Essays in Macroeconomic effects of Labor Market Heterogeneity and Impact of Public Policies on Labor outcomes.

A Dissertation
submitted to the Faculty of the
Graduate School of Arts and Sciences
of Georgetown University
in partial fulfillment of the requirements for the
degree of
Doctor of Philosophy
in Economics

By

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Washington, DC
May 16, 2017

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Abstract

My dissertation explores the macroeconomic implications of heterogeneity in labor markets and the role of public policy in improving labor market efficiency. First, I aim to shed light on the importance of individual and firm level decisions in determining aggregate labor market outcomes such as the level of mismatch in worker skills and job requirements. Second, I analyze the role of public policy in affecting these decisions and hence, the economy wide aggregates.

The first chapter analyzes the relationship between age and the skill requirements of jobs performed by workers. I document that the proportion of college degree holders working in occupations that do not require a college degree is U-shaped over the life cycle and that there is a rise in transitions to non-college jobs among prime age college workers. The downward trend at initial stages of the life cycle is consistent with workhorse models of labor mobility, however, the rising trend at middle stages of the career is not. Such movements down the occupation ladder are also accompanied by average wage losses of 10% from the previous year. I develop an equilibrium model of frictional occupation matching featuring skill accumulation and depreciation along with worker and firm heterogeneity that can match the life cycle profile of downward occupational mobility. The model shows that skill depreciation is the key driver of transitions to low skill jobs with age. Using the model, I simulate the impact of

different types of structural change in the labor market and find that the welfare consequences of long term changes depend on the interaction of the life cycle and human capital investment dimension.

The second chapter, coauthored with Adriana Kugler, examines whether greater Medicaid generosity encourages people to switch towards riskier but also better quality occupations. Exploiting variation in Medicaid eligibility expansions across states during the 1990s and 2000s, we find that moving from a state in the 10th to the 90th percentile in terms of Medicaid generosity increased occupational mobility by 5.2%. Higher Medicaid generosity also increased mobility towards occupations with greater wage spreads and higher median wages, and towards occupations with higher educational requirements. By contrast, a decrease in Medicaid generosity in Tennessee in the 2000s decreased occupation switches and increased mobility towards low quality occupations.

The third chapter, coauthored with Shaiza Qayyum, uses the change in health insurance options made available to young adults under the age of 26 under the Affordable Care Act in March 2010 to analyze the effects on their labor market outcomes. The key selling point of the ACA dependent coverage law was that young adults would not be locked into jobs for employer-provided health insurance, and would be willing to shop jobs or be willing to start new ventures. The aim of this paper is to see to what extent the ACA delivered on its promise to young adults, and how it affected the long-term career of these individuals. We find that young adults were more likely to get health insurance as dependents, be less likely to be employed and more likely to be self-employed. We also find that individuals aged 19-21 were more likely to be enrolled in school. Conditional on being employed, young adults exposed to the law earned lower wages and exhibited increased job mobility. In the long-run, self-employment among 24 year olds in 2010, exposed to the law

for two years, increased by 31% and employment among this group increased by 2.5%. Conditional on being employed, young adults were also less likely to switch occupations in the long-run, suggesting that after the initial job shopping, young adults were better able to match with their desired occupations.

INDEX WORDS: Occupational Mobility, Life-cycle Search, Matching, Human Capital, Occupational Mismatch, Job Lock, Public Health Insurance

Acknowledgments

I would like to thank my dissertation advisors James Albrecht and Susan Vroman and my dissertation committee members, Axel Anderson and Adriana Kugler for guiding me through my dissertation.

Table of Contents

List of Figures

List of Tables

Chapter 1

The U-shape of Over-education? Human Capital Dynamics & Occupational Mobility over the Life Cycle

1.1 Introduction

Unemployment has been a major focus of macroeconomic models of the labor market. The workhorse model in the literature, aptly named the DMP model, features equilibrium involuntary unemployment and has been used for various macroeconomic questions related to the labor market. However, within this literature there has been less focus on “unsuitable" employment in the labor market, such as a college graduates waiting tables and most of the research on this state of the labor market has focused on younger workers. This paper focuses on the incidence of one type of unsuitable employment, namely over-education, documents how it evolves over the course of the life cycle and develops a model that provides an explanation for the stylized facts.

I document that the proportion of college graduates working in jobs that do not require a college degree is U-shaped over the life cycle.[1] Around 30 percent of college graduates are working in non-college jobs at age 30. This percentage decreases until age 40 and then starts rising again. By the age of 65, around 35 percent of college graduates are working in non-college jobs. I call these workers over-educated and refer to their state as over-education or over-educated employment.[2] The downward trend

[1] I focus on college graduates since there is a natural “unsuitable" job for this group-jobs that do not require a college degree

[2] *Matched workers* are college graduates employed in jobs that require a college degree.

at initial stages of the career is consistent with existing models of labor mobility in which mismatch in worker skills and skill requirements of the job decreases over time as workers overcome search and learning frictions. However, the rise at later stages of the career presents a challenge to such commonly used theories of job ladder and career advancement.

Using longitudinal data I show that among college graduates, prime age workers are more likely to move from college jobs to non-college jobs than younger workers. There is a lot of heterogeneity in these transition probabilities across age which does not show up in the aggregate measure of over-education by age. As is well known, job switching declines with time spent in the labor market as workers accumulate occupation or job specific human capital. However, among those who switch occupations during prime working age years, a higher percentage make transitions to lower skill jobs. Hence, the flow of workers into over-educated jobs increases with age explaining the rise in the overall U-shape of over-education after age 40. Furthermore, I document that workers who make these downward switches in occupations suffer average wage losses of 10% and the college wage premium for the over-educated group is significantly lower than that for the matched workers.

The stylized fact on over-education over the life cycle survives various robustness checks such as restricting the sample to male full time workers and using alternative measures of over-education.[3] I also show that workers who transition to over-education come from the lower end of the wage distribution among college educated workers and almost half of them make such transitions without an intervening unemployment spell. Finally, using other measures of job quality such as experience requirements, cognitive skill requirements and median wages, I show that non-college jobs performed by college educated workers are similar to jobs held by non-college workers.

[3] These alternative measures are discussed in section 2.4

There could be two possible mechanisms that may cause a person to be over-educated in his/her job. The worker may be stuck in a low type job because of labor market imperfections. Such a worker would perform better if he/she were reallocated to a higher type job. This phenomenon is usually referred to as mismatch employment in the literature. The second possible explanation could be that the over-educated worker does not have the required skills to work in a high type job. Such a worker would not be classified as mismatched because the skill level of the worker is consistent with the requirements of the job.

To explain the documented empirical facts, I build a life cycle model of occupational matching with search frictions, on-the-job search and evolving worker productivities. Occupations are vertically differentiated with homogeneous firms within each occupation. The match level production function incorporates positive complementaries between worker ability and firm productivity while allowing for higher skill requirements in high skill occupations. Each worker draws his/her initial skills from a distribution that depends on the acquired education level. The key novel ingredient in my framework is that worker skills can be enhanced by investments in worker skills decided jointly by the worker and firm match. These investments along with a fixed depreciation rate and idiosyncratic shocks determine how worker productivities evolve over the course of the life cycle.

The equilibrium features Positive Associative Matching (or PAM) in which high ability workers match with firms in high productivity occupations. Workers with low skill levels are unable to form matches in high skill occupations due to higher skill requirements in those jobs. Employed workers receive offers from firms in other occupations and move to firms with higher match surpluses. On the job training for younger workers makes them more productive and they climb the occupation ladder through on-the-job search or following an unemployment spell. However, as workers become older and approach an exogenous retirement age, the incentive to invest in worker skills decreases. As a result, skill depreciation leads to a net decline in the productivity of the workers and they choose to move to lower rungs of the ladder if an outside offer comes their way. Workers also move down the occupation ladder after exogenous destruction shocks end high productivity matches.

The model is then calibrated to match (i) the over-education profile documented in the data, (ii) wage growth over the life cycle and (iii) the proportion of workers of each education level working in different occupation groups and (iv) the probability to transition to low skill jobs as a function of worker wages. The calibrated model shows that skill depreciation is the key ingredient for explaining transitions to lower skill jobs among prime age and older workers. A model without the fixed depreciation of skills leads to workers moving to higher skill jobs as they become older, a prediction inconsistent with the data.

The model is well suited for studying the effects of structural change in the labor market on the careers of workers and how long term changes interact with life cycle patterns. In a counter-factual exercise, I simulate a particular type of structural change in which the productivity of middle skill occupations is decreased permanently. I find that in comparison to the baseline results, the new steady state features “job polarization" with employment growth in low and high skill occupations at the expense of middle skill occupations. I also find that workers earn higher wages on average in the new economy. This is because high skill occupations gain more employment than low skill ones under this scenario. In another counter-factual exercise I increase the skill requirements of high skilled occupations from the baseline calibration. This also leads to a decline in employment in middle skill occupations but a larger part of the workforce is reallocated to low skill jobs. I find that workers earn lower wages on average in this new economy. This result is driven by the lack of progression up the occupation ladder due to the higher skill requirements of jobs.

1.1.1 Literature Review

The empirical results in this paper conform with some recent work on the occupational transitions of prime age and older workers. Focusing on occupational mobility within firms, [28] finds that a substantial amount of re-allocation within firms is to lower quality jobs, where the quality of a job is defined by measures taken from the O*NET database and includes the education requirements of jobs. She also documents that for young workers, the predominant move is to high skilled jobs while for older workers occupation changes are mostly towards low skill jobs.

Theoretically this paper is related to models of occupation choice ([48]). The main insight from this literature is that workers find their comparative advantage as they try different occupations. Occupations are assumed to be identical in skill requirements but workers have occupation specific ability which they discover over time. As workers sample more occupations they find the match with the highest ability. This mechanism generates worker turnover across occupations. Several papers have used such models to explain empirical regularities about labor turnover such as declining occupation switching by age, increasing wages by tenure and high unemployment rates for the young ([57]; [32]). A recent paper by [33] emphasizes the role of adding absolute advantage to the theory of comparative advantage. They introduce vertically differentiated occupations in an equilibrium environment to explain occupational mobility patterns across the wage distribution.

The mechanisms present in these models however, cannot generate the empirical patterns documented here. These models will predict that workers move to better matches over time and stay there. This will thus produce a downward sloping profile for over-education over the life cycle instead of a U-shape. To generate the life cycle patterns documented here, I borrow insights from the literature on life cycle wage growth and human capital (see [60], [62] and [44]). In these models, workers make active human capital investments over their career where the opportunity cost of investment is forgone earnings. Human capital investments decline with age and worker productivity is thus hump-shaped over the life cycle.

On a theoretical level, I combine vertical sorting into occupations with human capital investment and search frictions while endogenizing the vacancy posting decisions of the firms. Most matching models assume that the distribution of attributes on both sides of the market is exogenous and fixed. Recently, some dynamic matching papers have started to relax this assumption and analyze environments where the attributes change based upon the match [6]. In my setup, the attributes of the occupations stay fixed but the productivity of the workers evolves based on human capital investments. These investments in turn depend on the occupation that the worker is currently matched with and upon his chances of moving up the occupation ladder.

The two most closely related papers to my work are [27] and [52] which also incorporate investment in worker training by firms in a frictional environment. While the former abstracts from firm heterogeneity, the latter restricts training to be of two types, high and low. In contrast, this paper features ex-ante firm heterogeneity, continuous time investments in worker training from the interval $[0, 1]$ and skill depreciation during unemployment. Finally, compared to the two papers above, I allow unemployed workers to direct their search towards occupations with different production technologies and job finding rates. Moving beyond the technical differences, the motivation of my paper is to explain the occupational choice of workers over the life cycle with an added emphasis on downward mobility while these papers focus on explaining life cycle wage growth and the role of frictions in determining the returns to training.

1.2 Stylized Facts

1.2.1 Measuring Required Level of Education for Occupations

I use the Department of Labor's O*NET data to measure education requirements for each occupation. The O*NET program collects data on entry requirements, work styles and task content within occupations by surveying each occupation's working population. For educational requirements, I use the question that asks incumbent workers, "If someone was being hired to perform this job, indicate the level of education that would be required". The survey respondents are reminded that the question is not asking about the level of education that the incumbent has achieved. Respondents are given options such as less than high school, high school, some college, associate's degree, bachelor's degree, etc. To assign a required level of education to each occupation, I use the distribution of responses. If more than 50 percent of respondents within an occupation agree on the required education level then I assign that education category as the requirement. If less than 50 percent of respondents agree on the required level of education then I assign the mode of the responses as the required level of education but only if the difference between the mode and second largest category is greater than 5 percent. If the difference is less than 5 percent then I assume that both education categories can be the required level of education for that particular occupation.[4]

[4] In the appendix I use an alternative measure of required level of education in terms of years of education. The results over the life cycle are similar with that measure as well.

1.2.2 Measuring Over/Under Education

I combine the education requirement data with survey data on worker characteristics such as the Current Population Survey (CPS). The CPS data contains information on each worker's acquired level of education and the worker's current or most recent occupation. It is also a longitudinal dataset and workers can be observed one year apart and I use this feature to document transition patterns across labor market states by age.

I define two measures of over-education and focus only on individuals with a bachelor's degree or higher. In the first measure, I restrict attention to bachelor degree holders and define them as over-educated if they are working in non-college jobs. College jobs are defined as occupations that require at least a college degree or higher. For my second measure, I use individuals with more than a college education and define them as over-educated if they are working in a non-college job. The latter measure understates over-education at the top of the education distribution because it is highly unlikely that a person with a doctoral degree is working in a non-college job. Nevertheless, I use this measure to avoid misclassification of highly educated workers as over-educated. Most of the results on the second measure are reported in the appendix.

The method used for measuring education requirements of occupations is consistent with the approaches taken in the over-education literature [53]. It also matches up well with a subjective measure of over-education from the National Survey of College Graduates. The O*NET database matched with CPS has also been used by [2] to determine the aggregate level of over-education in the U.S economy and how it evolves over the business cycle. In the appendix, I show that the over-education measure used by [2], which uses a different definition of college jobs, produces similar patterns over the life cycle.

1.2.3 Over-Education over the Life cycle

I now present my main empirical finding regarding over-education over the life cycle. I use cross-sectional data from the Current Population Survey-Merged Outgoing Rotation Groups (CPS-MORG) to report the proportion of people of each age group who are over-educated in the years 2003-2010. The choice of time period is based upon the timing of the collection of education requirements in the O*NET data which started during the 2000s. Robustness results from the PSID are presented in the appendix in which I follow workers longitudinally for multiple years to produce life cycle profiles of over-education and find similar results to cross-sectional data.

Evidence from Current Population Survey

My benchmark method to estimate the life cycle profile of over-education is to perform a kernel-weighted local polynomial regression of the over-education status on the age of the individual. I choose a bandwidth of 5 and thus the results are similar to regressing the over-education status on dummy variables for 5 year age bins (without a constant) and plotting a best fit line through the co-efficients. I restrict the analysis to workers who are currently employed. All regressions are weighted by the cross-sectional weights and the number of hours worked by the respondent.

I find that, for bachelor degree holders, the incidence of over-education by age is U-shaped, as can be seen in Figure 1.1. Before age 30, more than 30 percent of bachelor degree holders are over-educated in their jobs. This proportion drops below 30 percent by age 40 as workers end up getting matched with jobs that require their level of education. However, the over-education ratio starts rising after age 40,

Figure 1.1: Data from CPS 2003-2010, merged with O*NET data

modestly at first and rapidly after age 50. The rise is such that by age 65 (the usual retirement age), there are more over-educated bachelor degree holders than there are at age 30. This fact is quite striking, especially with all the focus on the young college graduates not being able to secure good jobs. It seems that a higher proportion of workers suffer the same fate at later stages of their careers.

1.2.4 Robustness Checks

The U-shape of Over-Education for a Restricted Sample

Readers can perhaps question whether the pattern above is driven by particular demographic groups. In this section I repeat the analysis by restricting the sample to male full time workers. The results are shown in Figure 1.2. As can be seen the patterns across age for this sample are also very similar to the overall sample.

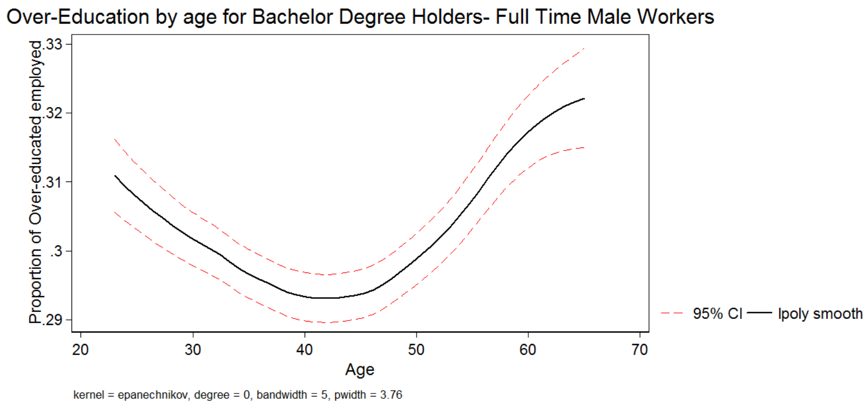


Figure 1.2: Sample Restricted to Male Full Time Workers from CPS

The U-shape of Over-Education after Controlling for Demographics and Year Fixed Effects

While it is true that being a female or a part-time worker has a positive impact on the incidence of over-education, the age profile of over-education after controlling for demographic characteristics is still U-shaped. In this section, I control for other demographic characteristics that might be important in explaining the incidence of over-education along with age. I also control for year fixed effects to show that this phenomenon is not driven by aggregate booms and busts. I then report the marginal effects with respect to age which can be interpreted as the residual effect of age on the incidence of over-education after controlling for demographics and year fixed effects. More specifically, I divide individuals into 5 year age bins and then estimate the following regression:

$$Y_{ia} = \beta_0 + \sum_{a=1}^{a=9} \beta_a D_{ia} + \gamma X_i + \delta_t \epsilon_{ia},$$

where Y_i is an indicator of over-education which equals 1 if person i is over-educated, and D_{ia} is a dummy variable which is 1 if individual i belongs to age group a. Demographic control variables are in the vector X_i which contains dummy variables for gender, marital status, self-employment status and a dummy variable for whether the individual was born in a foreign country. I plot the marginal effect of age on the incidence of over-education in Figure 1.3. As can be seen, the probability of being over-educated first declines and then rises with age. The results are thus similar to the ones presented in the previous sections where the proportion of over-education was U-shaped.

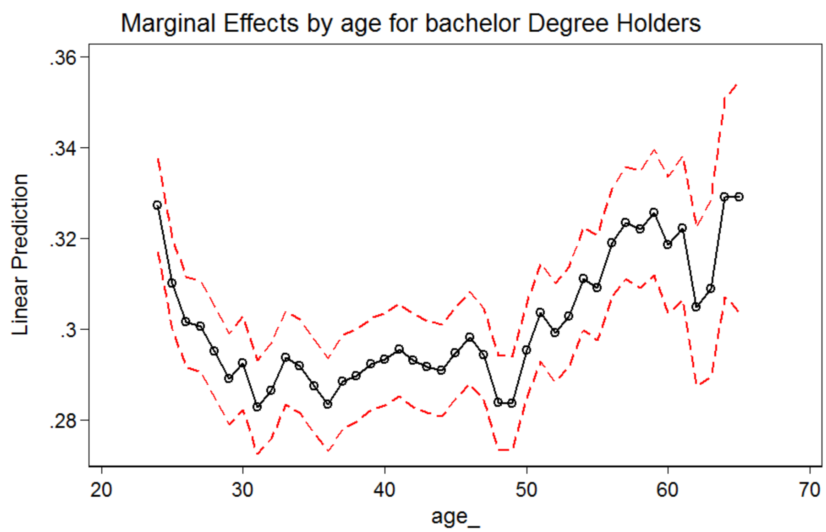


Figure 1.3: Controlling for Demographic Factors for Explaining Over-education

Evidence from National Survey of College Graduates

To provide corroborating evidence I use the National Survey of College Graduates (NSCG). The NSCG is conducted by the National Science Foundation and only contains college graduates, i.e., individuals with at least a bachelor's degree. Respondents who are employed at the time of the survey are asked the following question:

"Did your duties on this job(current job) require the technical expertise of a bachelor's degree or higher in ... ".

- Engineering, computer science, math or the natural sciences

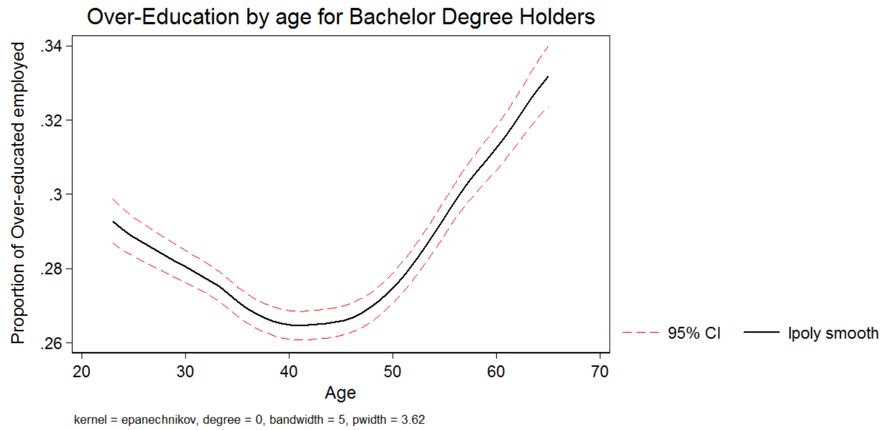


Figure 1.4: Subjective Measure of Over-education from NSCG, 2003-2012

- The social sciences
- Some other field (e.g., health business or education)-Specify

Respondents are asked to mark Yes or No for “each" item. I classify respondents as over-educated if they answer No to all three items. Notice that this measure is similar to the one developed above, where I defined some occupations as non-college jobs and defined over-education as college graduates working in non-college jobs. Thus, the life cycle profile of over-education from this measure should be the same as documented before using an objective measure. I use the NSCG samples from the years 2003, 2008 and 2010 in my empirical analysis.

Figure 1.4 provides evidence on over-education among college graduates in the NSCG. The magnitudes and the U-shape is similar to Figures 1.1, 1.2 and 1.4. This shows that the patterns in Figures 1.1 and 1.2 are not driven by the method used to construct education requirements using the O*NET data.

Transitions across Labor Market States

In this section I use the panel dimension of CPS-MORG data to document the transitions to and from the over-education state over the life cycle at yearly intervals. The results are shown below:

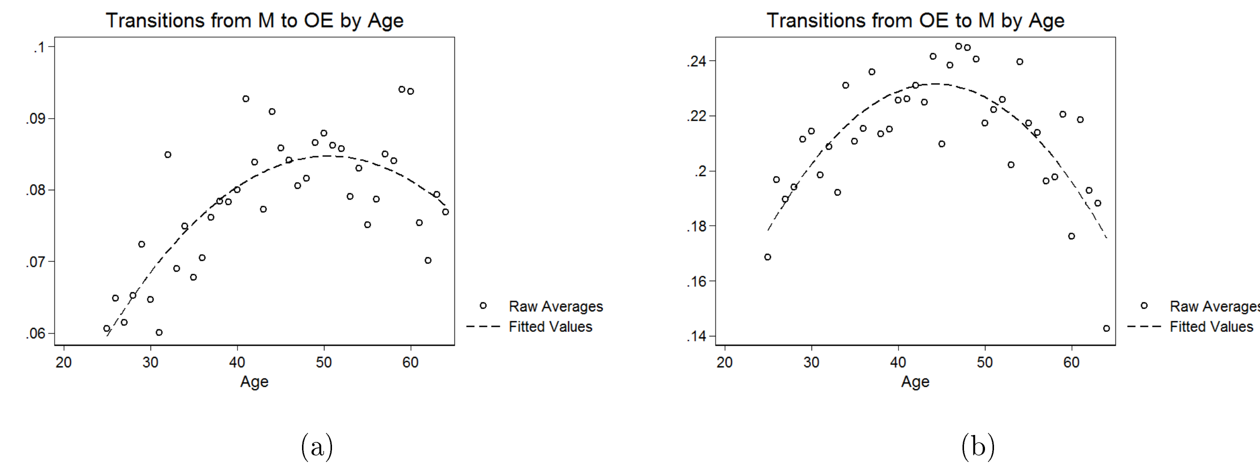


Figure 1.5: Transitions to Over-education (OE) by Age

Figure 1.5 shows that the probability of moving towards over-education increases with age. [5] Panel (a) shows that workers with a bachelor degree are more likely to move towards over-education with age. While transitions in the other direction decrease after the age of 40 as seen in panel (b). A noticeable feature of Figure 1.5 is that there is a lot of heterogeneity in the transition probabilities by age which is masked in the Figures 1.1 and 1.2. The probability to transition to over-education increases by 50% over the course of the life cycle while the probability to transition to matched state from over-education increases by 25% over the life cycle. Such large changes cancel each other out in the aggregate which leads to a change of 3% over the life cycle in the probability of being over-educated. Figure 1.6 shows these transitions conditional on an occupation switch. As can be seen the probability of moving

[5] The over-educated state is referenced by "OE" while the matched state is abbreviated by "M".

from over-education state to the matched state conditional on changing occupations is declining throughout the life cycle. On the other hand transitions to the over-education state stays relatively flat with age. Taken together these figures suggest that the U-shape of over-education with age observed in the cross-sectional data is driven by an increased flow of workers into over-education and a decreased outflow in the other direction.

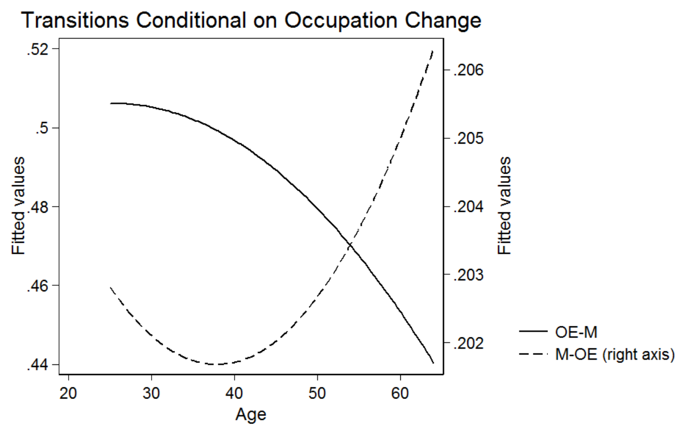


Figure 1.6: Transitions to Over-education (OE) by Age Conditional on Occupation Change

1.2.5 Implications of Over-education for Wages and Experience

Having established that college graduates make transitions to low skill jobs during prime working age, this section documents two additional facts associated with over-education. The literature has already documented that at the individual level, over-education is associated with lower wages and I corroborate this evidence across the life cycle in appendix Figure A.5. Here, I go one step further and show that workers who make transitions to over-education suffer real wage losses of around 10%. This would allay fears that transitions to over-education that I have presented before do not represent a movement down the occupation ladder. I also document that over-educated workers are more likely to be working in “Entry Level" jobs throughout the life cycle and there is no evidence that older over-educated workers are working in jobs that require more experience.

