model is replicating the data generating process by matching the conditional density. The resulting structural parameters are consistent with that mechanism, provided that the auxiliary models identify all the structural parameters. 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 by sampling the simulated data at the same frequency.

My model has initial heterogeneity 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 an auxiliary model in order to discipline this initial heterogeneity. In each specification, I denote the set of parameters to be matched through indirect inference with β_i, where i 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 δ.

With the exception of moments characterizing the borrowing constraint and initial wealth and earnings, I estimate my model on agents ages 25 to 54, two years after I start agents in the model (age 23). This is because I observe earnings at first jobs for very few agents, particularly for whom I also observe either wealth or proxies for human capital or learning ability. By matching my model to data on agents who are already employed, I allow for wage growth while still retaining inference on the structural parameters of interest.

Model Parameters

To identify and estimate the set of 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. Ex ante identification requires that conditional on observables, each individual’s borrowing constraint is identical. This is not an unreasonable assumption: a lender is likely to condition credit offered to a worker on their previous employment history and demographic characteristics. This regression largely follows my approach in section 2.3, with two modifications. I drop potential UI duration, as this is identical for all agents in my model, and I use an interaction between liquid wealth quintile and log of last wage rather than a spline. The specification that I use in both the SIPP and the simulated data is given in Equation 2.5.10.

$$ln(W_{i,j+1}) = \beta_0 + \sum_{q=1}^{5} \beta_1^q \times \mathbb{1}_q ln(UI_i) + \sum_{q=1}^{5} \beta_2^q \times \mathbb{1}_q ln(W_j) + \beta_3 \times Age \tag{2.5.10}$$

$$+ X_{1,i}\delta_1 + \epsilon_{i,j+1} \tag{2.5.11}$$

where j indexes the job of a worker. I match the set of auxiliary parameters $\beta_0, \beta_1^q, \beta_2^q, \beta_3$, and treat the set of data controls δ as nuisance parameters. The set of controls, $X_{1,i}$ is identical to those in section 2.3. 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.

For inference on the human capital evolution parameters, α_H and $(\mu_\epsilon, \sigma_\epsilon)$, 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 using Equation 2.5.12. I use the estimate of the standard deviation from this regression to match the standard deviation of earnings growth, σ_L.

$$\Delta ln(W_{i,j,a}) = \sum_{a=1}^{6} \beta_4^a \mathbb{1}_{Age \in [a,a+1)} + \Delta X_{2,i}\delta_2 + \Delta\epsilon_{i,j,a} \tag{2.5.12}$$

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 to estimate α_H and

$(\mu_\epsilon, \sigma_\epsilon)$.[10] I use a similar strategy to estimate the on-the-job search efficiency parameter, λ_E. I bin individuals using the same age categories and estimate a linear probability model whose dependent variable is whether an individual changed employers during the period, following Equation 2.5.13.

$$\text{SameJob}_{i,j,a} = \sum_{a=1}^{6} \beta_5^a \mathbb{1}_{Age\in[a,a+1)} + \delta_s + \delta_t + X_{3,i}\delta_3 + \epsilon_{i,j,a} \tag{2.5.13}$$

λ_E changes the rate at which individuals transition jobs, satisfying the requirement for ex-ante identification.

To identify leisure, I use a workers employment status at the time of interview to match the sample unemployment rate in the PSID. As in section 2.3, I restrict this sample to ages 25-54, to focus on prime age male workers. This takes the following form:

$$\text{URate} = \frac{1}{NT} \sum_{i=1}^{N} \sum_{t=25}^{54} \mathbb{1}_{Unemp.} \tag{2.5.14}$$

where N is the number of individuals in the PSID and T is the number of years for which I record their observations (30). The panel is not balanced, but I drop individuals in my estimation at the same frequency as in the data.

Marginal Distribution Parameters

Having identified the borrowing limit at age $t = 0$ (23 in my model), the marginal distribution of wealth (μ_A, σ_A) can be estimated from the data by using the income profiles of individuals from different wealth quantiles. I use the distribution of the last observation of liquid wealth in the PSID for men prior to entering the labor market and divide the sample into

[10]The use of this equation to identify α_H is identical to the approach taken by Bowlus and Liu (2013); this approach to human capital depreciation is similar to the approach used by Huggett et al. (2011), who restrict their sample to ages in which individuals are unlikely to accumulate human capital.

deciles. I include the mean of each decile as auxiliary parameters in the model.

Likewise, the borrowing constraint and parameters characterizing the marginal distribution of wealth identified, the marginal distribution of human capital (μ_H, σ_H) can be identified by matching the distribution of initial earnings in the data. In the model, jobs are determined by a worker's application strategy, which is characterized upon first entering the labor market by a workers wealth and human capital (learning plays a small role in initial placement, but is separately identified below). Thus, I use the distribution of earnings at the first job observed in the PSID. I use the same sample restrictions as in construction the liquid wealth deciles, and match deciles of the initial earnings distribution.

The marginal distribution of learning ability, (μ_L, σ_L) are identified from the variance of earnings growth rates by age (Equation 2.5.12), and the average growth rate over the life-cycle, estimated using Equation 2.5.15. σ_L influences the variability of earnings growth over the life-cycle by changing the dispersion of human capital growth, while μ_L alters the average rate of human capital growth.

Correlations

The final three parameters to estimate are the correlations between initial wealth, human capital, and learning ability, $\rho_{AH}, \rho_{AL}, \rho_{HL}$. To identify these parameters, as well as average learning ability μ_L, I estimate two Mincer equations on panel data and stratify individuals by their initial wealth in the PSID and AFQT scores in the NLSY79 (a proxy for learning ability). In both cases, I use specification Equation 2.5.15 on individuals ages 25 to 54.

$$ln(Y_i) = \beta_6 + \sum_{q=2}^{5} \mathbb{1}_q \beta_7^q + \beta_8 Age_i + \sum_{q=2}^{5} \beta_9^q \times \mathbb{1}_q Age_i + X_{4,i}\delta_4 + \epsilon_i \tag{2.5.15}$$

where q refers to either the quintile of initial wealth or AFQT scores. I add $N(0, 0.15)$ measurement error in my model-generated analog to avoid singularity.

Relating wealth to the slope and intercept of earnings profiles allows me to discipline the correlations between wealth and human capital as well as learning ability (ρ_{AH} and ρ_{AL}). This, in conjunction with the liquidity effects estimated from the re-employment elasticities, disciplines 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 quintiles allow me to discipline the correlation between initial wealth and learning ability.

Using the same Mincer equation stratified by AFQT scores, I discipline the correlation between initial human capital and learning ability, ρ_{HL}, as well as the average learning ability in my sample, μ_L. The NLSY79 records Armed Force Qualifying Test (AFQT) scores, a standardized test that is often used as a proxy for ability. Here, it serves as a proxy for learning ability. I classify individuals into quintiles 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 subsection A.1.3. Because learning ability acts as the dominant factor characterizing the slope for life-cycle profiles between ages 25 and 54, this yields inference on the correlation between human capital and learning ability, σ_{HL} as well as μ_L.

Implementation

Indirect inference can be implemented as either maximum likelihood, by minimizing a Gaussian objective function, or generalized method of moments. Because I use multiple datasets, the generalized method of moments approach is a more natural fit. This makes my estimation analogous to a seemingly unrelated regression (SUR) estimation. Indirect inference proceeds by first specifying an auxiliary model, (here, the specifications in: section 2.5.2, section 2.5.2, section 2.5.2), and minimizing the distance between auxiliary parameters from the data and model simulations. Let T denote the number of observations, who need not be observed for every moment included in the auxiliary model. I largely follow the notation from DeJong and Dave (2011) in the following explanation of the procedure. I estimate the following:

$$\beta(Z) = \arg\max_{\delta} \Delta(Z, \delta) \tag{2.5.16}$$

$$\beta(Y, \theta) = \arg\max_{\delta} \Delta(Y, \delta) \tag{2.5.17}$$

where $Z = [z_1, ..., z_M]$ and $Y = [y_1, ..., y_M]$ are observed data and model generated data for observations 1,...,M, respectively. Δ are specifications (Equation 2.5.10 - Equation 2.5.15) characterizing the auxiliary model, θ the structural parameters of the model, and β the auxiliary parameters estimated from the auxiliary model.

$$\beta_S(Y, \theta) = \frac{1}{S} \sum_{j=1}^{S} \beta(Y^j, \theta) \tag{2.5.18}$$

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:

$$min_\theta \Gamma(\theta) = g(Z, \theta)' \times \Omega \times g(Z, \theta) \tag{2.5.19}$$

$$g(Z, \theta) = \beta(Z) - \beta_S(Y, \delta) \tag{2.5.20}$$

where Ω is a positive-definite weighting matrix and $g(Z, \theta)$ the moments constructed from the binding functions. For the weighting matrix, I choose the inverse of the variance of the sample moments $var(\beta(Z))^{-1}$. Like Bowlus and Liu (2013), I estimate the variance-covariance matrix using the following:

$$Var(\hat{\theta}) = (1 + \frac{1}{S})[g\theta'\Omega^{-1}g\theta]^{-1} \tag{2.5.21}$$

where the jacobian matrix, $g\theta$, is approximated using forward differences. For the model generated data, I average over $S = 100$ simulations for each iteration, and impose identical sample restrictions and attrition rates as in the observed data. 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 randomly drop observations at the same frequency as in the data by age. I do this by wealth and AFQT quantiles so that the data generating process from the structural model is as close as possible to that in the data. I simulate separate sets of data for each dataset used in the auxiliary model. I start agents at age 23 with no labor market experience (i.e., unemployed without unemployment insurance) and a random draw from the joint distribution of initial conditions.

2.5.3 Estimation Results

I use simulated annealing to estimate the model. This allows me to solve for a global minimum distance by sampling from the parameter space and comparing objective function values. With some positive probability, it accepts a new point at which the objective function is higher than previous, and then searches nearby points. This allows the algorithm to test areas of the parameter space that other approaches would have ruled out, giving credibility to the global solution. This solution method is commonly used in search papers that are estimated using indirect inference, like Lise (2013) and Bowlus and Liu (2013). The parameter estimates are reported in Table 2.5.3. Notably, the standard errors fit tightly around the estimated values, with the exception of leisure utility. Because of the differences in scales, some of the parameters are not directly comparable with Huggett et al. (2011). However, the mean and standard deviation of human capital shocks are both within the 95% confidence intervals of Huggett et al.'s estimates. The human capital curvature is higher than estimated in previous search papers, but falls just

Table 2.5.3: Estimation Results

Category	Symbol	Model Value			Comment
Model Parameters					
Subsistence Benefits	b_L	0.0108			
		[0.0075,0.0141]			
Borrowing Constraint	$\underline{a}_t$				Qtrly Period-0 Value (2011\$): \$2939
On-the-job Search Efficiency	λ_E	0.3775			
		[0.3765,0.3785]			
Human Capital Curvature	α_H	0.4977			BHH: [0.5, 0.99]
		[0.4251,0.5704]			
Leisure Utility	ν	0.0065			
		[-0.0742,0.0873]			
Distributional Parameters					
Dist. of ϵ'	$(\mu_\epsilon, \sigma_\epsilon)$	$\mu_\epsilon = -0.0175$	$\sigma_\epsilon = 0.1350$		HVY: $(0.029, 0.111)$
		[-0.0239,-0.0111]	[0.0975,0.1724]		
Marg. Dist. of a_0	(μ_A, σ_A)	$\mu_A = 0.8458$	$\sigma_A = 1.7556$		Mean: \$35 011
		[0.6811,1.0106]	[1.7548,1.7563]		
Marg. Dist. of h_0	(μ_H, σ_H)	$\mu_H = -0.4278$	$\sigma_H = 0.1928$		Mean: \$3655
		[0.1919,0.1936]			
Marg. Dist. of ℓ	(μ_L, σ_L)	$\mu_L = -3.7251$	$\sigma_L = 0.2885$		
		[-3.7253,-3.7249]	[0.0363,0.5408]		
Correlations	$\rho_{AH}, \rho_{AL}, \rho_{HL}$	$\rho_{AH} = 0.4691$	$\rho_{AL} = 0.5811$	$\rho_{HL} = 0.4697$	HVY: $\rho_{HL} = 0.655$
		[0.4620,0.4762]	[0.5783,0.5839]	[0.4696,0.4698]	

Notes: BHH refers to Browning et al. (1999), and HVY refers to Huggett et al. (2011).

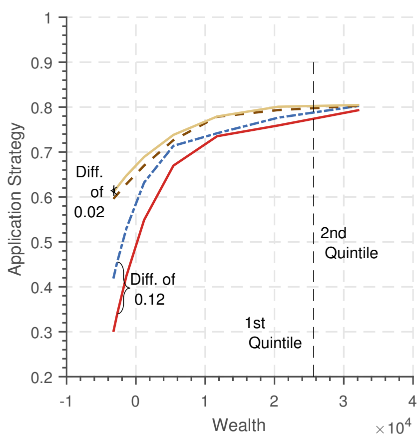
below the bottom of the estimates from Browning et al. (1999), who put the range at $[0.5, 0.99]$, for models without search frictions.

2.5.4 Fit

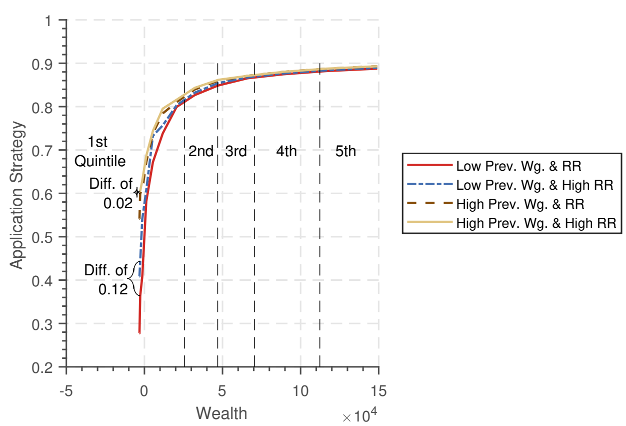
The fit for each of the auxiliary parameters is presented in Table A.2.3. There are 74 auxiliary parameters and 15 structural parameters, so the model should not be expected to perfectly fit each of the moments. It does fit a number of the auxiliary parameters well, matching the direction of the SIPP elasticities (though smaller in magnitude), and almost precisely matching the growth rates by initial conditions. Because the simulations are structured to precisely mirror the data generating processes of the auxiliary model specifications, I am able to test to see which simulated auxiliary parameters are statistically different from their empirical counterparts. These are also presented in Table A.2.3. I show plots comparing the initial distributions of wealth and earnings in Figure A.2.1. While the initial distributions visually fit well, the model predicts earnings more left skewed than the data and wealth more right skewed than the data. A comparison between the average earnings profile in the PSID and the average earnings profile generated by the model (a non-targeted moment) is shown in Figure 2.6.6a.

2.5.5 Identification

I show that the auxiliary model draws inference from the intended mechanisms. The left panel in Figure 2.5.1 shows that application strategies exhibit strong wealth effects as individuals approach the borrowing constraint. Additionally, individuals who enter unemployment with identical wages, but different UI replacement rates behave as predicted by Equation 2.5.10. The dashed blue line and solid red line are two sets of identically productive workers, with the same previous wages. However, the dashed blue workers receive a replacement rate on their previous wage of (54%), while the red line workers receive a replacement rate of (32%). The dashed brown line represents workers who are nearly at the UI cap, and solid yellow workers who are at the UI cap. The right panel shows that low wealth workers are the only workers affected by changes in UI replacement rates.



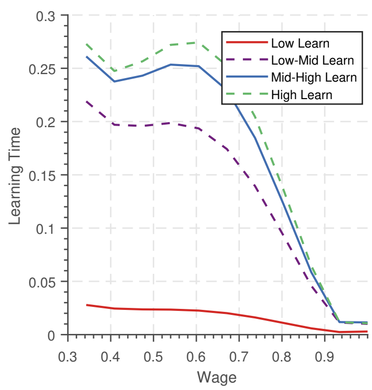
(a) First and second Quintiles.



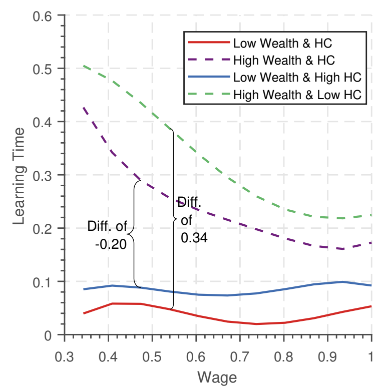
(b) Full wealth distribution.

Figure 2.5.1: Application Strategy by UI and Wealth, Age 25.

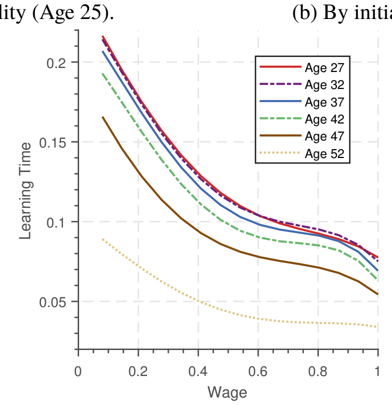
Figure 2.5.2 shows the human capital mechanism identified by the auxiliary model. The left panel shows that learning ability is associated with large differences in human capital growth, while the right panel shows that wealth is only weakly associated with human capital growth by age 25, consistent with the specifications in section 2.5.2. In the data, AFQT differences are associated with large growth rate differences, while wealth is weakly associated with growth rates after age 25, indicating that the auxiliary model identifies human capital growth correctly. The bottom panel shows that as workers age, they spend less time accumulating human capital, which suggests that using growth rates by age bins correctly identifies characteristics of human capital growth and depreciation (Equation 2.5.12).



(a) By learning ability (Age 25).



(b) By initial wealth (Age 25).



(c) By age.

Figure 2.5.2: Human capital decision rules.

2.6 Findings

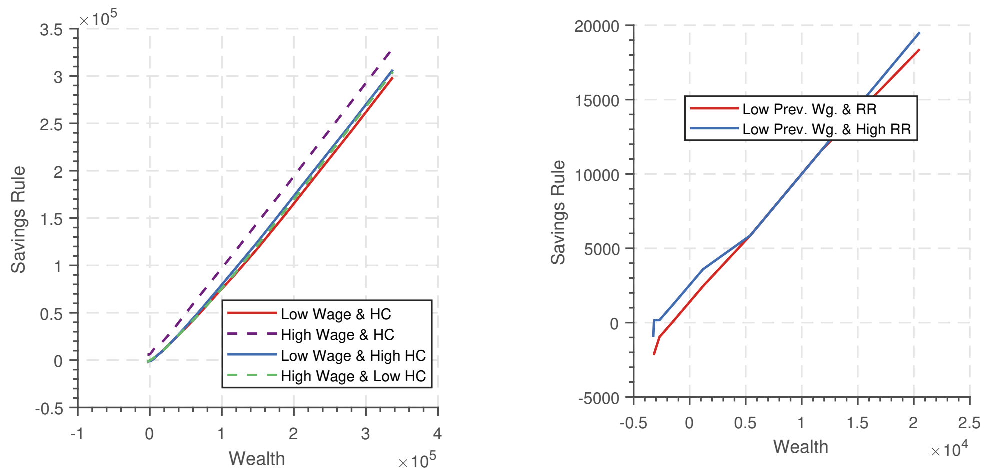
I now use the estimated model to address the central question posed in this paper: how do borrowing constraints interact with search frictions and human capital to alter life-cycle inequality? I start by exploring the key mechanisms in the model: worker application strategies and time allocations. I do this in subsection 2.6.1. Then I explore the contribution of each of these mechanisms contribute to earnings growth and dispersion over the life-cycle in subsection 2.6.2 through model simulations.

In subsection 2.6.3, I quantify how changes in initial wealth, human capital, and learning ability impact inequality. I do this two ways: first, in section 2.6.3 I compare the baseline simulation of the model from subsection 2.6.2 to simulations in which one of the initial conditions is either increased or decreased in isolation by a standard deviation. I extend this test by comparing 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. Then, in section 2.6.3, 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. In both cases, I show that unemployment risk plays an important role in human capital accumulation, that would not be captured in models of perfectly competitive labor markets.

2.6.1 Decision Rules

Savings

Age 25 agents in the model increase their savings approximately linearly as their wealth increases. Figure 2.6.1 shows the contour sets from savings policy functions for agents who are employed or unemployed with UI. The top left figure shows savings rates for high learning ability employed individuals (Figure 2.6.1a). The top right panel, Figure 2.6.1b, shows the savings decisions of unemployed individuals with different replacement rates, zoomed in on low-wealth agents. Like Figure 2.5.1a, this shows that borrowing constraints can cause wealth effects for poor enough agents.



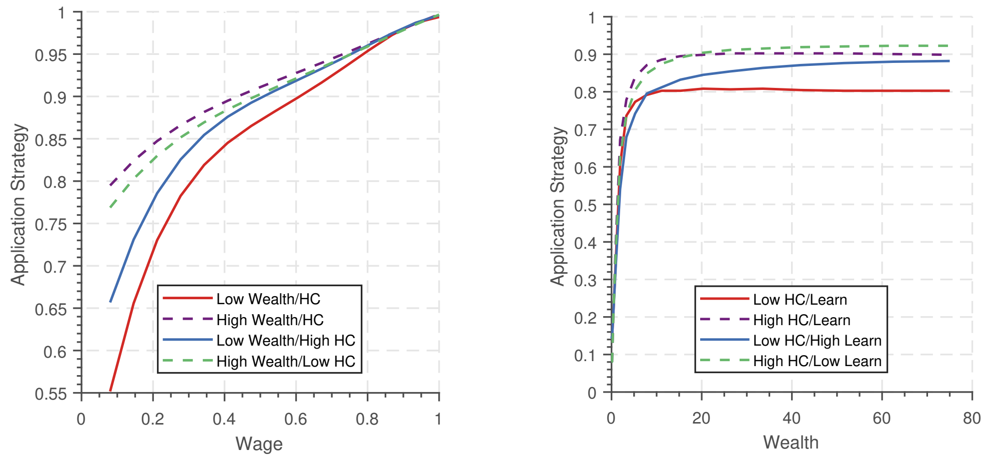
(a) Employed. (b) Unemployed with UI.

Figure 2.6.1: Savings rules by employment status.

Labor Market

In the labor market, low wage and low wealth agents respond in predictable ways. Figure 2.6.2 shows contour plots for agents application rules. The left panel depicts the application strategy in different wealth and human capital states for workers employed at different piece-rate. There is a strong wealth effect at low wages: for the same level of human capital, low wealth agents apply for much more readily available jobs. This is seen by comparing the solid red and dashed green lines. The right panel shows the application strategy of unemployed agents without UI, for both low and high learning agents.

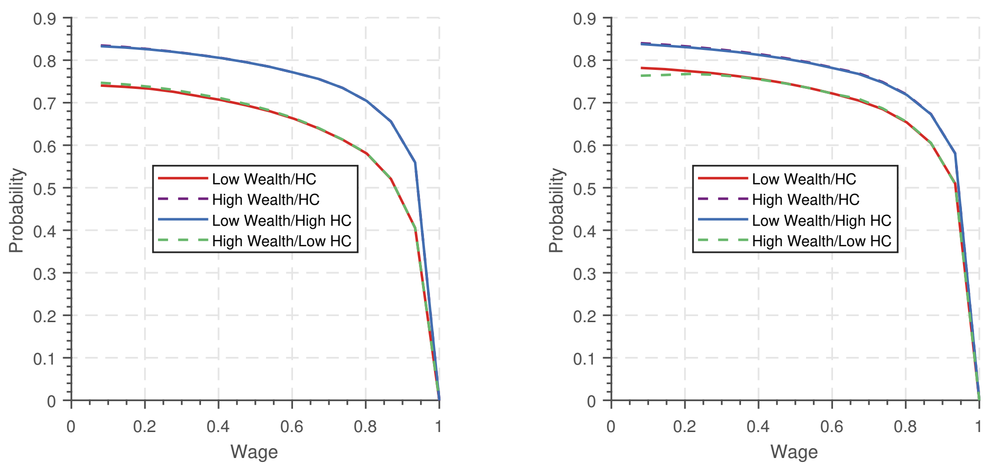
In equilibrium, submarket tightness is decreasing across the wage distribution. Figure 2.6.3 shows that each agent type faces a decreasing probability of finding a job as they apply for



(a) Employed. (b) Unemployed without UI.

Figure 2.6.2: Application strategies by employment status for high ability agents.

higher paid positions for both low learning and high learning agents (left and right panel).

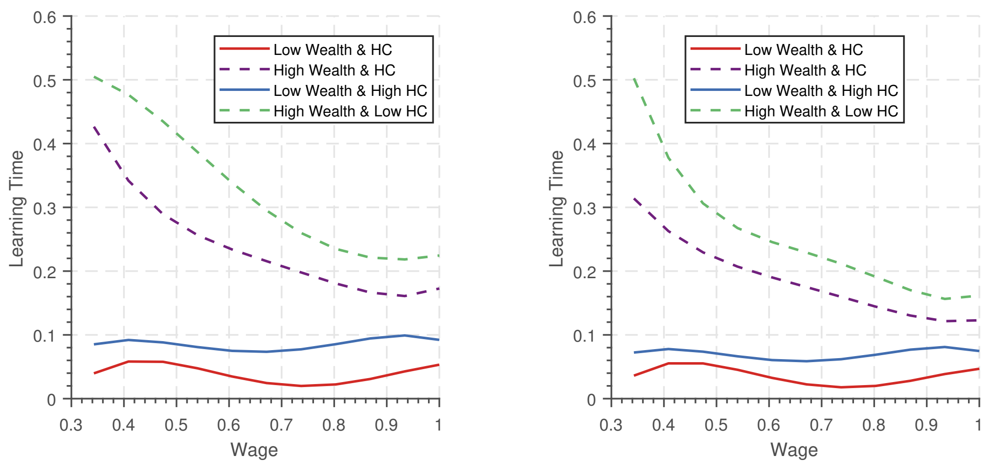


(a) Low learning ability. (b) High learning ability.

Figure 2.6.3: Employment probability by wage and learning ability.

Human Capital

The next figure (Figure 2.6.4) shows contour sets for time allocation decisions for different ages and state vectors. The top two panels show time allocation decisions for low and high learning ability agents at age 25. These show clear evidence of the effect that wealth has on time allocation decisions: the dashed green line shows that a low human capital agent spends in excess of half his time accumulating human capital when he is wealthy, while an equally productive but poor agent spends less than 10% of his time accumulating human capital (the solid red line). Likewise, a low wealth, but highly productive agent (the blue line) spends virtually none of his time accumulating human capital, while a wealthy and productive agent (the dashed purple line) spends a larger fraction of his time, unless employed in very lucrative careers. Note that while there are some high wealth (green line), there are relatively few by the end of the life-cycle, contributing to the overall decline in accumulation time (Figure A.2.1b).

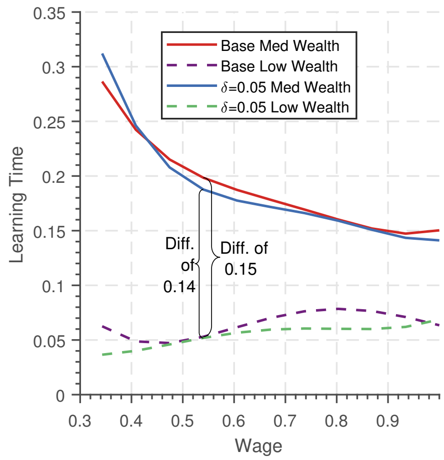


(a) Young with low learning ability. (b) Late career with low learning ability.

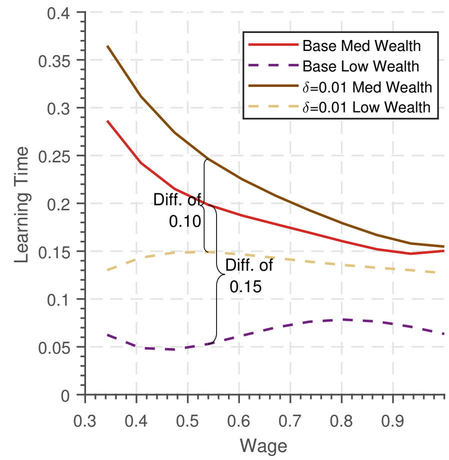
Figure 2.6.4: Time Accumulating Human Capital.

Some of the difference in human capital accumulation is due to a consumption smoothing motive, rather than a precautionary motive against unemployment shocks. A consumption smoothing motive would be present in a Huggett (1993), or Aiyagari (1994) heterogeneous agenst model; a precautionary motive against unemployment shocks would not. In Figure 2.6.5, I vary unemployment risk of an age 30 worker by changing δ to $\delta = 0.01$ and $\delta = 0.05$. The figure shows that when unemployment risk decreases, the gap in human capital accumulation between a low wealth and medium wealth agent declines for the entire wage distribution. This shows that unemployment risk has an important role in human capital accumulation.

