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

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ABSTRACT: This paper documents a new stylized fact: The proportion of college degree holders working in occupations that do not require a college degree is U-shaped over the lifecycle. The downward trend at initial stages of the lifecycle is consistent with existing models of labor mobility, however, the rising trend at later stages of the career presents a puzzle. Using panel data, I show that transitions to the over-education state increase with age and workers who make these transitions also suffer wage losses of around 10% from the previous year. I then develop an equilibrium model of frictional occupation matching and skill accumulation with worker and firm heterogeneity that can match the lifecycle profile of over-education quantitatively. The model delivers rich dynamics at the individual level in which human capital accumulation moves the workers up the occupation ladder and as they get older, depreciation in skills moves them down the same ladder.

KEYWORDS: Occupational Mobility, Life-cycle Search, Matching, Human Capital
JEL CLASSIFICATION: J24, J62, J31, I26

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1 Introduction

This paper presents a new stylized fact: The proportion of college graduates working in jobs that do not require a college degree is U-shaped over the lifecycle. Around 30 percent of college graduates are working in non-college jobs at age 30. This percentage decreases till 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 as over-educated and refer to their state as over-education or over-educated employment[1]. The downward trend at initial stages of the career is consistent with existing models of labor market mobility described above. However, the rise at later stages of the career presents a puzzle. I show that a dynamic matching model featuring vertically differentiated occupations, human capital investment and competition among workers for limited jobs can replicate the U-shape of over-education quantitatively.

To argue that the U-shape is a robust feature of the data, I perform certain robustness checks. Removing females from the sample and focusing only on male full time workers leads to very similar results. I also show that the pattern with respect to age is stable over the business cycle and cannot be explained by overall labor market tightness. Furthermore I compare different ways of defining workers as over-educated in their jobs and find strikingly similar pattern with respect to age.

After documenting this pattern in the cross-sectional data, I attempt to isolate the reason behind the rising part of the U-shape during the prime working age years. Using panel data, I document that during prime working age years, college educated workers are more likely to move from college jobs to non-college jobs upon an occupation switch. This shows that the overall U-shape of over-education by age for college graduates in the cross-section is driven by the flow of workers into the over-education state. This finding is interesting because, as is well known, occupational switching declines with age as workers accumulate occupation specific human capital. Yet, among those workers who switch occupations during prime working age years, a higher percentage make transitions into the over-educated state. Furthermore this allows me to rule out the possibility that older workers in my sample are wrongly classified as over-educated because occupation requirements have increased over time.

After documenting the transition patterns, I explore possible reasons for these job switches. It can be argued that older over-educated workers are in fact moving towards jobs that require more experience. This would imply that the nature of over-education at

[1]Workers who have college degrees and are working in jobs that require a college degree are referred to as matched workers or being in a matched state

older age is different than the over-education experienced at younger ages. To test this hypothesis I measure the experience requirements for older workers who are working in non-college jobs using the O*NET data. I find that over-educated workers are working in entry level jobs even at older ages and there does not seem to be a trade off between skill and experience at later ages. Thus they are not just moving towards over-education but they are also becoming over-experienced. I also document that workers who make these downward switches in occupations suffer substantial wage losses of up to 10%. The extent of wage losses makes the transitions to lower skilled jobs even more puzzling. At the same time it gives credibility to my measure of over-education, since making a switch to over-education is correlated with a loss in earnings.

I also provide a discussion of how well my preferred measure of over-education performs compared to other known measures of occupational skill used in the literature. In particular I show that the distribution of various measures of occupational skill among the over-educated college workers is similar to non-college workers. This gives further credence to my measure of over-education and shows the importance of using a coarse measure of over-education rather than a detailed one to avoid mis-classification issues. Consequently I argue that the measures of transition to and from over-education can be interpreted as transitions up or down the skill space. Identifying the direction of occupational mobility has been a challenge empirically because workers could change occupations horizontally as well as vertically (see Groes, Kircher, and Manovskii (2014)). I am however, able to identify movements across two big hierarchies which can be ranked in terms of productivity differences.

There could be two 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 is reallocated to a higher type job. This phenomenon is usually referred to as mismatch employment in the labor economics literature and it is an inefficient outcome. 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 then not be classified as mismatched in his/her job because the skill level of the worker is consistent with the requirements of the job. In reality, some part of over-education is probably explained by mismatch employment and some is not. The pattern observed in the data is probably a composite of mismatch employment and skill obsolescence. While at younger ages, mismatch may be the main reason for over-education, at older ages, the effect is more likely driven by workers becoming less productive and losing the necessary skills in order to remain employed in high productivity jobs.