Wage effects

One advantage of using the CPS-MORG data is that they have information on a worker's weekly earnings and usual hours of work. Using this information one can construct the hourly wage rate for all employed individuals in the sample. Since I have data from multiple years, I construct real wages in 1999 dollars and then estimate wage growth from one year to the next for workers making different types of transitions. To document how wage losses upon transition to over-education differ with age, I also interact the transition to over-education dummy with the age variable. More specifically I estimate the following equation:

$$\Delta logw_i = \beta_0 + \beta_1 \mathbf{1}\{\text{M} \rightarrow \text{OE} = 1\} + \beta_2 \mathbf{1}\{\text{OE} \rightarrow \text{M} = 1\} + \beta_3 \mathbf{1}\{\text{Occ change}\} + \sum_{a=1}^{a=9} \gamma_a D_{ia} + \sum_{a=1}^{a=9} \delta_a D_{ia} \times \mathbf{1}\{\text{M} \rightarrow \text{OE} = 1\} + \lambda_t + \theta X_i + \epsilon_i$$

where β_1, β_2 and β_3 measure the effect of making a transition to over-education, making a transition to a matched job and making a occupation switch respectively. Furthermore, I add age dummies, year fixed effects, other demographic controls and interact the age dummies with the dummy variable for making a transition to over-education. The equation was estimated jointly for all college graduates [6] and I show the marginal effect of age on wage growth for workers making a transition to over-education and those who do not in Figure 1.7. While wage growth typically declines

[6] The equation is not estimated separately for bachelor degree holders and those with higher degrees.

after age 40, those making a transition to over-education suffer wage losses of around 10 % even at the age of 45. For comparison, the wage growth for workers not experiencing a transition to over-education at 45 is about 1 %.

Figure 1.7: One Year Wage Growth, Computed from CPS-MORG

Experience Requirements for Over-educated Workers

It might be the case that over-educated old age workers are working in jobs that require high experience and thus the jobs are different than the ones held by over-educated young workers. This would imply a tradeoff between skill and experience in the labor market. To test this hypothesis, I use the O*NET data to determine the experience requirements for each occupation. The O*NET data program asks the following question from incumbents about their occupations:

"If someone was being hired to perform this job, how much RELATED WORK EXPERIENCE would be required? (that is having other jobs that prepare the worker for the job)".

The answer is based on a 12 point scale with the values less than 5 indicating less than one year of required experience (potentially entry level jobs) and values greater than 10 indicating at least ten years of related work experience in similar jobs. Thus, using the methods described above for calculating education requirements for each occupation, I also determine the experience requirements for each occupation and merge it with CPS data. I then calculate the experience requirements of jobs held by over-educated and matched workers at different stages of their careers. The results of this exercise can be seen in Figure 1.8. Older workers who are over-educated are working in jobs which are similar to the jobs done by young over-educated workers in terms of experience requirements and they are mostly entry level jobs. Thus, older over-educated are also over-experienced in their jobs.

Showing that over-educated workers suffer wage losses upon making a transition and that they are not working in jobs that require a lot of experience shows that I have identified non-college jobs correctly using my measure of over-education. I provide further evidence in the appendix that this measure does a very good job of capturing differences across college and non-college jobs in various dimensions such as median wages, cognitive skill requirements of occupations and earned wages.

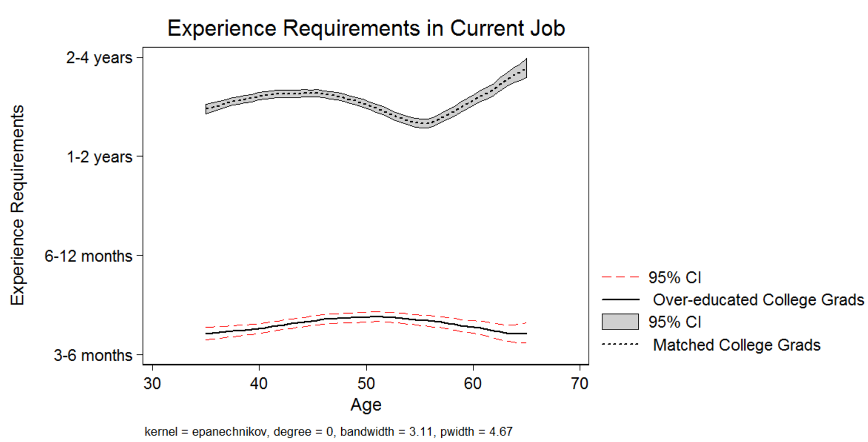


Figure 1.8: CPS Data Merged with Experience Requirements from O*NET

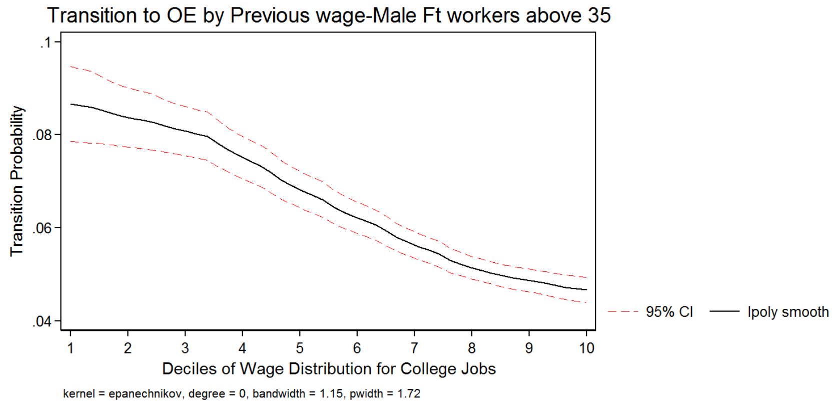


Figure 1.9: Transition to OE as a Function of Past Occupation Wage, CPS MORG

1.2.6 Who Transitions to Over-education and How?

To wrap up my stylized facts, I show that the probability of transitioning to over-education is monotonically decreasing in past wages and cognitive skill requirements and that such transitions do not occur only after unemployment spells. Figure 1.9 shows the probability of transitioning to over-education for male full time workers over the age of 35 as a function of their relative wage among workers working in college jobs. As can be seen workers at the lower end of the wage distribution are more likely to transition to over-education. This fact informs the model that I consider in the next section. Appendix Figure A.3 shows the rank of these workers (who made a transition to over-education) in the wage distribution of non-college jobs. Workers who made a transition to over-education are more likely to end up earning a higher wage relative to all workers in non-college jobs.

I also measure the probability of transitioning to over-education as a function of the skill requirements of the past occupation. The measure of skill requirements in a job is taken from [3] and it measures the cognitive skills required to perform a job.

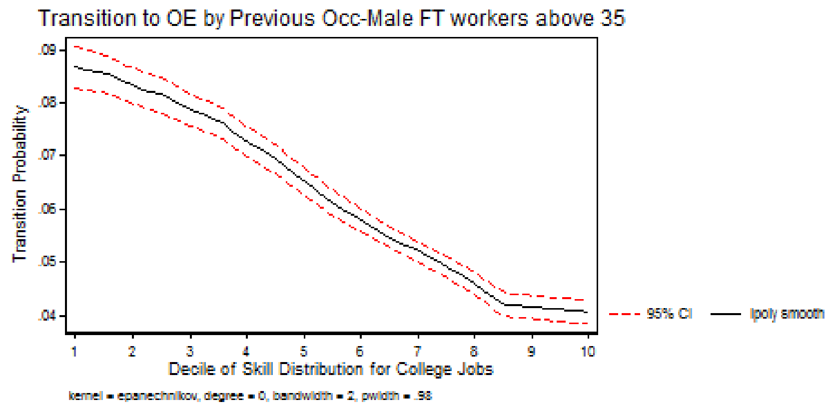


Figure 1.10: Transition to OE as a Function of Past Occupation Cognitive Skill Index

[3] argued that college educated workers are more likely to work in occupations that require more cognitive skills. I divide college occupations into 10 bins based on this measure. Thus, occupations in the 10th bin require the most cognitive skills among jobs that require a college degree.

I, then, estimate the probability of transitioning to over-education as a function of the skill requirement in the past job for male workers aged 35 and above who work more than 40 hours. The results are shown in Figure 1.10. Similar to Figure 1.9, workers in the lower end of the skill distribution are more than twice as likely to transition to over-education. Figure A.4 in the appendix shows that their most likely destination is the higher end of the skill distribution amongst non-college jobs.

Finally, I show that such downward transitions do not necessarily come after unemployment spells. In fact, as shown in Figure 1.11, almost half of the college workers moving to over-education had a job in the previous month. This fraction rises to 70% if one does not consider out of labor force workers as unemployed. The fact that a significant portion of these downward transitions happen without an intervening unemployment spell calls for a model which allows for job-to-job transitions. There is also significant upward mobility in terms of education requirements in the data, as can be seen from Figures 1.5 and 1.6, and most of such movements take place without intervening unemployment spells. This is another reason why job-to-job transitions should be allowed in a model which aims to explain movements up and down the job ladder in terms of education requirements.

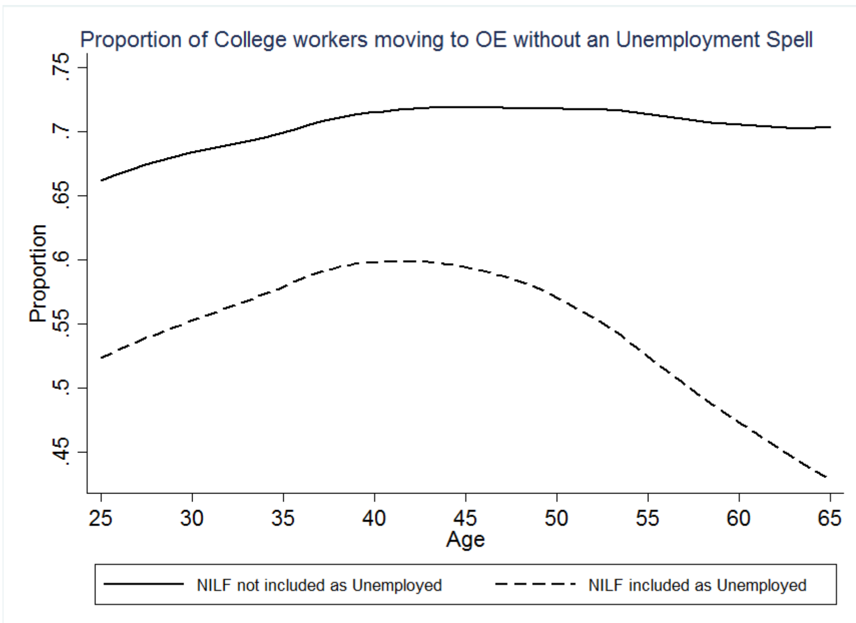


Figure 1.11: Transition to OE through Employment, CPS

1.3 Model

In this section, I present an equilibrium model of life cycle occupation search, with heterogeneous workers and firms, skill accumulation, idiosyncratic uncertainty and on-the-job search. Workers and firms encounter frictions in the matching process as in the canonical DMP model and they jointly decide how much to invest in worker skills.

1.3.1 Framework

Time is discrete and continues forever. There is a finite number of occupation submarkets indexed by $k = 1, 2, ...K$ which differ in terms of their production function, job finding probabilities and skill accumulation technology. Occupations are ranked in terms of their productivity with p_k being the productivity of the k^{th} occupation and $p_1 < p_2 < p_3....... < p_{K-1} < p_K$. Firms within each occupation submarket are assumed to be homogeneous and have access to the same production and skill accumulation technologies.

Each worker stays in the labor market for T periods and the age (or the time spent in the labor market) of the worker is indexed by t. Workers possess general human capital, h, which can be transferred across occupations and can be referred to as the skill or the productivity of the worker. The type of the worker can be summarized in the double $x = (h, t)$.

Workers are assumed to be risk neutral and discount the future at rate β. They choose to search in different occupations over time to maximize the sum of their discounted lifetime earnings. Unemployed workers have access to unemployment benefits which depend on the skill of the worker. Each occupation submarket has a DMP structure in which workers and firms match, production takes place, surplus is split and continuation decisions are made.

All workers enter the labor market with a starting level of productivity which is correlated with their level of education. When employed, a worker's productivity evolves endogenously based on the investment decisions made by the worker and firm within a match. Following the literature on endogenous human capital accumulation, it is assumed that each worker possesses a unit amount of time each period. This can be allocated to investments in human capital s, which lead to higher productivity in the future or to production activities $(1-s)$. In particular, a human capital evolution function is specified, $h' = g(s, h, z)$, which maps current human capital h to future human capital h' based on the investment decision s and shocks to skill accumulation, z. The level of worker skills that can be used in the production process is then $e = (1 - s)h$. Thus, the workers accumulate human capital by learning on the job as opposed to learning by doing. The key innovation of the current setup is that the investment decisions are not made by the worker but jointly by the worker and the firm as an outcome of a generalized Nash Bargain. [7] Workers do not accumulate human capital when unemployed.

Once matched within an occupation, the worker and the firm produce according to a occupation specific production technology. Defined at the match level, the production function combines worker skills and the productivity of the firm to create value added $f(e, p_k) \subset R$. I allow for the possibility that positive value added may require a threshold level of input from the worker. Thus, firms operating in higher productivity occupations might require workers to provide a minimum level of skill before they make positive profits. Another way to state this assumption is that high productivity jobs can only be performed by workers above a certain skill level. Such a restriction on the production technology has been used in the literature previously by [5] and more recently by [54]. Furthermore, I allow for complementaries between the worker and firm types, $f_{e,p_k} \geq 0$.

1.3.2 Hiring, Poaching and Separations

Unemployed workers can direct their search to different occupation submarkets while employed workers get random offers while employed. Unemployed workers searching in occupation k contact a vacancy with probability λ_k. Employed workers working in

[7] Such a setup has previously been formulated in [62].

occupation k get a job offer with probability λ_0 and the job offer is from occupation $l \neq k$ with probability

$$\eta_l = \frac{\lambda_l}{\sum_{i \neq k} \lambda_i}$$

Once a worker employed at a firm in occupation k receives an offer from a firm in occupation l, the worker ends up at the firm with the higher match surplus.

Wages and investment decisions are contingent upon the worker's type and also (potentially) on the outside option of the worker. For unemployed, the outside option is the value of unemployment and for employed, the outside option is either the total match value offered by a dominated firm (the one with a lower match surplus) or the value of unemployment if the worker has no offer from another firm. Hence, the value functions of the worker and the firm depend upon the type of the worker, the type of the firm and the outside option of the worker. Denote by $W_k(x, i)$ as the value function of a worker of type x working in occupation k with outside option i. Similarly, denote by $J_k(x, i)$ as the value function of a firm in occupation k in a match with a worker of type x with outside option i. Value of unemployment is denoted by $U(x)$ and the value of an open vacancy by V_k.

Define the surplus of a match between a worker of type x and a firm of type k as the sum of the surplus to the worker plus the surplus to the firm:

$$S_k(x) = W_k(x, i) - U(x) + J_k(x, i) - V_k \tag{1.1}$$

Here I am already assuming that the surplus is independent of the outside option of the worker. This is a standard result under the assumption of transferable utility and it will be shown later that this is indeed the case. Each period matches may end due to exogenous and endogenous reasons. Endogenous separation decisions are jointly efficient which implies that a worker and firm match ends if the match surplus is negative. Matches can also end due to exogenous reasons with probability δ. The separation probability can thus be described by the following function:

$$d_k(x) = \begin{cases} \delta, & \text{if } S_k(x) > 0 \\ 1, & \text{otherwise} \end{cases} \tag{1.2}$$

Based on the description of on-the-job search above, separation to another occupation is described by the following decision rule:

$$f_{l,k}(x) = \begin{cases} 1, & \text{if } S_l(x) > S_k(x) \\ 0, & \text{otherwise} \end{cases} \tag{1.3}$$

1.3.3 Worker's Problem

Now consider an unemployed worker characterized by the pair $x = (h, t)$ at the start of the period. The value function of the worker is given by:

$$U(x) = \max_{k(x)} bh + \beta \mathbb{E}_{x'|x,u} \left\{ (\lambda_k W_k(x', u) + (1 - \lambda_k) U(x')) \right\} \tag{1.4}$$

$$\begin{aligned} h' &= g_u(h, z) \\ t' &= t + 1 \\ U(x) &= bh \quad \text{when} \quad t = T \end{aligned} \tag{1.5}$$

where λ_k denotes the job finding probability in occupation k and $g_u(h, z)$ is the human capital evolution function during unemployment which depends upon the current productivity of the worker h and an exogenous shock process z. In the last period of the life cycle when $t = T$, the worker receives the flow value of unemployment and no continuation value.

The value of unemployment consists of the flow value of unemployment benefits, which are a linear function of worker human capital, and the discounted expected value at the start of next period. In the next period with probability $(1 - \lambda_k)$, the worker stays unemployed and with probability λ_k he finds a job in occupation k. In the latter scenario, the value function of the worker is denoted by $W_k(x, u)$ where the state variable u indicates that the outside option of the worker during bargaining was his value of unemployment. Workers choose the occupation k that maximizes their value today given their state variables. There is no direct (explicit flow cost) or indirect (through loss of human capital) reallocation cost to workers for switching occupations and thus they can switch to a new occupation in the next period. The occupation choice function associated with the above problem is $k(x)$.

Now consider an employed worker with state $x = (h, t)$ employed in occupation k. The value of employment depends upon the attributes of the worker, the type of the firm and the firm he or she uses as the outside option in Nash Bargaining. Using the terminology of [46], I refer to the latter firm as the "negotiation benchmark". I assume that when the worker receives no job offer when employed, wages and investment decisions are renegotiated and the negotiation benchmark becomes unemployment as is the case when the worker is hired out of unemployment.

The worker and the firm jointly agree upon the level of investment $s_k(x)$ which impacts worker productivity in the next period through the human capital production function. The units of worker skill used in the production process are given by $e_k(x) = (1 - s_k(x))h$. The expected value of employment for a worker of type x, matched to a firm of type k with negotiation benchmark i and investment in training, $s_k(x)$, is given by:

$$
\begin{aligned}
W_k(x,i) =& w_k(x,i) + \beta \mathbb{E}_{x'|x,k} \Bigg\{ d_k(x')U(x') + (1 - d_k(x')) \\
& \{\lambda_0 \sum_{l \neq k} \eta_l (f_{l,k}(x') W_l(x', k) + (1 - f_{l,k})(x') W_k(x', l)) \\
& + (1 - \lambda_0) W_k(x', u)\} \Bigg\}
\end{aligned}
\tag{1.6}
$$

$$
\begin{aligned}
h' &= g_k(h, s_k, z) \\
t' &= t + 1 \qquad\qquad (1.7)\\
W_k(x,i) &= w_k(x,i) \quad \text{when} \quad t = T
\end{aligned}
$$

The worker receives an outside offers in another occupation at rate λ_0. If the outside offer is from occupation l and $S(x,l) > S(x,k)$ then the worker moves to the firm of type l and firm k becomes the negotiation benchmark. On the other hand if $S(x,l) < S(x,k)$ then the worker stays with his current firm but firm l becomes the negotiation benchmark. At T, the worker receives the current wage and exits the labor market at the end of the period.

1.3.4 Firm's Problem

Consider the expected profit of firm in occupation k employing a worker of type $x = (h,t)$ and negotiation benchmark i assuming investment policy $s_k(x)$:

$$
\begin{aligned}
J_k(x,i) =& f(e_k(x), p_k) - w_k(x,i) + \beta \mathbb{E}_{x'|x,k} \Bigg\{ (1 - d(x')) \\
& \big\{ \lambda_0 \sum_{l \neq k} \eta_l ((1 - f_{l,k}(x')) J_k(x', l)) + (1 - \lambda_0) J_k(x', u) \big\} \Bigg\}
\end{aligned}
$$

where $d_k(x')$ is the separation decision defined above and is equal to 1 if the match surplus is negative. Otherwise matches break up with the exogenous probability δ. If the worker receives an outside offer from firm of type $l \neq k$ and $S(x,l) > S(x,k)$, the worker moves to firm l and firm $k's$ continuation value is given by V_k which is assumed to be equal to 0 in equilibrium and hence not presented in the firm value function above.

The amount of output produced by a worker firm pair depends on the production technology available to the firm in occupation k and the amount of worker skill used in the production process.

1.3.5 Bargaining, Wages and Investment Decisions

I assume that wages and investment decisions are determined by generalized Nash Bargaining. Following [25] and [14] I assume that when a worker encounters an outside offer, the worker moves to the firm with the higher match surplus and his outside option is the total match value offered by the dominated firm. This is the maximum value that the dominated firm can offer to the worker. When the worker does not have an outside offer or is hired from the unemployed pool, his outside option is the value of unemployment.

Define $M_k(x)$ as the total value of the match between worker of type x and firm of type k. This is equal to the sum of the value to the worker plus the value to the firm. Now consider a worker firm match in occupation k with worker type x and worker outside option $M_i(x)$ (total surplus from dominated firm i or the value of unemployment) that produces a positive surplus. The wage, $w_k(x,i)$, and investment, $s_k(x)$ solve the generalized Nash bargaining problem:

$$(w_k(x,i), s_k(x)) \in \arg\max \left[W_k(x,i) - M_i(x)\right]^q \left[J_k(x,i) - V_k\right]^{1-q} \tag{1.8}$$

where $q \in [0,1]$ is the exogenously specified bargaining power of the worker. Lemma 1 establishes a useful result.

Theorem 1.3.1 *$s_k(x) \in \arg\max S_k(x)$ iff $s_k(x)$ solves (8)*

Proof. Imposing the equilibrium free entry condition which leads to $V_k = 0$, the wage function $w_k(x)$ solves:

$$W_{k,i}(x) - M_i(x) = q[J_{k,i}(x) + W_{k,i}(x) - M_i(x)] = q[S_k(x) - S_i(x)] \tag{1.9}$$

Similarly, one can show that the wage function also solves the following equation

$$J_{k,i}(x) = (1-q)[S_k(x) - S_i(x)] \tag{1.10}$$

Substituting equations (9) and (10) into (8), the problem reduces to:

$$\begin{aligned} & s_k(x) \in \arg\max q^q (1-q)^{(1-q)} [S_k(x) - S_i(x)] \\ \iff & s_k(x) \in \arg\max S_k(x) \end{aligned} \tag{1.11}$$

Due to the bargaining protocol the current firm k takes the surplus of the match with firm i as given and hence the best response of firm k is to choose the level of investment to maximize its own surplus. Thus to determine the investment for each worker firm pair and the mobility decisions of the workers, it is useful to work with the surplus function rather than the individual value functions of the firm and the worker.

The surplus function can be written explicitly as

$$\begin{aligned} S_k(x) = \max \Big\{ 0, f(e(x), p_k) - bh + \beta \mathbb{E}_{x'|x,k}[(1 - d(x'))\{\eta_i \mathbf{1}_{\{S_i(x') > S_k(x')\}} q(S_i(x') - S_k(x')) \\ + S_k(x')\} + U(x')] - \beta \mathbb{E}_{x'|x,u}[U(x') + q \max_{j(x')} \lambda_j S_j(x')] \Big\} \end{aligned} \tag{1.12}$$

where the expectation operator is dependent on the state of the worker as human capital evolves differently during employment and unemployment. Note that the surplus function depends only on the attributes of the current firm and the worker and not on the type of the firm used as the negotiation benchmark.

The equation for the surplus function can be solved jointly with the value function for unemployment which can be rewritten as:

$$U(x) = bh + \mathbb{E}_{x'|x,u}\left[U(x') + q \max_{k(x')} \lambda_k S_k(x')\right] \tag{1.13}$$

1.3.6 Equilibrium

For the quantitative exercise in the next section, I consider the long run stationary equilibrium of the model economy and match data moments to model moments from the stationary equilibrium to calibrate model parameters. In a stationary equilibrium, the decisions of the workers are only dependent upon their type and not upon the distribution of workers in various states of the labor market. Similarly, the decisions of the firms depend upon the occupation in which they operate and the type of the worker they are matched with.

A stationary equilibrium is a set of value functions $U(x), W_k(x,i), S_k(x)$, occupation choice function $k(x)$, separation decision $d(x)$, wage function $w_k(x)$, investment functions $s_k(x)$ and laws of motion for the distribution of employed and unemployed workers over all states of the model such that:

1. The value functions satisfy equations (4), (6), (13) and (14).

2. Wages and investment decisions solve the generalized Nash bargaining problem (9).

3. The distribution of unemployed and employed workers across occupations is stationary and consistent with the policy functions above, shocks to the stock of human capital and job destruction shocks.

1.4 Quantitative Exercise

For the quantitative exercise I assume that there are three occupation sub-markets with $P_3 > P_2 > P_1$ and label 2 and 3 as college occupations while occupation 1 is referred to as non-college occupations. Within college occupations, occupation 3 refers to occupations that require more than a bachelors' degree. On the worker side heterogeneity comes from variation in initial human capital, h_0. I assume that workers with different education levels draw their initial productivity from the same distribution but with different means. These education levels or worker types are restricted to no-college workers (denoted by nc), bachelor degree holders (denoted by b) and workers with more than a college education (denoted by mc). These three types of workers draw initial human capital from log-normal distributions with mean μ_i, such that $\mu_{mc} > \mu_b > \mu_{nc}$, and variance 1. Hence, the quantitative exercise maps the observable level of education to unobservable worker productivity h and the model traces out the life cycle path of h which determines the occupations that workers work in.

1.4.1 Parametrization

The model period is set to one quarter and the workers are assumed to stay in the labor market for 160 time periods which implies a working life of 40 years. Value added at the match level in each occupation is parameterized in the following way:

$$f(e, p_k) = \tau_{1,k} e p_k - \tau_{0,k}$$

where I restrict $\tau_{1,k} = 1$ so that $f_{e,p_k} \geq 0$ and $\tau_{0,k} \geq 0$ and its value is to be estimated. This allows for the possibility that firms with higher p_k may operate with more costly non-labor inputs. If that is the case then only workers above a certain level of productivity would be able to deliver positive value added to the firms even if all their time is devoted to the production process and not divided between production and investment in human capital.

For the human capital transition function, I specify a functional form consistent with the literature that seeks to explain wage growth over the life cycle. In particular, the human capital transition function in occupation k is given by:

$$h' = g_k(s, h, \sigma, z) = exp(z)A_k(sh)^{\alpha} + (1 - \sigma_k)h$$

In the above specification, σ_k refers to the depreciation rate of human capital and A_k is referred to as the learning ability. I allow for both the learning ability and depreciation rate to be occupation specific.[8] I assume that worker skills cannot be augmented while the worker is unemployed. Idiosyncratic shocks to worker skills are captured through z which are i.i.d draws from a random normal distribution whose parameters have to be calibrated.

A direct consequence of this parametrization is that if $\tau_{0,k}$ is larger for high productivity occupations then young workers with lower human capital search and work in low productivity occupations, increase their productivity through costly investments and then move up the occupation ladder to higher productivity occupations. Similarly as workers get older, investments in human capital decline and depreciation leads to a fall in overall worker productivity which leads to workers separating from their matches in high productivity occupations and movement towards occupations with lower skill requirements.

[8]This is a departure from the literature on life cycle wage growth which assumes that ability is correlated with initial ability of the worker and depreciation rate is constant across individuals

1.4.2 Calibration

Some parameters of the model are set exogenously. In particular, the job finding probabilities for each occupation, λ_k, are calculated from the CPS data using the flows based approach of [63]. However, calculating the job finding probabilities for each occupation consistent with the definition in the model is not possible using CPS data. That is because when a worker is classified as unemployed in the CPS data, he is assigned the occupation that he was last working in. This may or may not be the occupation that he is currently searching in and this can lead to mis-measurement of the job finding rate for each occupation.