The reason is that for unemployed workers, wealth has a first-order effect on application strategies (Figure 2.5.1) as a worker approaches the borrowing limit. To minimize the cost of a possible unemployment spell, low-wealth workers substitute intertemporally by decreasing human capital accumulation.



(a) Low Unemployment Risk.



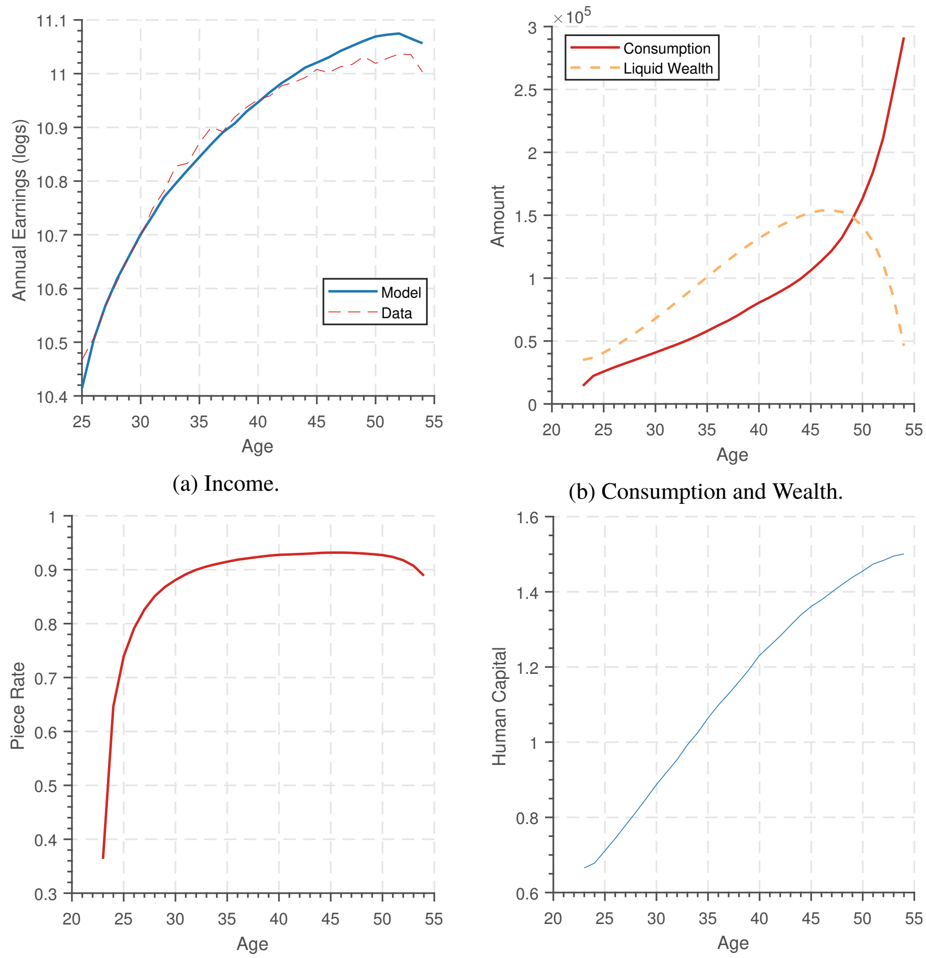
(b) High Unemployment Risk.

Figure 2.6.5: Human Capital Responses to Unemployment Risk.

2.6.2 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 2.6.6a). Consistent with previous work on inequality, earnings profiles begin to decline as agents approach retirement. Because the model has no intensive margin, this could be due to either hours or wages, consistent with Rupert and Zanella (2015) who note that much of the decline in earnings in the PSID is due to hours. 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 2.6.6b).

Over the life-cycle, the model predicts that growth comes from two sources in two distinct time periods. Agents initially move to jobs with higher piece-rates to increase their earnings,



(a) Income.

(b) Consumption and Wealth.

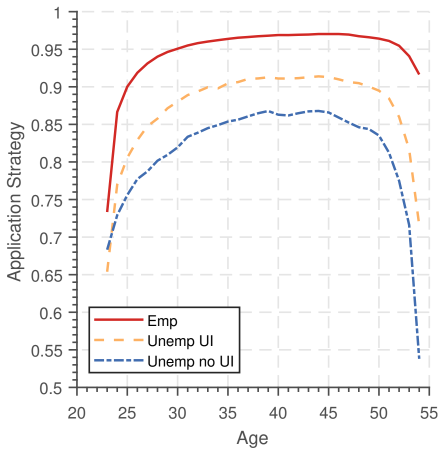
(c) Piece-rate.

(d) Human Capital.

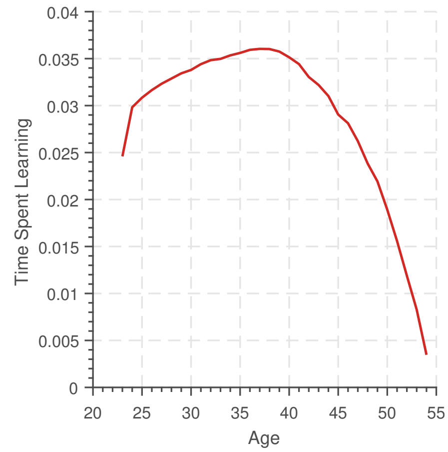
Figure 2.6.6: Profiles of key state and outcomes variables.

Figure 2.6.7a, and then devote substantial time during the middle of their careers to accumulating human capital, Figure A.2.1b. By the middle of their careers, they spend just enough time learning to maintain their human capital stocks.

Agents respond in substantively different ways based on their employment status. Figure 2.6.7a shows that unemployed agents apply for low-paying jobs (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 Figure 2.6.8a shows substantial differences in human capital among each of these groups. But, unemployed

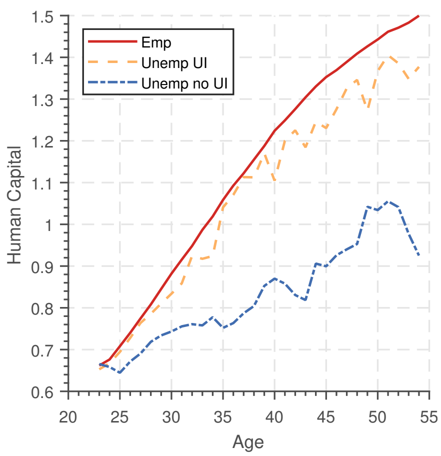


(a) Application strategy.

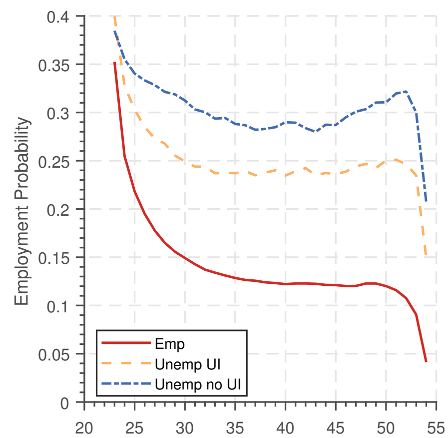


(b) Time allocation to human capital.

Figure 2.6.7: Decision rules by employment status.



(a) Human capital.



(b) Employment probability.

Figure 2.6.8: Human capital and job-finding rates by employment status.

agents without UI simultaneously apply for jobs that offer the highest likelihood of employment, despite the lower human capital. (Figure 2.6.8b). This is a direct result of borrowing constraints. Unemployed agents with no UI also have disproportionately lower wealth than their peers. Rather than face additional consumption risk, they take low-paying jobs that offer high probabilities of employment.

2.6.3 Initial Conditions and Life-Cycle Inequality

I run two tests to assess the effects of initial conditions on life-cycle iunequality. Test 1 compares outcomes of agents in the baseline simulation to agents who receive identical shocks, but whose initial conditions are changed by one standard deviation. After considering these results, I consider the outcomes of individuals for whom two of the initial conditions change simultaneously. Test 2 considers the impact of altering a 10th percentile agent's initial conditions. In test 2, each agent starts at the 10th percentile of the tested initial condition (with a correlated draw from the other two), and is compared with an individual at the median of the tested initial condition (the other two unchanged). The baseline as well as the counterfactuals for the tests are detailed in Table 2.6.1.

What is unclear is the role of unemployment risk relative to permanent income in human capital accumulation. To explore this, I alter the labor market so that wages are determined competitively ($\mu = 1, w = h \ \forall \ t$), and eliminate unemployment risk. This Bewley-style heterogeneous agent model is nested by my model in section 2.4. I expand on this further in section 2.6.3.

Test 1: Average Worker

For the average household a standard deviation change in any of the initial conditions is important. 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, shown in Table 2.6.2. The reason is that here wealth and human capital have similar effects: both human capital and wealth improve initial placement and 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

Table 2.6.1: Initial Conditions

	Variable	Test 1 Value	Test 2 10th Wealth	10th Human Capital	10th Learning
Wealth					
	Baseline	35 010.8	−2127.9	8750.2	3989.6
	Median		7546.5		
	+1 St. Dev.	116 503.4			
	-1 St. Dev.	5062.5			
Human Capital					
	Baseline	3014.0	2671.9	2313.0	2657.1
	Median			2962.2	
	+1 St. Dev.	3654.8			
	-1 St. Dev.	2485.9			
Learning Ability					
	Baseline	0.025	0.020	0.021	0.017
	Median				0.024
	+1 St. Dev.	0.034			
	-1 St. Dev.	0.019			

Notes: The table presents the initial conditions associated with the baseline as well as the comparison group for tests 1 and 2.

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.[11]

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 2.3). Then, they accumulate less human capital while employed. Figure 2.6.9b 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

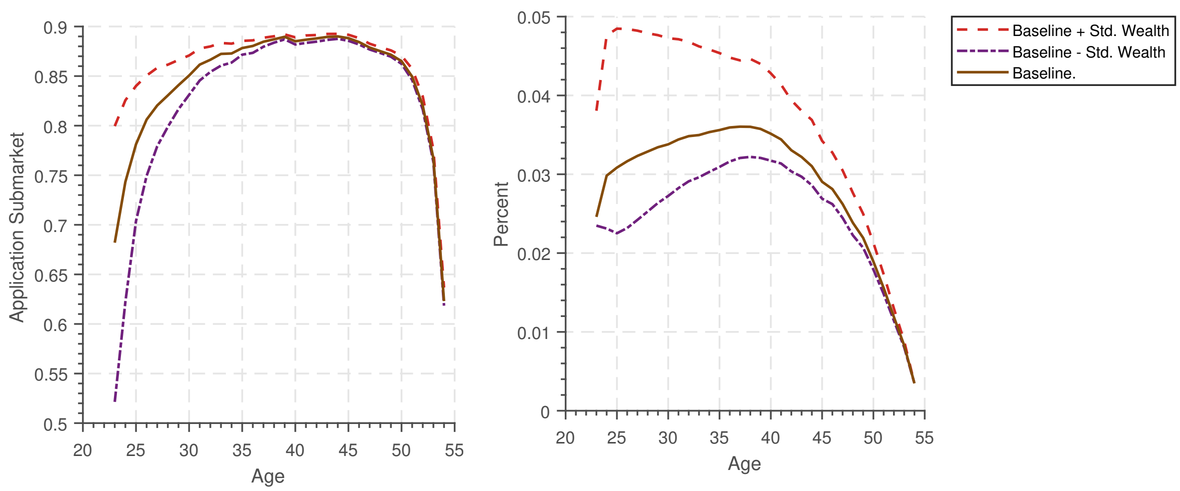
[11] In Huggett et al. (2011), they find that average learning ability is 0.321. They need such a large value to match earnings profiles, but here earnings growth is driven by search frictions. A model without search frictions would not be consistent with the empirical regularities from the SIPP.

Table 2.6.2: Test 1 Results

Change	Δ Consumption (%)	Δ Consumption HVY (%)	Δ Earnings (%)	Δ h (%)	Δ τ (%)	Δ μ' (%)
Wealth						
+1 St. Dev.	$+23.9$	$+7.1$	$+2.7$	$+1.8$	$+31.1$	$+1.0$
-1 St. Dev.	-10.5	-1.6	-2.3	-1.1	-13.8	-1.1
Human Capital						
+1 St. Dev.	$+9.7$	$+39.3$	$+10.0$	$+9.5$	$+0.8$	$+0.3$
-1 St. Dev.	-7.6	-28.3	-7.8	-7.5	-0.8	-0.3
Learning Ability						
+1 St. Dev.	$+24.7$	$+5.7$	$+29.7$	$+29.1$	$+32.3$	$+0.5$
-1 St. Dev.	-15.0	-2.6	-17.9	-17.5	-27.8	-0.3

Notes: 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 variables are left unchanged.

capital has a relatively small effect in both directions, and learning ability plays a big role in both directions (Figure 2.6.10b and Figure 2.6.11b respectively). While the initial wealth effect

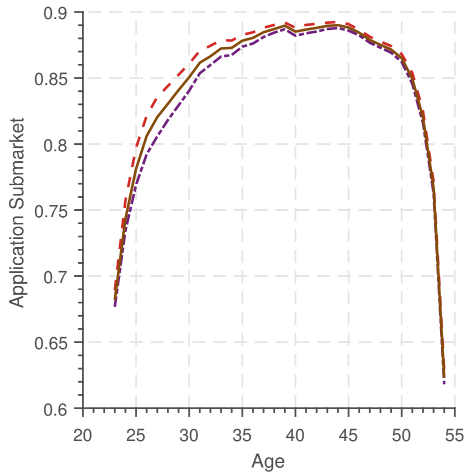


(a) Application strategy.

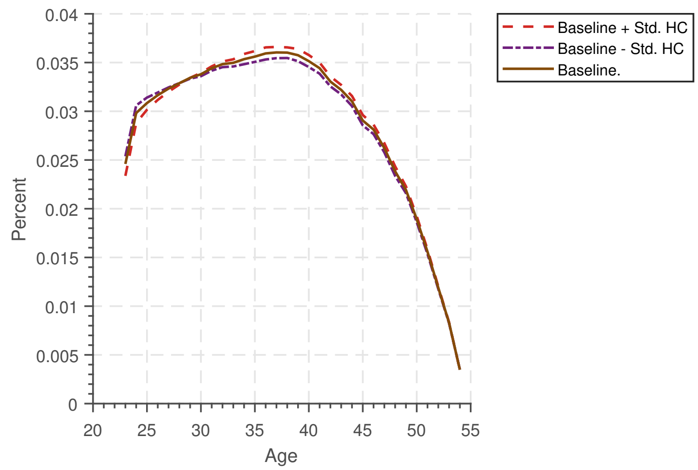
(b) Learning time.

Figure 2.6.9: Decision rules after wealth change (Test 1).

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

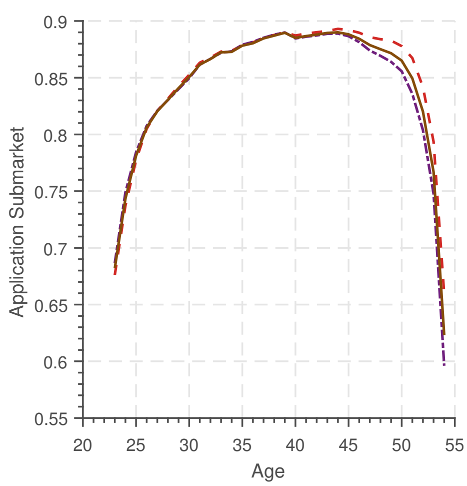


(a) Application strategy.

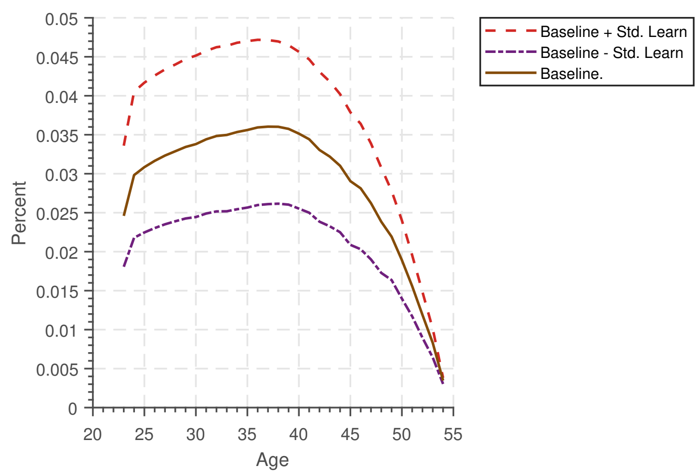


(b) Learning time.

Figure 2.6.10: Decision rules after human capital change (Test 1).



(a) Application strategy.



(b) Learning time.

Figure 2.6.11: Decision rules after learning change (Test 1).

capital drastically over the first 20 quarters of work, as shown in Figure 2.6.9b. A change in human capital does little to alter acquisition over the lifetime, as shown in Figure 2.6.10b. The interaction between wealth and human capital accumulation is substantial, causing a continued difference even late into the life-cycle. I consider the role of interactions in Table A.2.2. Among the notable results are that decreasing wealth and increasing learning ability, which could be thought of as roughly attending college, increase earnings substantially, but by less than a simple increase in learning ability (a 3%) difference). Increasing human capital and learning simultaneously has a larger effect on earnings than the two changes added together.

Test 2: 10th Percentile Worker

I now assess the impact of changing initial conditions for individuals at the bottom of the distribution. I test how the outcomes of an individual from the 10th percentile of one initial condition and the corresponding values of the other two initial conditions changes when they shift from the 10th percentile to the median for that initial condition (leaving the other two unchanged). The initial conditions as well as their counterfactuals are summarized in Table 2.6.1. The outcomes are summarized in Table 2.6.3. Table 2.6.3 indicates that wealth

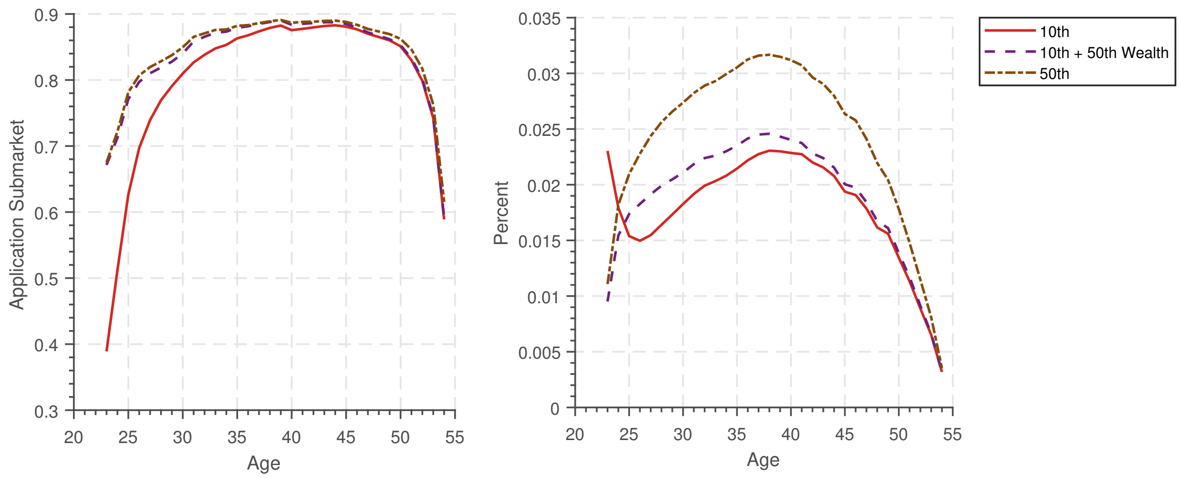
Table 2.6.3: Test 2 Results

	Percent Change				
Counterfactual	Δ Consumption	Δ Earnings	$\Delta\ h$	$\Delta\ \tau$	$\Delta\ \mu'$
$Wealth:\ 10th \to 50th$	+6.9	+3.5	+0.6	+4.7	+2.1
$Human\ Capital:\ 10th \to 50th$	+12.7	+11.8	+11.2	+4.1	+0.4
$Learning:\ 10th \to 50th$	+25.6	+27.4	+26.5	+59.7	+0.5

Notes: The rows represent comparisons between an individual from the 10th percentile of each initial condition (with correlated draws from the other two initial conditions), with an individual at the median of the tested initial condition.

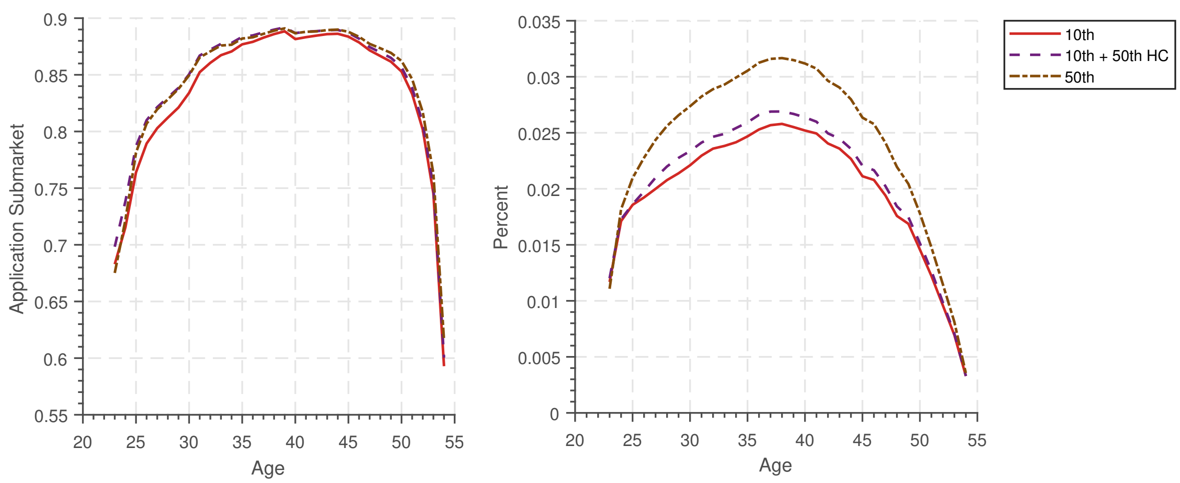
inequality is an important driver of earnings inequality among poor households. While the impact of an increase in human capital is large, wealth increases lifetime earnings by 3.5%. For low wealth households, the human capital channel is less active, increasing by 0.6% over the life-cycle, compared with the estimates for the average household in section 2.6.3 of 1.8% for a standard deviation increase. Human capital is more important in determining earnings, though again much of this is from a direct change in their productivity. As before, an increase in learning ability plays the largest role in both consumption and earnings inequality (25.6% and 27.4%).

Figure 2.6.12, Figure 2.6.13 and Figure 2.6.14 explore the mechanisms through which outcomes change. Figure 2.6.12b and Figure 2.6.14b shows that increases in wealth and learning ability cause large increases in time devoted to human capital accumulation, while changes in human capital (Figure 2.6.13b) plays little role on human capital accumulation over the life-cycle.



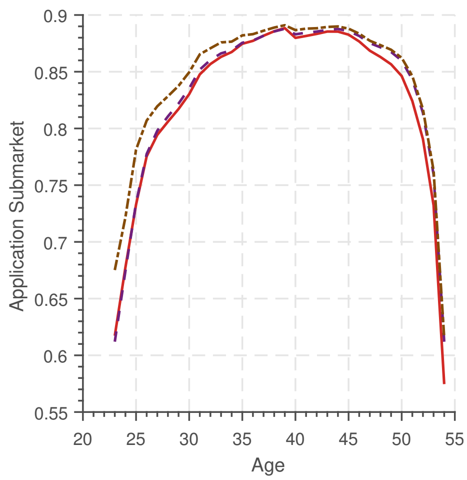
(a) Application strategy. (b) Learning time.

Figure 2.6.12: Changes in response to an increase in wealth.

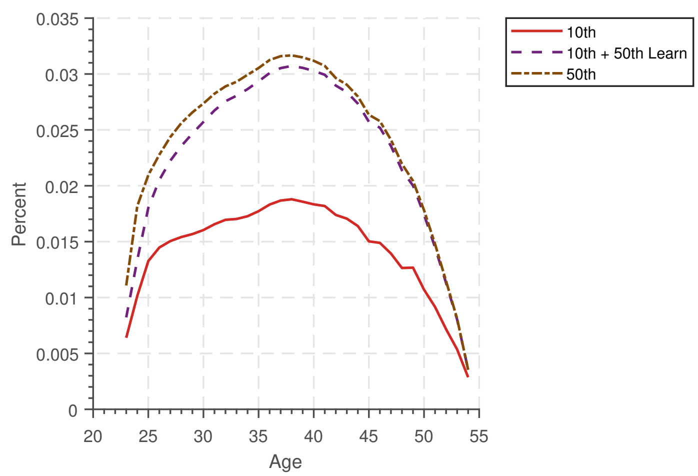


(a) Application strategy. (b) Learning time.

Figure 2.6.13: Changes in response to an increase in human capital.



(a) Application strategy.



(b) Learning time.

Figure 2.6.14: Changes in response to an increase in learning ability.

This shows that the effect of a change in human capital is largely direct: productivity increases directly translate into higher wages, but do not substantially alter decision rules. On the other hand, wealth and learning *do* alter decision rules. This is shown more clearly in Figure 2.6.12a, Figure 2.6.13a, and Figure 2.6.14a, each of which shows the change in application strategy for unemployed individuals. For these agents, wealth plays a substantial role in determining the jobs to which a household applies. A 10th percentile household initially applies for a job that offers a piece-rate of around 40%. After a change in their initial wealth, they find jobs that offer nearly a 70% piece-rate. At the same time, they accumulate more human capital, leading to higher income and more productivity overall. These tests are strongly indicative of the importance of wealth in determining inequality, suggesting that decreasing the debt of a 10th percentile household may be enough to increase their productivity and decrease inequality in earnings or consumption.

Human Capital and Unemployment Risk

There are two primary reasons human capital accumulation changes when wealth is altered: Workers intertemporally substitute in the model to smooth consumption (the permanent income effect), and to mitigate the earnings risk from potential unemployment spells in the immediate future (the unemployment risk effect). To disentangle the two, I make the following changes to the model presented in section 2.4: agents are paid competitively ($\mu = 1, w = h \; \forall \; t$), and they are continuously employed at every stage of the life-cycle. Because the model only allows employed workers to accumulate human capital, I include a probability δ (same as the calibrated value) that a worker is unable to spend time learning during any period. All parameter values remain the same. The problem is given in Equation 2.6.1.

$$V_t(a,h,\ell,E) = \max_{c,a' \geq \underline{a}',\tau} u(c) + \beta E[(1-\delta)V_{t+1}(a',h',\ell,H) + \delta V_{t+1}(a',h',\ell,D)] \tag{2.6.1}$$

$$\text{s.t. } c + a' \leq (1+r_F)a + (1-\tau)f(h) \tag{2.6.2}$$

$$\tau \in \begin{cases} 0 & \text{if } E = D \\ [0,1] & \text{if } E = H \end{cases} \tag{2.6.3}$$

$$h' = e^{\epsilon'}(h + H(h,\ell,\tau,E)) \tag{2.6.4}$$

$$\epsilon' \sim N(\mu_\epsilon, \sigma_\epsilon) \tag{2.6.5}$$

where H means that the worker is able to accumulate human capital and D means the worker is unable to accumulate human capital. I repeat the same exercise as in tests 1 and 2 and report the results for changes in wealth in Table 2.6.4. The same exercise for human capital and learning is shown in Table A.2.4. The table shows that unemployment risk plays a role in human capital determination. A standard deviation decrease in wealth decreases human capital by 0.3 percentage points, and time accumulating human capital by 3.8 percentage points, more than in the perfectly competitive case. In Test 2, moving from the 10th to the 50th percentile of the wealth distribution causes an additional 0.3 percentage point increase in human capital, indicating that unemployment risk decreases accumulation. In Test 2, time spent accumulating human capital increases when the market is perfectly competitive; this is because overall human

Table 2.6.4: Test 1 Results

	Δ Earnings		Δ h		Δ τ	
Wealth Change	Base	No Unemp.	Base	No Unemp.	Base	No Unemp.
$Test$ 1						
+1 St. Dev.	$+2.7$	$+1.0$	$+1.8$	$+1.5$	$+31.1$	$+19.8$
-1 St. Dev.	-2.3	-0.6	-1.1	-0.8	-13.8	-10.0
$Test$ 2						
10th→50th	$+3.5$	$+0.2$	$+0.6$	$+0.3$	$+4.7$	$+5.8$

capital increases for both the 10th and 50th percentile workers, and human capital production exhibits decreasing returns.

2.7 Conclusion

In this paper, I develop a quantitative model of labor market search to study inequality. The model considers risk averses workers who borrowing constraints and frictional labor markets, and accumulate human capital using Ben-Porath production. I estimate this model and use it to quantify the impact that wealth inequality has on earnings and consumption. I find that borrowing constraints cause low wealth workers to accept lower-paying jobs, and accumulate human capital at a slower pace than their wealthier peers. Both effects are important. The model predicts that a standard deviation decrease in wealth decreases consumption and earnings growth by more than a standard deviation decrease in human capital. Among poor workers, I find that increasing wealth can lead to large increases in earnings.