To explain the empirical pattern I propose a dynamic model of occupational matching and human capital accumulation over the lifecycle. The proposed model combines two influential literatures in labor economics on occupation choice and human capital investment. It features vertically differentiated occupations and endogenous productivity growth over the course of a worker's career. Complementaries between the ability of the worker and the productivity of an occupation induce high ability workers to work in high productivity occupations. Human capital investment at young ages allows workers to move up the occupation ladder while decline in productivity explains the movement of workers down the occupation ladder at older ages. The model is then calibrated to match the over-education profile documented in the data.

The experiences of young college graduates in the labor market have been under a lot of scrutiny in the last few years. It has been well documented that new graduates have had a hard time finding high quality jobs in the labor market. Some have used such facts to argue for and against the necessity of having a college degree. The academic literature has mostly remained on the sidelines of such a discussion. However, one strand of the literature that has been influential in this debate has tried to quantify the 'scarring effects' of graduating in a recession. According to some estimates it takes around 10 years for workers to recover from the harmful effects of starting a career in a recession. Various explanations have been offered to explain this fact and almost all of them contain a story about frictions in the labor market.

Relatively little attention has been paid to the career transitions of middle aged workers. Since the seminal work of Jovanovic (1979a) 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 then take a longer time to move to better job matches (see Papageorgiou (2013) for such a combination). One can also human capital accumulation and job switching costs to add more persistence to this phenomenon (see Wee (2013) for example). Nevertheless the underlying pattern generated by all such models is that workers should move to better job opportunities with experience (or age).

The paper is structured as follows: the next section surveys the related literature on topics of over-education, human capital accumulation and occupational choice. Section 3 discusses the data sources and presents the empirical evidence on over-education over the lifecycle. I first discuss my methodology for measuring required level of education for each occupation using the labor department's O*NET data. Then I present my main findings regarding over-education over the career by looking at the CPS Data and corroborate the results with findings from the National Survey of College Graduates (NSCG). I also document effects of over-education over the lifecycle in terms of earned wages and acquired occupation/job specific human capital. Section 4 presents the model and the quantitative exercise. Section 5 concludes.

2 Literature Review

My paper contributes to three separate literatures in economics. First, it relates to the literature on over-education that was started by Freeman (1976). 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 Freeman (1976) 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 [2]. 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. However, according to this literature, older workers are less likely to be over-educated. The finding regarding age is consistent with various theories about how labor is reallocated across jobs, such as job search theory or the career progression theory (Leuven and Oosterbeek (2011)). My findings on over-education over the lifecycle provide new insight on this fact and show that after a certain age, workers are equally likely to be over-educated as the new entrants to the labor market, something that has not been documented by previous studies. Consequently, some modification of existing theories is also required to reproduce this phenomenon.

More recently, Clark, Joubert, and Maurel (2014) show how over-education evolves over the early part of the career and explain why it is so persistent for some individuals. My research project is a close complement to their work in terms of defining over-education as a state of the labor market. However, the focus of their study is over-education during earlier years of the career, while I seek to explain why over-education rises in the later part of life. They cannot find the patterns that I document here because they restrict the analysis to the first 12 years of a worker's career.

Secondly, this paper contributes to the literature on occupational choice inspired by the work of Jovanovic (1979b). The main insight of 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 matched with an occupation find out about their match quality over time. As workers learn that their current occupation specific productiv-

[2] See Leuven and Oosterbeek (2011) for an excellent summary of this literature.

ity is low, they move to search for a new occupational match. This mechanism generates worker turnover across occupations. Several papers have tried to use these models to explain empirical regularities about labor turnover such as decreasing occupational switching by age, increasing wages by tenure and high unemployment rates for younger workers(Menzio, Telyukova, and Visschers (2012); Gervais et al. (2014)). A lot of advances have been made in this literature over time and a recent paper by Groes, Kircher, and Manovskii (2014) 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 lifecycle instead of a U-shape. To generate these patterns in a model, I borrow insights from the literature on lifecycle wage growth and human capital (see Rubinstein and Weiss (2006) and Sanders and Taber (2012)). This literature has successfully explained different moments of lifecycle wages such as mean and variance. 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. Most matching models have assumed 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 cases where the attributes change based upon the match (see for example Anderson and Smith (2010)). In my setup the attributes of the occupations stay fixed but the productivity of the workers evolves over time based on their human capital investments. Human capital investment in turn depend not only on the occupation that the worker is currently matched with but also upon his chances of moving up the occupation ladder. Thus there is a tight connection between the current and future attributes of the workers and the occupation that they are matched with. I also augment the model with search frictions and endogenize the vacancy posting decisions of the firms in different occupations. In this augmented model the human capital investment decisions are decided mutually by the worker and the firm as in Sanders and Taber (2012). Additional details on the theoretical model are provided in Section 5.