To circumvent this issue, I calculate the job finding probability for each occupation by education groups. The crucial assumption is that most non-college workers search in non-college occupations and college educated workers search in college occupations. Using this approach I find that $\lambda_1 > \lambda_2 > \lambda_3$. Moreover, it is always the case that non-college jobs are more easier to find than all college jobs. An alternative approach could be to estimate the job finding rates of each occupation group with the rest of the parameters by targeting transition rates into each occupation from employment and unemployment.

The rest of the parameters of the model are estimated to match certain moments from the data. The chosen moments include the fraction of people with bachelor degrees working in non-college occupations (or OE workers) by 5 year age bins, proportion of more-than-college workers who are in college jobs (or matched *mc* workers), proportion of non-college workers working in college jobs (or under-qualified *nc* workers), proportion of bachelor degree holders working in occupations requiring more than a bachelor's degree (occupation group 3), proportion of more-than-college workers working in occupation group 3, ratio of wages of OE workers to non-college workers, an unemployment rate of 5%,probability of transitioning to over-education as a function of worker's past wage percentile and life cycle wage growth. The probability of transitioning to over-education is normalized to 1 in the lowest percentile. Similarly, to capture wage growth over the life cycle wages are normalized to 1 for the youngest age group.

I now provide an informal identification argument that defends the moments chosen from the data. The proportion of workers in each occupation along with the job finding rates, helps identify the parameters of the production function and those of the initial distribution. The overall U-shape of over-education is informative about the human capital accumulation and depreciation process and provides information to identify both the production and the human capital evolution function parameters. These parameters are also disciplined by wage growth over the life cycle. The values for $\tau_{0,k}$ and σ_k are also directly related to the relationship between past wages and the probability to transition to over-education. The unemployment rate in the model depends upon the generosity of unemployment benefits conditional on the job finding rates and the parameters of the production function. Thus, the value of the unemployment rate helps identify the value of the parameter b.

Table 1.1 and Figure 1.12 show the fit of the model along these moments. The model does a good job of matching the overall shape of the life cycle profile of over-education observed in the data (see Table 1.1). However, it does over-predict the fraction of over-educated workers in the youngest age group. The model also matches the life cycle wage growth profile as well as the share of workers from different education groups working in occupations requiring college education or more. It also captures the empirical fact that the wages earned by over-educated workers are close to the wages earned by non-college workers, the ratio in the model being 1.05. The model also captures the decline in probability to transition to over-education as a function of

Table 1.1: Model Fit

Moment	Model	Target	Moment	Model	Target
% OE in bin 25-29	0.395	0.318	% “Matched" More than College Workers	0.908	0.908
% OE in bin 30-34	0.289	0.299	% “Under-qualified" Non-College Workers	0.197	0.212
% OE in bin 35-39	0.263	0.300	% Bachelor workers in Occ 3	0.086	0.072
% OE in bin 40-44	0.263	0.301	% More than Bachelor workers in Occ 3	0.319	0.387
% OE in bin 45-49	0.274	0.289	Ratio of wages: OE workers to Non-College Workers	1.054	1.073
% OE in bin 50-54	0.303	0.309	Unemployment Rate	0.046	0.050
% OE in bin 55-59	0.327	0.328			
% OE in bin 60-64	0.346	0.334			

the worker's past wage percentile however, it predicts lower probabilities for high past wages as compared to the data. This is because in the model high wage earners are high productivity workers who only transition to lower skill occupations if they suffer a separation or a human capital accumulation shock. Since all the moves down the occupation ladder are driven by a decline in worker productivity, high wage earners are less likely to move down the occupation ladder. The higher incidence of such transitions in the data for high wage earners could be driven by non-productivity related factors such as preference for job flexibility which are not captured by the model.

Table 1.2: Calibrated Parameters

Parameter	Value	Parameter	Values	Parameter	Values
P_1	3.20	μ_{nc}	1.820	σ_3	0.121
P_2	4.90	μ_b	3.275	μ_z	-0.05
P_3	6.85	μ_{mc}	4.203	$Var(z)$	0.100
τ_1	0	A_1	0.075	b	0.280
τ_2	-50	A_2	0.155		
τ_3	-200	A_3	0.175		
q	0.365	α	0.633		
λ_0	0.155	σ_1	0.088		
δ	0.012	σ_2	0.119		

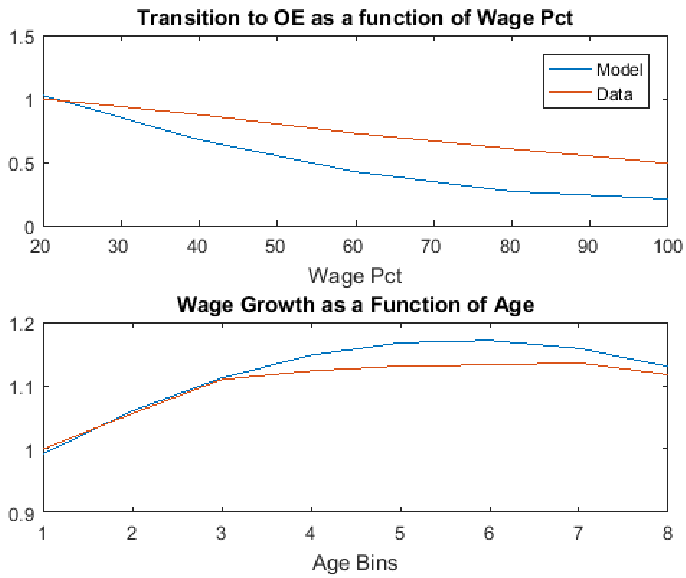
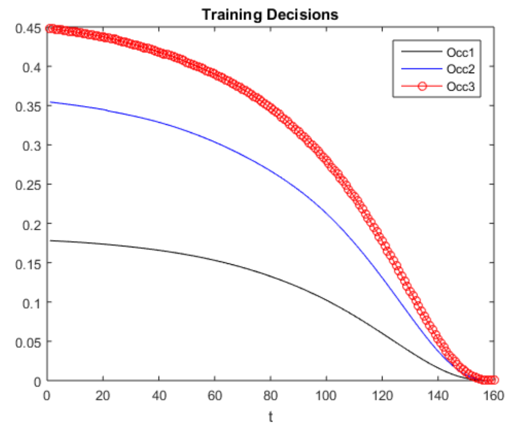
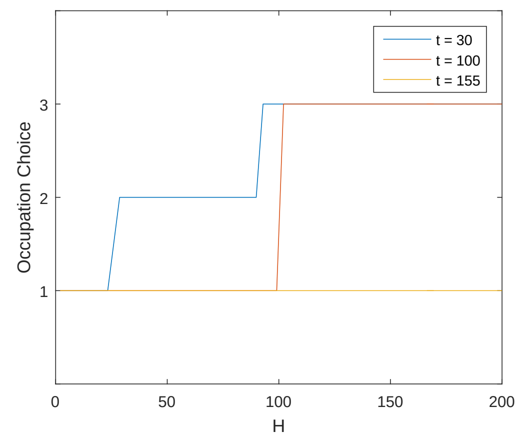


Figure 1.12: Targeted Moments

Table 1.2 shows the values of the estimated parameters. The calibrated values of the production function cannot be compared with any previous estimate. These values along with the human capital production functions and the job offer arrival probabilities of the employed workers determine the training decisions of the firms and the workers in each occupation group. Under the current calibration, as shown in Figure 1.13(a) firms in the most productive occupations invest the most in worker training. The production function parameters along with the job finding probability in each occupation also play an important role in the search strategies of workers across the age and productivity dimension. This interplay between the two can be seen in Figure 1.13(b) below. Young workers with low levels of human capital search in lower productivity occupations where the jobs are easier to find and the prospective matches are feasible. As their productivity evolves over the course of their careers, they



(a)



(b)

Figure 1.13: Model Results

start searching for higher productivity jobs. However, after a certain age threshold all workers search in the low productivity occupation because the jobs are easier to find. This is because at older ages the difference in the value a worker gets from a job in each occupation shrinks and the job search decision is driven by the differences in job finding rates which are constant across age.

The value of the bargaining power parameter is within the range of values estimated in the literature with on-the-job search (e.g see [58]). The human capital transition function parameters, A_k, α and σ_k are estimated from the average wage growth profile over the life cycle (Figure 1.12) as well as the transitions of workers towards lower productivity jobs as they become older (Table 1.1-column 1). The value of the on-the-job search parameter, λ_0, governs the transitions of workers across occupation groups without an intervening unemployment spell. The exogenous job destruction parameter is calibrated to achieve a reasonable steady state rate of unemployment. Under the current calibration, the steady state rate of unemployment is 4.58%. Notice that in this model, the unemployment rate is not only affected by the exogenous job destruction rate but also the search strategies of the workers. If all workers search in occupation 3 with the lowest job finding rate then the steady state unemployment rate would be higher for any given value of δ. Finally, the means of the education specific distribution from which workers draw their initial productivity, helps match the proportion of workers from each educational group working in different occupation categories.

1.4.3 Importance of Skill Depreciation

There are two forces which push older workers towards low productivity jobs, high job finding rates in low skilled occupations and skill depreciation which leads to less output being produced in high skill occupations. The importance of skill depreciation for matching the empirical facts can seen from Table 3. Here I perform a counter-factual experiment in which I set $\sigma_k = 0$ for all k, without changing the job finding rates for each occupation sub-market. Thus workers on average only gain skills and their skills do not depreciate with age. For this counter-factual economy I compute the steady state and compare the results to the baseline model with parameter values given in Table 2.

As the results show, without skill depreciation workers move towards occupation groups 2 and 3 as they become older even though it is easier to find jobs in lower productivity occupation group 1. About 75% of the workers without a college degree end up working in college occupations while in the baseline model this fraction is about 20%. Similarly, 85% of workers with a bachelor's degree are now working in occupation group 3 whereas the corresponding number in the baseline model is 7%. Hence, not surprisingly, the model does not produce the U-shape of over-education and instead the share of workers with college degrees working in non-college occupations declines

Table 1.3: Model Without Depreciation of Worker Productivity

Moment	No Depreciation	Baseline	Moment	No Depreciation	Baseline
% OE in bin 25-29	0.247	0.395	% "Matched" More than College Workers	0.989	0.908
% OE in bin 30-34	0.124	0.289	% "Under-qualified" Non-College Workers	0.753	0.212
% OE in bin 35-39	0.042	0.263	% Bachelor workers in Occ 3	0.653	0.072
% OE in bin 40-44	0.009	0.262	% More than Bachelor workers in Occ 3	0.842	0.387
% OE in bin 45-49	0.002	0.274	Ratio of wages OE workers to Non-College workers	0.643	1.073
% OE in bin 50-54	0.001	0.303	Unemployment Rate	0.059	0.045
% OE in bin 55-59	0.003	0.327			
% OE in bin 60-64	0.013	0.346			

with age. This exercise shows that human capital skill depreciation parameters play an important role in matching the empirical facts.

1.5 Model Applications

Having solved for the steady state of the model and matched the salient features of the data, one can recover the vacancy posting costs in each occupation using the free entry condition which stipulates that ex-ante profits of all firms in each occupation sub-market are 0. The model can then used for counter-factual analysis. The equilibrium nature of the model, with a substantial role for the firm in the career outcomes of workers, means that the model can be used to evaluate various policies and hypotheses and to simulate the effects of long run structural changes in the labor market on the careers of workers. In this section I describe the vacancy posting decisions of firms to back out the vacancy posting costs and then I analyze two types of structural change within the framework my model which lead to “job-polarization" and discuss the consequences on the careers of workers.

1.5.1 Vacancy Posting Decisions

Using the decisions of the workers, the steady state distribution and a specification of the matching function, one can back out the vacancy posting costs, which are assumed to be occupation specific, and these are used to conduct counterfactual experiments in section 5. I follow [54] for characterizing the vacancy posting decisions of the firms to back out these costs. Denote by $u_k(x)$ as the measure of workers who are unemployed of type x and searching in occupation submarket k. Similarly, denote by $e_k(x)$ as the measure of workers of type x and working in occupation k. For each occupation sub-market k, the effective search effort is

$$l_k = \int u_k(x)\,dx + \lambda_0 \sum_{i \neq k} f_{k,i}(x) \int e_i(x)\,dx \tag{1.14}$$

where λ_0 is the search effort of the employed workers relative to the unemployed and effective search effort of the employed workers in occupation k consists of all workers in ocupations $i \neq k$ such that they have a higher surplus in submarket k, which implies $f_{k,i}(x) = 1$. This is because only workers who have a higher surplus in occupation k will accept a job offer from that sub-market if they are already employed in occupation i and receive an offer on the job.

Denote by v_k as the number of vacancies posted by firms in sub-market k. The total measure of meetings in occupation k, m_k, is given by a Cobb-Douglas matching function

$$m_k \equiv min\left\{\zeta l_k^{\nu} v_k^{1-\nu}, l_k, v_k\right\}$$

The job finding probability for workers in occupation k, λ_k, can be written as $\lambda_k = m_k/l_k$. Similarly, $q_k = m_k/v_k$ is the probability per vacancy in sub-market k that a firm meets a searching worker. Given that the matching function is assumed to be

Cobb-Douglas, the probability q_k can be written as a function of market tightness $\theta_k = v_k/l_k$.

The value of posting a vacancy can now be written as:

$$V_k = -c_k + q(\theta_k)\left[\int J_k(x,u)\frac{u_k(x)}{l_k}\,dx + \lambda_0 \sum_{\{i\neq k\}} f_{k,i}(x)\int J_k(x,i)\frac{e_i(x)}{l_k}\,dx\right] \quad (1.15)$$

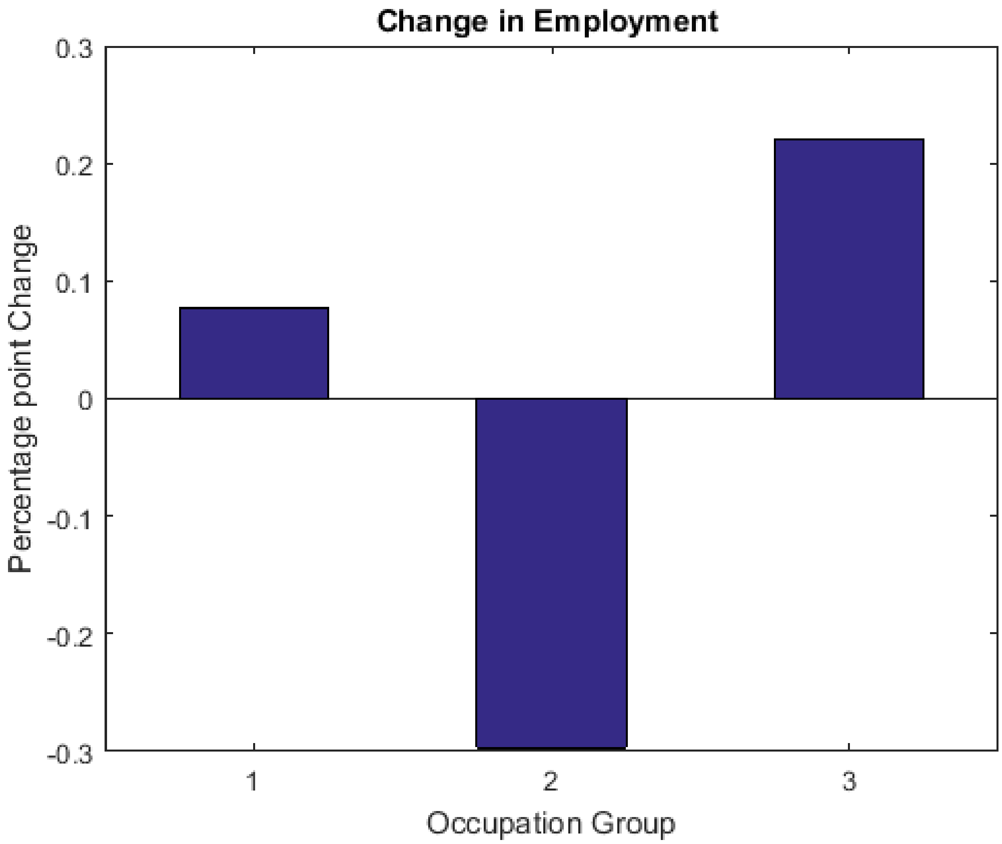
Equilibrium free entry condition would imply that $V_k = 0$ which can be used to back out vacancy posting costs c_k.

1.5.2 Job Polarization

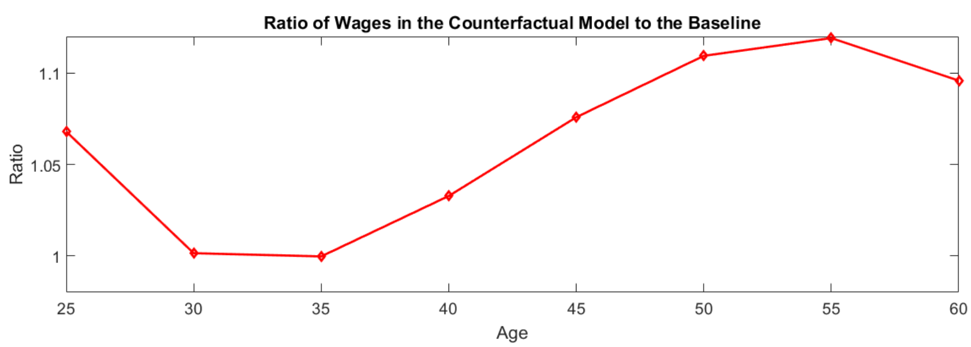
Consider a change in the relative productivity of one occupation submarket with respect to the others. If that occupation becomes more productive, then workers would try to work in that occupation and this could have significant impact on the careers of the workers along the transition path and in the new steady state.

The empirical work of [3] and numerous others has documented that the U.S labor market has gone through a period of polarization in the last three decades whereby middle skills jobs have disappeared while high and low skill jobs have increased. Although middle skill jobs in my setup are predominantly taken up by bachelor degree holders, I can simulate a similar change from the baseline model by decreasing the productivity of occupation group 2, p_2, from its calibrated value. In the new steady state of the model, see Figure 1.14(a), occupation group 2 has 30% less employment while occupation group 1 and 3 gain employment, with most of the increase going to group 3.

The effects on the overall welfare in the economy can be evaluated over the long run at the new steady state or during the transition to the new steady state. Here I compute the welfare effects in the new steady state and compare outcomes of workers



(a) Employment Changes



(b) Ratio of Wages

Figure 1.14: Effect of Decline in Middle Skill Occupation Productivity on Welfare and Jobs

of similar ages in the two economies. Figure 1.14(b) computes the ratio of average wages in the new economy to baseline model. As can be seen, the ratio is above 1 for all age groups which means that the workers are better off in the economy with lower productivity for middle skill occupation group. The ratio keeps increasing with age as well, this is because more older workers are working in occupation group 3 than before and hence earning higher wages.

To understand the result in Figure 1.14(b) it is useful to think about the consequences of a decline in occupation productivity on the investment decisions of the workers and the firms. In this new counter-factual economy workers and firms invest in more skills in the middle skill occupation group since the opportunity cost of training goes down[9]. This allows more workers to climb up the occupation ladder and work in the high skill occupation group and thus earn higher wages. Hence the wage growth at the latter part of the career is higher when workers are producing higher output as they are working in the high skill occupation with higher human capital.

1.5.3 Higher Skill Requirements in Jobs

In the above scenario, workers of all ages are better off in the new steady state of the model. In this sub-section I consider a counter-factual where young workers are better off in the new steady state and the older workers are worse off. The counter-factual scenario I consider here is one where the skill requirements of high productivity jobs increase, creating mismatch between the current skills of the workers and the requirements of the jobs. There has been a lot of debate in the policy and academic circles whether such a structural change in the economy or a "skill-gap" is contributing to the slow recovery in the labor market following the great recession. Some evidence

[9] The rental rate on human capital is now lower in the middle skill occupations

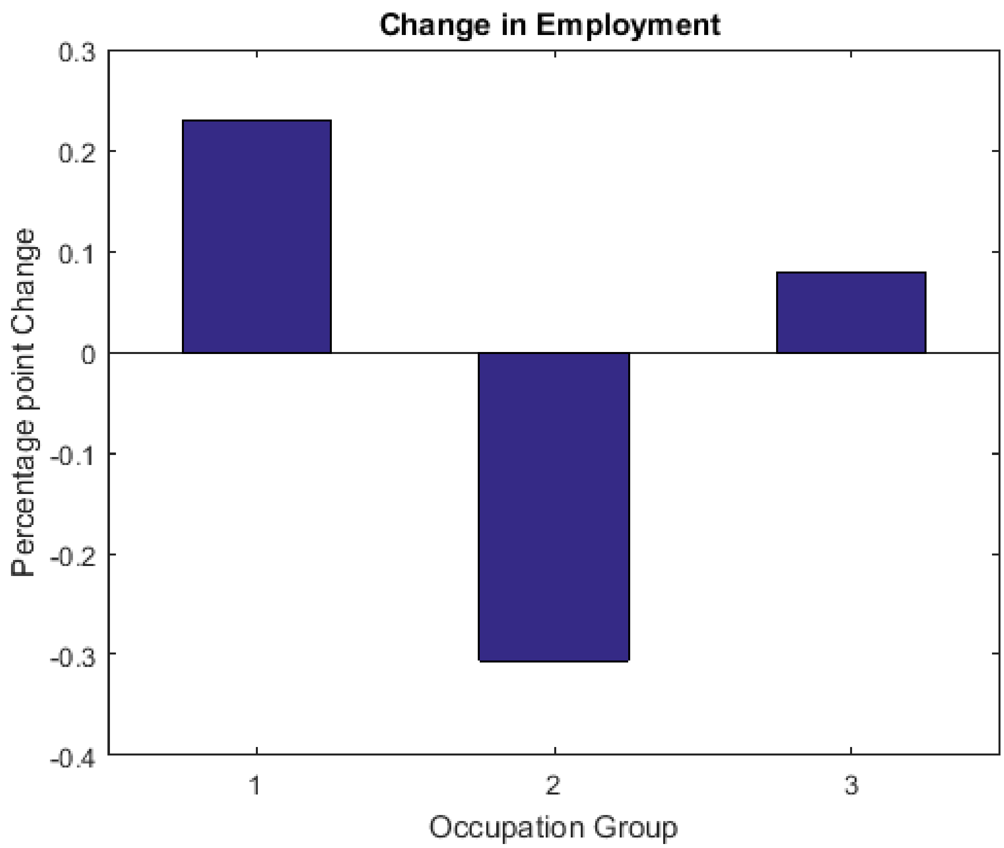
exists that such a change occurs in the aftermath of recessions [41] and that it contributes to the phenomenon of jobless recoveries [45]. [59] builds a model featuring such a structural shift that leads to a jobless recovery. For a detailed discussion of the “skills-gap" hypothesis see [15].

Some observers have pointed out that if indeed a skills-gap exists in the labor market then firms should hire workers with less skills and provide them with training on the job. The current model features such a mechanism. Once again I will not analyze the transition path to the new steady state but compare the worker outcomes in the long run steady state of a model which features higher skill requirements for high productivity occupations to the baseline model. The results are shown in Figure 1.16.

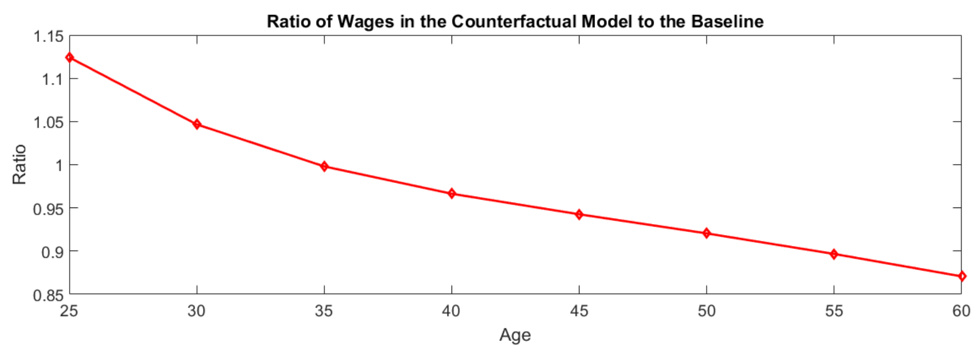
With higher skill requirements in occupation group 2 and 3. Workers find it hard to move up the occupation ladder as their path to higher skilled jobs is blocked. This leads to more workers in the lowest skill occupation group (Figure 1.15(a)). As can be seen from Figure 1.15(b), young workers earn higher wages in the new economy but older workers earn less. This is because in this counter-factual economy fewer workers at an older age are working in the high skill occupation. Since younger workers are unable to move up the occupation ladder, they invest less time in training and thus earn higher wages. Overall, the net effect on worker welfare is negative under this scenario. It is worthwhile to note that while the two counter-factual exercises produce a similar shift in relative employment, the welfare conclusions are very different.

1.5.4 Related Literature

As mentioned before, [28] also documents downward occupation mobility while focusing on within firm reallocation. She also documents contemporaneous and long-lasting earnings losses associated with moves to lower quality occupations. While I



(a) Employment Changes



(b) Ratio of Wages

Figure 1.15: Effect of Higher Skill Requirements on Welfare and Jobs

do not focus exclusively on reallocations within firms, I also find similar patterns of mobility towards lower quality jobs with age.

In a similar vein, [61] find that the set of employment opportunities for workers declines with age and they are more likely to transition to lower quality jobs upon a job switch. They define the quality of a job by the median wages within an occupation group and using the O*NET database find that older workers are less likely to be hired in jobs that require active learning and numerical ability.[10] In another paper with similar results, [12] show that workers switch to less cognitively demanding jobs as they age and this is correlated with age-related cognitive decline among individuals. Both these studies focus on workers aged 50 and older while I find that transitions to lower quality jobs is a phenomenon that is present even among prime aged workers.

This paper also relates to the literature on over-education that was started by [29]. He claimed that there was an excess supply of college graduates in the U.S. labor market in the 1970s because of the declining college wage premium. While the hypothesis of [29] was rejected by later researchers, the question of over-education was nevertheless brought to the attention of social scientists and policy makers. A large body of research has tackled the question of over-education at the individual and the aggregate level since then.[11] This literature has documented that, at the individual level, over-education is highly persistent and is associated with lower current as well as future wages. My findings on over-education over the life cycle provide a new fact for this literature as the focus of the earlier studies has been on younger workers.

More recently, [17] show how over-education evolves over the early part of the career and explain why it is so persistent for some individuals. [2] use similar mea-

[10] A recent New York Times article featuring this paper referred to these jobs as old-persons jobs. (http://www.nytimes.com/2016/08/18/upshot/as-more-older-people-seek-work-they-are-put-into-old-person-jobs.html)

[11] See Leuven and Oosterbeek [53] for an excellent summary of this literature.

sures of over-education[12] derived from the O*NET data to analyze how the aggregate measure of over-education behaves over the course of the business cycle. My paper is a close complement to their work in terms of defining over-education as a state of the labor market. However, they do not document the life cycle patterns reported in this paper because they restrict their analysis to the early years of a worker's career.

The paper is also related to the literature on worker transition across jobs. Since the seminal work of [47] economists have known that workers move to better job matches over time. The more time they spend in the labor market, the more precisely they know about their match quality. This simple model can explain some well known empirical facts such as rising wages with experience (and tenure in a job) and declining job mobility with age. Adding search frictions to such an environment can hamper the learning process and workers take a longer time to move to better job matches (see [58] for such a combination). One can also include human capital accumulation and job switching costs to add more persistence to this phenomenon (see [65] for such an example). Nevertheless, the underlying pattern generated by all such models is that workers should move to better job opportunities with experience (or age).