Using the SIPP, I show that borrowing constraints affect labor market outcomes following an unemployment spell. Constrained workers in the SIPP match to higher paying jobs when given more generous unemployment insurance replacement rates. I also find evidence that this effect persists. These results help to discipline borrowing constraints when I estimate the model.

I use indirect inference to estimate the model. To do this, I pick reduced-form models that identify key aspects of my structural model in the data. I target re-employment elasticities from the SIPP to gain inference on borrowing constraints, as well as life-cycle moments from the NLSY and PSID to identify the effects of wealth and human capital on growth, as well as their correlations. By matching these moments and treating the data in the same way, the model is asked to match the data generating process of the relevant mechanisms in the data. Despite substantially more moments than estimated parameters, the model fits the reduced-form moments well, indicating that the model can explain the key mechanisms in the data.

Quantitatively, I find that initial wealth has a larger effect on consumption inequality and earnings growth than initial human capital. A standard deviation decrease in initial wealth causes a -10.5% change in lifetime consumption, while a standard deviation decrease in human capital causes a change of -7.6%. Wealth has an important effect on earnings through both a worker's initial placement (-2.2%), as well as his human capital accumulation (-1.1%). For a worker at the 10th percentile of the initial wealth distribution, an increase to the median causes an increase in earnings of 3.5%.

My findings suggest that the importance of wealth inequality has previously been understated. I show that when workers face borrowing constraints and frictional labor markets, wealth occupies a similar role as human capital, and can alter productivity over the life-cycle. In terms of productivity growth, my counterfactual exercises suggest that increases in wealth lead to more productivity growth than increases in human capital. Policy and aggregate considerations are left out of this paper, but these findings suggest that policies aimed at helping constrained workers, both employed and unemployed, could decrease inequality. Furthermore, the effect of wealth on productivity indicates that they may increase aggregate productivity in the economy. Both questions of worthy of further research.

Chapter 3

Testing the Independence of Job Arrival Rates and Wage Offers in Models of Job Search

3.1 Introduction

Is the arrival rate of a job independent of the wage that it pays? The random search model of Pissarides (2000) assumes a worker's search intensity determines the number of job offers they receive, but productivity of the job is drawn randomly, and therefore wages are independent of arrival rates. Alternatively, the competitive search model of Moen (1997) assumes the existence of submarkets characterized by job arrival rates and wages. In this paper, we test the defining feature between these types of models. Specifically, we test the assumption that job finding rates and the wages offered are independent, conditional on a set of worker characteristics.

We show that a testable implication of the independence of job arrival rates and wages is that the semi-elasticity of the hazard rate with respect to unemployment insurance (UI) is constant across the wage distribution. We test this using a mixed proportional hazards competing risks (MPHCR) model with data from the National Longitudinal Survey of Youth 1997 (NLSY97).

We find that the semi-elasticity of the hazard with respect to UI and other worker characteristics is not constant across the wage distribution. Therefore, we reject the null hypothesis that the arrival rate of a job is independent of the wage that it pays.

We find that an increase in UI decreases the hazard rate more for low wages than for high wages. Specifically, if UI is collected in the first nine weeks of unemployment, the hazard rate decreases by 32% for wages above the 75th percentile and by 63% for wages between the 25th and 75th percentiles. The differences are robust to specifications of the baseline hazard rate and is particularly prominent for those with only a high school degree.

Beyond testing for independence, we analyze three prominent job-search models and show how they map into our testable implication. We show that in search models of random matching and bargaining with match-specific productivity, and on-the-job search, as described in Rogerson et al. (2005), job arrival rates and wage offers are independent while in competitive search they are not. Our results are in line with a competitive search environment but inconsistent with many models of random search and matching. Given how our results are applicable in differentiating types of job-search models, our work is similar to other work comparing random and competitive search such as Engelhardt and Rupert (2017) and Moen and Godøy (2011). Distinguishing between random and competitive search has implications for labor market policies. In models of random search, workers may inefficiently reject jobs in equilibrium. For this reason, labor market policies that reduce this inefficiency may be welfare improving in this class of models. Under competitive search, workers do not reject jobs in equilibrium. Absent additional frictions, labor market policies are not welfare improving in models of competitive search.

Aside from how our results map into prominent job-search models, we help shed some light onto the matching process. We show that conditional on observable characteristics and unobservable heterogeneity, the job arrival rate is correlated with the wage of a job. The presence of this correlation may have ramifications for empirical studies of frictional wage dispersion, as these studies rely on the independence of job offers and wages to quantify the degree to which wage dispersion is caused by search frictions, see for example Burdett et al. (2016) and Hornstein et al. (2011). Similarly, such a correlation has implications for modeling the way in which workers match to jobs and the degree of mismatch within the labor market. Recent studies of sorting and mismatch again fail to incorporate such a correlation by specifying a matching function that is independent of job productivity, see for example Gautier et al. (2010), Gautier and Teulings (2015), and Lise et al. (2016).

3.2 Independence of Wages and Job Arrival Rates

In this section, we present a theoretical framework in which the arrival rate of jobs is or is not independent of the wage offered conditional on worker characteristics. All of the tests will be conditional on worker characteristics and we will refer to this simply as independence. Assume that there exists J different wages, where $J = |\mathcal{J}|$ and $\mathcal{J} = \{w_1, w_2, \ldots, w_J\}$, and the probability of drawing each wage w_j is $P(X_i(t), w = w_j, t)$ where t is time, and $X_i(t)$ is worker i's characteristics at time t. The job arrival rate at time t for wage $w_j > w_R^i$, where w_R^i is the reservation wage of worker i, is composed of the probability the worker receives a job arrival, $\mu(X_i(t), t)$, times the probability of drawing wage w_j. The hazard rate for transitioning to a particular wage, when job arrival rates are independent of the wages offered is

$$h(X_i(t), w_j, t) = \mu(X_i(t), t) P(X_i(t), w = w_j, t), \tag{3.2.1}$$

a common assumption in many standard job-search models. The total hazard rate of transitioning to employment at time t is

$$\begin{aligned} h(X_i(t), t) &= \sum_{w_j \geq w_R^i}^{J} \mu(X_i(t), t) P(X_i(t), w = w_j, t) \\ &= \mu(X_i(t), t) P(X_i(t), w \geq w_R, t). \end{aligned} \tag{3.2.2}$$

Alternatively, if job arrival rates are dependent on the wage offered the hazard rate is

$$h(X_i(t), w_j, t) = \mu_j(X_i(t), t)P(X_i(t), w = w_j, t) \tag{3.2.3}$$

$$= \mu_j(X_i(t), t). \tag{3.2.4}$$

where the job arrival rate, $\mu_j(X_i(t), t)$, is specific to the wage w_j and therefore $P(X_i(t), w = w_j, t) = 1$. If the job arrival rate is wage specific, the total hazard of leaving unemployment to any wage above the reservation wage is

$$h(X_i(t), t) = \sum_{w_j \geq w_R^i}^{J} h(X_i(t), w_j, t).$$

Assume there exists a factor $\bar{X}$ that has no effect on the distribution of wages offered, i.e., $\partial P(X_i, w_j)/\partial \bar{X} = 0$, but has an effect on the job arrival rate, $\partial \mu_j(X_i, t)/\partial \bar{X} \neq 0$. Then if job arrival rates are independent of the wage offered, the semi-elasticity of the hazard with respect to $\bar{X}$ is

$$\frac{\frac{\partial h(X_i, w_i, t)}{\partial X}}{h(X_i, w_i, t)} = \frac{\frac{\partial \mu(X_i, t)}{\partial X} P(X_i, w_j)}{\mu(X_i, t)P(X_i, w_j)} = \frac{\frac{\partial \mu(X_i, t)}{\partial X}}{\mu(X_i, t)} \; for\ all\ w_j > w_R^i. \tag{3.2.5}$$

Factors that do not affect the wage offered should affect the hazard rate uniformly across the distribution of wages; the semi-elasticity with respect to $\bar{X}$ does not differ across wages.

We test for independence by examining how changes in unemployment insurance (UI) affects the hazard rate across the wage distribution. In the case of independence, if UI rises, the hazard rate changes uniformly across the wage distribution. Alternatively, if the job arrival rate and the wage offered are dependent, then the semi-elasticity of the hazard rate with respect to UI differs across the wage distribution.

3.3 Data

To test the independence assumption, we use data from the National Longitudinal Survey of Youth (1997), conducted by the U.S. Bureau of Labor Statistics, for the years 1997 through

2009. The survey tracks men and women in the United States over time who were between 12 and 16 in 1997. We use the individual-level panel data set information on gender, education, race, age, urban status, hourly wage, unemployment insurance collection status, searching for a job, and labor force status over time. With the information on labor force status, we are able to determine whether an individual is employed, not employed and searching for work, or not employed and not searching for work.

We use a flow sampling approach to construct the data set that we use in our analysis. This means that we record the beginning of each duration when an individual transitions into a new labor force state as defined by employed or not employed. We limit the number of observations per individual starting each state to ten and begin tracking an individual's weekly labor force status after an individual has completed his or her most recently obtained level of education. Our starting point follows Bowlus et al. (1995), Eckstein and Wolpin (1995) and Engelhardt (2010) among others. When a respondent transitions into a new labor force state, the duration is recorded as well as why the state ended. We cut the data in two ways and refer to each as the standard and inclusive data sets. In what we define as the "standard," we record the time the unemployed is in the unemployed state and capture whether he or she became employed. If an individual transitions out of the labor force during a spell, then the spell is excluded from the standard data set following van den Berg and Ridder (1998), Bontemps et al. (2000), among many others. We analyze this less inclusive cut of the data because it is effectively the standard as it aligns with most theoretical search models focused on those strictly in the labor force. Alternatively, the second "inclusive" data set estimates the model where unemployment is redefined as not employed. As a result, the number of spells greatly increases. To account for whether an individual is searching, we include a time varying covariate that records whether an individual is searching for a job. We do not estimate two states, unemployed and outside the labor force, because many individuals transition from outside the labor force to employment in our data (a standard empirical fact). To keep the notation and terminology of the empirical model simple, we will define the unemployed and those outside the labor force as not employed for both data sets. Estimation using the standard and inclusive data sets is effectively identical with this rewording.

In terms of notation, we account for how an individual spell ends. Our notation for individuals who are hired while not employed (or unemployed) is $d = 1$ and zero otherwise. The duration of time spent not employed is represented by t. Some of the durations are censored as seen by the fact that the mean number of individuals transition to employment is not one. The model we estimate assumes censoring occurs randomly and the estimation is adjusted accordingly. In these cases, $d = 0$. We cut the data into three submarkets at the 25th and 75th percentiles, as required by our empirical specification; therefore if a duration ends with a low, medium, or high wage draw, then we represent the event as $d_L = 1$, $d_M = 1$, and $d_H = 1$, respectively. If a duration ends and the wage offer is missing, then $d_i = 0$ for $i \in \{L, M, H\}$ and the missing observations are assumed to occur randomly and the probability is excluded. The covariates used in the analysis are the respondent's gender, years of schooling completed, race, urban status, age, wage at the time of transition to employment, and a dummy for whether the individual is collecting unemployment insurance. When using the inclusive data set, a dummy for whether an individual is searching for employment is incorporated into the covariates. We define $X(t)$ as the baseline covariates for the not employed, which includes unemployment insurance, and in the case of the inclusive data set, job searching. Due to the non-parametric baseline, computational weight of the model, and known measurement issues, the unemployment insurance (UI) collection status is a dummy variable equal to one if the individual collected UI in any particular 10 week interval. Similarly, whether a worker is searching for employment is averaged over 10 week intervals. Intervals are collected for the first 50 weeks and one final variable for all the time after 50 weeks.

The descriptive statistics of the not employed for each data set are in Table B.1.1.

3.4 Empirical Specification

We build our test on the duration literature and specifically the MPHCR model. If there exist J different wages, where $J = |\mathcal{J}|$ and $\mathcal{J}$ is the set of all wages, then the observed failure time T is the minimum of the failure time at each wage, that is, $T = min_{i \in \mathcal{J}}(T_i)$ and the cause of failure, I, is the argument minimum. In terms of a competitive search model, the cause of failure is observed by the wage, that is, if an individual leaves unemployment to a wage $j \in \mathcal{J}$, then failure is caused by matching at w_j. Thus, we observed the joint distribution (T, W) where W identifies the argument minimum I.

It is well known that without further assumptions the latent distribution of failure times is not identified from the observed distribution (T, W) (Cox, 1959). We impose a mixed proportional hazard structure so that latent failure times depend multiplicatively on the observed regressors, duration length and unobserved heterogeneity. Heckman and Honoré (1989) show identification of such models relies on variation in latent failure times with the regressors. Abbring and van den Berg (2003) relax this assumption and show that less variation is needed with multiple independent draws from an individual's observed distribution, that is, multiple spells.

We rely on the MPHCR model to identify a baseline hazard across time for each wage, $\lambda_{w_j}(t)$, that is constant for all individuals, an unobservable component, $V^n_{w_j}$, that is individual specific that varies across wages, and an individualized observable component $e^{\sum_{k=1}^{K} \beta_j^k X_i^k(t)} = e^{\beta_j X_i(t)}$, for wage j, individual i, and covariates $k = 1, ..., K$. The functional form is described in detail in Abbring and van den Berg (2003) including the notation we are using such as the matrix notation $X_i(t)$ and β_i. This results in three types of heterogeneity: matching rates across wages are heterogeneous in terms of matching time, and individuals are heterogeneous with respect unobservable and observable factors (e.g., value of leisure and age, respectively). We assume three wage categories, a low wage (w_L), a medium wage (w_M), and a high wage (w_H), in which individuals can find jobs; and three unobservable components, or $n = \{0, 1, 2\}$. For example, $V^0_{w_L}$ can imply low search intensity of an individual of type "0" in finding a low wage job and $V^1_{w_M}$ can imply high search intensity of an individual of type "1" in finding a medium wage job. Since we only use two continuous covariates, we are restricted to estimating three different wages due to identification restrictions. Furthermore, we do not include more than three individual unobservable factors because the fit does not improve significantly after three.

Given the unobservable components, number of markets, and non-parametric approach, we are left to identify a discrete distribution of agents with 3^3 points of support. For example, individual of type $X_i(t)$ with an unobservable type $n = 0$ across all wages will match at rate $\lambda_{w_L}(t)e^{\beta_L X_i(t)}V^0_{w_L}$ for w_L, at rate $\lambda_{w_M}(t)e^{\beta_M X_i(t)}V^0_{w_M}$ for w_M and at rate $\lambda_{w_H}(t)e^{\beta_H X_i(t)}V^0_{w_H}$ for

w_H making the worker's total hazard rate:

$$\lambda(t) = \lambda_{w_L}(t)e^{\beta_L X_i(t)}V^0_{w_L} + \lambda_{w_M}(t)e^{\beta_M X_i(t)}V^0_{w_M} + \lambda_{w_H}(t)e^{\beta_H X_i(t)}V^0_{w_H}. \tag{3.4.1}$$

The probability of observing an unemployment spell of length t ending with a wage w for the individual described above is:

$$f(t, w, X_i(t)) = \lambda(t)e^{-\lambda(t)}\left(\frac{\lambda_{w_L}(t)e^{\beta_L X_i(t)}V^0_{w_L}}{\lambda(t)}\right)^{d_L}\left(\frac{\lambda_{w_M}(t)e^{\beta_M X_i(t)}V^0_{w_M}}{\lambda(t)}\right)^{d_M}\left(\frac{\lambda_{w_H}(t)e^{\beta_H X_i(t)}V^0_{w_H}}{\lambda(t)}\right)^{d_H} \tag{3.4.2}$$

$$= e^{-\lambda(t)}(\lambda_{w_L}(t)e^{\beta_L X_i(t)}V^0_{w_L})^{d_L}(\lambda_{w_M}(t)e^{\beta_M X_i(t)}V^0_{w_M})^{d_M}(\lambda_{w_H}(t)e^{\beta_H X_i(t)}V^0_{w_H})^{d_H} \tag{3.4.3}$$

where d_j is a dummy that takes on the value 1 if $w = w_j$ is observed for $j \in \{L, M, H\}$ and 0 otherwise.

3.4.1 Likelihood Function

Since we allow for three types of unobserved heterogeneity in each wage hazard the support for the mixing distribution has 27 points. Denote p_k, $k = 1, \ldots, 27$ as the probability associated with each point in the support and $V = \{(V^0_{w_L}, V^0_{w_M}, V^0_{w_H}), (V^1_{w_L}, V^0_{w_M}, V^0_{w_H}), \ldots, (V^2_{w_L}, V^2_{w_M}, V^2_{w_H})\}$ as the set of points in the support. Following the identification restrictions in Heckman and Honoré (1989) and Abbring and van den Berg (2003), we normalize the mixing distribution in each market such that $V^0_{w_L} = V^0_{w_M} = V^0_{w_H} = 1$.

An individual's contribution to the likelihood function is:

$$l_i = \sum_{k=1}^{27} p_k \prod_{s=1}^{10} f(t_s, w_s | X_i(t), V) \tag{3.4.4}$$

where t_s is the length of unemployment spell, and $s = 1, 2, \ldots 10$ is the maximum number of possible spells per individual. Note the multiple spells for each individual, or *stratum*, provides both power and dependence between the covariates and unobservables. The total log likelihood function is:

$$L(\{p_k\}_{k=1}^{27}, \{\lambda_{w_j}(t), \beta_j\}_{j\in\{L,M,H\}}, \{V_{w_j}^n\}_{(j\in\{L,M,H\},n=1,2)}|X,t,w) = \sum_{i=1}^{N}\log(l_i) \tag{3.4.5}$$

We estimate the likelihood function for two specifications for the baseline hazard: Weibull, $\lambda_{w_j}(t) = \frac{k_j}{a_j}\left(\frac{t}{a_j}\right)^{k_j-1}$ where a_j is the scale parameter and k_j is the shape parameter in market j and piecewise exponential, $\lambda_{w_j}(t) = \lambda_{w_j}^q$, where $q = 1\ldots,6$ is allowed to vary at 10 week intervals and is constant after the first 50 weeks.

3.4.2 Likelihood Ratio Tests

We construct and estimate the MPHCR model to test for the independence between wage offers and job arrival rates, i.e., (3.2.2). We test for independence using (3.2.5), i.e., semi-elasticities are constant across wages. We test for a constant semi-elasticity by restricting the coefficients on individual characteristics and the mixing distribution. Since changes in individual characteristics such as age or education can change the reservation wage, we focus on changes across the medium and high wage hazards.

The semi-elasticities, such as those described in (3.2.5), for the MPHCR model with respect to unobserved heterogeneity at the medium and high wages are

$$\begin{aligned}
\frac{\frac{\partial h(X_i(t),w_M,t)}{\partial V_{w_M}^n}}{h(X_i(t),w_M,t)} &= \frac{\lambda_{w_M}(t)e^{\beta_M X_i(t)}}{\lambda_{w_M}(t)e^{\beta_M X_i(t)}V_{w_M}^n} \\
&= \frac{1}{V_{w_M}^n},\ and\ similarly \\
\frac{\frac{\partial h(X_i(t),w_H,t)}{\partial V_{w_H}^n}}{h(X_i(t),w_H,t)} &= \frac{1}{V_{w_H}^n}.
\end{aligned} \tag{3.4.6}$$

The semi-elasticitiies of the MPHCR model with respect to a specific individual characteristic

k in the medium and high wage markets are

$$\begin{aligned}
\frac{\frac{\partial h(X_i(t),w_M,t)}{\partial X_i^k(t)}}{h(X_i(t),w_M,t)} &= \frac{\lambda_{w_M}(t)\beta_M^k e^{\beta_M X_i(t)} V_{w_M}^n}{\lambda_{w_M}(t) e^{\beta_M X_i(t)} V_{w_M}^n} \\
&= \beta_M^k, \ and \ similarly \\
\frac{\frac{\partial h(X_i(t),w_H,t)}{\partial X_i(t)}}{h(X_i(t),w_H,t)} &= \beta_H^k. \qquad (3.4.7)
\end{aligned}$$

Therefore, if the independence assumption holds, or (3.2.2) and (3.2.5), then

$$\begin{aligned}
V_{w_M}^n &= V_{w_H}^n, \ and \qquad (3.4.8) \\
\beta_M^k &= \beta_H^k \qquad (3.4.9)
\end{aligned}$$

for βs of factors that do not effect the distribution of wages, i.e. $\partial P(X_i(t), w = w_j, t)/\partial X_i(t)^k = 0$. In other words, the the independence assumption implies a series of linear restrictions in the MPHCR model.

We test the linear restrictions using a likelihood ratio test. To explore the series of restrictions, we group them in several different ways to get an understanding of what might be the specific factor rejecting the null hypothesis of independence. Furthermore, the test requires $\partial P(X_i(t), w = w_j, t)/\partial X_i(t)^k = 0$. Therefore, we articulate a variety of restrictions in case the assumption does not hold for certain group of factors.

In what we call group 1, or restriction 1, we test all the restrictions we'll examine. Specifically, we test whether unobserved heterogeneity, unemployment insurance, search, and urban status affects the hazard rate differently for the high and medium wage market. If we fail to reject these restrictions, then we cannot reject that semi-elasticities for these variables are constant across the medium and high wage hazards. In other words, we will fail to reject the independence assumption under the assumption these variables do not affect the wage distribution. In terms of the parameters, we are testing

Restriction 1:

$$\begin{aligned} H_0^{(1)}: V_{w_M}^1 &= V_{w_H}^1 \\ V_{w_M}^2 &= V_{w_H}^2 \\ \beta_{w_M}^{UI} &= \beta_{w_H}^{UI} \\ \beta_{w_M}^{Urban} &= \beta_{w_H}^{Urban} \\ \beta_{w_M}^{Search} &= \beta_{w_H}^{Search} \end{aligned}$$

As some of the variables might not satisfy the assumption that they do not affect wage offers, we introduce several other groupings/restrictions. In restriction 2, we test for whether we can reject the null using only unobserved heterogeneity, or

Restriction 2:

$$\begin{aligned} H_0^{(2)}: V_{w_M}^1 &= V_{w_H}^1 \\ V_{w_M}^2 &= V_{w_H}^2 \end{aligned}$$

In restriction 3, we test whether the semi-elasticities of the hazard rate with respect to UI, urban status, and job search varies across the wage distribution:

Restriction 3:

$$\begin{aligned} H_0^{(3)}: \beta_{w_M}^{UI} &= \beta_{w_H}^{UI} \\ \beta_{w_M}^{Urban} &= \beta_{w_H}^{Urban} \\ \beta_{w_M}^{Search} &= \beta_{w_H}^{Search} \end{aligned}$$

Finally, we estimate our least strict restriction in which we assume only UI does not affect the underlying wage distribution and thus restrict its semi-elasticity across wage hazards to

Restriction 4:

$$H_0^{(4)}: \beta_{w_M}^{UI} = \beta_{w_H}^{UI}$$

To reiterate, Restriction 4 allows all other factors to affect the wage offer except UI. Also, the results related to this restriction is a key application to testing for the independence assumption.

In particular, as discussed in Acemoglu and Shimer (2000a) among others, UI could allow for workers to search for more productive jobs. If we fail to reject the independence assumption, then we will be putting such an analysis in doubt.

Given the restricted groupings, we refer to the unrestricted estimation of the model, as found in (3.4.5), as the baseline and use the unrestricted version to evaluate the restricted versions using likelihood ratio tests.

3.5 Estimation Results

The estimation results regarding the effect of demographic variables on the arrival rates of jobs, as well as the baseline time dependent hazard, line up with past studies. For references, Devine and Kiefer (1991) and Eckstein and Van den Berg (2007) provide in depth surveys on the empirical search literature with the former more closely related to our work given its focus on reduced form approaches. Tables B.1.2, B.1.4, B.1.6, and B.1.9 provide a summary of our results including the results from Restrictions 1-4 for the Weibull hazard with standard data, Weibull hazard with the inclusive data, the piecewise exponential hazard with the standard data, and the piecewise exponential with the inclusive data, respectively. Tables B.1.3, B.1.5, B.1.8, and B.1.11 provide the estimates from the demographic effects including UI for the Weibull hazard with standard data, Weibull hazard with the inclusive data, the piecewise exponential hazard with the standard data, and the piecewise exponential with the inclusive data, respectively. Finally, Tables B.1.7 and B.1.10 provide estimates for the piecewise exponential baseline using the standard and inclusive data sets, respectively. The estimated probabilities p_k for $k = 1, .., 27$ have been suppressed for brevity, but can be provided upon request.

In terms of race and gender, our estimates are in line with the broader wage literature as surveyed in Darity and Mason (1998) and many other places. Specifically, we estimate males are more likely to transition to high wage jobs and less likely to transition to low wage jobs across all the specifications and restrictions. Hispanics are relatively equally less likely to transition to any wage job while blacks are less likely to transition to high wage jobs with little or no effect for low wage jobs. Bowlus (1997) and Bowlus and Eckstein (2002) are two similar examples to ours that empirically analyze gender and racial discrimination, respectively.

In terms of education and experience, our results are in line with the classic Mincerian earning equations as pioneered in Mincer (1974a) and more generally surveyed in Card (1999). Specifically, we find the level of schooling as well as a high school diploma increases the rate of transition to employment and more so for high wage jobs. Individuals with a college diploma are less likely to transition to low and medium wage jobs while more likely to transition to high wage jobs. Similarly, experience, as proxied by age, generally increases transition to high wage jobs and reduces transitions to low wage jobs although note the low dispersion in our data's age distribution.

In terms of the baseline hazard, the Weibull and piecewise exponential estimates show duration dependence to be effectively constant in the standard data set. The estimates for the inclusive data set provide evidence for the theoretically intuitive result of negative duration dependence. Given the nature of each data set, the difference in the results under each data set suggests the ability to transition from outside the labor force decreases over time. Intuitively, job offers are less likely to arrive the longer you've been unemployed when you aren't searching. However, if searching, duration dependence is less of a factor, if at all. These estimates are in line with other empirical studies as surveyed in Devine and Kiefer (1991).

A critical insight of our work is to expand the literature regarding the effects of UI on job finding rates, such as in Meyer (1990a) and others. Our findings are consistent with those studies in that UI reduces job finding rates. However, we extend the work by showing the negative impact of UI on job finding rates falls for higher wage jobs. Specifically, individuals are much less likely to transition to low wage jobs when collecting UI. However, this effect is less pronounced at higher wages. Put differently, UI reduces the transition rate for medium wage jobs more than for higher wage jobs. Restriction 1, 3 and 4, or where the coefficients on UI are equal across the wage types, is rejected at the 1% level in both types of baseline specifications and data sets. As UI discourages search, the results strongly suggest UI discourages search at the low end of the wage distribution more and less so at the upper end. We note this was predicted by Moen (1997) and others assuming UI affects the value of leisure when unemployed. Put differently, the competitive search assumption is critical in the analysis of UI as shown in

Acemoglu and Shimer (2000a) and others. Given our empirical results, the assumption of changing job finding rates across the wage offer distribution should be used when considering the efficacy of UI.

In terms of Restrictions 1 & 3, urban status was also considered and constrained with the assumption it is affecting job search specifically. The estimates are relatively consistent and show those in urban areas are more likely to transition to high wage jobs and less likely to transition to low wage jobs. However, the estimates are small relative to the effect of UI as well as its standard errors. The estimates are in line with the empirical work such as that surveyed in Holzer (1991). Refer to Wasmer and Zenou (2002) for modeling the dynamics in a search environment.

Under the inclusive data set, we estimate the effect of job search on the arrival rate of jobs. Furthermore, we include it in the Restriction 1 & 3 tests. We find it increases the transition rate for the low and medium wage hazards as the search literature suggests and more so for the low wages. Its impact on high wage jobs appears ambiguous and is an interesting fact for further study. Note, the standard errors are relatively large.

Finally, we test for variation in the unobservable factors. Historically, the literature has suggested search costs, which are unobservable, can explain the fact that individuals with low wages spend more time unemployed ((Eckstein and Wolpin, 1995)). As a result, these factors can be interpreted as search intensity. Given this view, we reject that search intensity is constant across wages at the 1% level in Restrictions 1 and 2 in all our results: the Weibull and piecewise exponential baseline and the standard and inclusive data sets. In effect, unobservable search intensity is variable after controlling for the reservation wage. Our results along this line, as well as those testing urban status's semi-elasticity, should be interpreted with caution as these unobservable factors could be affecting the likelihood of accepting an offer and not simply finding an opportunity.

3.6 Test Results

As noted above in Section 3.5, we nearly uniformly reject at the 5% level the restrictions imposed by (3.2.2), or more specifically, (3.2.5) for either of the different specifications of the data or baseline hazard. In particular, the effects of all the variables considered affect the medium and high wage differently! In other words, we reject the idea that the wage offer and job arrival rate are independent even after controlling for worker characteristics.

We run two different types of robustness checks of our results. In particular, what happens when the low, medium, and high wage thresholds are dependent upon an individuals education. Furthermore, how does the functional form of the MPHCR model compare to a standard search model.