3 Stylized Facts about Over-education over the Life-cycle

3.1 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 incumbents, "If someone was being hired to perform this job, indicate the level of education that would be required". The survey respondents are reminded in a note right below the question that this does not mean the level of education that the incumbent has achieved. Respondents are given options such as less than high school, high school, some college, associates degree, bachelor's degree etc. To assign one required level of education to each occupation, I use the distribution of responses of the incumbents. If more than 50 percent of respondents within an occupation agree on the required education level then I assign that education level to the occupation in question. 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. I have tried to choose a measure that is deliberately conservative and that is perhaps biased downwards. This way of measuring education requirements is consistent with the approaches taken in the over-education literature (Leuven and Oosterbeek, 2011). Later I show that this measure performs very well in terms of classifying jobs as college or non-college.

The data on educational requirements by the O*NET program was collected during the 2000s (and is still being collected). Hence, one can safely assume that the educational requirements in the O*NET data are indeed the requirements for occupations that we observe in the last decade and a half in labor market survey data.

3.2 Measuring Over/Under Education

After I have determined the education requirements for each occupation, I can merge the data to survey datasets such as the Current Population Survey (CPS) which contains information on each workers' acquired level of education and the worker's current, or in the case of unemployed individuals, most recent occupation. Using my data on education requirements for each occupation, I can identify over-educated individuals by simply comparing the acquired level of worker's education with the level of education required for the occupation that he/she is working in. I use CPS data from 2003-2010 in my analysis below.

I define two measures of over-education in my analysis 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. This measure will perhaps understate 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 workers as over-educated. The codes and descriptions of occupation that are classified as non-college occupations according to my second measure are reported in Appendix A.

3.3 Over-Education over the Lifecycle

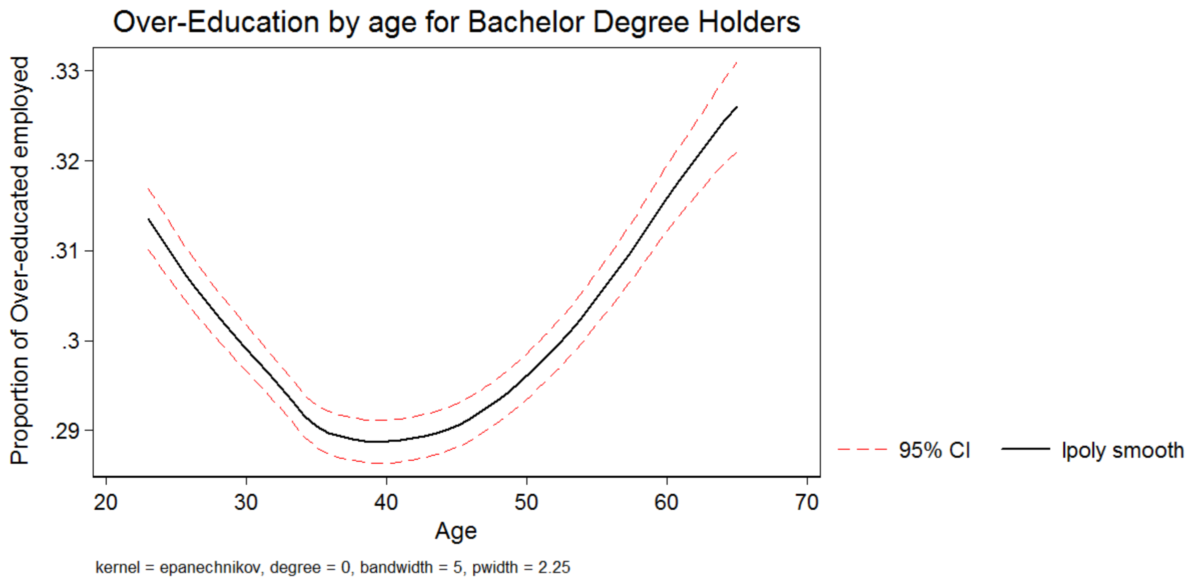
I now present my main empirical finding regarding over-education over the lifecycle. For my preliminary analysis, I am using cross-sectional data (CPS) to report the proportion of people of each age group that are over-educated in the years 2003-2010. The choice of such a time period is based upon the timing of the collection of the O*NET data which started asking questions about educational requirements during the 2000s. I will also provide evidence that this pattern is robust across different years in particular over the business cycle.