Finally this paper is also related to the literature that uses search models to rationalize large and persistent earnings losses at displacement. As shown by [23], the basic DMP model is not able to capture the earnings losses associated with displacement in the data. The model presented in this paper can potentially produce this phenomenon through two channels, job quality and loss of human capital from job displacement. Fully exploring the capabilities of the model to explore the forces behind earnings losses after displacement as done by [46] is beyond the scope of the current paper.

[12] They refer to over-education as underemployment.

1.6 Conclusion

In this paper, I document new stylized facts regarding occupation choice over the life cycle and the consequences for wages. I find that workers tend to move towards lower productivity occupations in the middle of their careers and earn lower wages upon such transitions. To explain these facts, I build a life cycle occupational search model with skill accumulation and depreciation. The model features heterogeneous workers and occupations which can be ranked in terms of their productivity. Workers choose occupations to maximize their lifetime earnings and also invest in human capital accumulation. However, unlike the previous literature on human capital accumulation, investment decisions are made jointly by the workers and the firms and not by the worker alone.

As the workers gain skills they are able to climb up the occupation ladder and this explains the declining half of the U-shape of over-education. After reaching a certain age, investments in skill accumulation decline and workers start losing their productivity as depreciation sets in. This leads to a movement down the occupation ladder and the proportion of over-educated workers rises with age. The model does a good job of matching the empirical facts and I show that skill depreciation is the key mechanism for matching the set of documented empirical facts.

The model can be used to determine the effects of structural change in the labor market on the careers of workers. In particular, I use the model to simulate polarization in the labor market driven by a decline in the relative productivity of the middle skill occupation group. In another counter-factual experiment, I simulate the impact of an increase in skill requirements of jobs. The results show that while the employment effects of both types of structural change are similar, the welfare consequences are very different and would require different policy prescriptions.

The model can also be used to quantitatively evaluate labor market policies such as unemployment insurance and hiring subsidies for firms. In a typical labor search model, unemployment insurance suppresses the job finding probability of the workers due to higher reservation wages, leading to a higher unemployment rate in equilibrium. However, in a model with heterogeneous workers and firms with complementaries among the two sides of the market, higher unemployment insurance would lead workers to search for high productivity jobs leading to higher life-time earnings. The welfare calculations of higher unemployment insurance in such a model become ambiguous and depend on the parameters of the model. This point has already been made by [4], albeit in a normative way. In the current paper, unemployment insurance has an additional impact on life cycle earnings of workers through the human capital investment channel. Since human capital investments depend upon the type of jobs a worker get matched with, the generosity of the benefit system could have long term effects on the careers of workers.

The empirical patterns documented in this paper also have important consequences for evaluation of pension policies that affect the retirement decisions of workers. Since workers are unable to hold high productivity jobs due to depreciating skills, policies to extend working age should be complemented with training programs that allow workers to update their skills. However, such an analysis would require the model to be extended to allow for savings and retirement decisions. Such extensions and evaluations of unemployment insurance policies are left for future work.

Chapter 2

Impacts of Public Health Insurance on Occupational Upgrading

2.1 Introduction

The absence of universal health care has led the United States to adopt a health insurance system that generates a tight link between health insurance and employment. While employer-provided health insurance provides health coverage to many (though not all), research on the U.S labor market shows that this health insurance system reduces labor mobility and generates “job lock" and “employment lock" [1].

The introduction of the Affordable Care Act (ACA) in the U.S expanded health insurance to about 20 million individuals, who were not previously covered [2]. There are moral as well as economic arguments for the provision of public health insurance. On the economic side, adverse selection in insurance markets is an important reason why the provision of health insurance is thought to improve efficiency (see [40]). Another economic rationale for this legislation was the creation of health insurance exchanges that allow the possibility for workers not to have to rely on employer-provided health insurance. Based on previous research, one may expect increased job separations, greater job switches and decreased labor force participation and, thus, a weaker link between employment and health insurance following the enactment of the

[1] These terms were coined to capture the phenomena of not changing jobs and staying employed simply to be able to retain health benefits.

[2] These statistics were taken from an analysis of the ACA by the Urban Institute: http://www.urban.org/research/publication/who-gained-health-insurance-coverage-under-aca-and-where-do-they-live

ACA [3]. The repeal or partial rollback of this piece of legislation will, thus, not only have consequences for the 20 million individuals with newly gained access to health insurance, but may also have important impacts on labor market efficiency.

In this paper, we depart from the existing literature on labor market effects of expanding public health insurance, which has focused on the job lock and employment lock hypotheses, and we instead focus on whether insurance affects other types of mobility in labor markets. In particular, we examine whether by providing insurance, public health coverage allows individuals to undertake the risky decision of switching occupations. The decision to switch occupations is an investment decision that is inherently risky, since a worker moving to a new occupation will generally have to invest in new skills either on the job or through re-training and the returns to these skills will be uncertain. Such risk might lead to higher separation rates from their jobs for workers and can also lead to higher wage spreads for workers switching occupations. Furthermore, starting jobs with new employers in a different occupation might also result in not being covered by health insurance provided by the employer.

A recent study by Hoynes and Luttmer ([43]) found that individuals derive both re-distributive and insurance value from public insurance programs, including Medicaid and SCHIP, and that this insurance value has increased over time. We focus on the insurance value of Medicaid/SCHIP and test whether greater generosity in Medicaid/SCHIP encourages individuals to switch towards riskier occupations and if these occupations are higher paying and have higher educational requirements.

We organize our hypotheses using a stylized model of occupational choice and show the potential effects of increasing government provided health insurance on the choice to change occupations. The model shows that if the generosity of public health insurance system increases, workers are more likely to switch occupations and

[3] See [1]

move to occupations which have higher wages on average but that are also riskier because of higher separation risk. When we test our predictions in the data we include another measure of labor market risk, wage spread in the new occupation, which is not a feature of our model. Finally, we use education requirements data at the occupation level to show that workers with access to more generous public health insurance benefits are not falling down the rungs of the âĂIJoccupation ladderâĂİ. In particular, workers move to occupations which have similar or higher education requirements than their previous occupation.

For our empirical analysis, we use the Current Populations SurveyâĂŹs (CPS) Merged Outgoing Rotation Group (MORG) files and exploit variation in Medicaid/SCHIP across states and over time through the 1990s and 2000s to study the impact of Medicaid/SCHIP on occupational mobility. We measure the generosity of public health insurance provided through Medicaid/SCHIP using income and age thresholds prescribed by state legislation to determine whether households qualify for the program in each state at each point in time [4]. Occupational mobility is measured as year-to-year changes in 3-digit level occupations. We define mobility towards riskier occupations as yearly transitions to a 3-digit level occupation that has higher variance of wages or higher separation rates over the entire period of analysis. Additionally, we measure whether workers transition towards occupations with higher median earnings and towards occupations requiring the same or higher educational credentials compared to their jobs one year earlier. This allows us to examine whether occupation switches induced by publicly-provided health insurance benefit workers by moving them towards the upper rungs of the occupation ladder.

[4] Following the approach in [43], we will not differentiate between the Medicaid and SCHIP programs but rather refer to both programs as simply Medicaid.

The identification strategy we use is essentially a difference-in-difference strategy comparing occupational mobility in states with minimal Medicaid benefits and states with more generous Medicaid benefits before and after the changes. The key identifying assumption is, thus, that labor mobility levels or trends for those in less and more generous states were similar before the policy change. We control for state- and time-effects, as well as region-specific trends to address this. A potential concern with our identification strategy is that there may be other policies introduced at the same time as the increased Medicaid generosity, which may be driving the increase in labor mobility. Therefore, we control for other policies that may have changed across states over this time period. In particular, we include the progressivity of the tax system as the differential in tax liabilities faced by individuals in the 75th and 25th percentiles; the median tax liabilities, and the generosity of TANF as controls. Another possible concern is that changes in Medicaid generosity may have themselves been the result of poor economic conditions or changes in the composition of populations that require health benefits. To address this concern, we regress the Medicaid income and age thresholds on the state unemployment rate, gross state product and characteristics of the state population in the state. We do not find any evidence that these factors explain income or age thresholds, thus allaying concerns of the potential endogeneity of these policies.

Our results show that increased access to health insurance for low-income households increases occupational mobility. The results show that moving from a state in the 10th percentile to a state in the 90th percentile in terms of the generosity of the Medicaid income threshold increases the probability of moving to another occupation by 5.2%. Moreover, we find that the effects on occupational mobility are greater for women, for those who are married and for those who have children. In addition, we do a falsification test by examining the impacts of Medicaid for those close and far away from the thresholds, since those far away from the thresholds should not be affected. We find that the impacts of increased Medicaid income threshold generosity on occupational mobility are largest for those in the lowest decile of the income distribution and, as one would expect, there are no effects for those in the second through the highest deciles of the income distribution.

Our main premise is that Medicaid generosity increases occupational mobility because public health insurance allows workers to make risky decisions that have a higher payoff. Thus, we estimate the likelihood that workers will move to occupations with a higher variance of wages and with higher average separation rates. We find that moving from a state in the 10th to the 90th percentile in terms of generosity of Medicaid income thresholds increases the likelihood of moving to occupations with a greater wage spread by 4.4%. Moreover, we find that these workers are not transitioning towards low quality jobs, but rather towards occupations with higher median wages, representing high quality jobs. In addition, we find that increased Medicaid generosity in terms of both income and age thresholds increases the likelihood that workers move towards jobs with the same or higher educational requirements than those in their previous jobs.

Finally, we exploit a reverse natural experiment that occurred in Tennessee, where Medicaid generosity declined substantially, to examine if occupational switches fell in this state. We find that after the fall in Medicaid generosity in Tennessee in 2000, occupational transitions fell and that workers moved towards occupations with smaller wage spreads. Moreover, the fall in Medicaid generosity increased worker transitions towards lower paid occupations and towards jobs with lower educational requirements. Thus, the decrease in Medicaid generosity had far reaching consequences for the fluidity of the labor market in Tennessee, beyond the decreased mobility and entry into the labor force documented by [30] [5].

The rest of the paper is organized as follows. In Section 2, we provide a review of the literature, discuss legislative changes in Medicaid generosity changes during the time period of our analysis and present a theoretical model to highlight the mechanisms through which health insurance can increase mobility towards better occupations. Section 3 describes the MORG data and the construction of the various variables used in our analysis, while Section 4 describes our identification strategy. In Section 5, we present the results of Medicaid generosity on occupational mobility and other outcomes of interest and Section 6 concludes.

2.2 Literature Review and Medicaid Changes after the 1990s

2.2.1 Literature on Relation between Public Health Insurance and Mobility

The effect of health insurance on labor mobility has been an active area of research for the last two decades. Health insurance can affect labor market outcomes directly through its effect on health of the individual or it can affect labor market outcomes indirectly by altering the payoff structures, modifying labor supply patterns and affecting labor market churn. The indirect effects of health insurance provision on labor market outcomes are mostly relevant in the case of the United States labor market, where health insurance has been provided mostly by employers until the passage of the Affordable Care Act. Currie and Madrian ([20]) provide an excellent review of the institutional details of the U.S. health insurance system and how it interacts with the labor market decisions of individuals.

[5] The change in Medicaid that we analyze is different from the one examined by [30] who examine the disenrollment of all adults from Medicaid in 2005.

The literature that has focused on the effects of health insurance on labor market outcomes, and that is most relevant to our paper, falls under two strands. One strand of the literature has focused on the effects of public health insurance on labor supply. Lack of health insurance from sources other than the employer may force individuals to stay employed just to receive employer-provided health insurance. Moreover, Medicaid may discourage labor force participation since receipt depends on income thresholds. The earlier empirical literature, using variation in qualifying conditions for Medicaid and Medicare, has generally found that the availability of alternative sources of health insurance depresses labor supply (see [66], [20] and [34] for reviews of this literature). Two recent papers relying on policy changes in Tennessee and Oregon examine whether there is “employment lock", the phenomenon of staying employed instead of non-employed just to be able to keep health insurance. [30] find evidence that labor supply and consequently employment of workers increased following a large public health disenrollment that occurred in Tennessee in 2005 compared to other Southern states. By contrast, [9] find that access to Medicaid has no impact on employment or earnings analyzing data from the Oregon health insurance randomized experiment, perhaps because the experiment took place in 2008 in the midst of the Great Recession.

The second branch of the literature focusing on the relation between health insurance on labor mobility has focused on the aforementioned “job lock" hypothesis. While the literature has more or less come to an agreement over the existence of job lock due to employer-provided health insurance, almost no attention has been paid to the welfare consequences of job lock for workers and the economy ([37]; and [1]). [35] is the only paper that attempts to measure the welfare gains from removing job lock for workers by examining re-employment wages. While measuring outcomes in terms of re-employment wages is a useful metric for welfare gains, it might be the case that workers “freed from job lock" would want to move to a job with flexible hours and working conditions or try out another career and are, thus, willing to take a pay cut. We attempt to fill this gap in the literature and examine how generous public health insurance influences the decisions of workers to switch occupations and measure outcomes in their destination occupation across multiple dimensions including the quality and the skill requirements of the job.

As mentioned before, there has been a divide in the literature about the existence and the magnitude of the “job lock" hypothesis, which comes down to differences in empirical strategies. The literature on job lock has for the most part relied on three identification strategies. First, a number of papers exploit variation on whether the worker has health insurance through a family member. Second, a number of other papers use worker's valuation of health benefits as a source of variation. Finally, only three papers use policy variation to examine the existence of “job lock".

The majority of papers relying on access to alternative sources of health insurance compare male workers who have access to health insurance through their spouse. Several studies, including [55], [19], [13], [35] and [7] have found that employer-provided health insurance depresses job turnover. The results of the impact of access to health insurance from a spouse on increased job separations range between $25\% - 50\%$.

The papers relying on the differential valuation of benefits by individuals also provide evidence on “job lock". [55] shows evidence of “job lock" for married men with employer provided-health insurance and who had a pregnant wife. [64] instead find evidence of “job lock" for those with chronic health conditions, or family members with chronic health conditions, who relied on employer-provided health insurance. By contrast, [50] finds no evidence using a similar strategy. A problem with this and the previous approach is that those with pregnant spouses, chronic health conditions, and insured spouses are likely to be different from the comparison groups in terms of unobserved characteristics.

There are only three papers in the "job lock" literature that rely on policy changes as a source of exogenous variation in health insurance access during periods of non-employment. [35] analyzed an exogenous change in law across states that allowed unemployed workers to have health insurance coverage from their past employer until they found a new job through the Consolidated Omnibus Reconciliation Act of 1985 (COBRA). They find that job separations increased by $12-15\%$, non-employment spells increased by 15% and reemployment earnings doubled one year after the introduction of COBRA. [11] instead rely on the expansion of State Children's Health Insurance Programs over the 1990s and find that separations increased by $5-6\%$ after the introduction of these state programs for fathers whose children qualified for SCHIP and whose spouses did not have employer-provided health insurance. Finally, a paper by [38] finds evidence that parental Medicaid expansions led to increases in job mobility of unmarried women, but not for married women or men.

Our research design is closest to the studies just described above, which use exogenous policy changes to analyze worker turnover. The novelty of our paper is not only to exploit policy changes to examine the impact of public health benefits, but to go beyond the effects of public health insurance on job separations and to examine the incentives it generates in terms of increased risk taking. Furthermore, we analyze the impacts of public health insurance in encouraging mobility towards occupations, which are higher paying and have higher educational requirements.

2.2.2 Medicaid/SCHIP Threshold Changes in the 1990s and 2000s

In our analysis, we rely on the increased generosity of Medicaid over the 1990s and 2000s. Medicaid was introduced in the U.S. following the Social Security Amendment of 1965 to provide health insurance to low-income individuals. From 1965 to 1985, only cash aid recipients of Aid to Families with Dependent Children (AFDC) were eligible for Medicaid. Starting in 1985, many states expanded eligibility of Medicaid to children and pregnant mothers with income thresholds above the AFDC income eligibility limits and with children below a certain age limit. We use the state income and age thresholds for children to capture the generosity of states in terms of public health insurance. The higher the state income and age limits, the more individuals and families are likely to benefit from Medicaid in a state.

During the late 1990s and the 2000s, many states chose to increase the income threshold, which determine the level of income as a percentage of the poverty line at which children within households qualify for Medicaid. Similarly, during this period several states chose to increase the age threshold, the maximum age that allows children in households under this more generous income threshold to qualify for Medicaid. Figures 1 and 2 show the evolution of the Medicaid income and age thresholds over time for the lowest 10th percentile terms of generosity as well as for the 50th and 90th percentiles [6]. Figure B.1 shows that substantial variation in Medicaid income thresholds. Back in 1997, the income threshold relative to the poverty line was 133% for the 10th percentile, but 185% for the median and 200% for the 90th percentile. Moreover, the generosity of Medicaid has increased substantially, particularly in the 90th percentile increasing from 200% in 1997 to 235% in 2005 and to 300% in 2011. By contrast, the 10th percentile has remained with an income threshold of 133% in the past decade and a half. States with thresholds equal to the 10th percentile have remained fairly constant-Alabama, Alaska, Colorado, Idaho, Montana, Nevada, North Dakota, Utah, Virginia and Wyoming were all in this group in 1997 and remain in this

[6] The data on income and age Medicaid thresholds through 2007 was kindly provided by Hilary Hoynes. We, then, updated the income and age Medicaid thresholds at the state level until 2012 by obtaining data from: http://ccf.georgetown.edu/.

group in 2011. However, some states have moved out of this group including Illinois, Louisiana, Ohio and South Dakota. Moreover, the states with Medicaid thresholds at the 90th percentile have changed substantially, with only Hawaii and Vermont remaining in that group from 1996-2011. Arkansas, California, Minnesota, Rhode Island, Tennessee and Washington all moved out of this group and the District of Columbia, Iowa, Maryland, New Hampshire and Wisconsin moved into the group of most generous states. At the bottom, age thresholds were zero for the least generous states and 18 for the most generous and there have been some increases from 5 to 6 years at the median (see Figure B.2) [7]. Our identification strategy is, thus, essentially a difference-in-difference strategy, which compares the changes in outcomes before and after the changes in income and age thresholds among less and more generous states [8].

2.2.3 Theoretical Framework of the Effects of Medicaid on Occupational Mobility

In this section, we present a simple model to show the potential effects of Medicaid on occupational mobility. The model is highly stylized and is intended to highlight the tradeoff between staying in an occupation and switching occupations as well as the role that publicly provided health insurance can play in that decision.

[7] Note that while these thresholds show the potential population covered by Medicaid, the actual take-up of Medicaid tends to be lower ([16]). However, a recent study by the Urban Institute estimates using the 2009 ACS that among eligible children 84.8% participated in Medicaid or SCHIP ([51]). Thus, the take-up for children is high, but even if it is not 100%, the availability and possibility to be covered by health insurance not offered by the employer may change the behavior of those who do not claim Medicaid.

[8] We rely on the actual income and age thresholds rather than relying on a simulated eligibility measure. The simulated eligibility measure uses information on the individual such as income, number and ages of children and pregnancies, which are all potentially endogenous and correlated with our outcomes of interest. By contrast, the thresholds are determined by statutory changes which are taken as given by the individual.

Consider a worker working in occupation j, who is currently getting health insurance from his/her employer in that occupation. The worker might want to shift to occupation i which offers a higher wage (either because occupation i is a better fit for his/her talent, tastes and education level or because occupation i is a better paying occupation on average). However, the chances of getting health insurance in occupation i are not certain. The worker can get health insurance from the employer in occupation i with probability q and with probability $(1-q)$, the worker does not get health insurance from the employer. The worker also has to pay a cost of switching to a new occupation, $c(a)$, which is a decreasing function of worker ability, $a \in R_+$. To keep the model exposition simple, the wages are not allowed to depend on worker ability and worker ability is also assumed to be one-dimensional. Finally, we assume that the separation risk is higher in occupation i compared to occupation j. This assumption is intended to capture the uncertainty associated with switching occupations. It is assumed that this uncertainty is higher in the new occupation than in the current occupation.

We assume that workers are risk neutral, cannot save and assign a monetary value to health insurance coverage. Consider a worker, working in occupation j, who can have higher earnings in occupation i and who is currently getting health insurance from his/her employer in occupation j. The worker is faced with the decision of whether to stay at his/her current occupation or move to occupation i. The workerâĂŹs decision can be captured by the following:

$$V^E(a) = \max\left\{V_j^E(a), V_i^E(a)\right\} \tag{2.1}$$

Where $V_j^E(a)$ represents the value the worker gets from staying in occupation j and $V_i^E(a)$ is the value that the worker gets from switching to occupation i.

The decision rule of the worker can be characterized by a threshold for ability. If $aa*$, then the worker does not switch from occupation j to i and the value function for occupation j can be characterized as follows:

$$V_j^E(a) = w_j + h_j + \delta_j U(a) + (1 - \delta_j) V_j^E(a) \tag{2.2}$$

The value for a worker currently in occupation j are the earnings currently in that occupation, w_j, plus the benefits from the health insurance, h_j, plus the probability of continuing in that job, $(1 - \delta_j)$, times the value of staying in that occupation given by $V_j^E(a)$, times the earnings plus the benefits from health insurance in that occupation in the next period plus the probability of leaving that occupation times the probability of going into unemployment, $\delta_j U(a)$. Using the recursive nature of the problem and working under the assumption that workers with ability below the threshold, $aa*$ would not switch, the value function above (2.2) can be re-written as:

$$V_j^E(a) = \frac{w_j + h_j + \delta_j U(a)}{\delta_j} \tag{2.3}$$

On the other hand, if $a > a*$, then the worker switches to occupation i, and the value function for occupation i can be characterized as:

$$V_i^E(a) = w_i + q h_i + (1 - q) h_m - c(a) + \delta_i U(a) + (1 - \delta_i) V_i^E(a) \tag{2.4}$$

The value to the worker of switching to the new occupation i, is the the lower earnings in the new occupation, w_i, minus the cost of training for the new occupation, $c(a)$ (which declines with ability, plus the) times the probability of not getting health insurance from an employer in the new occupation, q, , times the value health insurance from the employer, h_i, plus the probability of not getting health insurance from the employer times the value of health insurance from Medicaid,$(1 - q)h_m$, plus the probability of continuing in that job, $(1-\delta_i)$, times the value of staying in that occupation given by $V_i^E(a)$, plus the probability of leaving that occupation times the probability of going into unemployment, $\delta_i U(a)$. Again, using the recursive nature of the problem and the assumption that the solution to the occupation choice problem can be characterized by a threshold, $a*$, we can rewrite equation (2.4) as:

$$V_i^E(a) = \frac{w_i + qh_i + (1-q)h_m - c(a) + \delta_i U(a)}{\delta_i} \tag{2.5}$$

The value of unemployment is equal to the unemployment benefits, b, plus the value of Medicaid, h_m, plus the probability of getting a job offer times the value of being employed $V^E(a)$, plus the probability of not getting a job offer times the value of being unemployed. This can be expressed using the following value function:

$$U(a) = b + h_m + \lambda V^E(a) + (1-\lambda)U(a) \tag{2.6}$$

Here it is assumed that once the worker gets a job offer, the worker faces the same decision choice as outlined in equation (2.1). This means that the worker faces the value function $V^E(a)$ rather than an occupation specific value function [9]. Consequently, for values of ability such that $aa*$, equation (2.6) can be re-written as:

$$U(a) = b + h_m + \lambda V_j^E(a) + (1-\lambda)U(a) \tag{2.7}$$

And similarly, for values of ability less than $a*$ equation (2.6) can be re-written as:

$$U(a) = b + h_m + \lambda V_i^E(a) + (1-\lambda)U(a) \tag{2.8}$$

[9] We are also assuming here that the worker always accepts the job if he/she gets one or $V^E(a) - U(a) > 0$.

Given these value function, the threshold level $a*$, which determines the level of ability below which workers do not switch their occupations and above which they do, can be characterized by the following equality:

$$V_j^E(a^*) = V_i^E(a^*) \tag{2.9}$$

Which can be re-written as the following equality using equations (2.2) and (2.4)

$$w_j + h_j + \delta_j U(a^*) = w_i + qh_i + (1-q)h_m - c(a^*) + \delta_i U(a^*) \tag{2.10}$$

Or assuming that $c(a)$ is a continuous and differentiable function over the range of values taken by ability, a, we can solve for the threshold as

$$a^* = c^{-1}\left[(w_i - w_j) + [qh_i + (1-q)h_m - h_j] + U(a^*)[\delta_i - \delta_j]\right] \tag{2.11}$$

The threshold depends upon the wage differentials in the two occupations, the difference in health insurance choices available at both occupation and the difference in the separation risk associated with the two occupations and the value of being unemployed.

Based on the assumptions of our model, the worker can get higher wages in occupation i so that $w_i - w_j 0$ and the separation risk is also higher in occupation i so that $\delta_i - \delta_j 0$. To ensure that the value of the threshold, a^*, is a positive integer we assume that the following regulatory condition holds:

$$qh_i + (1-q)h_m - h_j < (w_i - w_j) + U(a^*)[\delta_i - \delta_j] \tag{2.12}$$

This is a regularity condition which ensures that there are some individuals who would switch occupations and others would not as the range values taken by ability are positive. If the threshold is negative, then no worker would be willing to switch occupations. Note that this regularity condition is only required if $qh_i+(1-q)h_m-h_j < 0$.

Prediction 1:

We want to highlight how a^* changes with respect to h_m. Using the chain rule on equation (2.11) we can show that:

$$\frac{\partial a^*}{dh_m} = \frac{1}{c^{'}()}\left\{(1-q) + \frac{dU(a^*)}{dh_m}\right\} \tag{2.13}$$

Where $c^{'}(.) < 0$, $(1-q) > 0$ and $(\partial U(a^*))/(dh_m) = 1$ (from equation 2.7) which implies $(a^*)/(dh_m) < 0$. Hence the threshold ability, a^* , for switching occupations decreases as h_m, the value of health insurance provided through Medicaid, increases. Consequently, more workers are willing to switch occupations as Medicaid becomes more valuable.

Prediction 2:

Prediction 2 is a corollary of prediction 1 and is based on the assumptions of the model. It describes the characteristics of the occupation to which the worker is moving to. Since occupation i has higher separation rates and higher wages on average, as h_m increases, workers move to occupations with more risk and higher wages.

2.3 Data Description

We use the Merged Outgoing Rotation Group (MORG) files of the Current Population Survey and merge these with the March CPS files to conduct this analysis. Households in the CPS are interviewed for four months, then let go for eight months, and are then interviewed again for another four months. Every month about one eighth of the households enter the sample and about one eighth leave the sample. The fourth and eighth interviews include information on wage income and hours worked and are called the outgoing rotations. The MORG files allow one to match households and individuals from one year to the next by matching the information from the 4th interview and the 8th interview. We merged the 4th to the 8th interview in the months of March that had unique household and individual identifiers. Then, we checked that individuals had the same gender and race. If they did not, we discarded them. We also checked that the absolute difference in age from one year to the next was either one or two and deleted those who had differences in age that were greater or smaller than two [10]. Finally, we merged these panels with the March supplements.

In the MORG sample, we have access to extensive demographic and labor market information, including information on the occupation of the worker. We are, thus, able to control for education, age, the number of children, gender, race, ethnicity and country of birth in all our regressions.

We use the March CPS supplement because it asks a series of questions on different income sources. This allows us to construct the tax liabilities and TANF benefits variables, which are important control variables since state taxes and TANF benefits changed during this time period. We construct state income tax liabilities using the TAXSIM software from the National Bureau of Economic Research (NBER) at the 75th and 25th percentiles of the national income distribution to construct a measure of tax progressivity, and at the 50th percentile of the national income distribution to construct the median income. The benefits under TANF are constructed using information on maximum benefits, benefit-reduction rates and flat earnings disregards

[10]We only lose around 3% to 4% in each pair of years from mismatches in age, gender, and race

which vary over time and across states [11], as well as using earned and unearned income for the 25th percentile of the national income distribution by year from the March CPS [12].