3.6.1 Test Results with Education Based Wage Thresholds

In terms of controlling for years of schooling and graduation status, we vary the duration of unemployment by these factors. However, education is not being used to determine the definition of low, medium, and high wage thresholds. As a check of our results given this restrictive assumption required by the MPHCR model, we re-estimate the model by education group, that is, we assume there are separate markets by level of education, and given the separate markets, we redefine low, medium, and high wages by education type.

The descriptive statics of wages by education and accompanying thresholds are provided in Table B.1.12. The results from the likelihood ratio tests are provided in Tables B.1.13 and B.1.14 for the Weibull and piecewise exponential specifications, respectively. In the separated case, we continue to reject all the restrictions at roughly the 5% significance level when looking at those with a High School education or less. We fail to reject the restrictions in the case of the College educated. However, the difference may be arising from the fact that we observe very few unemployment spells for the college educated relative to the number of parameters being estimated. However, it would be interesting to analyze the education component further if the identification strategy allowed it.

3.6.2 Applicability of Reduced-Form Estimates

We take a flexible reduced form approach to test the assumptions used in labor market search models. Therefore, our results can arguably be applied to the literature as a whole. However, the reduced form approach we take still contains some structure. In particular, we use a proportional hazard function. As a result, the identification strategy we employ may not be flexible enough to fit the entire class of search models. To investigate the issue, we simulate data using the model and parameter estimates from Eckstein and Wolpin (1995) and estimate our reduced from model using the simulated data. We then estimate the Kullback-Leibler (KL) divergence of our model to the true data generating model of Eckstein and Wolpin (1995). Define q as the probability distribution of duration times produced from our reduced from estimates, and p as the probability distribution of duration times from the true model. The KL distance is defined as

$$D_{KL}(p||q) = \int_0^\infty p(t) \ln\left(\frac{p(t)}{q(t)}\right) dt$$

where t represents time. As we note below, in our interpretation, D_{KL} is relative to the entropy of the true distribution, given by

$$H(p) = \int_0^\infty p(t) \ln[p(t)] dt,$$

and measures the additional data required to capture the true model using the incorrect one. The entropy of the true distribution, $H(p)$, measures the uncertainty of duration times, which can be interpreted as how informative a draw from the distribution is for understanding the underlying random variable, unemployment duration. The KL distance is the relative entropy between the true distribution of duration times and the distribution of duration times estimated by our reduced form approach. The entropy of our reduced form model is $H(p) + D_{KL}(p||q)$. If $D_{KL} = 0$ then a draw from our reduced form model is exactly as informative about the duration of unemployment as a draw from the true distribution; therefore, we use the KL distance as a measure of how informative our reduced form model it about the true distribution of unemployment duration times.

The Kullback-Leibler divergence values are in Table B.1.15 where we give the KL values for the different sub-markets estimated in Eckstein and Wolpin (1995). Although the Eckstein and Wolpin (1995) estimates have enormous flexibility by re-estimating the parameters for each sub-market, we estimate all the markets simultaneously. Therefore, our unobservable heterogeneity in particular is not as flexible as that found in what we assume to be the true model.

Given the interpretation of KL, we require between 1.65% and 5.37% additional bits of information to describe the distribution of unemployment duration using our reduced form version depending upon the sub-market one's considering. Given the limited amount of information required to describe the Eckstein and Wolpin (1995) versus our reduced form estimates, we argue the reduced form estimation can adequately capture more specific search models.

3.7 Application to Common Models

In this section, we discuss two sets of models our results reject. Due to the large and varied literature on labor market search models, we discuss two classic examples in which the hazard rate of unemployment does and does not respond as we have shown. Let $\lambda(w, X)$ equal the rate at which an individual transitions from not employed to employed with a wage w where X is observable and unobservable factors affecting an individual's transition rate. Finally, let w_R represent an individual's reservation wage. Specifically, if $w_i < w_R$, then $\lambda(w_i, X) = 0$. To reiterate, for a model's hazard rate to be consistent with the data it must satisfy the following criterion:

$$\frac{\frac{\partial h(X_i,w_i,t)}{\partial X}}{h(X_i, w_i, t)} \neq \frac{\frac{\partial h(X_i,w_j,t)}{\partial X}}{h(X_i, w_j, t)} \tag{3.7.1}$$

for any $w_i \neq w_j$, the semi-elasticity of the hazard rate with respect to some observable or unobservable factor that affects the offer rate cannot be constant across wages. To show how this applies to common search models of the labor market, we discuss the hazard rate of two well cited search models.

Example 1: Random Matching and Bargaining with Match-Specific Productivity

We are defining this example using the terminology described in Rogerson et al. (2005), which surveys a large group of search models found in Section 4.4 of their paper. The model describes a wide variety of models in the literature. Following the notation and description in Rogerson et al. (2005), one can determine the model's equilibrium with two conditions,

$$\begin{aligned} y_R &= b + \frac{\alpha_\omega \theta k}{\alpha_e(1-\theta)}, \text{ and} && (3.7.2) \\ (r+\lambda)k &= \alpha_e(1-\theta)\int_{y_R}^{\infty}(y-y_R)dF(y), && (3.7.3) \end{aligned}$$

where y is productivity, y_R the reservation wage, b is unemployment utility, θ is a bargaining parameter, k is the vacancy cost for a firm to hold a job open until filled, r is the discount rate, α_e is the rate a firm matches with a worker and α_ω is the rate a worker matches with a firm, and λ the job destruction rate.

Given the standard equilibrium conditions,

$$\lambda(w,b) = \alpha_\omega f\left(\frac{w-(1-\theta)y_R(b)}{\theta}\right) \tag{3.7.4}$$

because $w = y_R + \theta(y - y_R)$. Notice that the underlying unobservable characteristic that determines the reservation wage is the unemployment utility b. Therefore, the only observable or unobservable factor X that could change the hazard rate is b. Below we suppress the reservation wage's dependence on b, i.e. $y_R = y_R(b)$, for ease of notation. If one assumed that b is a function of unobservables and an observable unemployment insurance (UI) component, then the result would be

$$\frac{\frac{\partial\lambda(w,b)}{\partial b}}{\lambda(w,b)} = \frac{\frac{\partial\alpha_\omega}{\partial b} f\left(\frac{w-(1-\theta)y_R}{\theta}\right) + \alpha_\omega \frac{\partial f\left(\frac{w-(1-\theta)y_R}{\theta}\right)}{\partial y_R}\frac{\partial y_R}{\partial b}}{\alpha_\omega f\left(\frac{w-(1-\theta)y_R}{\theta}\right)}, \tag{3.7.5}$$

and the criterion $\dfrac{\frac{\partial \lambda(w_i,b)}{\partial b}}{\lambda(w_i,b)} \neq \dfrac{\frac{\partial \lambda(w_j,b)}{\partial b}}{\lambda(w_j,b)}$ in this model would simplify from

$$\frac{\frac{\partial \alpha_\omega}{\partial b} f\left(\frac{w_i-(1-\theta)y_R}{\theta}\right) + \alpha_\omega \frac{\partial f\left(\frac{w_i-(1-\theta)y_R}{\theta}\right)}{\partial y}\frac{\partial y_R}{\partial b}}{\alpha_\omega f\left(\frac{w_i-(1-\theta)y_R}{\theta}\right)} - \frac{\frac{\partial \alpha_\omega}{\partial b} f\left(\frac{w_j-(1-\theta)y_R}{\theta}\right) + \alpha_\omega \frac{\partial f\left(\frac{w_j-(1-\theta)y_R}{\theta}\right)}{\partial y}\frac{\partial y_R}{\partial b}}{\alpha_\omega f\left(\frac{w_j-(1-\theta)y_R}{\theta}\right)} \neq 0 \tag{3.7.6}$$

to

$$\frac{\frac{\partial f\left(\frac{w_i-(1-\theta)y_R}{\theta}\right)}{\partial y}}{f\left(\frac{w_i-(1-\theta)y_R}{\theta}\right)} - \frac{\frac{\partial f\left(\frac{w_j-(1-\theta)y_R}{\theta}\right)}{\partial y}}{f\left(\frac{w_j-(1-\theta)y_R}{\theta}\right)} \neq 0. \tag{3.7.7}$$

Given the simplified model and interpretation of b and UI, the criterion is satisfied and our results do not reject this model. Our criterion does not reject this model because the distribution $f(y)$ is not discrete or flat and bargaining exists. To put it differently, if the surplus was split evenly irrespective of the reservation wage, or drawing a particular wage is uniformly distributed, then the model would fail our criterion test.

However, the naive interpretation of b as being a function of UI is not correct. In particular, UI is only collected when an individual is laid off due to lack of work. Therefore, the workers outside option used during the bargaining does not include UI. As a result, the standard model must be rewritten. Following the notation of Rogerson et al. (2005), the flow utility for unemployed workers is either

$$rU = b + \alpha_\omega \int_{y_R}^{\infty} (W_y[w(y)] - U)dF(y), \text{ or} \tag{3.7.8}$$

$$rU_{UI} = b + b_{UI} + \alpha_\omega \int_{y_R}^{\infty} (W_y[w(y)] - U)dF(y) \tag{3.7.9}$$

where the latter is the asset value of unemployment for those laid off collecting UI, i.e., those who lose their jobs, and the former equation determines the asset value used as the threat point in the Nash bargaining process. As a result, the wage equation becomes

$$w = rU + \theta(y - rU), \tag{3.7.10}$$

and the hazard rate becomes

$$\lambda(w, b) = \alpha_\omega f\left(\frac{w - (1-\theta)rU(b)}{\theta}\right). \tag{3.7.11}$$

As U is not a function of whether an individual is collecting UI, our empirical results reject this more accurate representation of the model. Specifically,

$$\frac{\partial \lambda(w, b)}{\partial b_{UI}} = 0, \tag{3.7.12}$$

for all $w > y_R$ and as a result the elasticity is constant across w.

To summarize, our criterion for this class of models rejects them when UI does not change the bargaining position of the workers. However, in the naive case, we fail to reject these models due to bargaining.

Although we will not prove it here, it may be of interest that one could extend the model to include search intensity. In such a case, $\frac{\partial \alpha_\omega}{\partial b} \neq 0$. As it is equal across wage draws, we reject these predictions using our empirical estimates.

Example 2: On-the-Job Search via Burdett and Mortensen (1998)

Again following the notation in Rogerson et al. (2005), for the simplest case where the arrival rates of job offers while unemployed (α_0) and employed (α_1) are equal, $\alpha_0 = \alpha_1 = \alpha$ and the interest rate is approximately zero, $r \approx 0$, the wage offer distribution is

$$F(w) = \frac{\lambda^* + \alpha}{\alpha}\left(1 - \sqrt{\frac{y - w}{y - b}}\right) \tag{3.7.13}$$

where λ^* is the separation rate, y is the productivity of the job, and b is the worker's flow value of unemployment. The support of F is $[b, \bar{w}]$ for some $\bar{w} < y$ where the upper bound can be found using $F(\bar{w}) = 1$. It can be shown that (3.7.13) is continuous on its support; therefore, the derivative exists and the p.d.f. is:

$$f(w) = \frac{\lambda^* + \alpha}{2\alpha}\sqrt{\frac{y-b}{y-w}}. \tag{3.7.14}$$

Given the p.d.f of the wage distribution, the hazard rate of matching at wage w is,

$$\lambda(w,b) = \alpha f(w) \tag{3.7.15}$$

$$= \frac{\alpha(\lambda^* + \alpha)}{2}\sqrt{\frac{1}{(y-w)(y-b)}} \tag{3.7.16}$$

and the elasticity of the hazard rate with respect to b is,

$$\frac{\frac{\partial \lambda(w,b)}{\partial b}}{\lambda(w,b)} = \frac{1}{2(y-b)} \tag{3.7.17}$$

Since the elasticity of the matching function with respect to the workers unemployment insurance as defined by b is independent of the wage at which they match, the model fails to satisfy our empirical results.

Example 3: Competitive Search via Moen (1997)

Following notation from Moen (1997)[1], the probability a worker receives a job offer from sub market i is

$$p(\theta_i) = \frac{rU - b}{w_i - rU}(r+s). \tag{3.7.18}$$

The hazard rate to matching to wage w_i is given by

$$\lambda(w_i, b) = p(\theta_i) prob(w = w_i) \tag{3.7.19}$$

$$= \frac{rU - b}{w_i - rU}(r+s) \tag{3.7.20}$$

since $prob(w = w_i) = 1$ if matching in submarket i.

[1]We have changed the flow value of unemployment from z to b for consistency across examples.

The semi-elasticity of the hazard rate with respect to b is,

$$\frac{\frac{\partial \lambda(w,b)}{\partial b}}{\lambda(w,b)} = \frac{\frac{\partial rU}{\partial b}}{w - rU} + \frac{\frac{\partial rU}{\partial b} - 1}{rU - b}. \tag{3.7.21}$$

Since the value of search U must be the same across submarkets it is clear that the semi-elasticity of the hazard rate with respect to b is not constant across wages.

To summarize, our rejection of the independence assumption has the implication of rejecting two canonical job-search models: Random matching and Bargaining with Match-Specific Productivity, and On-the-Job Search. However, in a model of competitive search in which workers are identical, job arrival rates and wage offers are not independent.

3.8 Conclusion

Using a multi-spell mixed proportional hazards competing risks model with National Longitudinal Survey of Youth (1997) data, we reject the assumption that the semi-elasticity of the hazard rate is constant for factors which do not change the wage distribution. We show that this assumption can be rejected if these factors include unemployment insurance, urban status, and unobservable characteristics. In other words, after controlling for worker characteristics, we reject an assumption that the wage and job arrival rates are independent.

The implications are important in interpreting the effect of UI as well as job-search models in general. In particular, we have shown our results reject two well used models in the job-search literature. Furthermore, we provide empirical support for the hypothesis that UI affects job hiring rates differently across the wage offer distribution.

Given the importance of unemployment insurance and the use of search in modeling the duration of unemployment, our results are an important step in defining the future trajectory of the search literature. In particular, our results point heavily toward a world where workers search in a market where wage offers and the rate of job arrivals are not independent.

Chapter 4

The Effect of Public Education Expenditures on Intergenerational Mobility

4.1 Introduction

Does public education act as a vehicle for decreasing income persistence? This is an age-old question, contentious both in political and economic circles, for which there is no conclusive answer. The focus of this paper is intergenerational mobility, or income persistence across generations. Intergenerational mobility is a special branch of inequality studies that deals with the persistence of income across generations. It attempts to quantify the extent to which a parents' income explains their children's income in the future, thus establishing a generational link in poverty or economic status. While many studies have quantified the degree to which a parents' income is related to their child's income, few have explored the mechanisms. In particular, there are few papers that focus on the interplay between government programs and inequality. The papers that have sought to understand the role of education expenditures on intergenerational mobility have lacked identification, and thus either constructed a model or made descriptive claims. Here, I use court-mandated school finance reforms as exogenous shifters of per-pupil spending at the state level, following Jackson et al. (2015). I that a ten-percent increase in per-pupil spending implies between a 2 and 3.5 percent decrease in persistence of parental income. Given my research design, I believe these results strongly endorse the belief that government spending on public education has a persistent and causal effect in increasing intergenerational mobility.

My work follows in the footsteps of two papers that considered the role of government expenditures on intergenerational mobility. The first of these was Mayer and Lopoo (2008), which studied the effect of aggregate government spending at the state level. While they did not have a natural experiment with which to work, they showed that spending in the least wealthy states increased mobility. More recently, Chetty et al. (2014a) studied the determinants of mobility geographically as a small subsection of their tome on intergenerational mobility across the United States. Likewise, they were unable to come to any causal conclusions about spending, but noted that spending on education was strongly correlated with decreasing income persistence. What both of these papers suggest is that an instrument is necessary to isolate the effects of spending on education.

I use court-mandated school-finance reforms to obtain causal estimates of the impact that changing school spending has on intergenerational mobility. This identification strategy, as well as the set of court cases, were first employed by Jackson et al. (2015), though I change the research design to better suit my empirical goals. Because 45 states experienced court mandated school finance reform between 1960 and now, I have a great deal of variation in both time and space.

As a number of authors have done before, I employ the PSID to study these intergenerational links. The PSID is a panel of families that stretches from 1968 to now, and surveys individuals on a number of relevant characteristics. I then control for potentially competing explanations, as well as propose mechanisms for the decrease in persistence over time. I merge this with a number of state-specific, time-varying controls, including per-pupil spending by state over the same time period. This allows us to employ a two-stage estimation, in which I project spending per pupil in the first stage and then estimate how much this changes mobility in the second stage.

I conclude that a one percent increase in spending on public education will increase mobility by roughly 0.3 percent, which is significant at common statistical levels depending upon specification. In particular, my results show that gains are restricted to upward mobility among the least-wealthy, while there are no losses associated to those in the upper income percentiles. Given that my first stage would be stronger if I were using smaller areas of geographic observation, I believe that this strongly endorses the idea that public spending on education can improve intergenerational outcomes for lower-income families[1].

In the second section, I briefly discuss the papers most closely related to my empirical targets and identification strategy. Following this, I will further discuss the empirical strategy as well as the validity of my empirical design in the third section. In the fourth section of the paper, I will detail the sources of my data as well as provide descriptive statistics. In the fifth section, I describe the results of both the first-stage regression and the regression of interest. I preform robustness checks in section six, and finally conclude in section seven.

4.2 Related Literature

There is a very large empirical literature on the transmission of income status across generations. The most prominent measures of mobility are an intergenerational elasticity (IGE) specification (Solon, 1992) and an intergenerational rank association (IRA) (Dahl and DeLeire, 2008), which relates a parents peercentile rank within the income distribution to their child's. Among the first to study the intergenerational mobility using the IGE specification was Solon (1992), who noted that using single year measures of permanent income attenuates estimates of intergenerational mobility generated classical measurement error and biased estimates toward less income persistence. Since Solon's seminal work, authors have explored a number of topics relating to intergenerational mobility using the same IGE framework. Papers have explored mobility in other countries (Bjorklund and Jantti, 1997), mobility among daughters

[1]This is a novel conclusion in the literature: to my knowledge, I am the first to show that public spending on education increases intergenerational mobility

(Chadwick and Solon, 2002), as well as how this measure has evolved over time within the United States (Lee and Solon, 2009). Many papers have explored the extent to which education explains intergenerational mobility,[2] like Ueda (2013) who explores education and mobility in Asia. Few papers, however, have considered the role of government spending in changing the persistence of income. To my knowledge, there are two papers that have explored these issues in depth within the United States, and while both are well worth the read, each lacks strong identification and is thus unable to say anything causal about government spending's role in mobility.[3]

4.2.1 Intergenerational Mobility Background - Chetty et al. (2014a) and Mayer and Lopoo (2008)

The first paper that explicitly considers government spending in intergenerational mobility is Mayer and Lopoo (2008), which uses the log-log framework to describe how government spending might impact intergenerational mobility. They write an econometric model in the following way:

$$ln(Y_{st}) = \beta_0 + \beta_1 ln(\bar{X_{st}}) + \beta_2 ln(\bar{G_{st}}) + \beta_3 (ln(\bar{X_{st}}) * ln(\bar{G_{st}})) + \epsilon_{st} \tag{4.2.1}$$

Government spending is defined to be the all government expenditures (i.e., every government expenditure at the local, state and federal levels) that occur while a son is between 15 and 17 per child. Note that this framework is state-level spending, as they do not have observations of government spending at smaller geographic regions. They note that this framework can allow elasticity of son's income with respect to father's income to be written as:

[2] see Chusseau and Hellier (2012) for a more extensive discussion of the literature, as well as a discussion of some theoretical models relating human capital to intergenerational mobility.

[3] A third paper Liu et al. (n.d.), considers the impact of government spending in China on intergenerational mobility. They find a much higher degree of intergenerational persistence in income ($\beta_1 = 0.830$), and again are unable to say that β_3 is significantly negative. They attribute much of the persistence to differences in spending on education at the university level, for which there is very little governmental funding. To my knowledge, these are the only three papers to incorporate government spending in the literature.

$$\frac{\partial ln(Y_{st})}{\partial ln(\bar{X_{st}})} = \beta_1 + \beta_3 ln(\bar{G_{st}}) \tag{4.2.2}$$

Under this specification, if $\beta_3 < 0$, then government spending decreases intergenerational transmission of income. That is, government spending will make the outcomes of children less dependent upon their parents' incomes. They estimate three separate models: a baseline model, a model with state fixed effects, and a model controlling for individual characteristics as well as fixed effects. They find the sign of β_3 to be consistent under the hypothesis, showing that government spending decreases intergenerational elasticity. However, the coefficient is insignificant under any specification. Using an F-Test, they do find that government spending plays a significant role in explaining mobility. They interpret to mean that government spending is strongly correlated with income so that the individual effect is difficult to determine, but should still be considered when constructing a model. They reconsider the question by dividing the sample into three categories of state spending: high, medium, and low. They find that the differences between low and high-spending states turns out to be positive and significant. These results are not ideal when interpreting the relationship between government spending and mobility, as they only indicate that lower spending states have lower mobility.

The second paper, Chetty et al. (2014a), uses more than 40 million tax records of parent-child pairs and use the intergenerational rank association (IRA) specification first employed by Dahl and DeLeire (2008).[4] This relates a child's income percentile in the national income distribution to their parents' income percentile in the national distribution while they were children. That is, they estimate the following equation:

$$p_{ix} = \beta_0 + \beta_1 p_{iy} + \epsilon_i \tag{4.2.3}$$

while also including a number of controls. The authors analyze mobility across regions within the United States to explore whether different areas of the United States experience different degrees of mobility. They define the areas of study to be "commuting zones," areas that are

[4]The IRA specification has been shown to be more robust to a number of the concerns associated with the IGE specification. I choose to still employ the IGE specification for reasons that I detail below. See Dahl and DeLeire (2008) for a better discussion of the reasons one might use IRA instead of IGE

similar to metro areas, but designed to include rural communities as well. These commuting zones can generally be thought of as about the size of four counties. They find a great deal of differences in outcomes across these commuting zones, with regions accounting for as much as a 10 percent difference in expected outcomes within the national income distribution among children. They estimate model given in equation Equation 4.2.3 for each of the 709 commuting zones in the United States. In order to assess mobility within a region, they consider two measures of mobility:

- Relative mobility: a comparison of how unequal outcomes will be across generations within the region. They measure this by using β from equation Equation 4.2.3, which describes how much better off (in percentile ranks) a wealthy individual's child can expect to be than a poor individual's.

- Absolute mobility: a measure of the expected outcomes for children born to a family in the 25th percentile of the national income distribution within a region. This is given by $\alpha + 25\beta$, and measures where in the national income distribution a child can expect to end up having been born to a family in the 25th income percentile within a region.

A region could have low relative mobility, but high absolute mobility if everyone within a region improves over a generation, given by α. Using these measures of local mobility, the authors find a very large difference across commuting zones: a family at the 25th percentile living in Charlotte, North Carolina, (the least absolutely mobile location in the sample) can expect their children to end up 10 percentile ranks lower than an equally wealthy family living in Salt Lake City, Utah (the most mobile location in the sample). Differences are found in relative mobility as well: a family from the 100th percentile in Cincinnati, Ohio, have expected outcomes 42.4% higher than a family from the lowest percentile. Conversely, the wealthiest families in San Jose can only expect 23.5% better outcomes than the least wealthy in the same commuting zone.

They further explore the causes of local variation in mobility. They take each of the 709 absolute mobility values and regress plausible causes of different mobility against them. For example, consider the case of segregation as a cause for differences in mobility:

$$(\alpha + 25\beta_{CZ}) = \delta_0 + \delta_1 Segregation_{CZ} + \epsilon_{CZ} \tag{4.2.4}$$

Using this structure, they explore the impact of the following upon intergenerational mobility: racial makeup of the CZ, the level of segregation within a CZ, the degree of income inequality, public good provision and tax policies, school quality, access to higher education, labor market structure, migration rates, social capital, and family structure. They find three measures of government involvement to be significant: the local tax rate, government expenditures per capita and the level of earned-income tax credit provision. They find each measure of K-12 education to be significant in explaining differences in intergenerational mobility, with the rate of high school dropouts being the most strongly linked to intergenerational mobility. However, as with Mayer and Lopoo (2008), they do not have a good source of exogenous variation and are therefore unable to make causal claims about the sources of inequality across mobility, explicitly describing their results as "descriptive." For this reason, I explore an alternative research designs.

4.2.2 Educational Attainment Background - Jackson et al. (2015) and Johnson (2011)

My paper employs an identification strategy following the work of Jackson et al. (2015) and Johnson (2011). In these papers, the authors use exogenous variation in school spending generated by court rulings to assess the effect of per-pupil expenditures on a variety of long-run outcomes.

The first of these papers, Johnson (2011), addresses the differences in outcomes for minority students brought about by changes in school quality and funding. He uses court-ordered desegregation, which took place within specific school districts in the United States in the decades that followed the Brown v. Board of Education (1954) decision. This provides a great deal of within and across state variation in ways that he describes as "quasirandom." In other words, many school districts were exogenously ordered to desegregate, which he uses as a source of variation. In particular, his first stage focuses on changes following the announcement of desegregation decisions, because as he notes implementation times might be endogenous. He includes a very diverse set of school district, state, county and family characteristics in both his first and second stage estimations and finds that all the long-run outcomes in the study increase positively for treated minorities, while remaining constant for white students in schools that desegregated. He employs the restricted PSID matched to the child's school district, allowing for a great deal of variation in both the first and second stage. He first estimates the effect of desegregation on school finances using the following event study framework:

$$Y_{c,t} = \sum_{y=-5}^{-1} \pi_y 1(t - T_c^* = y) + \sum_{y=1}^{6} \tau_y 1(t - T_c^* = y) \tag{4.2.5}$$
$$+ X'_{ct}\beta + Z'_{ct}\gamma + (W_{1960c} * t)'\phi + \eta_c + \lambda_t + \psi_g * t + \epsilon_{ct}$$

The π_y parameters act as a placebo test, showing the increase in school spending in each of the five years prior to court implementation. The τ set of parameters track the change in spending during the six years following the date of the court ruling, mapping dynamic changes. His set of controls is quite robust, including a number of alternative war on poverty programs, local characteristics of school districts, census tract time trends and school district and time fixed effects. He finds a significant increase in spending for lower income districts. While I will be doing something similar and then using a projection of school spending in the first stage in order to assess the effect of spending on long-run outcomes, he embeds these court decisions in his second-stage event study using the following specification:

$$Y_{icb} = \sum_{t-T=-20}^{-2} \alpha^r_{t-T} 1(t_{icb} - T_c^* = t - T) + \sum_{t-T=0}^{12} \theta^r_{t-T} 1(t_{icb} - T_c^* = t - T) \tag{4.2.6}$$
$$+ \sum_{t-T=13}^{20} \delta^r_{t-T} 1(t_{icb} - T_c^* = t - T) + X_{icb}\beta + Z_{cb}\gamma$$
$$+ (W_{1960c} * t)\phi^r + \eta^r_c + \lambda^r_t + \psi^r_g * b + \epsilon_{icb}$$

The variable T is the year in which the individual is 17. This means that $t - T$ is the number of years until 17, which means that each of the indicator variables will take on the value 1 when a court case takes place $t_{icb} - T_c^*$ number of years Thus, the θ coefficients map the value of having additional exogenous spending for each year of schooling 5 through 17. This also includes placebo tests, by allowing for people who turned 17 before court financed reform took place (the α coefficients), and for additional years beyond their school age years from the set of δ coefficients.

In the first stage, he finds that school desegregation is associated with an increase of nearly $1000, which corresponds to almost a 33 percent change. He performs a number of robustness checks, all of which conclude that this increase is significant. In the second stage, he finds that each additional year of exposure to court-ordered reform increases adult wages by 1.2 percent. He further constructs a set of families in which one child was exposed to reforms, while another was not, and estimates the effect again. This placebo test produces the same results.

More pertinent to this study is Jackson et al. (2015). They use court-mandated school finance reforms in order to identify exogenous changes in school spending in much the same manner that I will in this study. In order to do so, they construct a list of school finance-relevant court cases, the timing of these cases, and the type of reform that was implemented.[5] They include a detailed history of school reform litigation in the United States:They first note that court mandated school finance reform took on two distinct legal philosophies separated in time. The earliest cases (1960s - 1970s) were argued on the basis of "equity," that many school districts were underfunded relative to their wealthier counterparts. Because school districts have historically been financed largely by local taxes, poorer neighborhoods had systematically lower levels of school funding, which litigants argued was unconstitutional (most states have equal protection clauses that have been interpreted to include a fundamental right to education). They show that these cases led to a lower variance of funding across states, but not necessarily an increase in funding. Later cases argued that school districts across the state simply did not have enough funding to provide "adequate" levels of schooling, thus receiving the moniker "adequacy cases." These cases were associated with a large increase in funding for lower income

[5] I have included their list of cases in the Appendix

schools districts across states, while showing no appreciable decrease in funding for wealthier districts. I replicate these results at both the state and county level. They further break down each case into the type of funding reform implemented to address policy questions aimed at describing the most efficient type of funding scheme.