Our main dependent variable is an indicator of whether a person changed 3-digit occupations from one year to the next. Since occupation codes have changed over time, we use a crosswalks to make sure that occupation codes are consistent over time [13]. Then, we construct transition probabilities of whether the person moved to a riskier occupation from one year to the next. We measure riskiness of occupations in two ways. First, we measure the variance of wages in each 3-digit occupation for the entire period from 1996-2012 and in all states.

Then, we define a variable measuring transitions towards riskier occupation, which takes the value of one if the current occupation has a greater variance of wages than the previous occupation and zero otherwise. Hence, whenever there is no change in occupation, this variable also takes the value of zero. We also measure riskiness in an occupation by looking at separation rates within occupations for the entire time period of analysis and in all states [14]. The second variable measuring transition to a riskier occupation takes the value of 1 if a person moved towards a 3-digit occupation/industry with a higher average separation rate than the one in which they were working at before. This variable can only take a value of 1 if there is an occupation switch by the worker.

[11] We are grateful to Hilary Hoynes for providing the information on maximum benefits, reduction rates and earnings disregards through 2007. To update the data till 2012, we obtained the information on maximum benefits, benefit reduction rate and earnings disregards for 2008-2012 from the Welfare Rules Database. (http://anfdata.urban.org/wrd/WRDWelcome.cfm)

[12] See Appendix for a detailed description of the construction of these variables.

[13] We use the crosswalks developed by [21] for occupations.

[14] The separation rates include both voluntary as well as involuntary separations, since the March CPS does not distinguish between the two types of separations.

Our final set of dependent variables measure whether workers make transitions towards better jobs. We measure the quality of jobs in two ways. First, we measure transitions towards 3-digit occupations with higher median wages than the previous job. Median wages are calculated for each 3-digit occupation over the entire period of analysis using data from all states. Second, we measure whether workers move towards occupations in which the educational requirement is the same or higher than the educational requirement in their previous occupation. This is a measure of whether the workers moved towards a job that is better or higher up in the job ladder. We construct this measure by using data from the U.S. Labor DepartmentâĂŹs O*NET database, which identifies the educational requirements for jobs in different occupations. The O*NET program collects data on entry requirements, work styles and task content within occupations by surveying each occupationâĂŹs working population. For educational requirements, we rely on the following question asked of current employees: "If someone was being hired to perform this job, indicate the level of education that would be required." The survey respondents are reminded that this does not refer to the level of education that an incumbent or current employee has achieved. Respondents are given the following options: less than high school, high school, some college, associate's degree, bachelor's degree, and graduate degree. To assign a required level of education to each occupation, we use the distribution of responses of the incumbents and use the mode of the responses as the required level of education for each occupation. This way of measuring education requirements is consistent with the approaches taken in the over-education literature [15].

Table B.1 provides descriptive statistics of the variables used in our analysis for the period from 1996 to 2012. In the sample, almost half of the individuals are women, 80% are married, have on average almost one child, are on average 43.5 years old and

[15] See Leuven and Oosterbeek (2011) for a review of this literature.

have on average 13.8 years of education, 84.4% of the individuals are white, 9.8% African American and 8.7% Hispanic. Only 13.1% are union members and 14.9% are foreign-born. A substantial fraction of those who change jobs experience occupational changes from year to year- 47.6% experience occupational changes. These numbers are in line with previous numbers documented in the literature measuring occupational mobility using CPS data [16]. Moreover, the likelihood of moving towards an occupation with greater variance of wages and higher average separation rates are 21.7% and 23%. Finally, the likelihood of transitioning to a higher paying occupation is 21.5%. The likelihood of moving to a better-matched occupation is 33.1%.

The Medicaid income threshold, as described in the previous section, is the maximum income relative to the poverty line that allows children within a household to qualify for Medicaid. The average income threshold is 191% of the Federal Poverty Line (FPL) over the entire period. The Medicaid age threshold is the maximum age of the children who can qualify for Medicaid given that they live in households with income below the aforementioned Medicaid income threshold. The average age threshold is 4.7 years over the entire period of analysis. The thresholds are statutory and, thus, determined by law. They are the source of variation that we use to determine public health insurance generosity in our analysis. Thus, we might expect the occupation change outcomes to differ between more and less generous states if Medicaid, indeed, changes the behavior of workers in terms of their willingness to move occupations. Occupational changes are higher in states with Medicaid income thresholds above the mean, although these changes are not significantly different between those above and below the mean when we do not control for covariates.

[16] See [49]. Note that they caution against using March CPS to measure annual mobility without matching individuals present in two consecutive years. When they match individuals present in two consecutive years and measure occupational and industrial mobility, their number is close to ours.

Table B.1 shows that worker characteristics in more and less generous states also vary. More generous Medicaid states have older workers, more dependent children, more foreign-born workers, higher unionization rates and more Hispanics and less whites and African-American workers. Thus, these differences highlight the importance of controlling for different worker characteristics in the analysis. Table B.1 also shows that the difference in mean taxes at the 75th and 25th percentile of the distribution over the period of analysis is 49.6% and the average median tax is 11%. While the tax progressivity is higher in states that are more generous in their provision of Medicaid benefits, the median tax rate is actually lower in these states. TANF benefits for a family of 3 at the 25th income percentile were $2,396 in states that also offered more generous Medicaid and $1,062 in states that offered less generous Medicaid. Differences in tax structure and transfer programs, thus, highlight the need to control for these policy variables in our analysis.

2.4 Identification Strategy

Our approach to establish a causal relation between labor mobility and public health insurance relies on statutory Medicaid program qualification rules, as opposed to the actual benefits received by an individual. As shown above, there were a number of states that remained constant at the low threshold of 133% of the FPL and the minimum child age, thus keeping the 1987 rules. However, many other states did increase their generosity by raising the income threshold beyond the AFDC threshold at the time, and by allowing older children to also qualify for Medicaid. Thus, we compare those states that became more generous to those that did not in terms of qualification for Medicaid. This is essentially a difference-in-difference approach with several before and after periods and several treatments.

We estimate the following regression of occupational mobility on the Medicaid income and age thresholds, other policy changes, individual characteristics, state and time fixed effects, and region-specific trends:

$$\begin{aligned} Y_{isrt} = {} & \phi \times \text{Medicaid Income Threshold}_{st} + \zeta \times \text{Medicaid Age Threshold}_{st} + \\ & \delta \times \text{Tax Progressivity}_{st} + \pi \times \text{Median Tax}_{st} + \rho \times \text{TANF benefits}_{st} + \\ & \beta X_{isrt} + \kappa_s + \tau_t + \Omega_{rt} + \epsilon_{isrt} \end{aligned} \tag{2.14}$$

where the Medicaid Income Threshold$_{st}$ is the maximum income relative to the poverty line that allows children within a household to qualify for health insurance through Medicaid in state s at time t; Medicaid Age Threshold$_{st}$ is the maximum age of a child who can qualify for Medicaid in state s at time t; the Tax Progressivity$_{st}$ is the difference in the average overall tax rate between the top and bottom quartile of the income distribution; Median Tax$_{st}$ is the average tax at the 50th percentile of the income distribution; and TANF benefits$_{st}$ are as described in the previous section. In addition, the XâĂŹs include controls for age, education, number of children, gender and indicators for foreign-born, union member, marital status, Hispanics, and African Americans. We control for state and time effects, κ_s and τ_t , to contrast states with more and less generous thresholds before and after the statutory changes. To allow for potential differential trends in states with more and less generous Medicaid or cost of living differences across regions, we include, Ω_{rt}, region-specific time trends that allow the time trend to vary in each of the large nine regions of the country as defined by the Census Bureau (New England, Mid-Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain, and Pacific).

While we control for other potential confounders that may have changed at the same time as the Medicaid statutory changes, a potential problem is that the statutory changes may had responded to underlying economic conditions or conditions in the labor market. We check for this possibility by estimating regressions of the Medicaid income and age thresholds on the unemployment rate, real gross state product, the percentage of the labor force in goods producing industries, and the percentage of the population that is white, male, and married as well as the average education level in the state. Table B.2 shows results of these regressions for the income and age thresholds, respectively. Columns (1)-(5) show that none of these variables are significant in predicting Medicaid income threshold. Columns (6)-(10) show no effects of the variables on the Medicaid age thresholds either. The only exception is the average education level, which is marginally significant in Columns (5) and (10) for both the Medicaid income and age thresholds in the specification with lagged GDP. Thus, there is little evidence that economic, labor market and demographic factors are behind the adoption of more generous Medicaid policies.

2.5 Results

2.5.1 Impacts of Taxes and Transfers on Occupational Mobility

A key element of a healthy labor market is the ability for workers to move across occupations over their working lives. As people learn about their talents and observe how their experiences evolve in the labor market, they may realize that their skills and characteristics do not suit a particular type of job but that rather they are more apt for another occupation. Thus, people may consider moving to a new occupation to utilize their talents, yet they may be reluctant to do so because there is uncertainty about the quality of their match in a new occupation. Employer-provided health insurance, however, stops many from changing jobs and may restrain many from leaving a job to retrain or to even move to another job with health insurance coverage but which may be risky because it requires a different set of skills and the likelihood of a low return may be high even when the average return is higher. Public health insurance may encourage individuals to undertake the risky investments necessary to change occupations. The impact of public health insurance on the decision to change occupations was the first prediction of our theoretical model outlined in section 2.2.3 It predicted that an increase in the provision of public health insurance would lead to more workers switching occupations.

Table B.3 shows that increased Medicaid generosity, indeed, induces individuals to change occupations more often than they would otherwise. Columns (1)-(3) show the results with basic demographic controls and adding state, time and region-specific trends, respectively. Columns (4) and (5) add policy controls including tax progressivity, the median tax and TANF benefits. The results become slightly smaller as more controls are added, but they are robust to all these controls and show a consistent picture. An increase in the Medicaid income threshold increases the likelihood that an individual changes occupation. By contrast, increasing Medicaid generosity by increasing the age threshold does not impact occupational change. The effect with the full set of demographic and policy controls in Column (5) shows that moving from a state with the lowest income threshold, 133% of the FPL, to a state in the 90th percentile in terms of the income threshold, 300% of the FPL, (or moving from Alabama to Vermont if they were the same in every other respect) increases the propensity to change occupations by 5.2% [17]. In the last column of Table B.3, we interact the thresholds with an indicator for women, to check if the effects vary by gender, but find

[17] This number is calculated by multiplying the point estimate by the difference between 300% and 133%, i.e. $0.0309x1.67 = 5.2\%$.

no difference between women and men in terms of the effects of Medicaid generosity on their occupational mobility [18].

Since the thresholds should be most important for those who are close to the threshold and likely to qualify for Medicaid, we examine differential effects of the income threshold for those at different deciles of the income distribution. Table B.4 presents the same results as Table B.3 occupational changes with all controls for workers in the 1st, 2nd, 3rd, 4th, and 5th or higher deciles. We, then, compare the marginal effect of the Medicaid income threshold for workers in different deciles. This serves as a falsification test since we should not expect to find effects in the higher deciles [19]. Column (1) in Table B.4 shows a positive and significant impact of the income thresholds on occupational mobility in the first decile of the income distribution. Moving from the least to the most generous states in terms of the income threshold, increases the mobility of individuals in households at the lowest decile by 6%. By contrast, columns (2)-(5) show no impact for those at the 2nd or higher deciles of the income distribution. These results confirm that the effect of Medicaid generosity on occupational mobility is mostly driven by the changes in threshold levels and not by other things affecting all individuals with high and low income in generous states.

In Table B.5, we also examine whether the effects were larger for women than men; for married or not married individuals, and for those with and without children. The results in Table B.5 show that the effects on occupational mobility are greater for women than men, when estimating a fully saturated model allowing other factors to

[18] We also found positive and significant effects of Medicaid Income thresholds on the propensity to change industries across all of our specifications.

[19] Note that those in the lowest quintile earn $\$20,703$ or less in 1999 dollars and the poverty line for a married couple with one child in 1999 was $\$13,410$. Thus, to qualify for Medicaid such family would have to earn less than $\$17,835.30$ in the least generous states and $\$25,210.80$ in the median state. This means that those at the lowest quintile are, indeed, more likely to be exposed to Medicaid over this time period.

affect women and men differently. Table B.5 also shows bigger effects of the Medicaid income thresholds on occupational mobility of married than non-married workers, although the latter effects are not significant. Moreover, this table shows bigger effects of Medicaid on occupational mobility for those with children than for those without children. These results are in line with other results in the literature, which show bigger effects for those who are likely to value health benefits more.

2.5.2 Moving to Riskier and Better Occupations?

If the insurance value of Medicaid is indeed driving individuals to undertake riskier decisions by moving them toward new occupations, they should be moving towards riskier occupations but also towards those that are more desirable. Prediction 2 from section 2.c highlighted that increased access to public health insurance should encourage workers to move to occupations with greater separation risk and to occupations which might have higher wages. In the empirical exercise that follows we measure riskiness at the occupation level using separation risk and using variance in wages. To proxy for better paying occupations, we use occupation level median wages. Furthermore, we also use occupation level education requirements to test whether workers with access to more generous public health insurance are moving to occupations which have similar or higher education requirements compared to their previous occupations.

Table B.6 shows transition probabilities towards riskier occupations. Columns (1) and (2) show results where the dependent variable takes the value of 1 if the person moved to an occupation with a higher variance of wages and if the person moved to an occupation with higher separation rates. The results show that both higher Medicaid and age thresholds increase the likelihood that a person will move towards an occupation with a wider wage spread. The effects are such that moving from the lowest 10th to the highest 90th percentile in terms of the income threshold increases the likelihood of moving towards riskier occupations by 4.4%. The results also show that a one unit increase in the age threshold for Medicaid Eligibility increases mobility towards occupations with greater wage spreads by 0.018 [20]. By contrast, the thresholds have no impact on the likelihood of moving to occupations with higher separation rates. These results are largely indicative of mobility towards riskier occupations when Medicaid is more generous.

Since another possible interpretation is that people are just pushed towards low quality jobs, we also test if these are not just riskier jobs but actually better jobs. Columns (3)-(6) in Table B.6 shows results of the impacts of Medicaid on the likelihood of transitioning towards more desirable jobs. Column (3) in Table B.6 shows results for transitions towards occupations that have higher median wages in an occupation on average. The results show that moving from the 10th to the 90th percentile in terms of the Medicaid income threshold increases transitions towards higher median pay occupations by 3.6% [21].

Another good measure of occupation quality is whether the occupation has higher education requirements. Therefore, we look at transitions to occupations that have similar or higher educational requirements compared to the educational requirements in the previous job held by the worker. Columns (4)-(6) in Table B.6 show the results for the likelihood of moving towards occupations in which the educational requirements of the job are above or equal to the education requirements at the previous

[20]Some examples of such transitions in our data are janitors becoming truck drivers or carpenters or construction workers; cashiers becoming salespersons or housekeepers; and maids becoming health and nursing aides.

[21]Some examples of such transitions in our data are health and nursing aides becoming medical technicians or secretaries and receptionists; child care workers becoming teachers; waiters and waitresses becoming retail salespersons; or cashiers becoming salespersons.

job [22]. We find that increasing Medicaid generosity from the level of the 10th percentile to the 90th percentile increases the likelihood that the worker moves to a job in which s/he is using the same or higher level of skills compared to her/his previous job by 3.9%. Columns (5) and (6) show this effects separately for non-college and college graduates. The effects of increased generosity in terms of the Medicaid income threshold are slightly bigger for non-college graduates. The results also show that an increase in the Medicaid age threshold also induce workers to move towards jobs with higher educational requirements. A one unit increase in the age threshold for Medicaid eligibility increases mobility towards occupations higher up the job ladder by 0.02. Overall, the evidence indicates that workers are moving towards riskier occupations, with higher median wages and which are presumably better matches for them [23].

2.5.3 The Tennessee Experiment: A Sharp Reduction of Medicaid

While many states increased their Medicaid income thresholds during the late 1990s and 2000s, as discussed above some states actually reduced their Medicaid generosity. Tennessee was the state with the biggest changes in its Medicaid income threshold. The income threshold in Tennessee was at 400% of the FPL in the late 1990âĂŹs but it fell to 200% of the FPL in 2000 and fell additionally to 185% of the FPL in 2002, staying at that level from then on [24]. Thus, contrary to many states in which

[22] Note that workers can still be over- or under- qualified in their current and past jobs. We do not take a stand on whether over- or under- qualification is a bad/good outcome.

[23] In separate specifications, we analyzed outcomes such as getting a wage increase in the new job, the probability of getting pension benefits in the new job and the probability of getting health insurance from the employer in the new job. We did not find any effects of Medicaid generosity on these variables.

[24] Note that this change in Medicaid is different from the one examined by [30] who examine the disenrollment of all adults from Medicaid in 2005. We also tested the effects of the adult disenrollment on our outcome variables and found similar results to our experiment above.

the generosity of public health insurance increased during the past few decades, we should expect for occupational mobility to fall in Tennessee.

Table B.7 shows difference-in-difference results of the Tennessee experiment, using data from 1997 onwards, where the specification includes a Tennessee indicator, a post-2000 indicator and an interaction of these two, as well as all the demographic and policy controls included in the previous analysis. In this experiment, we compare Tennessee only against the control states that did not change their Medicaid income thresholds during the entire period of analysis, which includes the following 10 states: Arizona, California, Kansas, Mississippi, North Dakota, Rhode Island, Texas, West Virginia and Wyoming.

The results in Table B.7 are consistent with the reduction in occupational mobility after the much less generous Medicaid system in Tennessee after 2000. Column (1) show a reduction in occupational mobility by 6.9%, in Tennessee after 2000. We also find that workers moved away from riskier occupations in Tennessee after 2000. In particular, columns (2) and (3) show that workers were 8.6% and 3.9% less likely to move towards occupations with greater wage spreads and higher separation rates in Tennessee after 2000, although the latter effect is not significant. Finally, columns (4) and (5) show that workers are also less likely to move towards better jobs. Column 4 shows that workers are 3.8% less likely to move towards occupations with higher median wages in Tennessee after 2000. Column (5) also shows that workers in Tennessee are 9.3% less likely to move towards jobs that have the same or higher educational requirements after 2000, an indication that workers are moving down the job ladder as Medicaid becomes less generous. Overall, this experiment shows that a sharp reduction in the generosity of Medicaid decreases occupational and industrial mobility and increases mobility towards safer and less desirable jobs.

2.6 Conclusion

In this paper, we go beyond the usual positive impacts of Medicaid in terms of reducing âĂŸjob lockâĂŹ and âĂŸemployment lockâĂŹ, and examine possible additional impact of Medicaid generosity on labor market outcomes. We focus on the role of Medicaid in increasing occupational mobility. While occupational mobility helps to reduce mismatches and is crucial for the healthy working of the labor market, changing occupations is risky and requires workers to undertake investments that workers are not always willing to make.

Here, we examined whether increased generosity of public health insurance in the form of Medicaid incentivizes individuals to undertake risk and change occupations. The paper uses statutory changes in Medicaid income and age thresholds during the 1990s and 2000s to examine how the generosity of health insurance affects occupational and industrial mobility. We are careful to control for other policy changes that were happening during this time period and we check whether Medicaid income and age threshold changes were driven by demographic factors, or by economic or labor market conditions. We find that these factors cannot explain these statutory changes.

We find substantial effects of an increase in income thresholds on occupational mobility of 5.2%, when income thresholds are increased from the level in states at the 10th to level in states at the 90th percentile of Medicaid income threshold generosity. We also do a falsification test by checking that those farther away from the threshold are not affected by Medicaid changes. We find big effects for workers in the lowest income decile and, thus, close to the threshold, but no effects for those higher up in the distribution relative to the threshold. More importantly the difference between the lowest and highest income groups are statistically significant. We also find bigger effects for women, for those with children, and for those who are married.

Importantly, the increases in Medicaid eligibility also increase movement towards jobs in occupations that are riskier but also better. We find that increased Medicaid income thresholds increase mobility towards occupations that are riskier in terms of having a higher variance of wages and higher separation rates. Moreover, when Medicaid generosity rises, workers not only move to riskier occupations but towards better quality jobs. We find that an increase in the Medicaid income threshold increases movement towards occupations with higher median wages. While it has been argued that public health insurance can improve the quality of matches, there is little evidence of this except for [35] who found that access to COBRA increases subsequent wages. In this paper, we actually measure match quality by comparing the educational requirements in the occupation the person moves to and the educational requirements in the previous occupation. We find that an increase in Medicaid income thresholds increases the likelihood that a worker will move to an occupation that has educational requirements that coincide or exceed the educational requirements in the previous occupation. Thus, we find evidence that increased generosity of Medicaid helps workers move up the occupation ladder.

Moreover, we examine a natural experiment due to a large reduction in Medicaid generosity in Tennessee, as the Medicaid income threshold fell from 400% to 200% of the FPL. We find that the reversal in generosity in Medicaid in Tennessee after 2000, not only decreased occupational mobility but it also decreased transitions towards riskier and better jobs. Thus, denying public health insurance benefits to more households in Tennessee reduced labor mobility and moved people towards safer jobs down the job ladder.

This analysis indicates that decreased uncertainty in the form of public health insurance should help encourage occupational mobility and greater flexibility in the labor market, but also allow workers to move towards riskier, better paid jobs and better matches. As states expand or rollback their Medicaid programs under the ACA, these changes in benefits of public health insurance should inform the relevant cost-benefit analyses. Additionally, our empirical results could also inform the theoretical literature on optimal generosity of social insurance policies, by explicitly taking into account the indirect role of such programs on workersâĂŹ careers and future income prospects.

Chapter 3

Shaping Careers through Public Policy: Evidence from ACA Dependent Coverage

3.1 Introduction

> *"Today, thanks to the health care law, young adults can stay on their parents' health insurance until they turn 26. — It gives you the freedom to try several jobs until you find the one you love, chase that new idea, or start your own business, without fear that the unexpected will derail your dreams."*

The above comments are from U.S. President Barack Obama when he answered a question on Quora about how the Affordable Care Act will affect the career and job choices of young people.[1] One of the key selling points of the Affordable Care Act proposed by President Obama and his administration was the portability of health insurance across employers. With private health insurance marketplaces, individuals could buy affordable health insurance and would not have to rely on employer provided coverage. This would lead to increased flexibility in the labor market for workers, allowing them to switch jobs and/or start their own business. Compared to European economies, such fluidity in the labor market has been a hallmark of the US economy. However, in the last two decades, there has been a secular downward trend in labor

[1] https://www.quora.com/Obamacare-Patient-Protection-and-Affordable-Care-Act/How-will-ACA-affect-career-and-job-choices-of-young-people-and-their-lives-in-general

market fluidity, with researchers arguing that this decline is directly related to the phenomenon of jobless recoveries and tepid economic growth during the same time.[2]

Health insurance can affect labor market outcomes directly through its effect on health of the individual or it can affect labor market outcomes indirectly by altering the payoff structures, modifying labor supply patterns and affecting labor market churn. The indirect effects of health insurance provision on labor market outcomes are mostly relevant in the case of the United States labor market, where health insurance has been provided mostly by employers. Until the passage of the Affordable Care Act, the majority of the U.S population could only get health insurance for themselves and their dependents through their employers.[3] For young adults, the Affordable Care Act provided a major policy change enacted in September 2010. Previously, as children reached the age of 19, they were removed from their parents' plan.[4] Under the policy change, it was mandated that health insurance providers who provide dependent coverage allow children to stay on their parents' health insurance plans until they turn 26. The idea behind this policy change was that having health coverage via their parents would allow young workers to try different careers and jobs without being forced to accept an unsuitable job that they may have accepted in order to benefit from employer-provided health coverage.

The aim of this project is to analyze the effect of the passage of the Affordable Care Act on the career transitions and trajectories of young workers aged 19-25. We start by documenting the effect of this reform on the source of health insurance for individuals aged 19-25. The empirical strategy we employ is a difference-in-differences estimator in which we compare individuals aged 19-21 with individuals aged 15-18, and those

[2] For example, see the discussion in [22].

[3] [20] provide an excellent review of the institutional details of the U.S health insurance system and how it interacts with the labor market decisions of individuals.

[4] Full time students were removed from their parents' plan at the age of 22.

aged 22-25 with the group of individuals aged 35-42, before and after the enactment of the dependent coverage mandate of the Affordable Care Act in September 2010. We find that for 19-21 year old workers, there was an increase of 6.6 percentage points in receiving dependent health coverage after the law enactment, and a decrease of 4.8 percentage points of receiving health insurance through an employer. For workers aged 22-25, health insurance through employer went down by approximately 7 percentage points, while receiving dependent health coverage increased by 12.4 percentage points.

After showing that the law significantly changed the source of health insurance for 19-25 year olds, we examine how the law impacted the labor supply choices of the treatment group. We find that for 19-21 year olds, there was an imprecise effect of being employed after the enactment of the law, however, the probability of being enrolled in school increased by 3 percentage points. On the other hand, for 22-25 year olds, the probability of being employed after the enactment of the law went down by 2.4 percentage points. Not only were the older workers less likely to be employed, conditional on being employed they also earned lower hourly wages. We also find that the probability of being self-employed increased by 1.1 percentage points for 22-25 year olds, and they also looked for jobs for 1 more week compared with individuals who were never exposed to the law. For 19-21 year olds, there was no significant change in the probability of being self-employed or searching longer for jobs, however, conditional on being employed, the treated group earned lower hourly wages, and had lower annual earnings.

Next, we explore whether exposure to the ACA dependent coverage law affected the job to job mobility of young adults, and find that immediately after the law was enacted, 19-21 year olds were more likely to switch between jobs (with and without an intervening unemployment spell), and were also more likely to separate from their jobs into non-employment. We explore the dynamic effects of the law change by looking at the impact of the law on the source of health insurance, labor and non-labor outcomes and job characteristics five and six years after the law was enacted. We find that six years after the law was enacted, employment among 24 year olds in 2010 (who were exposed to the law for two years) increased by 1.9 percentage points, while self-employment increased by 1.8 percentage points. In our sample, 77.5% of 30 year olds are employed, while 5.7% are self-employed. Therefore, due to the ACA dependent coverage, there was an approximately 2.5% increase in employment and a 31% increase in self-employment six years after being exposed to the law. We also find that five years after the law;s enactment, 22-25 year olds were less likely to switch occupations.

Taken together, our results point to multiple channels through which the ACA impacted young adults' careers. Immediately after the enactment of the law, 19-21 year olds were more likely to enroll in school, suggesting that the law led to a possible increase in the human capital accumulation of young workers who were at the cusp of deciding between working or investing in their education. For 22-25 year olds, there was an increase in job search time. However, in the long run, we found that a higher proportion of this group of individuals were self-employed, and conditional on being employed, they were better matched to their desired occupations (as suggested by lower likelihood of occupational switching). This suggests that the ACA did deliver on its promise of allowing young adults to take risks and search for their preferred job, or chase a business idea that they were not willing to pursue when their health insurance was tied to an employer.