They follow the same empirical strategy as Johnson (2011) for both the first and second stage, equations Equation 4.2.5 and Equation 4.2.6. As I will do, they employ the INDFIN dataset for school finance, which details spending per pupil (among other outcomes) for years 1967 to now and the PSID for individual characteristics. In the second stage, the authors address long-run outcomes using the same framework as Johnson (2011) in equation Equation 4.2.6. They include controls for a number of "War on Poverty" programs, as well as local characteristics like hospital desegregation, school desegregation and state funding for kindergartens, all at the county level. Both their event study and 2SLS frameworks imply large increases in long-run health, education and labor market indicators. In particular, they find that by increasing spending by 20% for all 12 years of schooling is associated with an additional year of education, as well as a 52.2 percent increase in income for children from poor families.

4.3 Empirical Strategy

Following previous literature, I will not explicitly model investment in children. Instead, I will consider what the literature has termed a "intergenerational elasticity" estimate. In essence, this can be thought of as how much a one percent increase in parents permanent income would increase their children's permanent income in percentage terms. I will improve upon the previous work by using the same court-identification strategy used by Jackson et al. (2015).

4.3.1 Court Rulings as Identification

The prior papers exploring the effect of government spending on intergenerational mobility lacked strong identification in order to draw causal conclusions from their estimates. Following Jackson et al. (2015), I have chosen to employ the initial date of school finance reform related court rulings as a source of exogenous variation in government spending on public education. The use of this particular timing is best discussed in Johnson (2011), who argues that it implies "quasirandom" changes in spending. What this means is that the particular date at which a court rules on a case is random, while either the implementation or the date at which the lawsuit was initiated would likely be endogenous.

Of potential importance is that the federal Supreme Court has ruled that there is no fundamental right to education. Many states, however, included clauses which have been interpreted to mean that children have a right to education. This allows a great deal of diversity in the timing of implementation, and allows for a control group that is apparent in a way that a nationally mandated standard does not[6]. There might, however, be some reason to believe that states with such clauses in their constitutions might have more concern about inequality. While I cannot explicitly address this concern, many states adopted constitutions written in a similar manner to the United States Constitution, and all adopted their constitution generations before these rulings.

Another potential concern is that the fact that such cases have been brought before a court indicates that there is an unobservable motivation to deal with inequality. I will address this by using placebo tests on states that heard cases, but did not overturn their previous funding system in my robustness checks. Presumably, if there was an underlying propensity to decrease inequality, these other states would see subsequent increases in their funding regardless of whether the court overruled the finance system or not. I find that this is not the case, and that states in which school finance was not reformed have higher degrees of persistence over time. In sum, I believe that these court rulings constitute a valid and strong instrument for identification.

I include a list of the court cases as well as descriptions in Appendix C. The court cases vary a great deal over time, both in terms of the location of implementation as well as the types of reform imposed by the court. By the end of my sample, more than 120 cases had been heard by states regarding school finance. Of these, more than 60 changed their school finance system. In sum, 29 states changed their school finance system at least once as a result of a court decision. This gives us a great deal of variation over time, and my empirical specification will allow even

[6]See Figure Figure 4.4.2 for Court Implementation

more flexibility.

4.3.2 First-Stage Estimation

I improve upon the work of Jackson et al. (2015) by using classifications of rulings (equity and adequacy) in my first stage. I also control for the resulting potential endoneity with a time trend. The reason this is necessary is that the types of rulings correspond to different funding methods, meaning that later cases would necessarily correspond to more spending. I believe that this presents less biased estimates of the coefficients upon both the adequacy ruling and equity ruling variable than simply including a indicator for whether a ruling had occurred in the past as Jackson et al. (2015) did when estimating their first-stage.

$$G_{st} = \beta_0 + \beta_1 \mathcal{AR}_{\{t \geq T_{st}\}} + \beta_2 \mathcal{ER}_{\{t \geq T_{st}\}} + W'_{st}\gamma + \delta_s * Year + \delta_s + \nu_{st} \tag{4.3.1}$$

The variables $\mathcal{AR}_{\{t \geq T_{st}\}}$ and $\mathcal{ER}_{\{t \geq T_{st}\}}$ take on the value one if an adequacy or equity ruling has already taken place in a state. I consider two specifications for time fixed effects: first, I simply use year fixed effects; second, I use a linear trend for each state in my sample. It is my belief that linear trends is the appropriate specification, because it seems likely that each state experiences its own trends in public spending on education based upon economic considerations. I use only the first ruling, as I believe this is less likely to be determined as a result of previous rulings. I also separate the rulings into those whose decisions are based on adequacy, and those based on equity. As a robustness check, I also estimate this only using the timing of the first ruling in my and the results still indicate a strongly positive coefficient, though the result is no longer significant. I also estimate two sets of event studies (at the state level and at the county level) in the following way:

$$G_{st} = \beta_0 + \sum_{i=-5}^{i=-1} \pi_t^{AR} 1_{t-T_{AR}=i} + \sum_{t=1}^{t=5} \alpha_t^{AR} 1_{t-T_{AR}=i} + \sum_{i=-5}^{i=5} \omega_t^{ER} 1_{t-T_{ER}=i} + W'_{st}\gamma + \delta_t + \delta_s + \nu_{st} \tag{4.3.2}$$

The omitted category here is states that had an adequacy ruling at time t. I include a set of state-level covariates, and changes my specification slightly to include state and year fixed effects. Finally, I repeat this exercise at the county level in order to show the strength of these results when using a smaller level of geographic variation.

4.3.3 Second-Stage: Intergenerational Elasticity Estimation

Following on the previous literature, I estimate a reduced-form specification of investment in children. If I believe that parental investment in children increases as income increases, then it is reasonable to assume that parents with higher income will have children with higher income. There may be some concern that including government spending may substitute for some of that spending (decreasing the effect), but because I have no way to deal with private investment in children, I am unable to address this in my specification. Regardless, this would only strengthen my results. This second stage equation follows closely from the equation employed by Mayer and Lopoo (2008), but includes additional state and family covariates, as well as better government spending data. My specification is given by the following:

$$ln(Y_{ist}) = \beta_0 + \beta_1 ln(\bar{X}_{ist}) + \beta_2 ln(\hat{G}_{st}) + \beta_3(ln(\bar{X}_{ist}) * ln(\hat{G}_{st})) + Z'_{ist}\alpha + W'_{st}\gamma + \delta_s + \delta_t \epsilon_{ist} \tag{4.3.3}$$

All of my analysis here is at the state level, with fixed effects for each state and each year. I choose Y_{ist}, child's income, to be recorded between ages 32-34, using the earliest age reported. This is chosen because lifecycle effects can artificially dampen the estimate of intergenerational elasticity for ages less than 32 (Haider and Solon, 2006). I average both parents income and public spending on education over ages 15-17 at the state level. Spending on education is taken from my first stage predictions. I choose this to maintain a reasonably large sample size as well as make the results comparable to the previous literature, but I include results for alternate year specifications below. I include a set of family and individual characteristics (Z_{ist}) and a set of state-level variables (W_{st}) to control for alternate explanations of my results. The family and individual characteristics include (depending upon specification) race, gender, household size, years of schooling for both parents, as well as the marital status of the family during childhood. These control for alternate stories of these results based upon different races, previous educational attainment and family structure. I include state-level measures of the poverty rate, the unemployment rate, proportion of the population that is black, and Aid for Dependent Children (AFDC) recipiency rate. Here, I attempt to control for time-varying state-level variables as well as the compassion for the poor by including the AFDC measure. As in Mayer and Lopoo (2008), if $\beta_3 < 0$ I would argue that spending on education significantly decreases persistence over generations. I would also expect positive values upon β_1 and β_2, as I expect that more parental income and government spending will increase children's income.

4.4 Data

I use the Panel Study of Income Dynamics (PSID) in order to obtain a rich set of covariates for a set of many birth cohorts. This allows me to include a number of personal and family characteristics in order to control for alternate interpretations of my results, which will discussed further in the next section. I measure family income as total family income during the year and average over the years in which the child is 15-17. A number of papers have shown bias when single year measures of permanent income are used for parents income (Solon, 1992). Following the literature, I attempt to control lifecycle effects by measuring child's income at age 32, when they are heads of households[7].

4.4.1 Public Spending Data

My school finance data was assembled using the school finance dataset maintained by National Center for Education Statistics (NCES). This data includes measures of per pupil spending for most states from 1967 until 2011. The years 1967 to 1991 are obtained from the Census of Government, INDFIN and the Common Core of Data Schol District Finance Survey (F-33); for these years, this dataset includes administrative data on school spending for every

[7]See Haider and Solon (2006) to see that these effects disappear after age 32.

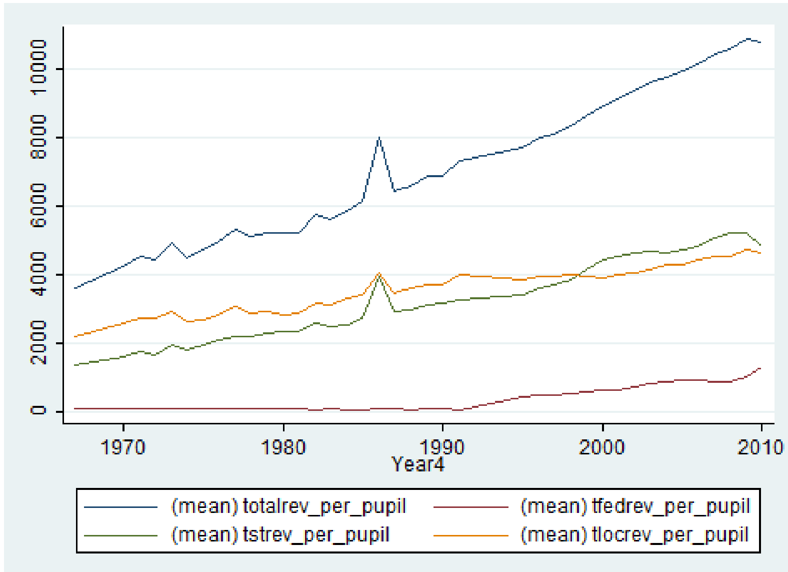


Figure 4.4.1: Spending per-pupil for 1967-2010. Source: NCES

school district in the United States.[8] From 1992 onward, data is available at an annual frequency from the NCES. Spending by different levels of government is shown in Figure 4.4.1.

I also employ state-level covariates including the poverty rate, the unemployment rate, proportion of the population that is black, and AFDC recipiency rate. The poverty rate is taken from the 1960 and 1970 censuses, with years following 1980 taken from the St. Louis Federal Reserve (FRED). The unemployment rate is available at the state level for years 1976-now, also from FRED. I use the employment to population ratio as well as state fixed effects and a time trend to project years 1968 to 1975 at the state level in order to make this available for all years of my study. The proportion of the population that is black is taken from the Survey of Epidemiology and End Results (SEER) dataset for all the years of my survey, which I include to control for differing mobility by racial composition of the state. Finally, AFDC measures at the state level are obtained from the Office of Family Assistance, and include years from 1960 to now. Missing years are linearly interpolated, and then the each variable is averaged over the years in which the child is age 15-17. I convert all of the school finance variables to 2000 dollars and then take the log of the corresponding average.

[8] For missing years, I use linear interpolation to fill in data.

4.4.2 Court Data

I use the list of school finance reform cases assembled by Jackson et al. (2015). Each of these cases was argued at the state level; that is, upon a school finance system being overturned, the effects are felt for all school districts within the state. These cases stretch from the 1970s until present and in total encompass 39 states. Only three states did not implement some type of finance reform during this time period, though some only implemented legislative measures. During the timeframe in this study, there are 68 cases in which the state school finance system was overturned via the court system. There were an additional 60 cases in which state courts upheld the prevailing school finance system; these are cases that I will employ in my robustness checks.

They classify court rulings into two types: equity and adequacy. Equity rulings happened earlier chronologically, and were associated with decreases in the variance of school funding. That is, the litigants argued that the state constitution mandated an equal quality of education (via funding) for all students in the state, regardless of income. The second type, adequacy, are classified to be cases in which the litigants argued that there was a minimum level of education that the state was required to provide students regardless of income status. While the outcomes may seem like an exercise in semantics, the results for funding were vastly different.[9] In total, some 25 states experience adequacy reforms, while 14 states undergo reforms via equity rulings. Here, I present the timings of these reforms:

[9] See first-stage section in results, or the event studies by county in the Appendix.

(a) Total number of adequacy rulings 1967-2010. (b) Total number of equity rulings 1967-2010.

Figure 4.4.2: Court Ruling Dates. Source: Jackson et al. (2015)

4.4.3 PSID

Data on children and parents come from the Panel Study of Income Dynamics (PSID) administered by the Survey Research Center at the University of Michigan. The PSID is a nationally representative, longitudinal survey of households and individuals in the United States beginning in 1968. A unique aspect of the PSID is that any member of a household surveyed in 1968 is surveyed in subsequent years even if they have joined another household or have started another household. Because of this the PSID is one of the most widely used data source among studies of intergenerational mobility in the United States. Following Lee and Solon (2009), I only use the Survey Research Center sample of the PSID.

Information on children's parents is collected when children respondents are five to seventeen years old. Household characteristics collected during these years include the household's state of residence, total family income, number of people in the household. Characteristics of the head of the household include the age, marital status, race, sex, age, employment status, and education of the household head, the marital status of the household head, the race of the household head. Information on children adult outcomes is collected when they are aged 32-34. This includes total family income, and years of schooling, employment status, and marital status.

Years of schooling is measured as 0-17 years, with 17 years indicating 17 or more years of schooling (from pursuit of an advanced degree). Following Lee and Solon (2009), I exclude families who had incomes of less than \$150 or greater than \$150,000 1967 dollars. I also exclude families whose incomes were imputed by major assignment. To calculate the intergenerational elasticity of income I first convert total family income to 2000 dollars and take the natural log of these values.

4.5 Results

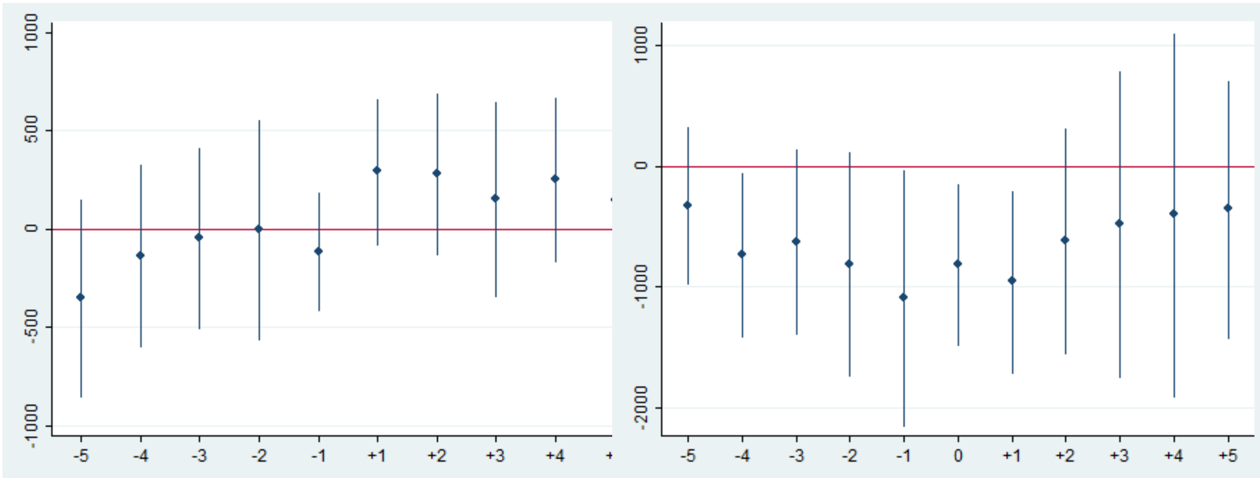
4.5.1 First-Stage Regressions

Both my regression and my event study framework strongly indicate that at the state level, spending increased in the years following adequacy rulings. I also include my event study at the state level that endorses the same position for both ruling types, though none are significantly different from zero.

	(1)	(2)
VARIABLES	Spending Per Pupil	
After First Adequacy Ruling	303.0	381.1**
	(290.3)	(182.6)
After First Equity Ruling	389.2	-41.86
	(408.7)	(222.9)
Constant	-280,554***	-305,110***
	(18,068)	(17,567)
Observations	1,698	1,698
R-squared	0.897	0.940
State FE	X	X
Year FE	X	
State Time Trends		X

Standard errors clustered at the state level
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Note that the year in which the adequacy ruling took place is excluded. I believe that these



(a) Per-pupil spending following adequacy ruling (b) Per-pupil spending following equity ruling

Figure 4.5.1: Effect of court ruling on per-pupil spending

results would indicate significance if a smaller geographic region were analyzed. Indeed, when I run a county-level regression and segment by per-pupil spending strata within a state, I see that adequacy rulings are associated with a large increase in spending for the lowest 75 percentiles, with no appreciable difference for the top 25 percentiles.[10] I also consider using an aggregate rulings variable instead of breaking the rulings down into categories in my robustness checks, but find similar results.

4.5.2 Intergenerational Elasticity Estimation Results

Using the constructed instrument from the first stage, I find that for nearly all specifications increased expenditure on public education causes an increase in mobility.

I include the first two specifications to show the results when I do not instrument for spending on education. As might be expected, the coefficient is negative and close to significant at the 10 percent level. Once I include the instrument under the same specification, I see that this becomes significant at the one percent level. I include alternate specifications for comparison: regression (5) includes a smaller subset of the family characteristics (race, gender) that are available in most years for most individuals. When I include the full set of covariates (equations (7) and (8)), I see

[10] See Appendix for these results.

VARIABLES	(1) Child's Inc	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ave Fam Inc	2.463*	2.545*	3.403***	2.703**	2.135**	2.790**	2.627	2.130
	(1.388)	(1.327)	(1.034)	(1.020)	(1.036)	(1.053)	(1.748)	(1.747)
Ed Spend	2.783	2.706						
	(1.773)	(1.768)						
Cross Term	-0.238	-0.253						
	(0.163)	(0.156)						
Ed Spend IV			4.112***	3.292**	2.771*	3.473**	3.102	2.547
			(1.337)	(1.388)	(1.420)	(1.459)	(2.202)	(2.200)
Cross Term IV			-0.355***	-0.277**	-0.219*	-0.288**	-0.296	-0.243
			(0.121)	(0.119)	(0.122)	(0.123)	(0.203)	(0.202)
Constant	-17.79	-16.93	-28.47**	-21.36*	-15.42	-22.48*	-17.74	-12.79
	(15.15)	(15.03)	(11.40)	(11.66)	(11.75)	(12.17)	(18.85)	(18.81)
Observations	1,382	1,382	1,166	1,166	1,157	1,166	789	789
R-squared	0.120	0.191	0.123	0.190	0.217	0.191	0.304	0.309
State FE	No	Yes	No	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	Yes	Yes	Yes	Yes	Yes
State Covariates	No	No	No	No	Yes	Yes	Yes	Yes
Characteristics	No	No	No	No	Yes	No	Yes	Yes

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

that the cross term is still negative and large, but no longer significant at typical statistical levels. Overall, I interpret these results to strongly endorse the position that government spending on education can make a positive and meaningful impact on intergenerational mobility.

4.6 Robustness

4.6.1 Averaging over Different Years

A number of studies have noted that education policies are most effective at a young age. Ideally, I would use years that are formative for the child's education; however, using these earlier years comes at a cost: my sample size gets smaller and smaller, making inference more difficult. It's important to note that having such strong results from ages 15 to 17, a time period in which many believe education does not play a long-run role in improving outcomes only strengthens my results that public spending on education can play a role in decreasing persistence. To address this concern, I average over all ages 5-17 in three year intervals:[11]

VARIABLES	(1) Child's Income	(2)	(3)	(4)	(5)
Family Income	0.271	1.651	0.546	0.309	1.715
	(1.142)	(1.369)	(1.190)	(0.942)	(1.393)
Ed Spending	0.437	1.844	0.412	-0.486	1.850
	(1.530)	(1.369)	(1.514)	(1.211)	(1.731)
Cross Term	-0.0122	-0.175	-0.0529	-0.0257	-0.195
	(0.135)	(0.162)	(0.140)	(0.113)	(0.164)
Constant	3.784	-8.651	3.613	12.20	-6.437
	(12.86)	(14.71)	(12.87)	(10.05)	(14.63)
Observations	657	814	913	928	839
R-squared	0.314	0.327	0.319	0.303	0.302
State FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Standard errors clustered at the state level
*** p<0.01, ** p<0.05, * p<0.1

Each specification, starting with (1), refers to three year intervals from 6 to 8, up to 14 to 16. I have included all of the same covariates as in my specification (8) from the results section. While none of the coefficients are significant, the coefficient is negative in every subset. In fact, any three year window that I choose results in a negative coefficient, except oddly a three-year timeframe from ages 5 to 7. I believe that the sample size is causing some problem for this age group.

4.6.2 States with Failed Rulings

One might be lead to argue that states in which lawsuits took place are more likely to be concerned with mobility. The argument is roughly that for a group of individuals to undertake a lawsuit, there must be a large groundswell of support. If this were true, perhaps the state is already more concerned with mobility, which would indicate that these children would exhibit the same levels of mobility even if they had not received an increase in education spending. To

[11] Additional specifications in Appendix.

address this concern, I construct a variable that takes on the value 1 if a state experienced a failed lawsuit (i.e. the state finance system was upheld in court) when a child was between ages 5 and 17. I choose this timeframe because of the potential lag in funding increases, so I cannot simply look at ruling during ages 15 to 17. For individuals who lived in a state with a ruling, I encode this variable with a 0, to make interpretation easy. I then include this variable in the regression. The results are as follows:

VARIABLES	(1) Child's Income
Average Family Income	2.354
	(1.750)
Ed Spending	2.837
	(2.220)
Cross Term	-0.268
	(0.203)
Ruling Upheld	-0.152
	(0.129)
Constant	-14.93
	(19.17)
Observations	767
R-squared	0.315
State FE	Yes
Year FE	Yes
State Covariates	Yes
Characteristics	Yes

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

I see that having a school finance system upheld during childhood is associated with lower income in adulthood (p-value 0.11). I believe this is a strong result, as it is likely that states in which school finance systems were upheld already had better systems in place than others. This suggests that education spending and not a state's propensity to be concerned with mobility is producing my results.

4.6.3 Differentiating by Ruling Type

It may also be the case that I made a mistake in separating adequacy rulings and equity rulings. While I do not believe this to be the case, I show that a first ruling is associated with positive amounts of spending in the future, though the estimate is no longer significantly positive. I have included the original two specifications for comparisons sake:

	(1)	(2)	(3)	(4)
VARIABLES	Spending Per Pupil			
After First Adequacy Ruling	303.0	381.1**		
	(290.3)	(182.6)		
After First Equity Ruling	389.2	-41.86		
	(408.7)	(222.9)		
After First Ruling			267.2	236.0
			(232.3)	(174.1)
Constant	-280,554***	-305,110***	-285,903***	-317,776***
	(18,068)	(17,567)	(18,014)	(16,627)
Observations	1,698	1,698	1,698	1,698
R-squared	0.897	0.940	0.896	0.940
State FE	X	X	X	X
Year FE	X		X	
State Time Trends		X		X

Standard errors clustered at the state level
*** p<0.01, ** p<0.05, * p<0.1

4.7 Concluding Remarks

Intergenerational mobility has been studied in a number of contexts, but very few papers have attempted to understand the interplay between government programs and mobility. In particular almost none have explored the extent to which spending on public education might change the intergenerational dependence in income. My study does this, while simultaneously using an instrument for government spending, which lends credence to the interpretation of my results as causal.

I employ court-mandated school finance reform as an exogenous source of identification. This allows us to construct a first-stage in which I predict per-pupil spending on education based upon a number of factors, including the timing of these reforms. I use these predictions to describe the extent to which government spending on public education might change intergenerational mobility in the second stage, constructing an intergenerational elasticity estimator. This is the first paper to employ this type of identification strategy in the context of intergenerational mobility.

My results indicate that government spending on education plays an importance role in determining intergenerational mobility. I find that a ten-percent increase in government spending is associated with around a 3 percent decrease in intergenerational persistence, and that for my specifications that allow for a large sample size this results is significant. I perform further robustness checks to determine if my assumptions are the driving force behind my results, and find the result of these checks to be consistent with my main findings.

This paper is one of few papers to address the issue of government spending's ability to decrease income persistence over time, which has applications to policy and understanding inequality. Unlike previous papers attempting to address the same topic, I employ a robust method of identification that gives us a causal interpretation to my coefficients. Given that I find significance under all except very restrictive specifications (in terms of the size of the remaining sample), this suggests that government spending on education can play an important role in increasing mobility for the least fortunate in the economy.

Appendix A

Appendix for Borrowing Constraints, Search, and Life-Cycle Inequality

A.1 Data Construction

A.1.1 Survey of Income and Program Participation (SIPP)

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

My selection criteria is similar to the previous literature on the liquidity effects of unemployment insurance[1]. I first pool SIPP panels from 1990 to 2008. From these panels, I restrict my sample to unemployment spells for males age 23 and older with at least 3 months work experience, who took up UI within one month of job loss, and who are not on a temporary layoff[2]. 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 A.2.1. This allows me to link 2,311 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 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 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.

A.1.2 Panel Study of Income Dynamics (PSID)

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

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

[2] Selecting on an endogenous variable, like unemployment insurance, may lead to biased estimates (Anderson and Meyer, 1997). I discuss this in section 2.3.1

(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 interview. In the United States, this is the only publicly available dataset that contains multiple cohorts, long-term observations on earnings, and measures of household wealth at ages close to or before labor market entry[3]. In addition to these variables, the PSID includes rich observations on demographics, labor market experience, as well as family history and behavioral characteristics.

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

A.1.3 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,

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

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. 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 use identical sample restrictions as subsection A.1.2.

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.

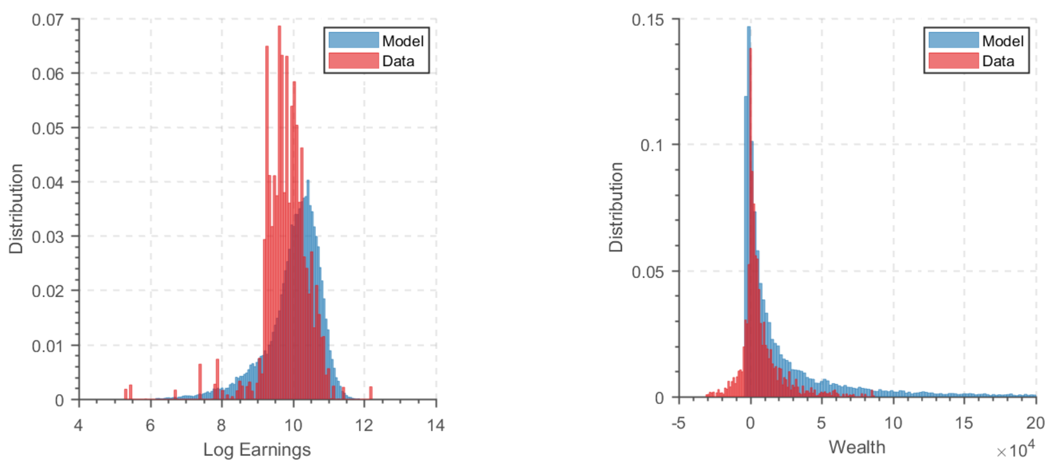
To assign individuals to initial quintiles in the wealth distribution, I first exclude observations who do not meet the following characteristics: first, agents must be the head of their household when I observe their assets; second, they must be age 30 or younger during a year in which I observe their 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[4]. 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

[4]Huggett et al. (2011) use a similar sample selection method.

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.

A.2 Tables and Figures



(a) Income (logs). (b) Liquid Wealth.

Figure A.2.1: Initial Distributions of Earnings and Wealth.

Table A.2.1: Summary Statistics by Liquidity Quintile and UI Generosity

	Avg. State UI				Avg. State UI		
	< Med	> Med	P-Val		< Med	> Med	P-Val
White				Duration			
Q1	0.700	0.790	0.0593	Q1	17.27	19.59	0.0939
Q2	0.552	0.684	0.00718	Q2	18.66	20.16	0.215
Q3	0.589	0.683	0.166	Q3	17.52	19.90	0.146
Q4	0.810	0.835	0.553	Q4	18.48	19.78	0.385
Q5	0.896	0.891	0.873	Q5	17.66	19.31	0.285
HS Degree				UI Reported			
Q1	0.353	0.378	0.606	Q1	250.3	329.5	1.62e-90
Q2	0.332	0.452	0.0117	Q2	246.7	324.1	3.20e-95
Q3	0.405	0.415	0.875	Q3	249.6	327.5	4.33e-72
Q4	0.314	0.352	0.465	Q4	253.1	332.2	5.47e-83
Q5	0.332	0.263	0.193	Q5	251.7	336.0	7.81e-95
Coll. Degree				Prev. Ann. Wage			
Q1	0.112	0.0798	0.275	Q1	36391.3	36471.7	0.967
Q2	0.0317	0.0456	0.391	Q2	28051.0	31679.2	0.0357
Q3	0.0536	0.0650	0.664	Q3	31155.4	33229.5	0.323
Q4	0.170	0.127	0.253	Q4	44891.5	46128.4	0.701
Q5	0.154	0.210	0.171	Q5	62213.4	55497.1	0.197
Age				Prev. Tenure (wks)			
Q1	36.62	37.14	0.609	Q1	44.08	43.94	0.969
Q2	37.26	36.81	0.641	Q2	36.82	43.52	0.0338
Q3	37.37	36.13	0.234	Q3	41.80	48.97	0.0955
Q4	40.54	38.89	0.113	Q4	48.73	41.02	0.0329
Q5	43.92	43.93	0.996	Q5	47.67	50.08	0.512
Observations	1210	1144	2354	Observations	1210	1144	2354

Notes: Means are weighted and variance is corrected for the survey design. Number of observations is unweighted.