Our paper contributes to three main strands of literature that has looked at the effect of health insurance on labor market outcomes. First, we contribute to the literature that has focused on how health insurance provision affects the labor supply decisions, particularly of the elderly, married women and single women with young children. These demographic groups can have access to health insurance through sources other than their employer and therefore can afford to supply less labor. The empirical literature on this issue has generally found a consistent result that the availability of alternative sources of health insurance depresses labor supply (see [20] and [34] for a review of this literature). With the passage of the Affordable Care Act's dependent coverage mandate, researchers have also looked at the labor supply responses of workers aged 19-26. The first such paper was by [8], who found evidence that since September 2010, workers aged 19-26 reduced their work hours since they had an alternative to employer provided health insurance. More recently, Depew [24] and Dillender [26] used geographical variation in the implementation of the dependent coverage extension prior to the ACA to identify the effect of dependent coverage on young adults' labor market outcomes, and found that state mandates led to a decrease in labor supply at the intensive margin.

Focusing on other labor market outcomes such as employment status, job characteristics and educational attainment, [39] do not find any impact of the dependent coverage on labor market outcomes of young adults. Using time use data, [18] find that young adults did indeed spend more time in job search activities since the passage of the dependent coverage mandate of ACA, thus providing suggestive evidence of increased job shopping among young adults. However, none of the above studies have looked at the long-run effects of the extended dependent coverage on the career trajectories of workers.

Another branch of the literature has focused on the effect of health insurance provision by employers on the wages offered to their employees. Basic economic theory predicts that there should be a negative relationship between the two, however, the empirical literature has failed to find a consensus ([20] and [34]). While there is a direct effect on earnings, health insurance provision could also affect wages indirectly if it enhances or depresses the job matching process. [56] was one of the first papers to provide evidence in favor of the “job-lock" hypothesis, according to which workers are less likely to change employers if health insurance provision is tied to their jobs. If this hampers mobility towards higher productivity jobs (as in the job matching framework of [48]), then wages could be depressed for workers as they are stuck in low quality jobs. Indeed, [36] found evidence that unemployed workers with continued access to health insurance from their past employer were more likely to spend more time unemployed but were rehired at higher wages, implying that they took longer to search for higher quality jobs. We contribute to this literature by focusing on wage growth of workers who are exposed to the expanded dependent coverage of the ACA.

Finally, a third branch of the literature has focused on the aforementioned job-lock hypothesis. There has been a divide in the literature about the existence and the magnitude of the job lock phenomenon. Some studies such as [56], [19], [13] and [35] have found that employer- provided health insurance depresses job turnover in an economically meaningful way. However, other studies such as [42], [50] and Baicker et al. [10] find little evidence to substantiate claims of job-lock. More recently, Garthwaite, Gross, and Notowidigdo [31] use the abrupt dis-enrollments of 170,000 Tennessee residents to quantify the effect of public health insurance on labor supply, and find that the dis-enrollment led to an immediate increase in job search, and increase in labor supply at the extensive margin.

In theory, to test the “job-lock" hypothesis, one would like to compare the probability of job turnover among otherwise observationally equivalent workers who differ only in the value that they place on their current employers' health insurance plan. Various measures for the value of current health insurance have been used in the literature, including health insurance coverage from a source other than the current employer, such as spousal health insurance or some sort of continuation coverage such as COBRA, family size, health conditions and health status. [35] analyzed an exogenous change in the law across states that allowed unemployed workers to have health insurance coverage from their past employer until they found a new job. They find that one year of such coverage is associated with a 12-15% increase in the mobility which suggests that health insurance does in fact impede job mobility. [36] extend this analysis and look at transitions to non-employment and re-employment earnings rather than job-to-job mobility. They find that one year of continuation coverage availability doubles the reemployment earnings of job leavers who take up that coverage. Similarly, we use ACA's extension of the dependent coverage mandate as an exogenous source of variation in the non-employment health insurance variability to identify the effect on job mobility.

3.2 Data Sources

Or main data source is the March Annual Social and Economic Supplement of the Current Population Survey which contains extensive information on demographics, labor market outcomes and health insurance coverage. We use data from the years 1996-2016 and restrict our attention to civilians aged 15-42.

To determine a respondent's health insurance status, we use questions from the March CPS which ask about the source of health insurance coverage. Respondents are asked whether they were covered by health insurance provided through an employer or through a parent or spouse. This allows us to construct indicators pertaining to sources of health insurance coverage that are used to test the effect of the law.

The March CPS also asks questions about the labor market status of the respondents in the last week and whether they were enrolled in school or college [5]. We use information about their employment status, class of work and hourly earnings for our

[5] The question about enrollment is asked only to 16-24 year olds until 2014

analysis of labor market outcomes. The March CPS also contains other information about the respondent's job such as whether the respondent had access to a pension plan through the employer and whether the respondent is currently working in the occupation of the longest job last year. We use the questions about the current occupation and the occupation of the longest job last year to create measures of occupation switching at the 3- digit and at the 2- digit level.

Finally we use the March CPS to construct measures of non-labor outcomes that could have been affected by the ACA dependent coverage mandate and which are highly correlated with labor market outcomes. In particular, we use the questions related to migration to determine whether a worker moved to a different state within the last year and the questions related to living arrangements to determine whether the respondents live with their parents or not. We also use the marital status of the respondents to test if the law change had any impact on the rates of family formation.

To provide evidence on job shopping behavior induced by the ACA dependent coverage mandate we use data from the Longitudinal Employer-Household Dynamics Program which publishes aggregate job-to-job transition rates at the quarterly level by different age groups. The data does not provide any detailed demographic information like the March CPS. We use data from 2000-2016 for our analysis. The dependent variables that we use include job-to-job transition rates without a non-employment spell, job-to-job transition rates with a non-employment spell and rates of separation to persistent non-employment.

We divide the March CPS data into multiple subsamples. Our first subsample contains 22-42 year olds in which 22-25 year olds are part of the treatment group while 35-42 year olds are part of the control group. Our second subsample contains individuals from the ages of 15-21 where the 19-21 year olds form the treatment group and the 15-18 year olds form the control group. Finally, to analyze long term outcomes we also define subsamples based on age of the individual in 2010.

3.2.1 Summary Statistics

Descriptive statistics for the different age groups in our sample are provided in Table C.1. The first two columns present summary statistics for the first treatment group (22-25 year olds) and the control group (35-42 year olds). Among 22-25 year olds, 31.2% have health insurance through their employers and 17.6% receive health insurance as a dependent. 71.5% of these individuals are employed, while 21.7% are not in the labor force. On the other hand, among 35-42 year olds in 2010, 49.5% have health insurance through their employer and 24.7% report that they dependent health insurance. Among this group, 79.7% are employed and 16.1% are not in the labor force. The average years of education for both the treatment and control group is 13 years.

Among the older treated group, 2.4% are self-employed. The average search duration of this group is 12 weeks, while their average real hourly wages are $11.8. Their real annual earnings are $18,542 and 19% of them have a pension plan through their employers. In terms of their demographic characteristics, 73% have never been married and 31.5% are living with their parents. 78% of these individuals are white, 15% are black and 19% are hispanic. In contrast, the older control group search for jobs for an average 13 weeks, have an average hourly wage rate of $18, and 40% report that they have a pension plan through their employer. Among the control group, 13% report changing their occupation from their longest tenure occupation. In terms of their demographics, due to the fact that this group is older, their demographic characteristics also differ substantially from the treatment group. Among the control group, 17% individuals have never been married and only 4.6% individuals are living with their parents. The racial composition of the control group is somewhat similar, with 80.3% respondents being white, 13% blacks and 15.2% hispanics.

In columns (3) and (4) we report the descriptive statistics for the younger treatment and control group. The treatment group is individuals between ages 19-21, while the control group is 15-18 year olds. Among the younger treatment group, 11% have health insurance through their employer, while 38% claim health insurance as a dependent. Among this group, 56% are employed, 36% are not in labor force, and conditional on being out of the labor force, 71.3% are enrolled in school. Only 1.1% of the younger treatment group is self-employed, and they search for jobs, on average, for 13 weeks. The real annual wage rate for this group is $9, and 5.4% report that they have a pension plan through their employer. This group also exhibits more occupational switching, with 31.5% reporting having switched an occupation from their longest tenure occupation. As expected, 91.5% of the individuals in this age group have never been married, and 61% are living with their parents. In contrast, among the younger control group, 2.2% have health insurance through an employer while 58% report getting health insurance as a dependent. Only 23% of them are employed and 72% are not in labor force. Conditional on being out of the labor force, 64% are enrolled in school. For those who are part of the labor force, the average search duration is 10 weeks, and conditional on being employed, their average hourly wage rate is $7.5. Among this group, 25% report having switched occupation from their longest tenure occupation. Lastly, 98% of them have never been married, and 87% are living with their parents.

In columns (5) - (8), we report summary statistics for four different age groups that correspond with the treatment group for the long-run analysis, and will be used to interpret the magnitudes of results of our long-term analysis.

3.3 Econometric Framework

The main empirical strategy will be a Difference-in-Differences regression model that compares the outcomes of a treatment group, before and after the enactment of the ACA dependent coverage mandate with those of a control group over the same time period. The regression model is presented more formally below:

$$Y_{igst} = \beta_0 + \beta_1 Treat_g + \beta_2 After_t + \beta_3 (After_t \times Treat_g) + \gamma X_{igst} + \delta_t + \omega_s + \epsilon_{igst} \quad (3.1)$$

where Y_{igst} represents various labor market outcomes such a job switching, occupational switching, industry switching etc for individual i in age range g, state s and time t, X_{igst} represent individual characteristics, $After_t$ is a dummy variable which takes on the value 1 after September 2010 and $Treat_g$ is a dummy variable which takes on the value 1 for those who are part of the treatment group. The parameter of interest is β_3 which captures the average effect since the policy change by comparing outcomes before and after September 2010 among the treatment group relative to the control group. Since the enactment of the law coincides with the a tepid recovery in the labor market, it is important to control for time and state fixed effects which are captured by δ_t and ω_s.

3.4 Results

Table 2 reports the results of the law change for 22-25 year olds, who are part of the treatment group, where they are compared to 35-42 year olds who are are part of the control group. The control group starts from age 35 because by 2016, workers who are 30 year old or younger have been affected by the law in 2010. The main identifying assumption in the difference-in-differences specification is that the two groups have common trends in the years prior to the law change and we analyze this condition in Table 2.

Columns (1) of Table C.2 shows that in the years after 2010, young adults between the age of 22-25 were 7 percentage point less likely to have health insurance through their employer. The proportion of people in this age group who have health insurance through their employer is 31% (see Table C.1), which suggests that the passing of the ACA dependent care mandate led to a 22.5% decrease in the proportion of workers between the age of 22-25 who have health insurance coverage through their employers. Column (2) shows that this effect was absent in the years prior to 2010 and it increased in magnitude with time.

Column (3) of Table C.2 shows that in the years after 2010, young adults between the age of 22-25 were 12 percentage point more likely to have health insurance through their parent or spouse which represents an increase of 66%. Column (4) and Figure 1 shows that there were some differences between the treatment and the control group in the years preceding the implementation of the law but the magnitude of the effect increased in the years after 2010.

Column (5) of Table C.2 also shows that the passage of the law also led to a decrease of 2 percentage points in the employment levels of individuals aged 22-25 which represents a 6% decrease in employment for this age group. This result is similar to those documented by [8] and [24] for the case of young adults and also confirms the conclusions of [31], although here the relaxation of "employment lock" led to a decrease in employment.

Table C.3 focuses on additional outcomes for 22-25 year olds and shows that in the years after 2010, the self-employment rate for this group increased by 1.1 percentage points, which represents an increase of 45%. The law also had a positive impact on search duration of individuals in the age group 22-25 as they searched for jobs 1 week longer post 2010 [6]. The treatment group was also 1.5 percentage points more likely to have access to a pension plan through their employer. While this might suggest that the workers who were not bound to a particular employer to have access to health insurance were able to move to better quality jobs, we do find that the same workers were not able to obtain higher hourly wages or yearly earnings. In fact, for hourly wages we find a highly precise estimate which reflects a decline of 5% in hourly wages after the year 2010 for the treatment group. This could be due to the fact that some people drop out of the labor force and enroll in universities and colleges. The treatment group was also 4 percentage point more likely to live with their parents and 1 percentage point less likely to have moved to a different state within a year.

Taken together, these results suggest that the flexibility offered by the ACA dependent coverage mandate could have changed the margin at which individuals enroll in higher education and it could have simultaneously induced more experimentation in the labor market which can explain the decreased hourly wages after the enactment of the law.

Tables C.4 and C.5 show results from a similar exercise for 19-21 year olds but now the control group is 15-18 year olds as they are never exposed to the law. The results in these tables corroborate those in Tables C.2 and C.3 as the treatment group was less likely to have health insurance through their employers and more likely to have it through their parents. They were also more likely to be enrolled in school, an increase of 2.8 percentage points which constitutes an increase of 4%. As the ACA dependent coverage mandate changed the marginal individual who enrolls in college, we see in Table C.5 that those who continue to work end up in low paying jobs (column (3)) with lower yearly earnings (column (5)) and with less of a chance to have access to a pension plan from their job.

[6] The dependent variable is in log (weeks searched)

3.4.1 Evidence on Job Switching from LEHD data

This section provides evidence from the LEHD job-to-job (J2J) aggregate data that the passage of the ACA dependent care mandate led to increased job switching by the 19-21 year olds when compared to the 14-18 year olds. Table C.6 shows that for the treatment group, the job-to-job transition rate without any spell of non-employment increased by 0.0038 percentage points after 2010 which represents an increase of 4.7% given that the average rate in the population was 8%. Column (3) shows that the rate of transition from Employment to Persistent Non-Employment also increased significantly which could be due to enrollment in college and universities.

3.4.2 Long Term Outcomes

Table C.7 and C.8 report results on the long term outcomes of the workers who were exposed to the law for different years. We start with the year 2016 and compare outcomes of workers who are 28-30 year old with those who are 32-35 years old. The former constitutes our treatment group as they were 22-24 years old in 2010 and were able to benefit from this change of law for 4, 3 and 2 years respectively. The control group contains those who belong to the age group 32-35 as they were never exposed to the law. To ensure that our control group does not contain any individuals exposed to the law, we restrict our attention to the years $1996-2012$ and 2016. Similarly to asses the effects in 2015, the treatment group comprises of 27-29 year olds and the control group comprises of $31-34$ year olds while we restrict our attention to the years 1996-2011 and 2015.

Results of the long-run analysis for 22-24 year olds is presented in Table C.7. Panel (A) shows results for the year 2016 (i.e. 6 years after the enactment of the law), while panel (B) shows results for 2015 (i.e. 5 years after the law enactment).

Column (1) shows that six years after the law was enacted, individuals who were 24 year old in 2010 and were therefore exposed to the law for 2 years, had 0.16 fewer years of completed education. These individuals were also more likely to be employed and self-employed. In particular, we find that six years after the law was enacted, employment among 24 year olds in 2010 increased by 1.9 percentage points, while self-employment increased by 1.8 percentage points. In our sample, 77.5% of 30 year olds are employed, while 5.7% are self-employed. Therefore, due to the ACA dependent coverage for 24 year olds, there was an approximately 2.5% increase in employment and a 31% increase in self-employment six years after being exposed to the law. Interestingly, we find no significant effects on hourly wages and yearly earnings after six years for any of the age groups.

In panel (B), we report the same outcome variables five years after law enactment, and find a significant increase in self-employment among 22 year olds in 2010. In 2015, these individuals were 27 years old, and the proportion of 27 year olds who are self-employed in our sample is 4.2%. Therefore, being exposed to the law for four years led to an increase in self-employment of approximately 33% after five years. We also find a decrease in hourly wages and annual earnings of 23 and 22 year olds in 2010 five years after the law was enacted. 22 year olds in 2010 are also less likely to have health insurance through an employer five years later, which is a measure of job quality.

In Table C.8, we report results for long-run occupation changes and non-labor outcomes such as being single and living with parents. Panel (A) shows results for the year 2016, where we find that among 24 year olds who were exposed to the law for two years, occupational switching decreased by 1.4 percentage points. Occupation change here is defined as having changed occupation from the longest held occupation to something else. For all age groups, we find a significant increase in the proportion of people living with their parents, and see an increase in the proportion of people who are never married among 22 and 24 year olds in 2010.

Panel (B) shows the long-run outcomes of these individuals five years after law enactment. We see that for all age groups, there is a decrease in the proportion of individuals who report changing their longest tenure occupation. For all age groups, there is also a decrease in the likelihood of changing the state of residence, and an increase in the probability of being never married for 22 and 23 year olds. Lastly, for 23 and 24 year olds, the likelihood of living with parents five year after law enactment is also higher if they were exposed to the law.

These results highlight the multiple channels through which the ACA dependent coverage extension impacted young adults. While some of these young adults were more likely to be self-employed, and less likely to switch occupations, suggesting more stable career choices, we do see some mixed effects in terms of their non-labor outcomes. Individuals exposed to the law were more likely to be living with their parents, which could suggest that the dependent coverage extension led to more risk-taking in terms of starting their own business, but it also led to individuals putting off marriage and living with parents.

3.5 Conclusion

We study the effect of the ACA dependent coverage extension on the career trajectories of young adults. The dependent coverage extension led to a significant increase in the proportion of young adults claiming health insurance as dependents, and a significant decrease in the proportion of 22-25 year olds obtaining health insurance from their employers. The removal of dependency on employers to provide health insurance led to 22-25 year olds taking more risks in the short-run, in terms of searching longer for jobs and being more likely to be self-employed. Among 19-25 year olds, the age group that was at the cusp of deciding whether to work or invest in human capital accumulation, we see that having access to their parent's health insurance plan resulted in an increase in the proportion of individuals enrolling in school. In the long-run, being exposed to the law led to an increase in self-employment and a decrease in occupational switching conditional on being employed.

In the short-run, the law induced young individuals to enroll in school, search longer for jobs, increase job mobility and be more likely to be self-employed. These short-run investments paid off five and six years later, as self-employment increased by 31% and occupational switching went down, suggesting more stable career choices in the long-run. However, we do see some mixed effects in terms of their non-labor outcomes. Individuals exposed to the law were more likely to be living with their parents, which could suggest that the dependent coverage extension led to more risk-taking in terms of starting their own business, but it also led to individuals putting off marriage and living with parents.

Appendix A

Appendix for Chapter 1

A.1 Further Stylized Facts and Robustness Checks

A.1.1 Sample of Workers with more than a Bachelor's Degree

This section shows the incidence of over-education over the life cycle for workers who have more than a Bachelor's degree. For this group the over-education measure takes a value of 1 if they are working in a non-college job, where the college jobs are defined as in section 2. When I use the National Survey of College Graduates, I use the same question as the main text to determine over-educated workers among this group. Figures A1-A2 show that for this education group, the incidence of over-education also rises over the course of the life cycle.

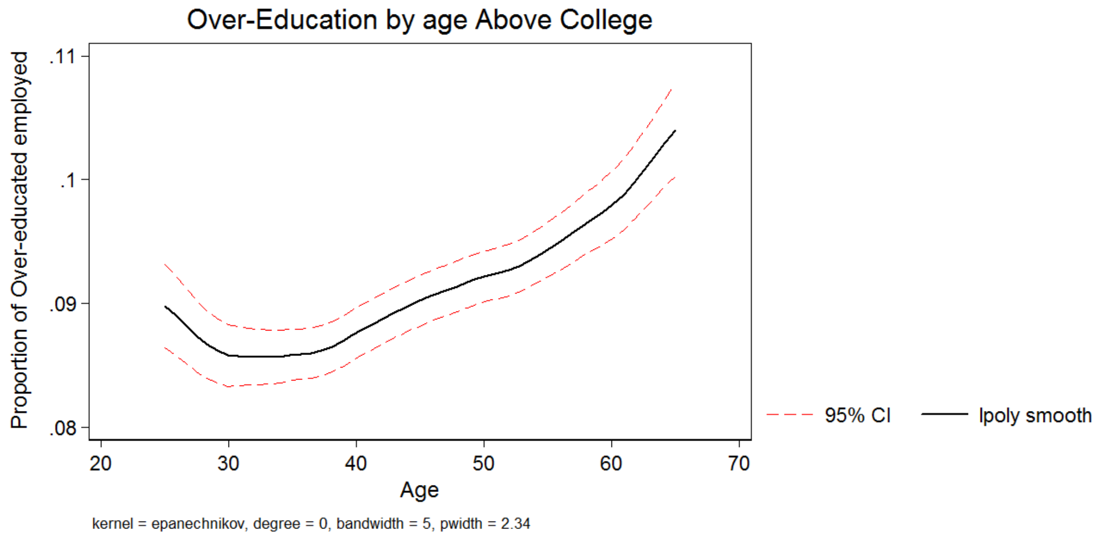


Figure A.1: CPS Data- Sample of Workers with More than a Bachelor's Degree

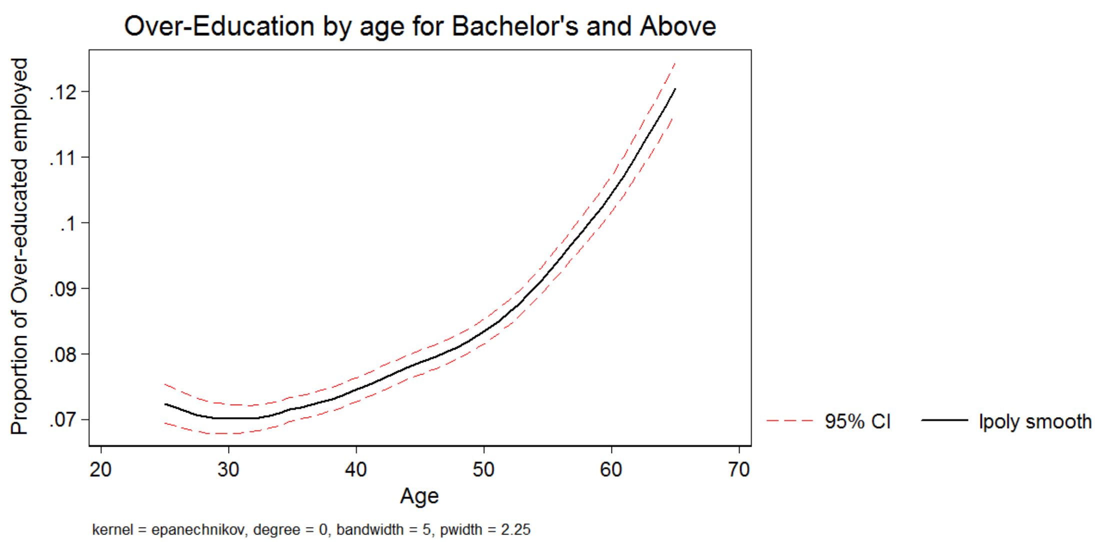


Figure A.2: NSCG Data- Sample of Workers with More than a Bachelor's Degree

A.1.2 Destination Occupation Characteristics

This section documents the wage percentiles and cognitive skill percentiles in the destination occupation of workers who make a downward transition. The cognitive

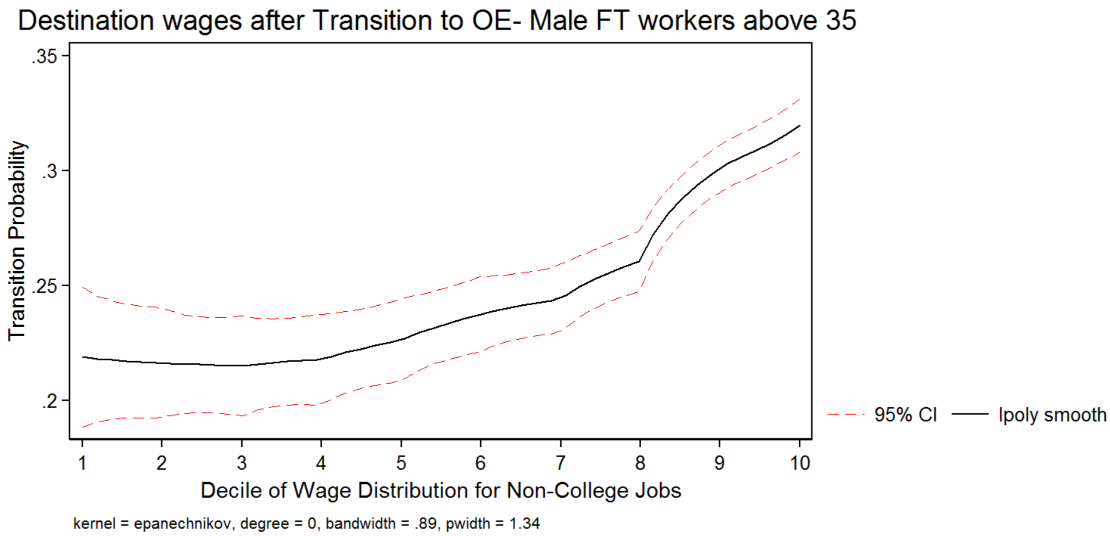


Figure A.3: Wages Deciles of Workers Who Make Downward Transitions

skill percentiles are based on the cognitive skill score for each occupation from [3]. For both these measures, the percentiles are computed by restricting the sample to workers who are working in non-college jobs. Both these measures are used as proxies for worker productivity to infer the relative productivity of over-educated workers relative to non-college workers. Figures A3 and A4 show that whether one defines productivity through wages or cognitive skill requirements, workers who make downward transitions end up near the top of these distributions among non-college workers. This empirical fact is consistent with the model.

Wages Profiles of OE Workers

Figure A.5 shows the wage premium in cross-sectional data CPS. The wage premium for over-educated college graduates is lower than matched workers, specially at younger and older ages. Another striking feature of this figure is that the overall

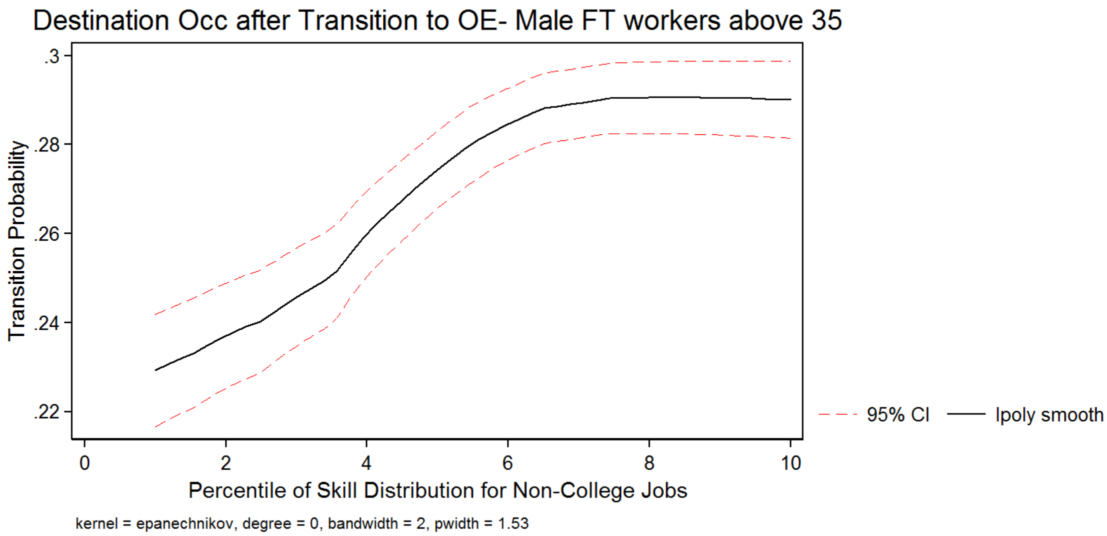


Figure A.4: Cognitive Skill Deciles of Workers Who Make Downward Transitions

college wage premium that is considered the main benefit from going to college is entirely driven by adequately matched college graduates while the 30-40 percent of over-educated college graduates receive relatively less premium on their investment.

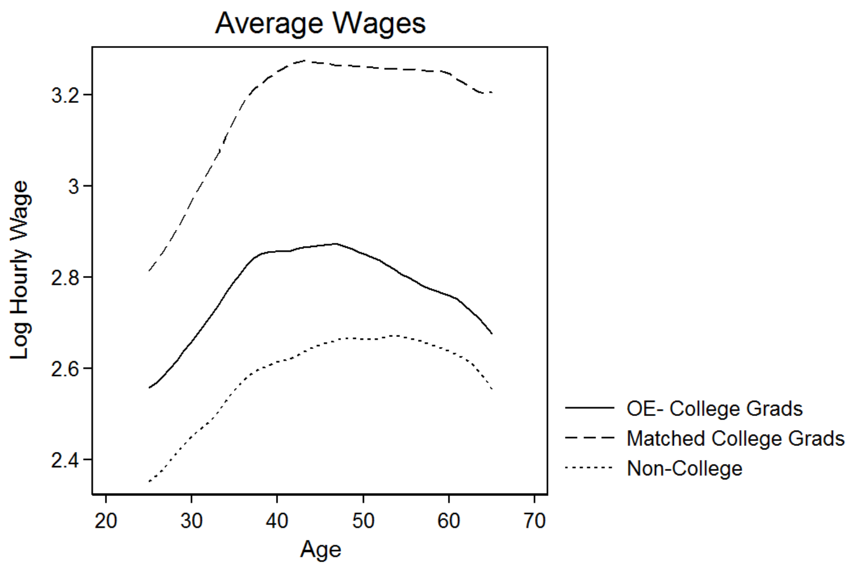


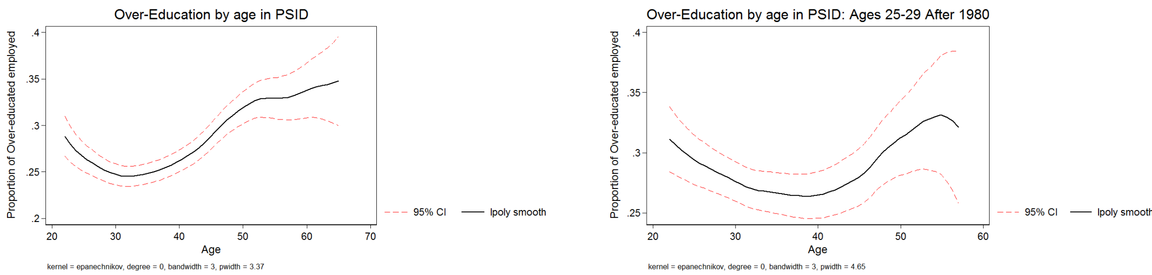
Figure A.5: Wage Premium over Age across Different Groups

The U-shape of Over-Education from PSID

For the PSID sample, I restrict attention to male head of households with a bachelor's degree. Figure A6 shows the results from the analysis of PSID data for different cohorts. The U-shape is more pronounced for older cohorts that it is for younger ones. For this analysis I used the occupational crosswalks to identify high skilled occupations in 1980s and 1970s. Misclassification of jobs to high skilled categories in the 1970s might explain the rise in U-shape for earlier cohorts in the PSID. It is worth noting that the proportion of workers with a bachelor's degree in the PSID who are over-educated in their jobs is very similar to the proportion documented from CPS-MORG data from 2003-2010.

Over-education measure and job quality

In this subsection I compare the over-education measure with other measures of occupation quality used in the literature such as occupation median wages and skill



(a) All Cohorts-BA

(b) Cohorts 25 or younger in 1980 -BA

Figure A.6: Over-education in the PSID Sample-Bachelor's Degree Holders

requirements of occupations developed by [3]. Figure A7-A8 show that it is highly correlated with other measures of job quality. In particular, over-educated college workers are working in jobs that have similar characteristics to jobs performed by non-college workers.

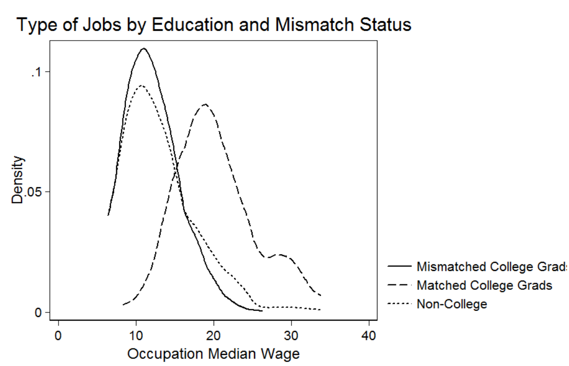


Figure A.7: Occupation Median Wage for Jobs Performed by Various Groups

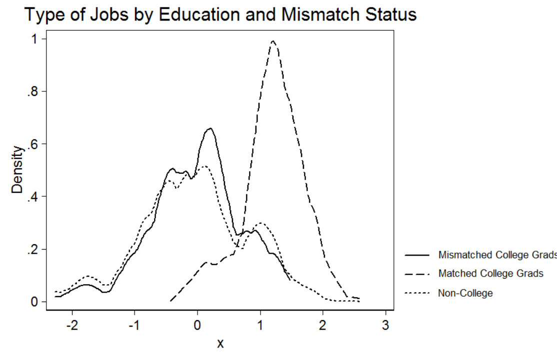


Figure A.8: Cognitive Skills for Jobs Performed by Various Groups

Alternative Over-Education Measures

In this section I consider two alternative over-education measures. The first is a measure developed by [2] using the O*NET database in which they consider college jobs as occupations in which at least 50% of the respondents say that at least a bachelor's degree was necessary to perform the job. Using this measure I can construct measures of over-educated college graduates as in section 2. Figure A.9 shows the resulting life cycle profiles which are qualitatively similar to figures 1.1 and 1.2.

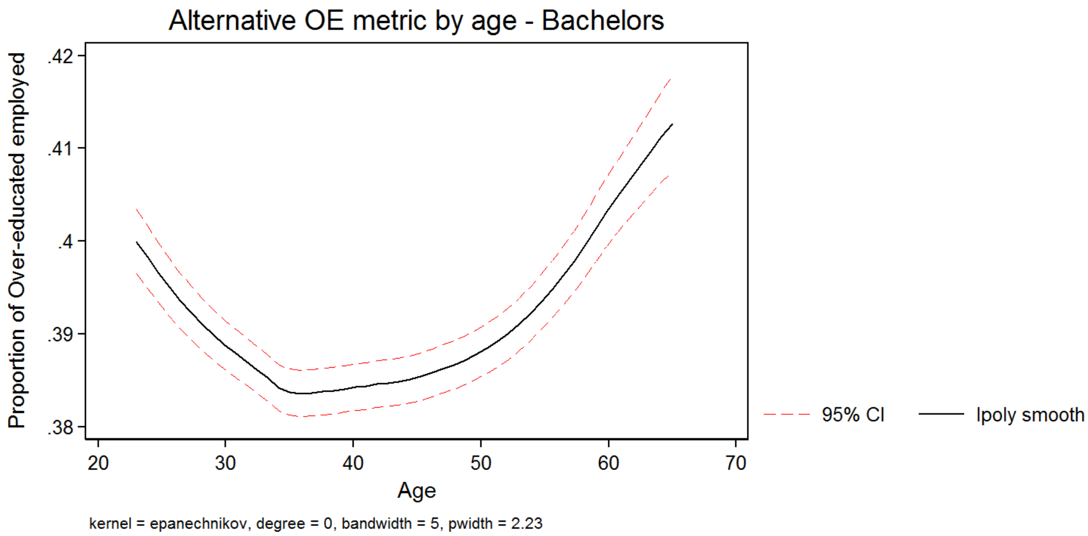
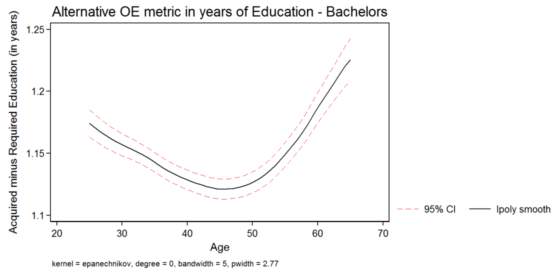
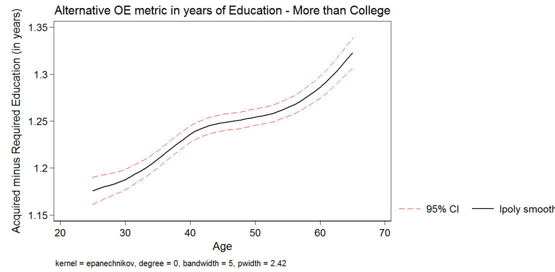


Figure A.9: Over-education Using the Metric of [2]

I also develop another over-education measure in terms of years of education required to perform a job. Using the complete distribution of responses in the O*NET database and assigning years of education to each response category, one can calculate the average number of years of education required to work in an occupation. For example, if 75% of the respondents within an occupation agree that a Bachelor's degree is required to perform an occupation and the remaining 25% respond that a Doctoral degree is required, then the average years of education required for that occupation would be $0.75 \times 16 + 0.25 \times 18 = 16.5$. Here the underlying assumption is that a Bachelor's degree is equal to 16 years of education and a Doctoral degree is equal to 18 years of education. This information can then be merged with the worker level datasets as in section 2 to compute a measure of over-education in terms of years of education. The life cycle profile of this measure is shown in Figure A.10. It also shows that the proportion of college workers who are over-educated in their jobs increases over the life cycle.



(a) Bachelor's Degree Holders



(b) More than a Bachelor's Degree

Figure A.10: Over-education in Terms of Years of Education

A.2 Computation Details

For the quantitative exercise, I solve the surplus function (12) and the value of unemployment (13) together on a grid for h and three types of occupations using backward induction with $T = 160$. The continuation value at $T = 160$ is assumed to be equal to 0. The investment decision, s_k, is solved by maximizing (12) such that the surplus function and the match output is positive for all values of $s_k \in [0, 1]$. Wages are computed by solving equation (9) and (6) together. For computing the stationary distribution, I simulate 10,000 agents for 160 time periods which equals 40 years of working life. For the simulation exercise, all the required information is contained in the surplus function, the value of unemployment, the investment function and the wage function.

Appendix B

Appendix for Chapter 2

B.1 Data Construction

Since tax systems were changing during the time period of analysis, we construct measures of tax progressivity and median taxes. To construct a measure of tax progressivity, we start by constructing state income tax liabilities using the TAXSIM software from the National Bureau of Economic Research (NBER) jointly with the information from the March Supplement of the Current Population Survey (CPS) to calculate the earned income, assets, pensions, disability, etc. for those at the 75th and 25th percentile of the total income distribution. The average tax rate is then obtained by dividing the tax liabilities by the average income at the 75th and 25th percentile. We construct tax liabilities for those at the 75th and 25th percentile of the national income distribution to hold constant the characteristics of the population for all states and capture solely on the differences in tax rates, credits and exemptions across states. To construct the tax liabilities, we assume that the person is married and with one child and we use the averages for those at the 75th and 25th percentiles of the national income distribution of the following variables: wage and salary income of taxpayer, wage and salary income of spouse, dividend income, interest income, rent income, alimony income, fellowships, taxable IRA distributions, taxable pensions, gross social security benefits, other taxable transfer income, child care expenses, and unemployment compensation. Similarly, we measure the average tax rate for those at the median of the national income distribution, assuming the person is married with one child and using the various income variables to construct the tax rate for those at the 50th percentile of the income distribution.

We also construct measures of cash transfers since these were also changing importantly during the period of study. We construct a measure of Temporary Assistance for Needy Families (TANF) benefits. TANF provides cash assistance to low-income families with children. When TANF was introduced in 1996 to replace the Aid to Families with Dependent Children (AFDC) program, the system was reformed by the legislation but also through state waivers introducing work requirements, lifetime time limits, financial sanctions and enhanced-earnings disregards. The benefits under TANF are constructed using information on maximum benefits, benefit-reduction rates and flat earnings disregards which vary over time and across states, as well as using earned and unearned income for the 25th percentile by year from the March CPS. In particular, we estimate TANF benefits using the following formula from Hoynes and Luttmer (2011):

$$TANFBenefit_{st} = Max.Benefit_{st} - \tau_{st} \times (Earnings_{t25th} - D_{st}) - UnearnedIncome_{t25th} \tag{B.1}$$

where $Max.Benefit_{st}$ is the maximum benefit in state s at time t, τ_{st} is the benefit-reduction rate in state s at time t and D_{st} is the flat earnings disregard in state s at time t. We construct these Benefits for the average individual at the lowest 25th percentile of the income distribution, so the earnings and unearned income are for the average individual in the 25th percentile of the national income distribution.

Table B.1: Descriptive Statistics

	All Sample	Above Mean Medicaid Income Threshold	Below Mean Medicaid Income Threshold
Medicaid Income Threshold (% of FPL)	1.91	2.129*	1.69
	(0.36)	(0.34)	(0.23)
Age Limit for Medicaid Threshold	4.69	5.215*	4.17
	(7.38)	(7.96)	(6.71)
Real TANF Benefits (1000s of Dollars)	1.73	2.396*	1.06
	(4.30)	(4.16)	(4.34)
Average Median Tax	0.11	0.105*	0.12
	(0.02)	(0.02)	(0.02)
Average Tax at the 25th Percentile	(0.26)	-0.273*	(0.25)
	(0.05)	(0.06)	(0.04)
Average Tax at the 75th Percentile	0.24	0.24	0.24
	(0.02)	(0.02)	(0.03)
Occupation Change	0.48	0.48	0.48
	(0.50)	(0.50)	(0.50)
Transition to Risky Occ. ÂŬ Greater Wage Variance	0.22	0.22	0.22
	(0.41)	(0.41)	(0.41)
Transition to Risky Occ. ÂŬ Higher Separation Rates	0.23	0.23	0.23
	(0.42)	(0.42)	(0.42)
Transition to Better Occ. ÂŬ Higher Median Wage	0.22	0.22	0.21
	(0.41)	(0.41)	(0.41)
Transition to Better Match ÂŬ Higher Educational Requirement	0.33	0.33	0.33
	(0.47)	(0.47)	(0.47)
Highest Grade Completed	13.81	13.89*	13.73
	(2.77)	(2.86)	(2.67)
Age	43.50	43.79*	43.22
	(10.68)	(10.66)	(10.69)
Number of Children	0.81	0.884*	0.74
	(1.09)	(1.11)	(1.06)
Male	0.52	0.52	0.52
	(0.50)	(0.50)	(0.50)
Foreign Born	0.15	0.197*	0.10
	(0.36)	(0.40)	(0.30)
Married	0.80	0.80	0.79
	(0.40)	(0.40)	(0.41)
Union Members	0.13	0.146*	0.12
	(0.34)	(0.35)	(0.32)
White	0.84	0.829*	0.86
	(0.36)	(0.38)	(0.35)
Black	0.10	0.0949*	0.10
	(0.30)	(0.29)	(0.30)
Hispanic	0.09	0.0980*	0.08
	(0.28)	(0.30)	(0.26)
Maximum No. of Observations	65,209	30,508	34,701

Notes: This table reports means and standard deviation in parentheses. Medicaid income threshold is the most generous income threshold for receiving Medicaid benefits in each state (units: % of poverty line). Medicaid age threshold is the age at which the most generous income threshold expires for each state. TANF benefits are calculated for a family of 3 using the following formula: TANF Benefit = Maximum Benefit-t(Earnings-D)-Unearned Income. Average tax rates at different income percentiles are calculated using data from the March CPS ASEC supplement and using NBERâĂŹs taxsim software. We construct two measures of transitions to risky occupations, transitions to occupations with higher separation rates and transitions to occupations with higher wage variance. We construct two measures of quality of matches. The first is based on median wages paid in the occupation and we construct at transitions to higher paying occupations. The second measure is only at the occupation level and looks at the education requirements of each occupation using the Labor DepartmentâĂŹs O*NET database. A transition to a better match in terms of education requirement occurs if a worker moves to an occupation with a similar or higher education requirement as his/her previous occupation.

Table B.2: Effects of State Economic Conditions on Medicaid Income Threshold

	Medicaid Income Threshold					Medicaid Age Threshold				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Unemployment Rate	(0.0040200)	(0.0054700)	(0.0046200)	(0.0048500)	(0.0000729)	0.0383000	(0.0054700)	(0.0046200)	(0.0048500)	(0.0000729)
	(-0.95)	(-0.76)	(-0.56)	(-1.04)	(-0.02)	(0.5600000)	(-0.76)	(-0.56)	(-1.04)	(-0.02)
Real GDP (Millions of 2009 dollars)	(0.0000000)	(0.0000000)	(0.0000000)	(0.0000003)	(0.0000005)	(0.0000005)	(0.0000000)	(0.0000000)	(0.0000003)	(0.0000005)
	(-0.30)	(-0.30)	(-0.31)	(-0.44)	(-0.73)	(-1.36)	(-0.30)	(-0.31)	(-0.44)	(-0.73)
Percent of White in Population	0.0381000	0.0385000	0.0399000	0.0373000	(0.0402000)	(1.4970000)	0.0385000	0.0399000	0.0373000	(0.0402000)
	(0.5800000)	(0.5800000)	(0.5600000)	(0.5200000)	(-0.65)	(-1.41)	(0.5800000)	(0.5600000)	(0.5200000)	(-0.65)
Percent of Male in Population	(0.3140000)	(0.3120000)	(0.3270000)	(0.3260000)	(0.0245000)	3.1170000	(0.3120000)	(0.3270000)	(0.3260000)	(0.0245000)
	(-0.86)	(-0.85)	(-0.82)	(-0.82)	(-0.07)	(0.5300000)	(-0.85)	(-0.82)	(-0.82)	(-0.07)
Average Age of Population	(0.0056900)	(0.0055100)	(0.0050500)	(0.0054300)	0.0012500	-0.224**	(0.0055100)	(0.0050500)	(0.0054300)	0.0012500
	(-0.91)	(-0.88)	(-0.74)	(-0.80)	(0.2100000)	(-2.24)	(-0.88)	(-0.74)	(-0.80)	(0.2100000)
Percent of Married in the Population	(0.1330000)	(0.1310000)	(0.1420000)	(0.1560000)	(0.1080000)	3.2570000	(0.1310000)	(0.1420000)	(0.1560000)	(0.1080000)
	(-0.89)	(-0.87)	(-0.86)	(-0.95)	(-0.75)	(1.3600000)	(-0.87)	(-0.86)	(-0.95)	(-0.75)
Average Education level	0.0296000	0.0303000	0.0331000	0.0304000	0.0362*	(0.0556000)	0.0303000	0.0331000	0.0304000	0.0362*
	(1.5200000)	(1.5400000)	(1.5500000)	(1.4500000)	(1.9300000)	(-0.18)	(1.5400000)	(1.5500000)	(1.4500000)	(1.9300000)
Percent of Workforce in Goods Producing Ind.	0.0010700	0.0010700	0.0012200	0.0012600	(0.0010200)	0.0017800	0.0010700	0.0012200	0.0012600	(0.0010200)
	(0.4700000)	(0.4700000)	(0.4900000)	(0.5000000)	(-0.46)	(0.0500000)	(0.4700000)	(0.4900000)	(0.5000000)	(-0.46)
First Lag: Unemployment Rate		0.0021200	(0.0007910)				0.0021200	(0.0007910)		
		(0.2500000)	(-0.06)				(0.2500000)	(-0.06)		
Second Lag Unemployment Rate			0.0037700					0.0037700		
			(0.3400000)					(0.3400000)		
First Lag: Real GDP				0.0000003	0.0000006				0.0000003	0.0000006
				(0.4300000)	(0.5400000)				(0.4300000)	(0.5400000)
Second Lag: Real GDP					(0.0000001)					(0.0000001)
					(-0.18)					(-0.18)
No. of Observations	714	714	663	663	612	714	714	663	663	612

Notes: The table reports results from a OLS model with standard errors in parentheses. State level unemployment rate was taken from the Bureau of Labor StatisticsâĂŹ Local Area Unemployment Statistics program. State level GDP was taken from the Bureau of Economic AnalysisâĂŹ Regional Economic Accounts. The rest of the variables were constructed from the CPS sample we use for the rest of our analysis. * p<0.10,** p<0.05, ***p<0.01.

Table B.3: Occupational Change as Dependent Variable

	(1)	(2)	(3)	(4)	(5)	(6)
Medicaid Income Threshold	0.0349***	0.0292***	0.0297***	0.0306***	0.0309***	0.0323***
	(0.01310)	(0.00939)	(0.00921)	(0.00959)	(0.01010)	(0.01090)
Medicaid Age Threshold	0.00087	0.00052	0.00037	0.00035	0.00044	0.00028
	(0.00068)	(0.00060)	(0.00061)	(0.00062)	(0.00060)	(0.00050)
Tax Progressivity 75th & 25th Pct.				(0.08160)	(0.05070)	(0.05030)
				(0.20600)	(0.22300)	(0.22300)
TANF Benefits at the 25th Percentile				(0.00055)	(0.00044)	(0.00044)
				(0.00108)	(0.00112)	(0.00111)
Average Median Tax					0.89400	0.89300
					(0.92300)	(0.92200)
Medicaid Income Threshold X Female						(0.00289)
						(0.00999)
Medicaid Age Threshold X Female						0.00033
						(0.00066)
State Effects	Yes	Yes	Yes	Yes	Yes	Yes
Time Effects	No	No	Yes	Yes	Yes	Yes
Regional Trends	No	Yes	Yes	Yes	Yes	Yes
No. of Observations	65,209	65,209	65,209	65,209	65,209	65,209

Notes: The table reports marginal effects from a probit model with standard errors in parentheses. All specifications include the following controls: years of education, age, number of children, marital status and dummies for sex, race, ethnicity and country of birth. TANF benefits are calculated for a family of 3 using the following formula: TANF Benefit = Maximum Benefit-t(Earnings-D)-Unearned Income. Standard Errors are clustered at the state level. *p<0.10, **p<0.05, ***p<0.01.

Table B.4: Occupation Change by Deciles of Household Income

	(1)	(2)	(3)	(4)	(5)
	D1	D2	D3	D4	D5 and Above
Medicaid Income Threshold	0.0360**	(0.00379)	(0.00199)	0.01650	0.00590
	(0.01810)	(0.01430)	(0.01310)	(0.01260)	(0.00374)
Medicaid Age Threshold	(0.00073)	0.00010	0.00132	-0.00198*	(0.00048)
	(0.00123)	(0.00116)	(0.00100)	(0.00108)	(0.00044)
Tax Progressivity 75th & 25th Percentiles	(0.27800)	0.08610	0.33700	0.06650	0.08650
	(0.49100)	(0.31900)	(0.30100)	(0.16100)	(0.11800)
TANF Benefits at the 25th Pct.	0.00283*	(0.00148)	0.00146	(0.00147)	(0.00051)
	(0.00145)	(0.00357)	(0.00145)	(0.00101)	(0.00071)
Average Median Tax	0.02350	(1.70300)	1.15700	1.92600	0.23200
	(1.99400)	(1.66700)	(1.86700)	(1.92300)	(0.75900)
State Effects	Yes	Yes	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes	Yes	Yes
Regional Trends	Yes	Yes	Yes	Yes	Yes
No. of Observations	14,470	22,379	27,187	30,556	22,175

Notes: The table reports marginal effects from a probit model with standard errors in parenthesis. All specifications include the following controls: years of education, age, number of children, marital status and dummies for race, ethnicity and country of birth. TANF benefits are calculated for a family of 3 using the following formula. TANF Benefit = Maximum Benefit-t(Earnings-D)-Unearned Income. *p<0.10, **p<0.05, ***p<0.01.

Table B.5: Occupation Change for Subgroups

	(1)	(2)	(3)	(4)	(5)	(6)
	Females	Males	Married	Non-Married	No Children	1 or More Children
Medicaid income threshold	0.0381**	0.0230***	0.0298***	0.03100	0.0322***	0.0465***
	(0.01740)	(0.00746)	(0.01140)	(0.02040)	(0.01120)	(0.01310)
Medicaid age threshold	0.00068	0.00021	0.00088	(0.00049)	0.00188	0.00016
	(0.00127)	(0.00045)	(0.00061)	(0.00153)	(0.00129)	(0.00109)
Tax Progressivity 75th & 25th Pct.	(0.21000)	0.09620	(0.30300)	0.994**	(0.23700)	(0.27700)
	(0.31400)	(0.18800)	(0.24400)	(0.45800)	(0.27300)	(0.30600)
TANF Benefits at the 25th Percentile	(0.00011)	(0.00102)	0.00027	-0.00264**	0.00006	0.00083
	(0.00149)	(0.00090)	(0.00139)	(0.00133)	(0.00231)	(0.00201)
Average Median Tax	0.92800	0.72100	1.09100	1.40500	1.29600	0.67800
	(1.53200)	(0.90700)	(1.02800)	(1.40500)	(1.25300)	(1.36100)
State Effects	Yes	Yes	Yes	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes	Yes	Yes	Yes
Regional Trends	Yes	Yes	Yes	Yes	Yes	Yes
No. of Observations	31,789	33,420	52,438	12,771	26,832	27,918

Notes: The table reports marginal effects from a probit model with standard errors in parenthesis. All specifications include the following controls: years of education, age number of children, marital status and dummies for sex, race, ethnicity and country of birth. TANF benefits are calculated for a family of 3 using the following formula. TANF Benefit = Maximum Benefit-t(Earnings-D)-Unearned Income. Standard Errors are clustered at the state level. *p<0.10, **p<0.05, ***p<0.01.

Table B.6: Transitions Across Jobs

	(1)	(2)	(3)	(4)	(5)	(6)
	Transition to Risky Occ-Higher S.D of Wages	Transition to Risky Occ-Higher Sep Rates	Transition to Better Occ-Higher Median Wage	Transition to a job with higher or similar education Requirements	Transition to a job with higher or similar education Requirements-Non-College Workers	Transition to a job with higher or similar education Requirements-College Workers
Medicaid Income Threshold	0.0263***	0.00853	0.0214***	0.0231**	0.0240**	0.0202*
	(0.00949)	(0.00596)	(0.00530)	(0.00946)	(0.01160)	(0.01070)
Medicaid Age Threshold	0.00100*	0.00012	0.00009	0.00112*	0.00091	0.00168*
	(0.00055)	(0.00048)	(0.00031)	(0.00060)	(0.00076)	(0.00093)
Tax Progressivity. 75th & 25th Pct.	(0.06960)	(0.06740)	(0.04860)	0.08880	0.08790	(0.01660)
	(0.12700)	(0.15500)	(0.27500)	(0.30200)	(0.35000)	(0.18300)
TANF Benefits at the 25th Pct.	0.00013	(0.00026)	0.00011	0.00103	0.00177**	(0.00025)
	(0.00067)	(0.00114)	(0.00070)	(0.00090)	(0.00070)	(0.00181)
Average Median Tax	0.28400	0.70800	(0.48000)	1.11900	0.52200	1.72900
	(1.09700)	(0.52900)	(0.89900)	(0.96400)	(1.34900)	(1.13700)
State Effects	Yes	Yes	Yes	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes	Yes	Yes	Yes
Regional Trends	Yes	Yes	Yes	Yes	Yes	Yes
No. of Observations	64,248	65,209	64,248	61,246	41,359	19,887

Notes: The table reports marginal effects from a probit model with standard errors in parentheses. All specifications include the following controls: years of education, age, number of children, marital Status and dummies for sex, race, ethnicity and country of birth. TANF benefits are calculated for a family of 3 using the following formula. TANF Benefit = Maximum Benefit-t(Earnings-D)-Unearned Income. Separation rates and wages for each occupation are calculated from our sample. Education requirements for each occupation are calculated from the Labor DepartmentâĂŹs O*NET database. Standard Errors are clustered at the state level. *p<0.10, **p<0.05, ***p<0.01.