Table A.2.2: Test 1 Interaction Results

Change			Consumption	Earnings
$Wealth$	$Human\ Capital$	$Learning\ Ability$		
↑	↑		32.9	12.7
↑	↓		16.9	−5.2
↑		↑	49.0	33.3
↑		↓	8.8	−15.8
↓	↑		−0.7	7.6
↓	↓		−18.2	−10.2
↓		↑	14.0	26.8
↓		↓	−25.4	−19.9
	↑	↑	35.7	41.4
	↑	↓	−6.5	−9.3
	↓	↑	15.9	20.3
	↓	↓	−21.5	−24.5

Notes: This table presents the change in earnings and consumption as two of the initial conditions are varied by one standard deviation.

Table A.2.3: Estimated Auxiliary Parameters

Slopes and Intercepts by Wealth (PSID)			
Var.	Data	Model	P-Val
Age	0.0219	0.0262	0.3320
	(0.0030)	(0.0007)	
Wealth Q2 x Age	0.0002	0.0020	0.3797
	(0.0053)	(0.0013)	
Wealth Q3 x Age	−0.0069	0.0014	0.0178
	(0.0036)	(0.0012)	
Wealth Q4 x Age	−0.0079	0.0010	0.0072
	(0.0032)	(0.0011)	
Wealth Q5 x Age	−0.0082	0.0040	0.0002
	(0.0031)	(0.0008)	
Wealth Q2	0.0072	0.0588	0.3852
	(0.1616)	(0.0452)	
Wealth Q3	0.2564	0.1767	0.2616
	(0.1139)	(0.0430)	
Wealth Q4	0.3759	0.2930	0.2563
	(0.0972)	(0.0381)	
Wealth Q5	0.4578	0.3524	0.1647
	(0.0945)	(0.0305)	
Cons.	9.6977	9.7336	0.2619
	(0.1375)	(0.0254)	

Slopes and Intercepts by AFQT (NLSY)			
Var.	Data	Model	P-Val
Age	0.0206	0.0244	0.4145
	(0.0047)	(0.0016)	
AFQT Q2 x Age	0.0003	−0.0006	0.2611
	(0.0012)	(0.0020)	
AFQT Q3 x Age	0.0013	0.0013	0.4118
	(0.0016)	(0.0019)	
AFQT Q4 x Age	0.0054	0.0041	0.3039
	(0.0010)	(0.0019)	
AFQT Q5 x Age	0.0118	0.0131	0.4391
	(0.0027)	(0.0018)	
AFQT Q2	0.0649	0.1594	0.1404
	(0.0757)	(0.0671)	
AFQT Q3	0.1354	0.2138	0.1721
	(0.0550)	(0.0659)	
AFQT Q4	−0.0016	0.2420	0.0011
	(0.0367)	(0.0641)	
AFQT Q5	−0.1798	0.1923	0.0004
	(0.0916)	(0.0637)	
Cons.	9.5107	9.7462	0.0339
	(0.1491)	(0.0524)	

Re-Employment Elasticities (SIPP)			
Var.	Data	Model	P-Val
Q1 x Ln(UI)	0.6974	0.5581	0.2912
	(0.2492)	(0.0529)	
Q2 x Ln(UI)	0.3819	0.4965	0.3429
	(0.2637)	(0.0540)	
Q3 x Ln(UI)	−0.0550	0.4835	0.0224
	(0.2733)	(0.0524)	
Q4 x Ln(UI)	0.0724	0.4498	0.0308
	(0.2046)	(0.0508)	
Q5 x Ln(UI)	0.1509	0.2417	0.3301
	(0.2660)	(0.0428)	
Q2	2.0829	−0.2161	0.1428
	(2.1167)	(0.2981)	
Q3	5.5140	−0.7378	0.0040
	(2.3008)	(0.2803)	
Q4	5.6164	−1.2227	0.0010
	(2.5393)	(0.2348)	
Q5	6.6118	−2.1769	0.0003
	(2.5393)	(0.2348)	
Cons.	−1.1684	0.7406	0.1802
	(2.1378)	(0.1956)	
Age	−0.0009	−0.0051	0.0067
	(0.0018)	(0.0006)	
Wealth	0.0000	0.0000	0.0344
	(0.0000)	(0.0000)	
Q1 x Ln(LstWg)	0.3296	0.3472	0.4396
	(0.2492)	(0.0551)	
Q2 x Ln(LstWg)	0.4540	0.4246	0.3657
	(0.0744)	(0.0563)	
Q3 x Ln(LstWg)	0.3806	0.4909	0.1998
	(0.0762)	(0.0536)	
Q4 x Ln(LstWg)	0.3693	0.5664	0.0167
	(0.0641)	(0.0499)	
Q5 x Ln(LstWg)	0.3738	0.8182	0.0000
	(0.0629)	(0.0364)	

Within Job Wage Growth (NLSY)			
Var.	Data	Model	P-Val
Cons.	0.0654	0.0711	0.4022
	(0.0030)	(0.0007)	
Age 30 - 34	−0.0328	−0.0339	0.4769
	(0.0029)	(0.0013)	
Age 35 - 39	−0.0318	−0.0456	0.0288
	(0.0035)	(0.0053)	
Age 40 - 44	−0.0430	−0.0510	0.2030
	(0.0038)	(0.0056)	
Age 45 - 49	−0.0571	−0.0570	0.2589
	(0.0042)	(0.0061)	
Age 50 - 54	−0.0589	−0.0642	0.4819
	(0.0043)	(0.0079)	

Job-Stay Rate (NLSY)			
Var.	Data	Model	P-Val
Age 25 - 29	0.7790	0.7572	0.0169
	(0.0080)	(0.0043)	
Age 30 - 34	0.8277	0.8134	0.0957
	(0.0091)	(0.0046)	
Age 35 - 39	0.8524	0.8271	0.4118
	(0.0039)	(0.0055)	
Age 40 - 44	0.8710	0.8324	0.0187
	(0.0158)	(0.0060)	
Age 45 - 49	0.8853	0.8312	0.0073
	(0.0190)	(0.0068)	
Age 50 - 54	0.8971	0.8536	0.0033
	(0.0107)	(0.0098)	

Within Job Wage Growth Variance (NLSY)			
Var.	Data	Model	P-Val
Cons.	0.0168	0.0672	0.4955
	(4.0856)	(1.7467)	

Unemployment Rate (PSID)			
Var.	Data	Model	P-Val
Age 25 - 29	0.0311	0.0562	0.4545
	(0.0013)	(0.2331)	

Table A.2.4: Unemployment Risk Results

Change	Δ Earnings Base	Δ Earnings No Unemp.	Δ h Base	Δ h No Unemp.	Δ τ Base	Δ τ No Unemp.
$Test\ 1:\ Human\ Capital$						
+1 St. Dev.	$+10.0$	$+9.6$	$+9.5$	$+9.6$	$+0.8$	$+0.2$
-1 St. Dev.	-7.8	-7.8	-7.5	-7.8	-0.8	-0.7
$Test\ 2:\ Human\ Capital$						
10th→50th	$+11.8$	$+11.8$	$+11.2$	$+11.9$	$+4.1$	$+5.6$
$Test\ 1:\ Learning\ Ability$						
+1 St. Dev.	$+29.7$	$+27.9$	$+29.1$	$+28.9$	$+32.3$	$+29.3$
-1 St. Dev.	-17.9	-17.8	-17.5	-18.4	-27.8	-26.4
$Test\ 2:\ Learinig\ Ability$						
10th→50th	$+27.4$	$+26.3$	$+26.5$	$+27.5$	$+59.7$	$+57.6$

A.3 Proofs

A.3.1 Existence of a Block Recursive Equilibrium

The existence proof of a block recursive equilibrium 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 2.4.8, Equation 2.4.12, and Equation 2.4.1 respectively, satisfy the following in period T.

$$U_T(b_{UI}, a, h, \ell; \psi) = u((1 + r_F)a + b_{UI}) \tag{A.3.1}$$

$$U_T(b_L, a, h, \ell; \psi) = u((1 + r_F)a + b_L) \tag{A.3.2}$$

$$W_T(\mu, a, h, \ell; \psi) = u(\mu f(h) + (1 + r_F)a) \tag{A.3.3}$$

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, ψ can be dropped from the state space and the value functions rewritten as $U_T(b_{UI}, a, h, \ell; \psi) = U_T(b_{UI}, a, h, \ell; z)$, $U_T(b, a, h, \ell; \psi) = U_T(b_{UI}, a, h, \ell; z)$, and $W_T(\mu, a, h, \ell; \psi) = W_T(\mu, a, h, \ell; z)$. 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

$$J_T(\mu, a, h, \ell; \psi) = (1-\mu)f(h) \tag{A.3.4}$$

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:

$$V(\mu, a, h, \ell; \psi) = -\kappa + q(\theta_T(\mu, a, h, \ell; \psi))(1-\mu)f(h) \tag{A.3.5}$$

Free entry of firms yields the following:

$$\kappa = q(\theta_T(\mu, a, h, \ell; \psi))(1-\mu)f(h) \tag{A.3.6}$$

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

$$\theta_T(\mu, a, h, \ell; \psi) = \begin{cases} q^{-1}(\frac{\kappa}{(1-\mu)f(h)}) & : \text{if } (1-\mu)f(h) \geq \kappa \\ 0 & : \text{else} \end{cases}$$

This again does not depend upon the distribution of workers; thus, $\theta_T(\mu, a, h, \ell; \psi) = \theta_T(\mu, a, h, \ell; z)$. 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:

$$\begin{aligned} R_T^U(b_{UI}, a, h, \ell; \psi) = \max_{\mu'} & P(\theta_T(\mu', a, h, \ell; \psi))W_T(\mu', a, h, \ell; \psi) \\ & + (1 - P(\theta_T(\mu', a, h, \ell; \psi)))U_T(b_{UI}, a, h, \ell; \psi) \end{aligned} \tag{A.3.7}$$

$$R_T^U(b_L, a, h, \ell; \psi) = \max_{\mu'} P(\theta_T(\mu', a, h, \ell; \psi))W_T(\mu', a, h, \ell; \psi)$$
$$+ (1 - P(\theta_T(\mu', a, h, \ell; \psi)))[\gamma U_T(b_L, a, h, \ell; \psi) \quad \text{(A.3.8)}$$

Imposing the conditions for θ_T, as well as the value functions in the terminal production and consumption period yields the following

$$R_T^U(b_{UI}, a, h, \ell; \psi) = \max_{\mu'} P(\theta_T(\mu', a, h, \ell; z))W_T(\mu', a, h, \ell; z)$$
$$+ (1 - P(\theta_T(\mu', a, h, \ell; z)))U_T(b_{UI}, a, h, \ell; z) \quad \text{(A.3.9)}$$

$$R_T^U(b_L, a, h, \ell; \psi) = \max_{\mu'} P(\theta_T(\mu', a, h, \ell; z))W_T(\mu', a, h, \ell; z)$$
$$+ (1 - P(\theta_T(\mu', a, h, \ell; z)))[\gamma U_T(b_L, a, h, \ell; z) \quad \text{(A.3.10)}$$

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 $R_t^U(b_{UI}, a, h, \ell; \psi) = R_t^U(b_{UI}, a, h, \ell; z)$, and $R_t^U(b_L, a, h, \ell; \psi) = R_t^U(b_L, a, h, \ell; z)$, and the optimal application strategy is independent of the aggregate distribution of workers. Performing the same exercise for employed workers similarly yields

$$R_T^E(\mu, a, h, \ell; \psi) = \max_{\mu'} P(\theta_T(\mu', a, h, \ell; \psi))W_T(\mu', a, h, \ell; \psi)$$
$$+ (1 - P(\theta_T(\mu', a, h, \ell; \psi)))W_T(\mu, a, h, \ell; \psi) \quad \text{(A.3.11)}$$

$$R^E_T(\mu, a, h, \ell; \psi) = \max_{\mu'} P(\theta_T(\mu', a, h, \ell; z))W_T(\mu', a, h, \ell; z)$$
$$+ (1 - P(\theta_T(\mu', a, h, \ell; z)))W_T(\mu, a, h, \ell; z) \quad \text{(A.3.12)}$$

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 $R^E_T(\mu, a, h, \ell; \psi) = R^E_T(\mu, a, h, \ell; z)$. Now consider the consumption, savings, and human capital decisions of age $T - 1$ unemployed workers:

Note that in this economy, the aggregate state is assumed to be $z_t = z \forall t$. To prove that this exhibits a block recursive equilibrium, it must be the case that the value of an employed agent in the same time period is also independent of the distribution of agents across types. Consider the problem of an employed agent at time T - 1:

$$U_{T-1}(\underline{U}I, a, h, \ell; \psi) = \max_{c,a'} u(c) + \nu + \beta E[(1-\gamma)R^U_T(b_{UI}, a', h', \ell; \psi) + \gamma R^U_T(b_L, a', h', \ell; \psi)] \quad \text{(A.3.13)}$$

$$\text{s.t. } c + a' \leq (1 + r_F)a + b_{UI} \quad \text{(A.3.14)}$$

$$a' \geq \underline{a}' \quad \text{(A.3.15)}$$

$$h' = e^{\epsilon'}(h + H(h, \ell, \tau, U)) \quad \text{(A.3.16)}$$

$$U_{T-1}(b_L, a, h, \ell; \psi) = \max_{c,a'} u(c) + \nu + \beta E[R^U_T(b_L, a', h', \ell; \psi)] \quad \text{(A.3.17)}$$

$$\text{s.t. } c + a' \leq (1 + r_F)a + b_L \quad \text{(A.3.18)}$$

$$a' \geq \underline{a}' \quad \text{(A.3.19)}$$

$$h' = e^{\epsilon'}(h + H(h, \ell, \tau, U)) \quad \text{(A.3.20)}$$

Substituting in the age T value functions yields the following:

$$U_{T-1}(b_{UI}, a, h, \ell; \psi) = \max_{c,a'} u(c) + \nu + \beta E[(1-\gamma)R^U_T(b_{UI}, a', h', \ell; z) + \gamma R^U_T(b_L, a', h', \ell; z)] \tag{A.3.21}$$

$$\text{s.t. } c + a' \leq (1 + r_F)a + b_{UI} \tag{A.3.22}$$

$$a' \geq \underline{a}' \tag{A.3.23}$$

$$h' = e^{\epsilon'}(h + H(h, \ell, \tau, U)) \tag{A.3.24}$$

$$U_{T-1}(b_L, a, h, \ell; \psi) = \max_{c,a'} u(c) + \nu + \beta E[R^U_T(b_L, a', h', \ell; z)] \tag{A.3.25}$$

$$\text{s.t. } c + a' \leq (1 + r_F)a + b_L \tag{A.3.26}$$

$$a' \geq \underline{a}' \tag{A.3.27}$$

$$h' = e^{\epsilon'}(h + H(h, \ell, \tau, U)) \tag{A.3.28}$$

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 $U_{T-1}(\mu, a, h, \ell; \psi) = U_{T-1}(\mu, a, h, \ell; z)$ and $U_{T-1}(b_L, a, h, \ell; \psi) = U_{T-1}(b_L, a, h, \ell; z)$. By essentially the same argument, the value function during the consumptiono and savings period of an employed worker can be written as

$$W_{T-1}(\mu, a, h, \ell; \psi) = \max_{c, a', \tau} u(c) + \beta E[(1-\delta) R^E_T(\mu, a, h', \ell; \psi') + \delta R^U_T(b_{UI}, a', h', \ell; \psi')] \tag{A.3.29}$$

$$\text{s.t. } c + a' \leq (1 + r_F)a + \mu(1-\tau) f(h) \tag{A.3.30}$$

$$a' \geq \underline{a} \tag{A.3.31}$$

$$h' = e^{\epsilon'}(h + H(h, \ell, \tau, E; \psi)) \tag{A.3.32}$$

$$b_{UI} = b(1-\tau)\mu f(h) \tag{A.3.33}$$

$$b \sim N(\mu_b, \sigma_b) \tag{A.3.34}$$

$$\tau \in [0, 1] \tag{A.3.35}$$

$$W_{T-1}(\mu, a, h, \ell; \psi) = \max_{c, a', \tau} u(c) + \beta E[(1-\delta) R^E_T(\mu, a, h', \ell; z) + \delta R^U_T(b_{UI}, a', h', \ell; z)] \tag{A.3.36}$$

$$\text{s.t. } c + a' \leq (1 + r_F)a + \mu(1-\tau) f(h) \tag{A.3.37}$$

$$a' \geq \underline{a} \tag{A.3.38}$$

$$h' = e^{\epsilon'}(h + H(h, \ell, \tau, E; z)) \tag{A.3.39}$$

$$b_{UI} = b(1-\tau)\mu f(h) \tag{A.3.40}$$

$$b \sim N(\mu_b, \sigma_b) \tag{A.3.41}$$

$$\tau \in [0, 1] \tag{A.3.42}$$

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 $W_{T-1}(\mu, a, h, \ell; \psi) = W_{T-1}(\mu, a, h, \ell; z)$, 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

$$J_{T-1}(\mu, a, h, \ell; \psi) = (1-\mu)(1-\tau)f(h) + \beta E[(1-\delta)(1-P((\theta_T(\mu', a', h', \ell; \psi')))J_T(\mu, a', h', \ell; \psi')] \tag{A.3.43}$$

$$h' = e^{\epsilon'}(h + H(h, \ell, \tau, E; \psi)) \tag{A.3.44}$$

$$\tau = g_\tau(\mu, a, h, \ell; \psi) \tag{A.3.45}$$

$$a' = g_a(\mu, a, h, \ell; \psi) \tag{A.3.46}$$

$$\mu' = g_\mu(\mu, a', h', \ell; \psi) \tag{A.3.47}$$

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

$$J_{T-1}(\mu, a, h, \ell; \psi) = (1-\mu)(1-\tau)f(h) + \beta E[(1-\delta)(1-P((\theta_T(\mu', a', h', \ell; z)))J_T(\mu, a', h', \ell; z)] \tag{A.3.48}$$

$$h' = e^{\epsilon'}(h + H(h, \ell, \tau, E; z)) \tag{A.3.49}$$

$$\tau = g_\tau(\mu, a, h, \ell; z) \tag{A.3.50}$$

$$a' = g_a(\mu, a, h, \ell; z) \tag{A.3.51}$$

$$\mu' = g_\mu(\mu, a', h', \ell; z) \tag{A.3.52}$$

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

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

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

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

$$\begin{aligned} R^U_{T-1}(b_{UI}, a, h, \ell; \psi) = \max_{\mu'} & P(\theta_{T-1}(\mu', a, h, \ell; \psi))W_{T-1}(\mu', a, h, \ell; \psi) \\ & + (1 - P(\theta_{T-1}(\mu', a, h, \ell; \psi)))U_{T-1}(\mu, a, h, \ell; \psi) \end{aligned} \tag{A.3.53}$$

$$\begin{aligned} R^U_{T-1}(b_L, a, h, \ell; \psi) = \max_{\mu'} & P(\theta_{T-1}(\mu', a, h, \ell; \psi))W_{T-1}(\mu', a, h, \ell; \psi) \\ & + (1 - P(\theta_{T-1}(\mu', a, h, \ell; \psi)))U_{T-1}(b_L, a, h, \ell; \psi) \end{aligned} \tag{A.3.54}$$

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

$$\begin{aligned} R^U_{T-1}(b_{UI}, a, h, \ell; \psi) = \max_{\mu'} & P(\theta_{T-1}(\mu', a, h, \ell; z))W_{T-1}(\mu', a, h, \ell; z) \\ & + (1 - P(\theta_{T-1}(\mu', a, h, \ell; z)))U_{T-1}(\mu, a, h, \ell; z) \end{aligned} \tag{A.3.55}$$

$$\begin{aligned} R^U_{T-1}(b_L, a, h, \ell; \psi) = \max_{\mu'} & P(\theta_{T-1}(\mu', a, h, \ell; z))W_{T-1}(\mu', a, h, \ell; z) \\ & + (1 - P(\theta_{T-1}(\mu', a, h, \ell; z)))U_{T-1}(b_L, a, h, \ell; z) \end{aligned} \tag{A.3.56}$$

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

$$\begin{aligned} R^E_{T-1}(\mu, a, h, \ell; \psi) = \max_{\mu'} & P(\theta_{T-1}(\mu', a, h, \ell; \psi))W_{T-1}(\mu', a, h, \ell; \psi) \\ & + (1 - P(\theta_{T-1}(\mu', a, h, \ell; \psi)))W_{T-1}(\mu, a, h, \ell; \psi) \end{aligned} \tag{A.3.57}$$

$$\begin{aligned} R^E_{T-1}(\mu, a, h, \ell; \psi) = \max_{\mu'} & P(\theta_{T-1}(\mu', a, h, \ell; z))W_{T-1}(\mu', a, h, \ell; z) \\ & + (1 - P(\theta_{T-1}(\mu', a, h, \ell; z)))W_{T-1}(\mu, a, h, \ell; z) \end{aligned} \tag{A.3.58}$$

where again, $R^E_{T-1}(\mu, a, h, \ell; \psi) = R^E_{T-1}(\mu, a, h, \ell; z)$; 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.3.2 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.

Appendix B

Appendix for Testing the Independence of Job Arrival Rates and Wage Offers in Models of Job Search

B.1 Tables

Table B.1.1: Descriptive Statistics of Unemployed

	Standard Data Set		Inclusive Data Set	
	Mean	Std. Dev.	Mean	Std. Dev.
Hired ($d = 1$)	0.92	0.27	0.9	0.31
Duration unemployed (t)	11.15	14.2	24.34	44.06
Wage	12.81	24.24	16.56	131.04
Low wage ($d_L = 1$)	0.22	0.41	0.21	0.41
Medium wage ($d_M = 1$)	0.42	0.49	0.41	0.49
High wage ($d_H = 1$)	0.21	0.41	0.21	0.41
Male	0.61	0.49	0.52	0.5
Black	0.31	0.46	0.29	0.45
Hispanic	0.19	0.4	0.21	0.41
Education, years completed	11.75	2.25	11.79	2.31
High School, completed	0.82	0.38	0.81	0.39
College, completed	0.09	0.28	0.09	0.29
Urban	0.89	0.31	0.89	0.31
Age	22.99	3.04	22.89	2.99
UI Collected, weeks 1-9	0.12	0.32	0.05	0.22
Searched for Employment, weeks 1-9	1	0	0.39	0.45
Observations	5308		17593	

Note: Observations are based on each spell not employed and not on each individual who could be not employed one or more times. Durations are weekly. Transitions do not sum to one due to right censoring. Wage bins do not sum to one due to missing values. Missing data on wages, education, and urban status is assumed to occur randomly and observations are excluded from the estimation.

Table B.1.2: Summary of Results: Weibull Hazard with Standard Data

	Restriction				
	(1)	(2)	(3)	(4)	unrestricted
$V^1_{w_L}$	0.2139	0.2119	4.0578	0.2478	4.0918
$V^2_{w_L}$	4.7575	0.0472	18.3742	4.5099	18.5591
$V^1_{w_M}$	0.1954	0.1900	0.2360	0.0990	0.2338
$V^2_{w_M}$	3.6357	3.5354	2.4196	0.4169	2.4549
$V^1_{w_H}$	0.1954	0.1900	0.0215	0.1905	0.0262
$V^2_{w_H}$	3.6357	3.5354	0.1914	0.0213	0.2036
UI-low	-1.4427	-1.4670	-1.4382	-1.4384	-1.4656
	(-1.82,-1.09)	(-1.86,-1.11)	(-1.82,-1.08)	(-1.82,-1.09)	(-1.87,-1.11)
UI-medium	-0.8398	-1.0468	-0.8542	-0.8551	-1.0393
	(-1.01,-0.68)	(-1.25,-0.83)	(-1.03,-0.69)	(-1.03,-0.69)	(-1.23,-0.83)
UI-high	-0.8398	-0.4607	-0.8542	-0.8551	-0.5169
	(-1.01,-0.68)	(-0.76,-0.24)	(-1.03,-0.69)	(-1.03,-0.69)	(-0.80,-0.27)
Urban-low	-0.0873	-0.0910	-0.0968	-0.1017	-0.1017
	(-0.31,0.18)	(-0.31,0.18)	(-0.32,0.16)	(-0.32,0.17)	(-0.32,0.15)
Urban-medium	0.2249	-0.0487	0.2159	-0.0511	0.1872
	(0.03,0.41)	(-0.07,-0.03)	(0.04,0.40)	(-0.07,-0.03)	(-0.01,0.38)
Urban-high	0.2249	0.2557	0.2159	0.3122	0.3099
	(0.03,0.41)	(-0.06,0.63)	(0.04,0.40)	(-0.06,0.72)	(-0.05,0.69)
a_L	0.0657	0.0143	0.2356	0.0597	0.2441
	(0.03,0.15)	(0.01,0.04)	(0.11,0.66)	(0.03,0.15)	(0.11,0.65)
a_M	9.2550	10.0264	9.6728	4.1466	10.4067
	(5.09,26.69)	(5.82,29.89)	(5.78,24.71)	(2.08,8.66)	(6.24,25.88)
a_H	1313.2464	1006.1187	182.1945	186.3248	175.2755
	(570.04,3745.22)	(440.75,3068.80)	(61.38,635.00)	(62.66,710.94)	(60.57,631.72)
k_L	1.0219	1.0217	1.0209	1.0211	1.0217
	(0.98,1.08)	(0.98,1.08)	(0.97,1.08)	(0.98,1.09)	(0.97,1.08)
k_M	1.0537	1.0643	1.0415	1.0413	1.0502
	(1.00,1.10)	(1.02,1.12)	(1.01,1.09)	(1.01,1.09)	(1.01,1.10)
k_H	1.0745	1.0555	1.1076	1.1084	1.0861
	(1.02,1.15)	(1.01,1.13)	(1.05,1.20)	(1.05,1.20)	(1.03,1.17)
$\ln L$	-19347.7622	-19339.3965	-19340.2380	-19340.0085	-19333.1813
LR test	29.1618	12.4303	14.1133	13.6544	
p-value	0.0000	0.0020	0.0009	0.0002	

Note:The number of degrees of freedom used in the likelihood ratio test for Restriction 1,2,3, and 4 are 4,2,2, and 1, respectively. 95% bootstrap intervals in parenthesis.

Table B.1.3: Coefficient Estimates: Weibull Hazard with Standard Data

	Restriction				
	(1)	(2)	(3)	(4)	unrestricted
w_L market					
Male	-0.6463	-0.6447	-0.6410	-0.6411	-0.6423
	(-0.81,-0.47)	(-0.81,-0.47)	(-0.80,-0.48)	(-0.80,-0.47)	(-0.80,-0.48)
Black	-0.0394	-0.0364	-0.0195	-0.0188	-0.0229
	(-0.24,0.18)	(-0.24,0.17)	(-0.21,0.18)	(-0.23,0.18)	(-0.21,0.17)
Hispanic	-0.2974	-0.3010	-0.2985	-0.2972	-0.2984
	(-0.53,-0.04)	(-0.53,-0.06)	(-0.54,-0.07)	(-0.53,-0.06)	(-0.54,-0.08)
Education	-0.0553	-0.0552	-0.0559	-0.0560	-0.0559
	(-0.10,0.00)	(-0.10,0.00)	(-0.10,0.00)	(-0.10,0.00)	(-0.10,0.00)
High School	0.0580	0.0596	0.0730	0.0735	0.0731
	(-0.18,0.30)	(-0.19,0.29)	(-0.15,0.29)	(-0.19,0.30)	(-0.15,0.30)
College	-0.4867	-0.4812	-0.4722	-0.4709	-0.4723
	(-1.02,-0.03)	(-1.03,-0.02)	(-1.01,-0.02)	(-1.02,-0.03)	(-1.03,-0.01)
Urban	-0.0873	-0.0910	-0.0968	-0.1017	-0.1017
	(-0.31,0.18)	(-0.31,0.18)	(-0.32,0.16)	(-0.32,0.17)	(-0.32,0.15)
Age	-0.2530	-0.2523	-0.2539	-0.2538	-0.2527
	(-0.29,-0.22)	(-0.29,-0.22)	(-0.29,-0.22)	(-0.29,-0.22)	(-0.29,-0.22)
UI	-1.4427	-1.4670	-1.4382	-1.4384	-1.4656
	(-1.82,-1.09)	(-1.86,-1.11)	(-1.82,-1.08)	(-1.82,-1.09)	(-1.87,-1.11)
w_M market					
Male	0.0304	0.0316	0.0136	0.0130	0.0135
	(-0.13,0.15)	(-0.13,0.15)	(-0.11,0.14)	(-0.11,0.14)	(-0.12,0.14)
Black	-0.4741	-0.4899	-0.4549	-0.4537	-0.4668
	(-0.60,-0.32)	(-0.62,-0.34)	(-0.59,-0.31)	(-0.59,-0.31)	(-0.60,-0.33)
Hispanic	-0.1905	-0.1959	-0.1787	-0.1759	-0.1779
	(-0.34,-0.02)	(-0.35,-0.03)	(-0.33,-0.01)	(-0.33,-0.01)	(-0.33,-0.02)
Education	0.0429	0.0432	0.0386	0.0386	0.0398
	(-0.00,0.09)	(-0.00,0.10)	(-0.00,0.09)	(-0.00,0.09)	(0.00,0.09)
High School	0.2407	0.2431	0.2693	0.2708	0.2706
	(0.05,0.48)	(0.05,0.51)	(0.07,0.49)	(0.08,0.49)	(0.07,0.49)
College	-0.4962	-0.5014	-0.4656	-0.4636	-0.4751
	(-0.84,-0.20)	(-0.85,-0.20)	(-0.80,-0.17)	(-0.80,-0.17)	(-0.80,-0.20)
Urban	0.2249	0.2194	0.2159	0.1883	0.1872
	(0.03,0.41)	(0.00,0.42)	(0.04,0.40)	(0.01,0.39)	(-0.01,0.38)
Age	-0.0534	-0.0487	-0.0517	-0.0511	-0.0472
	(-0.07,-0.03)	(-0.07,-0.03)	(-0.07,-0.03)	(-0.07,-0.03)	(-0.07,-0.03)
UI	-0.8398	-1.0468	-0.8542	-0.8551	-1.0393
	(-1.01,-0.68)	(-1.25,-0.83)	(-1.03,-0.69)	(-1.03,-0.69)	(-1.23,-0.83)
w_H market					
Male	0.3740	0.3735	0.3691	0.3693	0.3758
	(0.19,0.59)	(0.18,0.58)	(0.15,0.61)	(0.14,0.61)	(0.13,0.60)
Black	-1.0700	-1.0383	-1.1103	-1.1127	-1.0666
	(-1.33,-0.83)	(-1.30,-0.81)	(-1.38,-0.86)	(-1.39,-0.86)	(-1.34,-0.81)
Hispanic	-0.1253	-0.1461	-0.1778	-0.1867	-0.1693
	(-0.39,0.14)	(-0.40,0.13)	(-0.41,0.13)	(-0.42,0.11)	(-0.42,0.13)
Education	0.1994	0.1958	0.1955	0.1943	0.1941
	(0.14,0.28)	(0.14,0.27)	(0.13,0.27)	(0.12,0.28)	(0.13,0.27)
High School	0.4156	0.3850	0.4685	0.4734	0.4335
	(0.05,0.80)	(0.06,0.76)	(0.10,0.82)	(0.09,0.83)	(0.08,0.75)
College	0.1770	0.2103	0.2636	0.2624	0.2671
	(-0.18,0.54)	(-0.15,0.54)	(-0.19,0.63)	(-0.20,0.63)	(-0.14,0.59)
Urban	0.2249	0.2557	0.2159	0.3122	0.3099
	(0.03,0.41)	(-0.06,0.63)	(0.04,0.40)	(-0.06,0.72)	(-0.05,0.69)
Age	0.0553	0.0440	0.0619	0.0601	0.0461
	(0.02,0.09)	(0.01,0.08)	(0.02,0.10)	(0.02,0.10)	(0.01,0.08)
UI	-0.8398	-0.4607	-0.8542	-0.8551	-0.5169
	(-1.01,-0.68)	(-0.76,-0.24)	(-1.03,-0.69)	(-1.03,-0.69)	(-0.80,-0.27)

Note: 95% bootstrap intervals in parenthesis.

Table B.1.4: Summary of Results: Weibull Hazard with Inclusive Data

	Restriction (1)	(2)	(3)	(4)	unrestricted
$V^1_{w_L}$	0.0299	0.0301	3.5387	0.0307	0.0308
$V^2_{w_L}$	0.2829	0.2836	0.1053	0.2845	0.2846
$V^1_{w_M}$	0.1036	0.0942	0.0545	0.0588	0.0590
$V^2_{w_M}$	3.6067	3.6119	0.3203	0.3262	0.3253
$V^1_{w_H}$	0.1036	0.0942	0.0956	0.0851	0.0857
$V^2_{w_H}$	3.6067	3.6119	5.1366	4.8292	4.7895
UI-low	-1.0486	-1.0498	-1.0491	-1.0467	-1.0499
	(-1.31,-0.82)	(-1.30,-0.82)	(-1.30,-0.82)	(-1.30,-0.82)	(-1.31,-0.82)
UI-medium	-0.7563	-0.7945	-0.7647	-0.7201	-0.7901
	(-0.86,-0.65)	(-0.94,-0.67)	(-0.87,-0.65)	(-0.83,-0.62)	(-0.93,-0.66)
UI-high	-0.7563	-0.5763	-0.7647	-0.7201	-0.5914
	(-0.86,-0.65)	(-0.76,-0.38)	(-0.87,-0.65)	(-0.83,-0.62)	(-0.78,-0.38)
Search-low	0.6342	0.6464	0.6350	0.6468	0.6474
	(0.54,0.73)	(0.55,0.75)	(0.54,0.74)	(0.55,0.75)	(0.55,0.75)
Search-medium	0.2651	0.4617	0.2727	0.4574	0.4657
	(0.20,0.32)	(0.39,0.54)	(0.20,0.33)	(0.38,0.54)	(0.39,0.54)
Search-high	0.2651	-0.2322	0.2727	-0.2075	-0.2343
	(0.20,0.32)	(-0.35,-0.12)	(0.20,0.33)	(-0.32,-0.07)	(-0.35,-0.09)
Urban-low	-0.1189	-0.1203	-0.1164	-0.1190	-0.1192
	(-0.24,0.02)	(-0.25,0.02)	(-0.24,0.02)	(-0.25,0.02)	(-0.25,0.02)
Urban-medium	0.1202	0.1062	0.1177	0.1008	0.0998
	(0.01,0.22)	(-0.00,0.21)	(0.01,0.21)	(-0.01,0.20)	(-0.01,0.20)
Urban-high	0.1202	0.1790	0.1177	0.1932	0.1955
	(0.01,0.22)	(-0.08,0.38)	(0.01,0.21)	(-0.06,0.41)	(-0.06,0.42)
a_L	0.1318	0.1316	0.6396	0.1326	0.1326
	(0.05,0.31)	(0.05,0.22)	(0.20,1.14)	(0.04,0.29)	(0.04,0.22)
a_M	542.9676	565.4240	102.8465	102.5173	104.3179
	(330.95,881.33)	(356.80,888.65)	(56.65,157.13)	(52.30,327.17)	(54.08,163.32)
a_H	49855.9353	49854.7140	49853.9882	49854.3001	49854.1379
	(49854.80,49875.31)	(49853.49,49859.27)	(49853.92,59498.28)	(49854.28,56203.36)	(49854.09,83603.59)
k_L	0.8039	0.8036	0.8041	0.8038	0.8038
	(0.79,0.82)	(0.78,0.82)	(0.78,0.83)	(0.78,0.82)	(0.78,0.82)
k_M	0.7956	0.7999	0.7934	0.7971	0.7981
	(0.78,0.81)	(0.78,0.82)	(0.78,0.81)	(0.78,0.81)	(0.78,0.81)
k_H	0.8337	0.8316	0.8468	0.8485	0.8459
	(0.81,0.86)	(0.81,0.86)	(0.82,0.87)	(0.82,0.87)	(0.82,0.87)
$\ln L$	-70434.2613	-70370.9237	-70420.6155	-70360.0084	-70358.2940
LR test	151.9346	25.2594	1013.3394	3.4290	
p-value	0.0000	0.0000	0.0000	0.0641	

Note:The number of degrees of freedom used in the likelihood ratio test for Restriction 1,2,3, and 4 are 5,2,3, and 1 respectively. 95% bootstrap intervals in parenthesis.

Table B.1.5: Coefficient Estimates: Weibull Hazard with Inclusive Data

	Restriction (1)	(2)	(3)	(4)	unrestricted
w_L market					
Male	-0.2933	-0.2927	-0.2932	-0.2929	-0.2929
	(-0.40,-0.20)	(-0.42,-0.20)	(-0.42,-0.20)	(-0.42,-0.20)	(-0.42,-0.20)
Black	-0.0255	-0.0254	-0.0204	-0.0217	-0.0222
	(-0.18,0.07)	(-0.16,0.07)	(-0.16,0.07)	(-0.16,0.07)	(-0.16,0.07)
Hispanic	-0.1854	-0.1865	-0.1833	-0.1861	-0.1868
	(-0.35,-0.07)	(-0.35,-0.06)	(-0.35,-0.06)	(-0.36,-0.07)	(-0.34,-0.07)
Education	0.0140	0.0138	0.0143	0.0142	0.0141
	(-0.03,0.05)	(-0.03,0.05)	(-0.03,0.05)	(-0.03,0.05)	(-0.03,0.05)
High School	0.1115	0.1114	0.1081	0.1093	0.1091
	(-0.03,0.26)	(-0.02,0.26)	(-0.04,0.25)	(-0.03,0.25)	(-0.03,0.25)
College	-0.1578	-0.1441	-0.1564	-0.1462	-0.1467
	(-0.43,0.17)	(-0.47,0.18)	(-0.48,0.18)	(-0.45,0.18)	(-0.46,0.19)
Urban	-0.1189	-0.1203	-0.1164	-0.1190	-0.1192
	(-0.24,0.02)	(-0.25,0.02)	(-0.24,0.02)	(-0.25,0.02)	(-0.25,0.02)
Age	-0.2174	-0.2173	-0.2174	-0.2173	-0.2173
	(-0.24,-0.20)	(-0.24,-0.20)	(-0.24,-0.20)	(-0.24,-0.20)	(-0.24,-0.20)
UI	-1.0486	-1.0498	-1.0491	-1.0467	-1.0499
	(-1.31,-0.82)	(-1.30,-0.82)	(-1.30,-0.82)	(-1.30,-0.82)	(-1.31,-0.82)
Searching	0.6342	0.6464	0.6350	0.6468	0.6474
	(0.54,0.73)	(0.55,0.75)	(0.54,0.74)	(0.55,0.75)	(0.55,0.75)
w_M market					
Male	0.2055	0.1704	0.2090	0.1746	0.1752
	(0.13,0.29)	(0.10,0.25)	(0.14,0.29)	(0.10,0.26)	(0.11,0.26)
Black	-0.3691	-0.3766	-0.3671	-0.3727	-0.3748
	(-0.46,-0.27)	(-0.46,-0.28)	(-0.46,-0.28)	(-0.46,-0.28)	(-0.47,-0.28)
Hispanic	-0.1568	-0.1508	-0.1625	-0.1558	-0.1562
	(-0.26,-0.06)	(-0.25,-0.05)	(-0.26,-0.06)	(-0.25,-0.06)	(-0.26,-0.06)
Education	0.1009	0.1012	0.1004	0.1003	0.1007
	(0.07,0.13)	(0.07,0.13)	(0.08,0.13)	(0.07,0.13)	(0.07,0.13)
High School	0.3064	0.3003	0.3073	0.3021	0.3029
	(0.17,0.42)	(0.18,0.43)	(0.18,0.44)	(0.18,0.43)	(0.18,0.43)
College	-0.4377	-0.4504	-0.4342	-0.4459	-0.4490
	(-0.64,-0.26)	(-0.63,-0.27)	(-0.61,-0.25)	(-0.63,-0.26)	(-0.63,-0.26)
Urban	0.1202	0.1062	0.1177	0.1008	0.0998
	(0.01,0.22)	(-0.00,0.21)	(0.01,0.21)	(-0.01,0.20)	(-0.01,0.20)
Age	-0.0013	-0.0016	-0.0019	-0.0034	-0.0027
	(-0.01,0.01)	(-0.01,0.01)	(-0.01,0.01)	(-0.01,0.01)	(-0.01,0.01)
UI	-0.7563	-0.7945	-0.7647	-0.7201	-0.7901
	(-0.86,-0.65)	(-0.94,-0.67)	(-0.87,-0.65)	(-0.83,-0.62)	(-0.93,-0.66)
Searching	0.2651	0.4617	0.2727	0.4574	0.4657
	(0.20,0.32)	(0.39,0.54)	(0.20,0.33)	(0.38,0.54)	(0.39,0.54)
w_H market					
Male	0.6730	0.6928	0.6901	0.7110	0.7097
	(0.51,0.83)	(0.56,0.87)	(0.52,0.86)	(0.58,0.89)	(0.57,0.89)
Black	-1.0501	-1.0267	-1.1085	-1.0789	-1.0677
	(-1.22,-0.87)	(-1.20,-0.85)	(-1.27,-0.86)	(-1.25,-0.84)	(-1.25,-0.84)
Hispanic	-0.1828	-0.1653	-0.2375	-0.2047	-0.1946
	(-0.35,0.02)	(-0.34,-0.00)	(-0.40,0.01)	(-0.38,0.03)	(-0.39,0.03)
Education	0.1947	0.1943	0.1929	0.1942	0.1942
	(0.16,0.23)	(0.16,0.23)	(0.15,0.24)	(0.15,0.23)	(0.15,0.24)
High School	0.4333	0.4265	0.5088	0.4707	0.4666
	(0.19,0.71)	(0.18,0.73)	(0.21,0.79)	(0.21,0.78)	(0.21,0.79)
College	0.3867	0.3067	0.3811	0.3198	0.3284
	(0.07,0.69)	(0.09,0.65)	(0.06,0.77)	(0.07,0.67)	(0.05,0.67)
Urban	0.1202	0.1790	0.1177	0.1932	0.1955
	(0.01,0.22)	(-0.08,0.38)	(0.01,0.21)	(-0.06,0.41)	(-0.06,0.42)
Age	0.1222	0.1208	0.1245	0.1228	0.1211
	(0.10,0.14)	(0.10,0.14)	(0.10,0.14)	(0.10,0.14)	(0.10,0.14)
UI	-0.7563	-0.5763	-0.7647	-0.7201	-0.5914
	(-0.86,-0.65)	(-0.76,-0.38)	(-0.87,-0.65)	(-0.83,-0.62)	(-0.78,-0.38)
Searching	0.2651	-0.2322	0.2727	-0.2075	-0.2343
	(0.20,0.32)	(-0.35,-0.12)	(0.20,0.33)	(-0.32,-0.07)	(-0.35,-0.09)

Note: 95% bootstrap intervals in parenthesis.

Table B.1.6: Summary of Results: Piecewise Exponential with Standard Data

	Restriction				
	(1)	(2)	(3)	(4)	unrestricted
$V_{w_L}^1$	0.2396	0.2388	0.2402	0.2411	0.2414
$V_{w_L}^2$	0.0729	0.0714	0.0748	0.0756	0.0751
$V_{w_M}^1$	0.2597	0.2689	0.5213	0.5293	0.5364
$V_{w_M}^2$	0.0684	0.0632	0.1461	0.1488	0.1493
$V_{w_H}^1$	0.2597	0.2689	0.1590	0.1585	0.1796
$V_{w_H}^2$	0.0684	0.0632	3.9545	3.9680	3.8295
UI-low	-1.3166	-1.3446	-1.3189	-1.3188	-1.3454
	(-1.71,-0.98)	(-1.72,-1.01)	(-1.70,-0.98)	(-1.70,-0.98)	(-1.71,-1.01)
UI-medium	-0.7534	-0.9995	-0.7609	-0.7613	-0.9957
	(-0.88,-0.63)	(-1.17,-0.81)	(-0.89,-0.63)	(-0.89,-0.63)	(-1.17,-0.81)
UI-high	-0.7534	-0.3487	-0.7609	-0.7613	-0.3841
	(-0.88,-0.63)	(-0.59,-0.17)	(-0.89,-0.63)	(-0.89,-0.63)	(-0.59,-0.18)
Urban-low	-0.1057	-0.1024	-0.1023	-0.1062	-0.1058
	(-0.31,0.14)	(-0.31,0.14)	(-0.31,0.14)	(-0.31,0.14)	(-0.31,0.14)
Urban-medium	0.2027	0.1940	0.2009	0.1817	0.1788
	(0.06,0.36)	(0.03,0.37)	(0.07,0.36)	(0.02,0.35)	(0.02,0.36)
Urban-high	0.2027	0.2574	0.2009	0.2636	-0.9957
	(0.06,0.36)	(-0.02,0.60)	(0.07,0.36)	(-0.04,0.61)	(-1.17,-0.81)
$\ln L$	-19290.6370	-19279.2253	-19286.6209	-19286.5107	-19276.1730
LR test	28.9280	6.1047	20.8959	20.6754	
p-value	0.0000	0.0472	0.0001	0.0000	

Note: The number of degrees of freedom used in the likelihood ratio test for Restriction 1,2, and 3 are 28,26, and 2, respectively. 95% bootstrap intervals in parenthesis.

Table B.1.7: Baseline Hazard Rate Estimates: Piecewise Exponential with Standard Data

	Restriction				
	(1)	(2)	(3)	(4)	unrestricted
λ_L^1	66.9170	65.3203	68.1360	67.9360	66.3688
	(33.23,70.00)	(31.76,70.00)	(32.99,70.00)	(33.27,70.00)	(32.22,70.00)
λ_L^2	49.0532	47.9645	50.0648	49.9075	48.8300
	(24.92,59.91)	(24.00,59.66)	(24.49,59.92)	(24.56,59.92)	(23.94,60.12)
λ_L^3	46.8569	45.8900	47.8259	47.6626	46.6878
	(22.18,60.32)	(21.86,60.54)	(21.62,60.02)	(22.72,60.17)	(21.23,60.26)
λ_L^4	51.8568	50.9190	52.9481	52.7805	51.6902
	(26.19,70.00)	(24.95,70.00)	(24.65,70.00)	(25.71,70.00)	(24.87,70.00)
λ_L^5	42.8708	41.9775	43.4805	43.3459	42.4506
	(18.68,65.68)	(18.05,65.64)	(18.45,66.61)	(18.45,66.45)	(17.88,66.68)
λ_L^6	38.1520	37.5770	38.4766	38.3071	37.5366
	(14.78,70.00)	(14.56,69.71)	(15.00,69.96)	(16.00,69.30)	(14.70,70.00)
λ_M^1	0.4893	0.4150	0.2231	0.2206	0.1930
	(0.20,1.05)	(0.18,0.97)	(0.10,0.55)	(0.10,0.55)	(0.09,0.48)
λ_M^2	0.3255	0.2820	0.1493	0.1477	0.1318
	(0.14,0.67)	(0.12,0.63)	(0.07,0.37)	(0.07,0.36)	(0.06,0.33)
λ_M^3	0.3214	0.2820	0.1472	0.1455	0.1310
	(0.12,0.74)	(0.12,0.67)	(0.07,0.37)	(0.07,0.36)	(0.06,0.33)
λ_M^4	0.3919	0.3500	0.1783	0.1762	0.1596
	(0.15,0.90)	(0.13,0.89)	(0.08,0.45)	(0.08,0.44)	(0.07,0.41)
λ_M^5	0.3741	0.3381	0.1686	0.1667	0.1512
	(0.13,0.85)	(0.11,0.89)	(0.07,0.47)	(0.07,0.43)	(0.07,0.40)
λ_M^6	0.2148	0.1990	0.0956	0.0945	0.0856
	(0.08,0.55)	(0.07,0.57)	(0.04,0.27)	(0.04,0.27)	(0.03,0.23)
λ_H^1	0.0020	0.0042	0.0010	0.0010	0.0013
	(0.00,0.01)	(0.00,0.01)	(0.00,0.00)	(0.00,0.00)	(0.00,0.00)
λ_H^2	0.0015	0.0030	0.0008	0.0008	0.0010
	(0.00,0.01)	(0.00,0.01)	(0.00,0.00)	(0.00,0.00)	(0.00,0.00)
λ_H^3	0.0011	0.0022	0.0006	0.0006	0.0007
	(0.00,0.00)	(0.00,0.01)	(0.00,0.00)	(0.00,0.00)	(0.00,0.00)
λ_H^4	0.0014	0.0027	0.0007	0.0007	0.0009
	(0.00,0.01)	(0.00,0.01)	(0.00,0.00)	(0.00,0.00)	(0.00,0.00)
λ_H^5	0.0010	0.0019	0.0005	0.0005	0.0006
	(0.00,0.00)	(0.00,0.01)	(0.00,0.00)	(0.00,0.00)	(0.00,0.00)
λ_H^6	0.0010	0.0021	0.0006	0.0006	0.0007
	(0.00,0.00)	(0.00,0.01)	(0.00,0.00)	(0.00,0.00)	(0.00,0.00)

Note: 95% bootstrap intervals in parenthesis.

Table B.1.8: Coefficient Estimates: Piecewise Exponential with Standard Data

	Restriction				
	(1)	(2)	(3)	(4)	unrestricted
w_L market					
Male	-0.5981	-0.5936	-0.5897	-0.5893	-0.5909
	(-0.74,-0.43)	(-0.74,-0.44)	(-0.74,-0.44)	(-0.74,-0.43)	(-0.75,-0.44)
Black	0.0352	0.0291	0.0296	0.0298	0.0276
	(-0.15,0.21)	(-0.15,0.21)	(-0.15,0.20)	(-0.15,0.20)	(-0.15,0.20)
Hispanic	-0.2638	-0.2623	-0.2617	-0.2611	-0.2610
	(-0.49,-0.04)	(-0.48,-0.04)	(-0.49,-0.04)	(-0.49,-0.04)	(-0.48,-0.04)
Education	-0.0496	-0.0498	-0.0496	-0.0495	-0.0493
	(-0.09,0.00)	(-0.09,0.00)	(-0.08,0.00)	(-0.08,0.00)	(-0.08,0.00)
High School	0.0219	0.0255	0.0249	0.0246	0.0252
	(-0.19,0.22)	(-0.19,0.22)	(-0.19,0.22)	(-0.19,0.22)	(-0.19,0.22)
College	-0.5022	-0.5101	-0.5140	-0.5142	-0.5156
	(-1.05,-0.07)	(-1.08,-0.08)	(-1.14,-0.08)	(-1.14,-0.08)	(-1.11,-0.08)
Urban	-0.1057	-0.1024	-0.1023	-0.1062	-0.1058
	(-0.31,0.14)	(-0.31,0.14)	(-0.31,0.14)	(-0.31,0.14)	(-0.31,0.14)
Age	-0.2387	-0.2377	-0.2391	-0.2390	-0.2380
	(-0.27,-0.21)	(-0.27,-0.21)	(-0.27,-0.21)	(-0.27,-0.21)	(-0.27,-0.21)
UI	-1.3166	-1.3446	-1.3189	-1.3188	-1.3454
	(-1.71,-0.98)	(-1.72,-1.01)	(-1.70,-0.98)	(-1.70,-0.98)	(-1.71,-1.01)
w_M market					
Male	0.0270	0.0298	0.0277	0.0277	0.0258
	(-0.08,0.14)	(-0.09,0.14)	(-0.09,0.14)	(-0.09,0.14)	(-0.09,0.13)
Black	-0.3919	-0.4127	-0.3912	-0.3903	-0.4042
	(-0.51,-0.27)	(-0.53,-0.28)	(-0.51,-0.27)	(-0.50,-0.27)	(-0.52,-0.28)
Hispanic	-0.1699	-0.1743	-0.1675	-0.1655	-0.1680
	(-0.31,-0.03)	(-0.32,-0.03)	(-0.31,-0.02)	(-0.31,-0.02)	(-0.31,-0.02)
Education	0.0366	0.0394	0.0398	0.0399	0.0415
	(-0.00,0.08)	(-0.00,0.08)	(0.00,0.08)	(0.00,0.08)	(0.00,0.08)
High School	0.2215	0.2111	0.2150	0.2153	0.2167
	(0.04,0.41)	(0.04,0.41)	(0.04,0.40)	(0.04,0.40)	(0.04,0.41)
College	-0.4773	-0.4932	-0.4842	-0.4834	-0.4963
	(-0.79,-0.21)	(-0.80,-0.22)	(-0.79,-0.23)	(-0.79,-0.23)	(-0.79,-0.24)
Urban	0.2027	0.1940	0.2009	0.1817	0.1788
	(0.06,0.36)	(0.03,0.37)	(0.07,0.36)	(0.02,0.35)	(0.02,0.36)
Age	-0.0456	-0.0405	-0.0452	-0.0448	-0.0394
	(-0.06,-0.03)	(-0.06,-0.02)	(-0.06,-0.03)	(-0.06,-0.03)	(-0.06,-0.02)
UI	-0.7534	-0.9995	-0.7609	-0.7613	-0.9957
	(-0.88,-0.63)	(-1.17,-0.81)	(-0.89,-0.63)	(-0.89,-0.63)	(-1.17,-0.81)
w_H market					
Male	0.3913	0.3781	0.3724	0.3725	0.3660
	(0.21,0.57)	(0.19,0.56)	(0.18,0.58)	(0.18,0.58)	(0.17,0.58)
Black	-0.9528	-0.9379	-0.9809	-0.9828	-0.9348
	(-1.20,-0.74)	(-1.17,-0.69)	(-1.24,-0.74)	(-1.24,-0.74)	(-1.18,-0.70)
Hispanic	-0.1105	-0.1449	-0.1595	-0.1658	-0.1470
	(-0.37,0.13)	(-0.37,0.10)	(-0.38,0.10)	(-0.40,0.10)	(-0.39,0.11)
Education	0.1948	0.1854	0.1870	0.1862	0.1833
	(0.13,0.25)	(0.13,0.25)	(0.13,0.25)	(0.13,0.25)	(0.13,0.25)
High School	0.3282	0.3313	0.3894	0.3919	0.3659
	(0.01,0.68)	(-0.00,0.65)	(0.05,0.72)	(0.04,0.72)	(0.05,0.67)
College	0.2121	0.2531	0.2579	0.2571	0.2808
	(-0.10,0.55)	(-0.07,0.56)	(-0.10,0.58)	(-0.11,0.58)	(-0.09,0.61)
Urban	0.2027	0.2574	0.2009	0.2636	0.2608
	(0.06,0.36)	(-0.02,0.60)	(0.07,0.36)	(-0.04,0.61)	(-0.02,0.60)
Age	0.0604	0.0431	0.0626	0.0615	0.0463
	(0.03,0.09)	(0.01,0.08)	(0.03,0.09)	(0.03,0.09)	(0.01,0.08)
UI	-0.7534	-0.3487	-0.7609	-0.7613	-0.3841
	(-0.88,-0.63)	(-0.59,-0.17)	(-0.89,-0.63)	(-0.89,-0.63)	(-0.59,-0.18)

Note: 95% bootstrap intervals in parenthesis.

Table B.1.9: Summary of Results: Piecewise Exponential with Inclusive Data

	Restriction				
	(1)	(2)	(3)	(4)	unrestricted
$V^1_{w_L}$	0.0168	0.0173	0.0171	0.0180	0.0180
$V^2_{w_L}$	0.2924	0.2939	0.2938	0.2950	0.2950
$V^1_{w_M}$	0.1245	0.1236	0.1549	0.1614	6.4302
$V^2_{w_M}$	3.3067	3.2538	2.9993	2.9250	19.0479
$V^1_{w_H}$	0.1245	0.1236	46.3672	46.2589	43.9762
$V^2_{w_H}$	3.3067	3.2538	8.6475	8.9545	8.7443
UI-low	-1.0611	-1.0619	-1.0614	-1.0600	-1.0620
	(-1.32,-0.82)	(-1.32,-0.82)	(-1.32,-0.82)	(-1.32,-0.81)	(-1.32,-0.82)
UI-medium	-0.7301	-0.8037	-0.7312	-0.7042	-0.7945
	(-0.83,-0.64)	(-0.93,-0.68)	(-0.84,-0.63)	(-0.80,-0.60)	(-0.92,-0.68)
UI-high	-0.7301	-0.5135	-0.7312	-0.7042	-0.5288
	(-0.83,-0.64)	(-0.70,-0.33)	(-0.84,-0.63)	(-0.80,-0.60)	(-0.74,-0.33)
Search-low	0.4115	0.4203	0.4118	0.4199	0.4201
	(0.31,0.51)	(0.32,0.52)	(0.31,0.51)	(0.32,0.52)	(0.32,0.52)
Search-medium	0.0189	0.2053	0.0266	0.1989	0.2080
	(-0.04,0.08)	(0.13,0.27)	(-0.03,0.08)	(0.13,0.27)	(0.14,0.28)
Search-high	0.0189	-0.4354	0.0266	-0.3902	-0.4224
	(-0.04,0.08)	(-0.55,-0.32)	(-0.03,0.08)	(-0.51,-0.28)	(-0.54,-0.31)
Urban-low	-0.1303	-0.1311	-0.1277	-0.1287	-0.1294
	(-0.25,0.01)	(-0.25,0.00)	(-0.24,0.01)	(-0.24,0.01)	(-0.24,0.01)
Urban-medium	0.1255	0.1115	0.1295	0.1034	0.1039
	(0.04,0.22)	(-0.00,0.21)	(0.04,0.22)	(-0.01,0.20)	(-0.01,0.20)
Urban-high	0.1255	0.1581	0.1295	0.1834	0.1798
	(0.04,0.22)	(-0.05,0.41)	(0.04,0.22)	(-0.01,0.45)	(-0.01,0.44)
$\ln L$	-70061.1868	-70005.3872	-70048.1990	-69997.4836	-69993.9136
LR test	134.5463	22.9473	108.5708	7.1401	
p-value	0.0000	0.0000	0.0000	0.0075	

Note:The number of degrees of freedom used in the likelihood ratio test for Restriction 1,2,3, and 4 are 5,2,3 and 1, respectively. 95% bootstrap intervals in parenthesis.