Table B.7: Tennessee Experiment

	(1)	(2)	(3)	(4)	(5)
	Occupation Change	Transition to Risky Occ- Higher S.D of Wages	Transition to Risky Occ- Higher Sep Rates	Transition to Better Occ- Higher Median Wage	Transition to a Job with Higher or Similar Education Requirements
Treat X After	-0.0691***	-0.0855***	(0.03920)	-0.0382***	-0.0930***
	(0.01290)	(0.01440)	(0.02480)	(0.01160)	(0.01010)
After 2000	0.190***	0.08870	(0.02740)	0.01360	0.01750
	(0.04900)	(0.05590)	(0.02070)	(0.02880)	(0.03960)
Treat (Tennessee)	-0.968***	(0.50600)	0.986***	-0.602*	-1.000***
	(0.06250)	(0.45000)	(0.06890)	(0.35100)	(0.00115)
Tax Progressivity 75th & 25th Pct	-0.512*	-0.786**	-0.719***	(0.38900)	0.27800
	(0.30600)	(0.34300)	(0.23200)	(0.29800)	(0.27200)
TANF Benefits at the 25th Percentile	-0.00253***	0.00023	-0.00128**	-0.00230**	-0.00220***
	(0.00085)	(0.00083)	(0.00063)	(0.00095)	(0.00073)
Average Median Tax	4.917***	0.98500	4.097*	2.21900	3.25800
	(1.49900)	(1.68600)	(2.32200)	(2.42100)	(2.06100)
State Effects	Yes	Yes	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes	Yes	Yes
Regional Trends	Yes	Yes	Yes	Yes	Yes
N	20,426	20,113	20,426	20,086	19,174

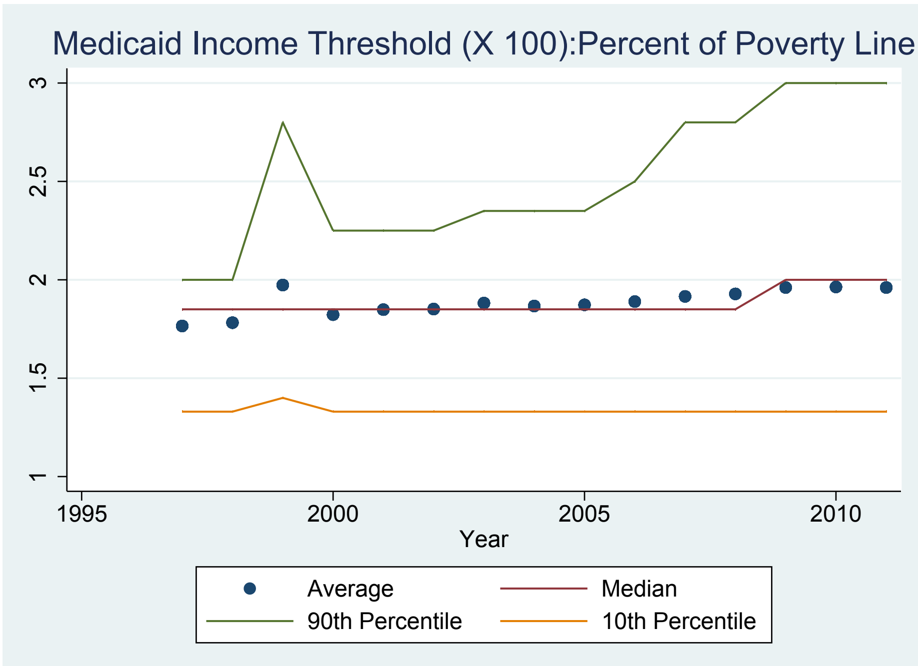


Figure B.1: Income Thresholds

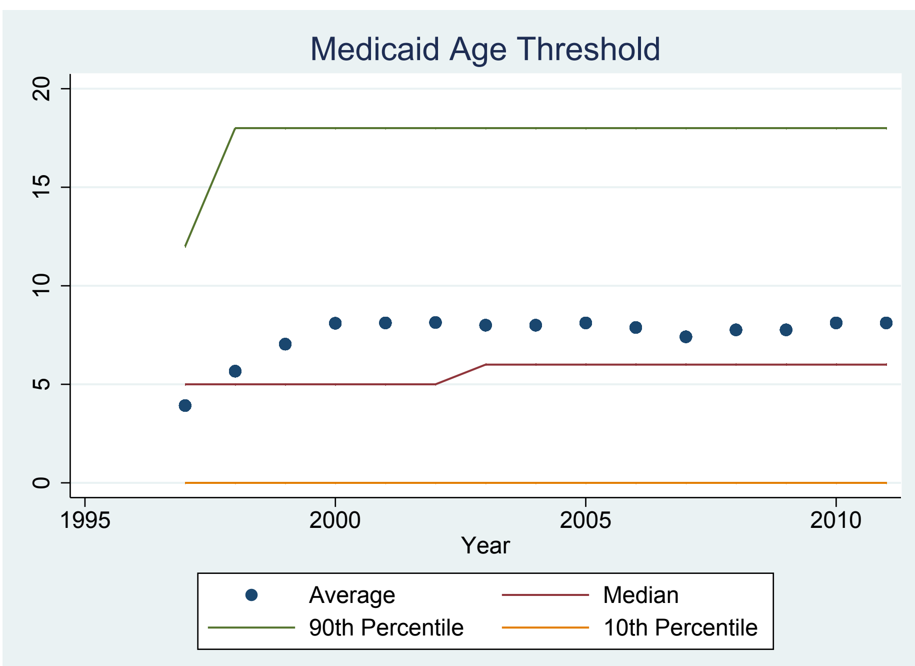
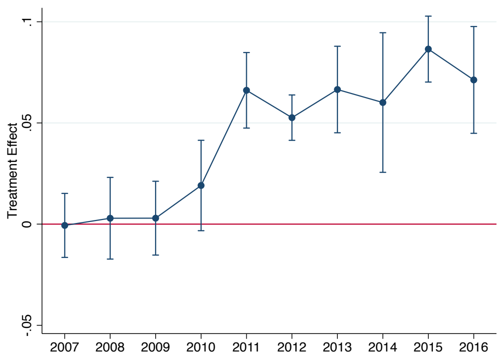


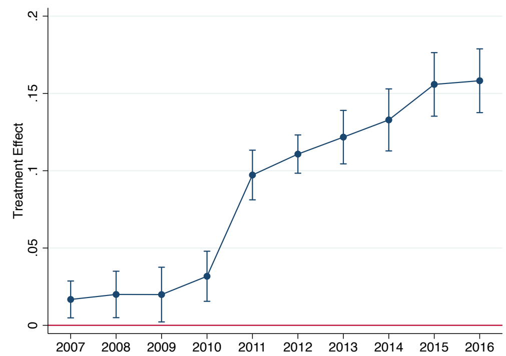
Figure B.2: Age Thresholds

Appendix C

Appendix for Chapter 3



(a) 19-21 Year Olds



(b) 22-25 Year Olds

Figure C.1: Health Insurance as Dependent

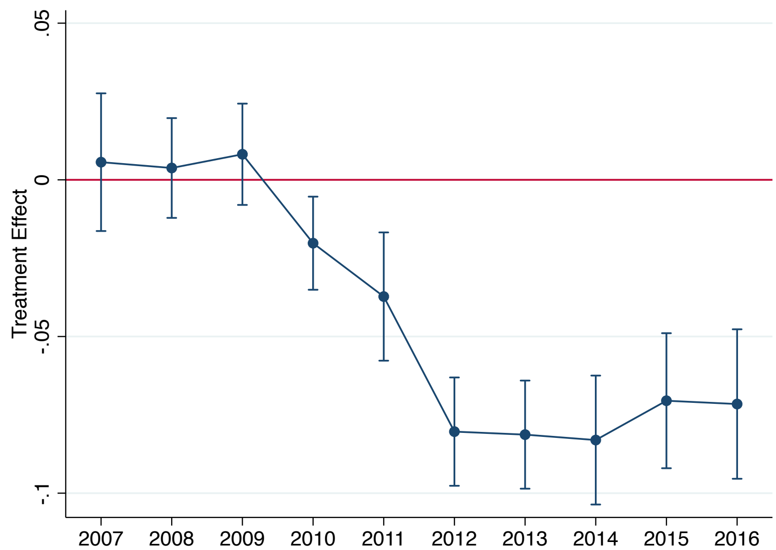
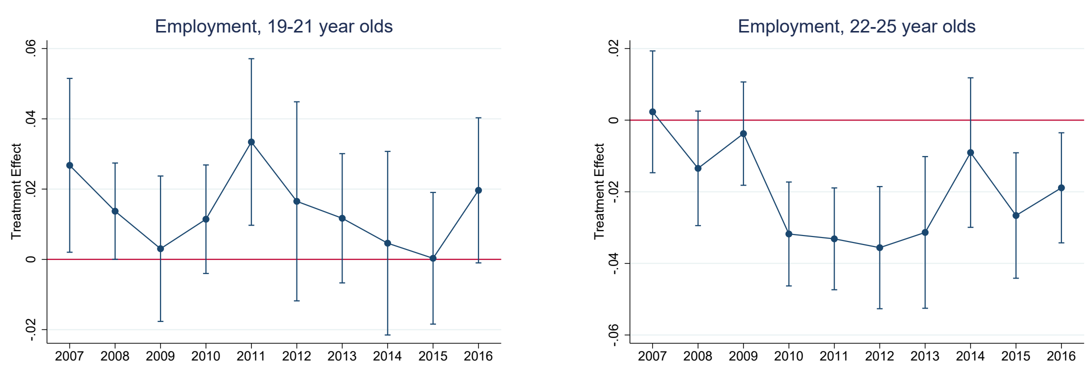


Figure C.2: Health Insurance through Employer, 22-25 Year Olds



(a) 19-21 Year Olds (b) 22-25 Year Olds

Figure C.3: Employment Outcomes

Table C.1: Descriptive Statistics for the Sample

	Age 22-25	Age 35-42	Age 19-21	Age 15-18	Age 27	Age 28	Age 29	Age30
Health Insurance Through Employer	0.312	0.495	0.111	0.022	0.463	0.468	0.474	0.476
	(0.463)	(0.500)	(0.314)	(0.147)	(0.499)	(0.499)	(0.499)	(0.499)
Health Insurance as Dependent	0.176	0.247	0.382	0.575	0.149	0.162	0.174	0.189
	(0.381)	(0.431)	(0.486)	(0.494)	(0.356)	(0.368)	(0.379)	(0.391)
Employed	0.712	0.797	0.558	0.229	0.764	0.773	0.776	0.775
	(0.453)	(0.402)	(0.497)	(0.420)	(0.425)	(0.419)	(0.417)	(0.417)
Not in Labor Force	0.217	0.161	0.358	0.716	0.178	0.173	0.171	0.172
	(0.412)	(0.367)	(0.479)	(0.451)	(0.382)	(0.378)	(0.377)	(0.377)
Enrolled in School			0.713	0.637				
			(0.452)	(0.481)				
Education Attainment -Years	13.010	13.420	12.260	9.939	13.380	13.410	13.460	13.420
	(2.242)	(2.816)	(1.427)	(1.577)	(2.630)	(2.650)	(2.693)	(2.749)
Self Employed	0.024	0.090	0.011	0.005	0.042	0.047	0.050	0.057
	(0.154)	(0.286)	(0.104)	(0.068)	(0.199)	(0.213)	(0.218)	(0.231)
Search Duration in Weeks (log)	2.527	2.606	2.558	2.303	2.577	2.527	2.583	2.569
	(0.941)	(0.887)	(0.991)	(1.146)	(0.919)	(0.907)	(0.915)	(0.907)
Real Hourly Wages (log)	2.472	2.898	2.213	2.018	2.689	2.728	2.743	2.775
	(0.491)	(0.614)	(0.450)	(0.410)	(0.512)	(0.556)	(0.574)	(0.545)
Pension Plan Through Employer	0.189	0.402	0.054	0.007	0.300	0.316	0.331	0.342
	(0.391)	(0.490)	(0.227)	(0.085)	(0.458)	(0.465)	(0.471)	(0.474)
Real Yearly Earnings	18542.800	41947.900	8765.600	1517.100	28439.400	29919.500	31376.900	32659.100
	(24035.400)	(54955.500)	(15832.800)	(6102.700)	(32450.700)	(34236.500)	(33834.200)	(38671.800)
Occupation Change	0.249	0.128	0.315	0.247	0.183	0.177	0.170	0.171
	(0.432)	(0.334)	(0.465)	(0.431)	(0.387)	(0.381)	(0.375)	(0.376)
Occupation Change (Major Group)	0.103	0.037	0.128	0.102	0.067	0.065	0.060	0.058
	(0.304)	(0.189)	(0.334)	(0.303)	(0.250)	(0.247)	(0.238)	(0.233)
Changed State in the Last Year	0.047	0.021	0.030	0.017	0.040	0.040	0.037	0.034
	(0.213)	(0.142)	(0.171)	(0.127)	(0.197)	(0.196)	(0.188)	(0.180)
Never Married	0.730	0.168	0.915	0.983	0.499	0.441	0.391	0.353
	(0.444)	(0.374)	(0.279)	(0.129)	(0.500)	(0.497)	(0.488)	(0.478)
Living With Parents	0.315	0.046	0.609	0.867	0.147	0.122	0.108	0.092
	(0.465)	(0.208)	(0.488)	(0.340)	(0.354)	(0.327)	(0.311)	(0.290)
Married	0.232	0.676	0.071	0.009	0.434	0.483	0.522	0.555
	(0.422)	(0.468)	(0.256)	(0.093)	(0.496)	(0.500)	(0.500)	(0.497)
White	0.784	0.803	0.784	0.787	0.786	0.789	0.786	0.788
	(0.411)	(0.398)	(0.411)	(0.409)	(0.410)	(0.408)	(0.410)	(0.409)
Black	0.149	0.130	0.156	0.157	0.142	0.138	0.140	0.136
	(0.356)	(0.337)	(0.363)	(0.364)	(0.349)	(0.345)	(0.347)	(0.342)
Hispanic	0.187	0.152	0.180	0.168	0.190	0.185	0.183	0.195
	(0.390)	(0.359)	(0.384)	(0.374)	(0.392)	(0.388)	(0.386)	(0.396)
Foreign Born	0.157	0.199	0.118	0.082	0.189	0.196	0.199	0.213
	(0.364)	(0.399)	(0.323)	(0.274)	(0.391)	(0.397)	(0.400)	(0.409)
Observations	138,070	334,063	103,946	170,554	35,478	36,031	36,683	38,268

Mean coefficients; sd in parentheses

Table C.2: Impact of the Law on Health Insurance & Employment: 22-25 Year Olds

	(1)	(2)	(3)	(4)	(5)	(6)
	HI Through Employer	HI Through Employer	HI as Dependent	HI as Dependent	Employed	Employed
Treat	0.288*** (0.0151)	0.288*** (0.0150)	-0.374*** (0.0227)	-0.380*** (0.0222)	0.141*** (0.0084)	0.144*** (0.0084)
Post 2010	-0.0802*** (0.0072)		(0.0102) (0.0069)		-0.0282*** (0.0059)	
Treat X Post 2010	-0.0698*** (0.0063)		0.124*** (0.0063)		-0.0237*** (0.0059)	
Treat X 2007		0.0056 (0.0109)		0.0167*** (0.0059)		0.0023 (0.0085)
Treat X 2008		0.0038 (0.0079)		0.0200** (0.0075)		-0.0135* (0.0080)
Treat X 2009		0.0082 (0.0081)		0.0199** (0.0088)		(0.0038) (0.0072)
Treat X 2010		-0.0202*** (0.0074)		0.0317*** (0.0081)		-0.0318*** (0.0072)
Treat X 2011		-0.0373*** (0.0102)		0.0972*** (0.0080)		-0.0331*** (0.0071)
Treat X 2012		-0.0804*** (0.0086)		0.111*** (0.0062)		-0.0356*** (0.0085)
Treat X 2013		-0.0813*** (0.0086)		0.122*** (0.0086)		-0.0314*** (0.0105)
Treat X 2014		-0.0830*** (0.0102)		0.133*** (0.0100)		(0.0091) (0.0104)
Treat X 2015		-0.0705*** (0.0107)		0.156*** (0.0102)		-0.0266*** (0.0087)
Treat X 2016		-0.0716*** (0.0119)		0.158*** (0.0103)		-0.0189** (0.0077)
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	472,133	472,133	472,133	472,133	472,133	472,133

Table C.3: Impact of the Law on Job Characteristics & Non-Labor Outcomes- 22-25 Year Olds

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Self-Employed	Search Duration	Log Hourly Wage	Pension Plan from Employer	Yearly Earnings	Moved State	Living With parents
Treat	-0.00966**	0.05690	0.0710***	0.100***	2242.0***	0.0258***	-0.252***
	(0.00439)	(0.05380)	(0.02630)	(0.01190)	(525.00000)	(0.0062)	(0.0172)
Post 2010	-0.0169***	0.02210	0.181***	-0.125***	1222.9**	-0.00903***	0.0041
	(0.00287)	(0.04040)	(0.01810)	(0.00768)	(562.40000)	(0.0027)	(0.0031)
Treat X Post 2010	0.0110***	0.0778***	-0.0593***	0.0156**	(406.60000)	-0.0108***	0.0394***
	(0.00251)	(0.01810)	(0.00982)	(0.00604)	(453.00000)	(0.0026)	(0.0072)
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	472,133	38,722	82,188	472,133	472,133	472,133	472,133

The table reports results from a Linear Probability Model. All specifications include the following further controls: Dummies for Race, Education, marital status,sex and a square polynomial in age. Standard Errors are Clustered at the State Level.
The control group is 35-42 year olds in all years.
* p<0.10,** p<0.05, ***p<0.01

Table C.4: Impact of the Law on Health Insurance & Employment: 19-21 Year Olds

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	HI Through Employer	HI Through Employer	HI as Dependent	HI as Dependet	Employed	Employed	Enrolled in School	Enrolled in School
Treat	0.0128***	0.0177***	-0.102***	-0.104***	-0.0193*	-0.0227**	-0.319***	-0.320***
	(0.0021)	(0.0021)	(0.0048)	(0.0050)	(0.0108)	(0.0103)	(0.0072)	(0.0076)
Post 2010	-0.0354***		-0.0383***		-0.0909***		0.0337***	
	(0.0031)		(0.0105)		(0.0095)		(0.0077)	
Treat X Post 2010	-0.0482***		0.0659***		0.0115		0.0282***	
	(0.0020)		(0.0043)		(0.0079)		(0.0071)	
Treat X 2007		(0.0043)		(0.0006)		0.0268**		0.0013
		(0.0043)		(0.0079)		(0.0123)		(0.0135)
Treat X 2008		-0.0165***		0.0029		0.0137**		0.0071
		(0.0043)		(0.0100)		(0.0068)		(0.0147)
Treat X 2009		-0.0250***		0.0029		0.0030		(0.0084)
		(0.0043)		(0.0091)		(0.0103)		(0.0127)
Treat X 2010		-0.0341***		0.0191*		0.0114		0.0070
		(0.0042)		(0.0111)		(0.0077)		(0.0130)
Treat X 2011		-0.0544***		0.0661***		0.0334***		0.0325***
		(0.0042)		(0.0093)		(0.0118)		(0.0115)
Treat X 2012		-0.0585***		0.0526***		0.0165		0.0177
		(0.0042)		(0.0056)		(0.0141)		(0.0115)
Treat X 2013		-0.0616***		0.0665***		0.0117		0.0269*
		(0.0042)		(0.0106)		(0.0092)		(0.0143)
Treat X 2014		-0.0464***		0.0601***		0.0046		0.0116
		(0.0051)		(0.0172)		(0.0130)		(0.0128)
Treat X 2015		-0.0495***		0.0865***		0.0003		0.0494***
		(0.0043)		(0.0081)		(0.0093)		(0.0118)
Treat X 2016		-0.0462***		0.0713***		0.0197*		0.0287*
		(0.0044)		(0.0131)		(0.0103)		(0.0159)
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	274,500	274,500	274,500	274,500	274,500	274,500	155,367	155,367

The table reports results from a Linear Probability Model. All specifications include the following further controls: Dummies for Race, Education, marital status,sex and a square polynomial in age. Standard Errors are Clustered at the State Level.
The control group is 15-18 year olds in all years.
* $p<0.10$,** $p<0.05$, ***$p<0.01$

Table C.5: Impact of the Law on Job Characteristics & Non-Labor Outcomes- 19-21 Year Olds

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Self-Employed	Search Duration	Log Hourly Wage	Pension Plan from Employer	Yearly Earnings	Moved State	Living With parents
Treat	0.0010	0.115***	0.0298**	0.0011	1197.7***	0.00766***	-0.0644***
	(0.0006)	(0.0401)	(0.0112)	(0.0018)	(129.9000)	(0.0015)	(0.0056)
Post 2010	-0.00304**	0.0199	0.202***	0.0015	33.1500	(0.0042)	-0.0207**
	(0.0014)	(0.0735)	(0.0206)	(0.0029)	(209.9000)	(0.0037)	(0.0086)
Treat X Post 2010	0.0008	0.0485	-0.0319*	-0.0192***	-1519.4***	-0.00675***	0.0090
	(0.0011)	(0.0455)	(0.0180)	(0.0015)	(131.1000)	(0.0015)	(0.0073)
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	274,500	20,600	24,022	274,500	274,500	274,500	274,500

The table reports results from a Linear Probability Model. All specifications include the following further controls: Dummies for Race, Education, marital status,sex and a square polynomial in age. Standard Errors are Clustered at the State Level.
The control group is 15-18 year olds in all years.
* p<0.10,** p<0.05, ***p<0.01

Table C.6: Evidence on Increased Job-Job Mobility from LEHD- 19-21 Year Olds

	(1)	(2)	(3)
	Job-to-Job Hires (Continuous Employment)	Job-to-Job Hires (Through Separation)	Separation to Persistent Non-Employment
Treat X Post 2010	0.0038833***	0.0064615***	0.0052429***
	(0.0013)	(0.0017)	(0.0014)
Treat	0.01905***	0.0285385***	-0.0411***
	(0.0007)	(0.0009)	(0.0060)
Post 2010	0.0064824**	0.0062	0.0059972*
	(0.0032)	(0.0042)	(0.0034)
Mean for 19-21 Year Olds	0.081	0.126	0.127
Quarter Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
N	114	114	114

The table reports results from a Linear Regression Model. All specifications include the Quarter and Year Fixed Effects.
The table uses data from Job-to-Job Flows aggregate data product from the U.S. Census Bureau. The control group is 14-18 year olds in all years.
* p<0.10,** p<0.05, ***p<0.01

Table C.7: Impact of the law on Long Term Employment Outcomes in Years 2016 and 2015: 22-24 Year Olds in 2010

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Years of Education	Employed	Self-Employed	Health Insurance through Employer	Hourly Wages	Yearly Earnings	Pension Plan through Employer
Panel A- Year 2016							
22 in 2010 x 2016	0.0172	0.0038	0.0056	(0.0066)	(0.0476)	(1134.8000)	(0.0014)
	(0.0692)	(0.0108)	(0.0067)	(0.0129)	(0.0326)	(1049.0000)	(0.0124)
23 in 2010 x 2016	(0.0991)	(0.0007)	0.0089	(0.0100)	(0.0381)	(682.9000)	0.0266**
	(0.0685)	(0.0107)	(0.0067)	(0.0127)	(0.0325)	(1038.5000)	(0.0122)
24 in 2010 x 2016	-0.159**	0.0186*	0.0175***	0.0030	(0.0271)	248.6000	0.0040
	(0.0697)	(0.0109)	(0.0068)	(0.0130)	(0.0326)	(1057.3000)	(0.0125)
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	236,914	236,914	236,914	236,914	41,601	236,914	236,914
Panel B- Year 2015							
22 in 2010 x 2015	0.0506	(0.0118)	0.0137**	-0.0501***	0.0077	-1818.6*	0.0021
	(0.0674)	(0.0106)	(0.0064)	(0.0126)	(0.0304)	(970.1000)	(0.0121)
23 in 2010 x 2015	0.0887	(0.0025)	0.0014	(0.0165)	-0.0683**	(854.1000)	0.0068
	(0.0666)	(0.0105)	(0.0063)	(0.0125)	(0.0312)	(958.9000)	(0.0119)
24 in 2010 x 2015	0.0969	0.0081	0.0058	(0.0191)	(0.0013)	(68.8900)	0.0012
	(0.0680)	(0.0107)	(0.0065)	(0.0127)	(0.0303)	(979.5000)	(0.0122)
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	220,964	220,964	220,964	220,964	39,072	220,964	220,964

The control group for models in Panel A contains 32-35 year olds. The treatment group contains 28-30 year olds who were 22-24 in 2010. The years are 1996-2012 and 2016. The control group for models in Panel B contains 31-34 year olds. The treatment group contains 27-29 year olds who were 22-24 in 2010. The years are 1996-2011 and 2015.
The table reports results from a Linear Models. All specifications include the following further controls: Dummies for Race, Education, marital status,sex. Standard Errors are Clustered at the State Level.
* $p<0.10$,** $p<0.05$, *** $p<0.01$

Table C.8: Impact of the law on Long Term Outcomes in Years 2016 and 2015: 22-24 Year Olds in 2010

	(1)	(2)	(3)	(4)	(5)
	Occ Change	Occ Change- Major group	Changed State	Never Married	Living with Parents
Panel A- Year 2016					
22 in 2010 x 2016	(0.0095)	(0.0067)	(0.0018)	0.0297**	0.0182**
	(0.0108)	(0.0070)	(0.0048)	(0.0120)	(0.0073)
23 in 2010 x 2016	(0.0038)	(0.0063)	-0.00883*	0.0076	0.0163**
	(0.0108)	(0.0069)	(0.0047)	(0.0118)	(0.0072)
24 in 2010 x 2016	(0.0075)	-0.0143**	0.0009	0.0225*	0.0134*
	(0.0109)	(0.0070)	(0.0048)	(0.0121)	(0.0073)
State fixed effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
N	218,302	118,461	236,914	236,914	236,914
Panel B- Year 2015					
22 in 2010 x 2015	-0.0188*	(0.0022)	-0.0101**	0.0416***	0.0111
	(0.0109)	(0.0072)	(0.0049)	(0.0120)	(0.0075)
23 in 2010 x 2015	-0.0410***	(0.0067)	-0.00895*	0.0335***	0.0340***
	(0.0108)	(0.0071)	(0.0048)	(0.0118)	(0.0074)
24 in 2010 x 2015	-0.0366***	(0.0117)	-0.0125**	0.0122	0.0149**
	(0.0109)	(0.0072)	(0.0049)	(0.0121)	(0.0076)
State fixed effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
N	204,243	107,585	220,964	220,964	220,964

The control group for models in Panel A contains 32-35 year olds. The treatment group contains 28-30 year olds who were 22-24 in 2010. The years are 1996-2012 and 2016. The control group for models in Panel B contains 31-34 year olds. The treatment group contains 27-29 year olds who were 22-24 in 2010. The years are 1996-2011 and 2015.
The table reports results from a Linear Models. All specifications include the following further controls: Dummies for Race, Education, marital status,sex. Standard Errors are Clustered at the State Level.
* p<0.10,** p<0.05, ***p<0.01

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