Table B.1.10: Baseline Hazard Rate Estimates: Piecewise Exponential with Inclusive Data

	Restriction				
	(1)	(2)	(3)	(4)	unrestricted
λ_L^1	3.7085	3.7136	3.5854	3.6268	3.7308
	(2.58,6.24)	(2.56,6.33)	(2.57,6.50)	(2.56,6.67)	(2.55,6.67)
λ_L^2	2.1442	2.1454	2.0712	2.0952	2.1552
	(1.43,3.72)	(1.44,3.72)	(1.46,3.74)	(1.45,3.82)	(1.46,3.88)
λ_L^3	1.7842	1.7840	1.7232	1.7419	1.7917
	(1.22,3.10)	(1.22,3.14)	(1.21,3.28)	(1.22,3.16)	(1.23,3.25)
λ_L^4	1.7721	1.7713	1.7071	1.7287	1.7787
	(1.23,3.22)	(1.22,3.19)	(1.24,3.19)	(1.20,3.23)	(1.21,3.21)
λ_L^5	1.7042	1.7029	1.6421	1.6618	1.7099
	(1.16,3.16)	(1.14,3.12)	(1.15,3.07)	(1.16,3.22)	(1.14,3.24)
λ_L^6	1.1105	1.1073	1.0723	1.0812	1.1120
	(0.77,2.01)	(0.76,2.00)	(0.76,2.03)	(0.77,2.03)	(0.76,2.03)
λ_M^1	0.0065	0.0063	0.0072	0.0073	0.0011
	(0.00,0.01)	(0.00,0.01)	(0.01,0.01)	(0.01,0.01)	(0.00,0.00)
λ_M^2	0.0034	0.0033	0.0037	0.0038	0.0006
	(0.00,0.01)	(0.00,0.01)	(0.00,0.01)	(0.00,0.01)	(0.00,0.00)
λ_M^3	0.0029	0.0028	0.0031	0.0032	0.0005
	(0.00,0.00)	(0.00,0.00)	(0.00,0.01)	(0.00,0.01)	(0.00,0.00)
λ_M^4	0.0030	0.0029	0.0033	0.0034	0.0005
	(0.00,0.00)	(0.00,0.00)	(0.00,0.01)	(0.00,0.01)	(0.00,0.00)
λ_M^5	0.0027	0.0027	0.0030	0.0030	0.0005
	(0.00,0.00)	(0.00,0.00)	(0.00,0.01)	(0.00,0.01)	(0.00,0.00)
λ_M^6	0.0017	0.0016	0.0018	0.0019	0.0003
	(0.00,0.00)	(0.00,0.00)	(0.00,0.00)	(0.00,0.00)	(0.00,0.00)
λ_H^1	0.0001	0.0001	0.0000	0.0000	0.0000
	(0.00,0.00)	(0.00,0.00)	(0.00,0.00)	(0.00,0.00)	(0.00,0.00)
λ_H^2	0.0001	0.0001	0.0000	0.0000	0.0000
	(0.00,0.00)	(0.00,0.00)	(0.00,0.00)	(0.00,0.00)	(0.00,0.00)
λ_H^3	0.0001	0.0001	0.0000	0.0000	0.0000
	(0.00,0.00)	(0.00,0.00)	(0.00,0.00)	(0.00,0.00)	(0.00,0.00)
λ_H^4	0.0001	0.0001	0.0000	0.0000	0.0000
	(0.00,0.00)	(0.00,0.00)	(0.00,0.00)	(0.00,0.00)	(0.00,0.00)
λ_H^5	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.00,0.00)	(0.00,0.00)	(0.00,0.00)	(0.00,0.00)	(0.00,0.00)
λ_H^6	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.00,0.00)	(0.00,0.00)	(0.00,0.00)	(0.00,0.00)	(0.00,0.00)

Note: 95% bootstrap intervals in parenthesis.

Table B.1.11: Coefficient Estimates: Piecewise Exponential with Inclusive Data

			Restriction		
	(1)	(2)	(3)	(4)	unrestricted
w_L market					
Male	-0.2668	-0.2670	-0.2658	-0.2678	-0.2689
	(-0.38,-0.17)	(-0.38,-0.17)	(-0.38,-0.17)	(-0.38,-0.17)	(-0.38,-0.17)
Black	-0.0031	-0.0025	0.0029	0.0016	0.0002
	(-0.13,0.09)	(-0.12,0.09)	(-0.12,0.09)	(-0.12,0.09)	(-0.12,0.09)
Hispanic	-0.1927	-0.1933	-0.1875	-0.1898	-0.1903
	(-0.33,-0.07)	(-0.33,-0.07)	(-0.33,-0.07)	(-0.33,-0.07)	(-0.33,-0.07)
Education	0.0074	0.0072	0.0092	0.0089	0.0075
	(-0.03,0.04)	(-0.03,0.04)	(-0.03,0.04)	(-0.03,0.04)	(-0.03,0.04)
High School	0.1034	0.1030	0.0945	0.0929	0.0948
	(-0.02,0.24)	(-0.02,0.24)	(-0.03,0.23)	(-0.03,0.24)	(-0.03,0.24)
College	-0.1896	-0.1839	-0.1958	-0.1901	-0.1843
	(-0.48,0.14)	(-0.48,0.14)	(-0.48,0.12)	(-0.48,0.14)	(-0.48,0.15)
Urban	-0.1303	-0.1311	-0.1277	-0.1287	-0.1294
	(-0.25,0.01)	(-0.25,0.00)	(-0.24,0.01)	(-0.24,0.01)	(-0.24,0.01)
Age	-0.2090	-0.2089	-0.2083	-0.2086	-0.2090
	(-0.23,-0.19)	(-0.23,-0.19)	(-0.23,-0.19)	(-0.23,-0.19)	(-0.23,-0.19)
UI	-1.0611	-1.0619	-1.0614	-1.0600	-1.0620
	(-1.32,-0.82)	(-1.32,-0.82)	(-1.32,-0.82)	(-1.32,-0.81)	(-1.32,-0.82)
Searching	0.4115	0.4203	0.4118	0.4199	0.4201
	(0.31,0.51)	(0.32,0.52)	(0.31,0.51)	(0.32,0.52)	(0.32,0.52)
w_M market					
Male	0.2444	0.2145	0.2425	0.2120	0.2127
	(0.18,0.32)	(0.15,0.29)	(0.18,0.32)	(0.15,0.29)	(0.15,0.29)
Black	-0.3397	-0.3486	-0.3341	-0.3406	-0.3432
	(-0.43,-0.25)	(-0.43,-0.25)	(-0.43,-0.25)	(-0.43,-0.25)	(-0.43,-0.25)
Hispanic	-0.1420	-0.1383	-0.1515	-0.1469	-0.1466
	(-0.25,-0.04)	(-0.24,-0.04)	(-0.25,-0.05)	(-0.25,-0.05)	(-0.24,-0.05)
Education	0.0920	0.0915	0.0920	0.0913	0.0920
	(0.07,0.12)	(0.07,0.12)	(0.07,0.12)	(0.07,0.12)	(0.07,0.12)
High School	0.3058	0.3032	0.3021	0.2953	0.2965
	(0.18,0.43)	(0.18,0.43)	(0.18,0.43)	(0.17,0.42)	(0.17,0.42)
College	-0.4170	-0.4210	-0.4152	-0.4183	-0.4215
	(-0.59,-0.24)	(-0.59,-0.25)	(-0.59,-0.24)	(-0.59,-0.24)	(-0.59,-0.24)
Urban	0.1255	0.1115	0.1295	0.1034	0.1039
	(0.04,0.22)	(-0.00,0.21)	(0.04,0.22)	(-0.01,0.20)	(-0.01,0.20)
Age	0.0013	0.0017	0.0008	0.0003	0.0012
	(-0.01,0.01)	(-0.01,0.01)	(-0.01,0.01)	(-0.01,0.01)	(-0.01,0.01)
UI	-0.7301	-0.8037	-0.7312	-0.7042	-0.7945
	(-0.83,-0.64)	(-0.93,-0.68)	(-0.84,-0.63)	(-0.80,-0.60)	(-0.92,-0.68)
Searching	0.0189	0.2053	0.0266	0.1989	0.2080
	(-0.04,0.08)	(0.13,0.27)	(-0.03,0.08)	(0.13,0.27)	(0.14,0.28)
w_H market					
Male	0.7198	0.7680	0.7363	0.7955	0.7942
	(0.57,0.85)	(0.63,0.90)	(0.59,0.89)	(0.65,0.94)	(0.65,0.94)
Black	-0.9742	-0.9468	-1.0099	-0.9761	-0.9638
	(-1.13,-0.80)	(-1.11,-0.78)	(-1.17,-0.81)	(-1.14,-0.79)	(-1.13,-0.78)
Hispanic	-0.1737	-0.1641	-0.2175	-0.2006	-0.1954
	(-0.33,0.01)	(-0.34,0.01)	(-0.36,0.03)	(-0.37,0.02)	(-0.38,0.03)
Education	0.1875	0.1926	0.1901	0.1917	0.1955
	(0.15,0.24)	(0.15,0.24)	(0.15,0.25)	(0.15,0.25)	(0.15,0.25)
High School	0.4109	0.4014	0.5206	0.5168	0.5063
	(0.15,0.66)	(0.15,0.66)	(0.20,0.75)	(0.21,0.75)	(0.21,0.75)
College	0.5449	0.5331	0.4983	0.5116	0.5101
	(0.02,0.81)	(0.05,0.82)	(0.02,0.81)	(0.04,0.79)	(0.04,0.81)
Urban	0.1255	0.1581	0.1295	0.1834	0.1798
	(0.04,0.22)	(-0.05,0.41)	(0.04,0.22)	(-0.01,0.45)	(-0.01,0.44)
Age	0.1251	0.1243	0.1284	0.1293	0.1273
	(0.11,0.14)	(0.10,0.14)	(0.11,0.15)	(0.11,0.15)	(0.11,0.15)
UI	-0.7301	-0.5135	-0.7312	-0.7042	-0.5288
	(-0.83,-0.64)	(-0.70,-0.33)	(-0.84,-0.63)	(-0.80,-0.60)	(-0.74,-0.33)
Searching	0.0189	-0.4354	0.0266	-0.3902	-0.4224
	(-0.04,0.08)	(-0.55,-0.32)	(-0.03,0.08)	(-0.51,-0.28)	(-0.54,-0.31)

Note: 95% bootstrap intervals in parenthesis.

Table B.1.12: Wage Distributions by Eduction

	Standard Data		Inclusive Data	
	High School	College	High School	College
Mean	12.59	17.22	16.45	20.00
Std. Dev.	24.43	15.50	142.83	37.46
25^{th} Percentile	7.33	10.00	7.5	10.7
75^{th} Percentile	12.36	19.17	13.24	21.63
Observations	3,343	384	10,617	1,362

Table B.1.13: Likelihood Ratio Tests by Education: Weibull Hazard

	Specification				
	(1)	(2)	(3)	(4)	unrestricted
Standard data: Highschool					
ln L	-14254.8164	-14248.9368	-14250.9355	-14249.8313	-14245.6054
LR test	18.4221	6.6628	10.6602	8.4517	
p-value	0.0010	0.0357	0.0048	0.0036	
Standard data: College					
ln L	-1572.5371	-1571.9408	-1572.7105	-1571.8639	-1571.8331
LR test	1.4081	0.2156	1.7548	0.0617	
p-value	0.8428	0.8978	0.4159	0.8038	
Inclusive data: Highschool					
ln L	-51367.6426	-51318.8019	-51356.6103	-51310.4165	51308.9126
LR test	117.4601	19.7785	95.3954	3.0078	
p-value	0.0000	0.0001	0.0000	0.0829	
Inclusive data: College					
ln L	-5680.1866	-5675.2052	-5673.9313	-5669.8700	-5669.7648
LR test	20.8437	10.8809	8.3330	0.2104	
p-value	0.0009	0.0043	0.0396	0.6465	

Table B.1.14: Likelihood Ratio Tests by Education: Piecewise Exponential Hazard

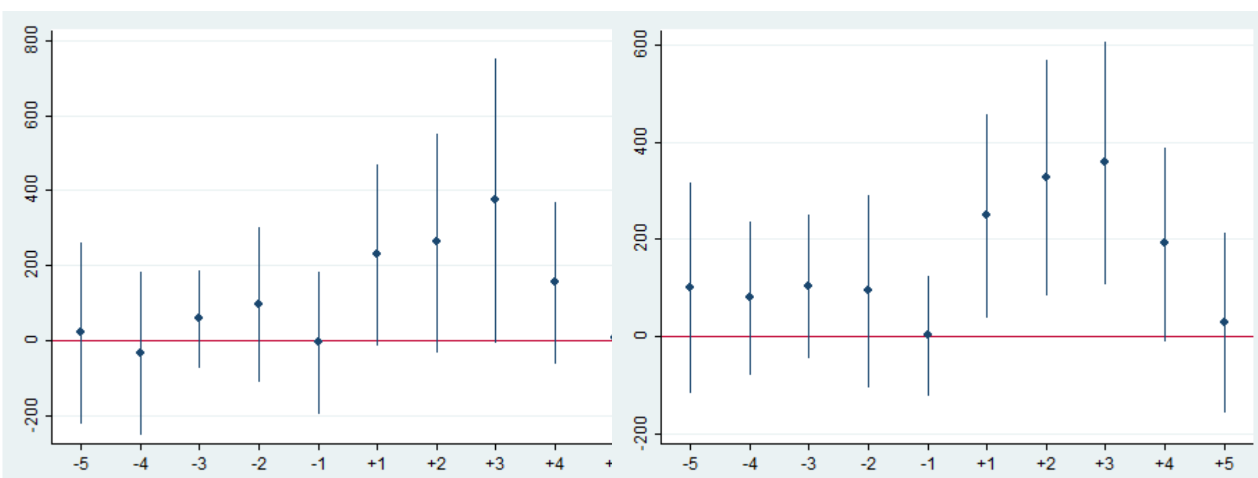
	Specification				
	(1)	(2)	(3)	(4)	unrestricted
Standard data: Highschool					
$\ln L$	-14209.8386	-14204.9645	-14208.4759	-14207.8358	-14201.4364
LR test	16.8043	7.0560	14.0789	12.7986	
p-value	0.0021	0.0294	0.0009	0.0003	
Standard data: College					
$\ln L$	-1584.1900	-1583.1533	-1584.1869	-1583.2134	-1583.1533
LR test	2.0733	0.0001	2.0673	0.1201	
p-value	0.7223	1.0000	0.3557	0.7289	
Inclusive data: Highschool					
$\ln L$	-51109.3769	-51070.3267	-51098.9918	-51063.9213	-51062.2604
LR test	94.2329	16.1327	73.4629	3.3218	
p-value	0.0000	0.0003	0.0000	0.0684	
Inclusive data: College					
$\ln L$	-5626.4299	-5621.3700	-5626.3282	-5621.3424	-5621.3360
LR test	10.1878	0.0680	9.9844	0.0127	
p-value	0.0701	0.9666	0.0187	0.9102	

Table B.1.15: Kullback-Leibler Divergence

Sub-Market	$D_{KL}(p\|\|q)$	H(p)
Black High-School Non-completers	0.0589	3.5677
Black High-School Graduates	0.0764	2.9850
Black College Non-completers	0.0597	2.3401
White High-School Non-completers	0.0657	3.0358
White High-School Graduates	0.0626	2.4240
White College Non-completers	0.046	1.7345
White College Graduates	0.0905	1.6845

Appendix C

Appendix for The Effect of Public Education Expenditures on Intergenerational Mobility



(a) Spending Per-Pupil for all counties

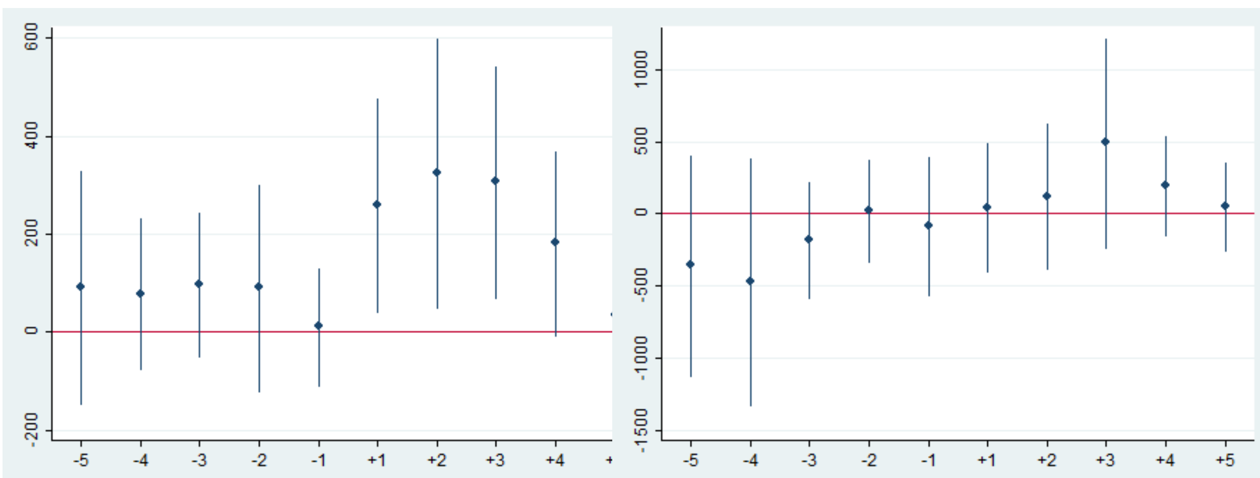
(b) Spending Per-Pupil for Counties with previously below mean spending

Figure C.0.1: Event study for court reform at county level

VARIABLES	(1) All Counties	(2) Bottom 50 Percent	(3) Top 25 Percent	(4) Bottom 25 Percent
L.a_r	231.7*	249.9**	44.66	259.5**
	(119.8)	(104.2)	(223.0)	(108.9)
L2.a_r	263.9*	327.2***	123.2	326.0**
	(145.1)	(120.5)	(251.9)	(137.2)
L3.a_r	376.5*	358.3***	494.8	306.5**
	(187.9)	(124.8)	(362.4)	(117.9)
L4.a_r	157.0	190.8*	198.1	181.8*
	(107.7)	(99.50)	(172.9)	(93.68)
L5.a_r	8.478	29.77	49.75	35.78
	(92.86)	(92.33)	(153.0)	(91.10)
F.a_r	-2.905	2.616	-82.42	11.07
	(94.76)	(61.61)	(240.7)	(60.52)
F2.a_r	99.16	94.23	19.03	90.56
	(102.4)	(98.73)	(177.7)	(105.6)
F3.a_r	59.16	104.1	-181.2	96.63
	(64.39)	(73.45)	(201.0)	(73.54)
F4.a_r	-30.51	80.95	-469.8	78.93
	(107.5)	(78.75)	(427.8)	(77.38)
F5.a_r	24.71	101.6	-356.8	91.72
	(120.0)	(108.2)	(381.6)	(118.5)
L.e_r	-1,303***	-924.0***	-2,361***	-822.7***
	(182.1)	(148.0)	(219.9)	(184.4)
L2.e_r	-1,065***	-822.3***	-1,620***	-752.2**
	(354.0)	(257.0)	(220.5)	(373.4)
L3.e_r	-687.8**	-522.5**	-1,260***	-500.7
	(282.9)	(254.4)	(177.8)	(310.1)
L4.e_r	-487.3***	-353.2***	-1,300***	-397.1***
	(88.40)	(90.07)	(447.4)	(145.3)
L5.e_r	105.7	43.39	267.1	17.00
	(127.3)	(116.9)	(345.3)	(135.9)
F3.e_r	-390.4***	-238.8***	-832.9***	-278.5***
	(73.40)	(55.59)	(170.7)	(52.04)
F4.e_r	-238.0***	-157.4***	-433.2***	-185.4***
	(53.34)	(45.37)	(101.8)	(48.99)
F5.e_r	64.22	38.79	176.6*	42.31
	(71.03)	(64.56)	(101.7)	(60.53)
Constant	6,005***	5,765***	7,580***	5,945***
	(33.88)	(22.59)	(57.68)	(29.14)
Observations	18,749	11,524	4,560	4,793
R-squared	0.918	0.953	0.913	0.967
County FE	X	X	X	X
Year FE	X	X	X	X

Standard Errors Clustered at the State Level

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



(a) Spending per-pupil for counties in bottom 25 percent

(b) Spending per-pupil for counties in bottom 25 percent

Figure C.0.2: Event study for court reform at county level

Table C.0.1: School Finance Cases and Litigation

State	Year	Constitutionality of finance system	Type of Reform
Alabama	1993	Overturned	Adequacy
Alaska	1999	Overturned	Adequacy
Arizona	1994	Overturned	Adequacy
Arizona	1997	Overturned	Adequacy
Arizona	1998	Overturned	Adequacy
Arizona	2007	Overturned	Adequacy
Arizona	1973	Upheld	
Arizona	1980		Legislative
Arkansas	2002	Overturned	Adequacy
Arkansas	2005	Overturned	Adequacy
Arkansas	1983	Overturned	Equity
Arkansas	1994	Overturned	Equity
California	1971	Overturned	Equity
California	1977	Overturned	Equity
California	1986	Upheld	
California	1988		Legislative
Colorado	1982	Upheld	
Colorado	1994		Legislative
Connecticut	1995	Overturned	Adequacy
Connecticut	2010	Overturned	Adequacy
Connecticut	1978	Overturned	Equity
Connecticut	1982	Overturned	Equity
Connecticut	1985	Upheld	
Delaware			
Florida	1996	Upheld	
Florida	2006	Upheld	
Florida	2009	Upheld	
Florida	1973		Legislative
Georgia	1981	Upheld	
Georgia	1986		Legislative
Hawaii			
Idaho	1998	Overturned	Adequacy
Idaho	2005	Overturned	
Idaho	1975	Upheld	
Idaho	1990	Upheld	

State	Year	Constitutionality of finance system	Type of Reform
Iowa	1972		Legislative
Iowa	1992		Legislative
Kansas	2005	Overturned	Adequacy
Kansas	1972	Overturned	Equity
Kansas	1981	Upheld	
Kansas	1994	Upheld	
Kansas	1992		Legislative
Kentucky	1989	Overturned	Adequacy
Kentucky	2007	Upheld	
Louisiana	1976	Upheld	
Louisiana	1987	Upheld	
Louisiana	1998	Upheld	
Louisiana	1992		Legislative
Maine	1995	Upheld	
Maine	1978		Legislative
Maine	1985		Legislative
Maine	1996		Legislative
Maine	2004		Legislative
Illinois	1973	Upheld	
Illinois	1976	Upheld	
Illinois	1996	Upheld	
Illinois	1973		Legislative
Illinois	1980		Legislative
Illinois	1999		Legislative
Indiana	1993		Legislative

State	Year	Constitutionality of finance system	Type of Reform
Maryland	2005	Overturned	Adequacy
Maryland	1972	Upheld	
Maryland	1983	Upheld	
Maryland	1996	Upheld	
Maryland	2002	Upheld	
Maryland	1987		Legislative
Maryland	2002		Legislative
Massachuset ts	1993	Overturned	
Massachuset ts	2005	Upheld	
Massachuset ts	1978		Legislative
Massachuset ts	1985		Legislative
Michigan	1997	Overturned	Adequacy
Michigan	1973	Upheld	
Michigan	1984	Upheld	
Michigan	1973		Legislative
Michigan	1994		Legislative
Minnesota	1971	Upheld	
Minnesota	1993	Upheld	
Minnesota	1973		Legislative
Minnesota	1989		Legislative
Mississippi	1997		Legislative
Missouri	1993	Overturned	Adequacy
Missouri	1977		Legislative
Montana	2005	Overturned	Adequacy
Montana	2008	Overturned	Adequacy
Montana	1989	Overturned	Equity
Montana	1993	Overturned	Equity

State	Year	Constitutionality of finance system	Type of Reform
Nebraska	1993	Upheld	
Nebraska	2007	Upheld	
Nebraska	1967		Legislative
Nebraska	1990		Legislative
Nebraska	1997		Legislative
Nevada			
New Hampshire	1993	Overturned	Adequacy
New Hampshire	1997	Overturned	Adequacy
New Hampshire	1999	Overturned	Adequacy
New Hampshire	2002	Overturned	Adequacy
New Hampshire	2006	Overturned	Adequacy
New Hampshire	1985		Legislative
New Jersey	1990	Overturned	Adequacy
New Jersey	1991	Overturned	Adequacy
New Jersey	1994	Overturned	Adequacy
New Jersey	1973	Overturned	Equity
New Jersey	1976	Overturned	Equity
New Mexico	1998	Overturned	Equity
New Mexico	1974		Legislative
New York	2003	Overturned	Adequacy
New York	2006	Overturned	Adequacy
New York	1972	Upheld	
New York	1982	Upheld	
New York	1987	Upheld	
New York	1993	Upheld	

State	Year	Constitutionality of finance system	Type of Reform
North Carolina	1997	Overturned	Adequacy
North Carolina	2004	Overturned	Adequacy
North Carolina	1987	Upheld	
North Carolina	1994	Upheld	
North Dakota	1993	Upheld	
North Dakota	2007		Legislative
North Dakota			
Ohio	1997	Overturned	Adequacy
Ohio	2000	Overturned	Adequacy
Ohio	2002	Overturned	Adequacy
Ohio	1979	Upheld	
Ohio	1991	Upheld	
Ohio	1975		Legislative
Ohio	2010		
Oklahoma	1987	Upheld	
Oklahoma	1981		Legislative
Oregon	2009	Overturned	Adequacy
Oregon	1991	Upheld	Legislative
Oregon	1976	Upheld	

State	Year	Constitutionality of finance system	Type of Reform
Oregon	1991	Upheld	
Oregon	1995	Upheld	
Oregon	1999	Upheld	
Oregon	1978		Legislative
Pennsylvania	1975	Upheld	
Pennsylvania	1979	Upheld	
Pennsylvania	1987	Upheld	
Pennsylvania	1991	Upheld	
Pennsylvania	1991		Legislative
Pennsylvania	2008		Legislative
Rhode Island	1995	Upheld	
Rhode Island	1985		Legislative
Rhode Island	1996		Legislative
South Carolina	2005	Overturned	Adequacy
South Carolina	1988	Upheld	
South Carolina	1993	Upheld	
South Carolina	1977		Legislative
South Carolina	1984		Legislative
Tennessee	1995	Overturned	Adequacy
Tennessee	2002	Overturned	Adequacy
Tennessee	1993	Overturned	Equity
Tennessee	1977		Legislative

State	Year	Constitutionality of finance system	Type of Reform
Texas	2004	Overturned	Adequacy
Texas	1989	Overturned	Equity
Texas	1991	Overturned	Equity
Texas	1992	Overturned	Equity
Texas	1973	Upheld	
Texas	1995	Upheld	
Texas	1986		Legislative
Utah	1973		Legislative
Utah	1993		Legislative
Vermont	1997	Overturned	Equity
Vermont	1994	Upheld	
Vermont	1969		Legislative
Vermont	1982		Legislative
Vermont	1987		Legislative
Vermont	2003		Legislative
Virginia	1994	Upheld	
Virginia	1972		Legislative
Virginia	1975		Legislative
Virginia	1989		Legislative
Washington	1977	Overturned	Adequacy
Washington	1991	Overturned	Adequacy
Washington	2007	Overturned	Equity
Washington	1974	Upheld	
West Virginia	1979	Overturned	Adequacy
West Virginia	1995	Overturned	Adequacy
West Virginia	1984	Overturned	Equity
West Virginia	1998		Legislative
Wisconsin	1976	Overturned	Equity
Wisconsin	1989	Upheld	
Wisconsin	2000	Upheld	
Wisconsin	1973		Legislative
Wyoming	1995	Overturned	Adequacy
Wyoming	2001	Overturned	Adequacy
Wyoming	1980	Overturned	Equity

Table C.0.2: Source: Jackson et al. (2015)

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