3.3.1 Evidence from Current Population Survey -Merged Outgoing Rotation Groups(CPS-MORG)

My benchmark method to estimate the lifecycle 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 variables on dummy variables for 5 year age bins (without a constant) and fitting a best fit line through the co-efficients.

I restrict the analysis to workers who are currently employed, since they always report their current occupation. Thus, the estimates on β_a above can be interpreted as the proportion of employed workers within age bin a who are over-educated. All regressions are weighted by the weight provided in the CPS-MORG files.

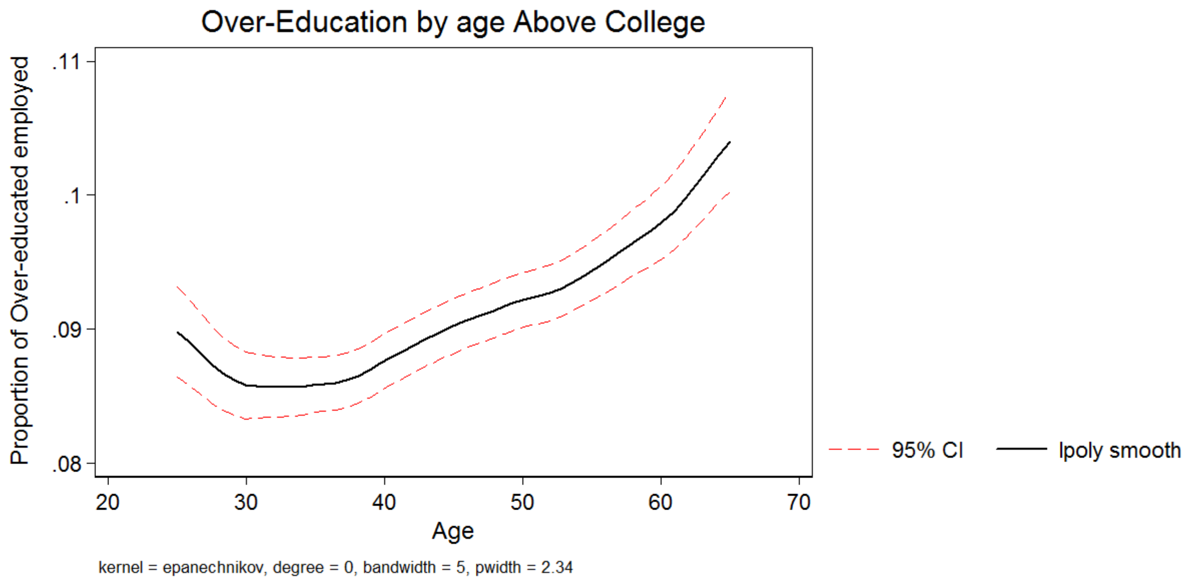
Figure 1: Over-Education across Age Groups among Bachelor Degree Holders, Source CPS-MORG, 2003-2010



I find that, for bachelor degree holders, the incidence of over-education by age is U-shaped, as can be seen in Figure 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 more and more workers end up getting matched with jobs that require their level of education. However, the over-education ratio starts rising after age 40, 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 an equal, if not higher proportion of workers suffer the same fate at later stages of their careers.

Figure 2 shows the incidence of over-education for individuals with more than a bachelor's degree. I define them as over-educated if they are working in non-college jobs, where college jobs are ones that require at least a bachelors degree. The overall shape is rising with age with the incidence of over-education declining till age 40 and then rising again, though at a muted rate. This muted pattern is a result of the definition of the over-education measure used in this figure, which understates the mismatch for people with professional, doctoral or masters' degrees.

Figure 2: Over-Education across Age Groups among Above College Workers, Source CPS-MORG, 2003-2010



3.4 Robustness Checks

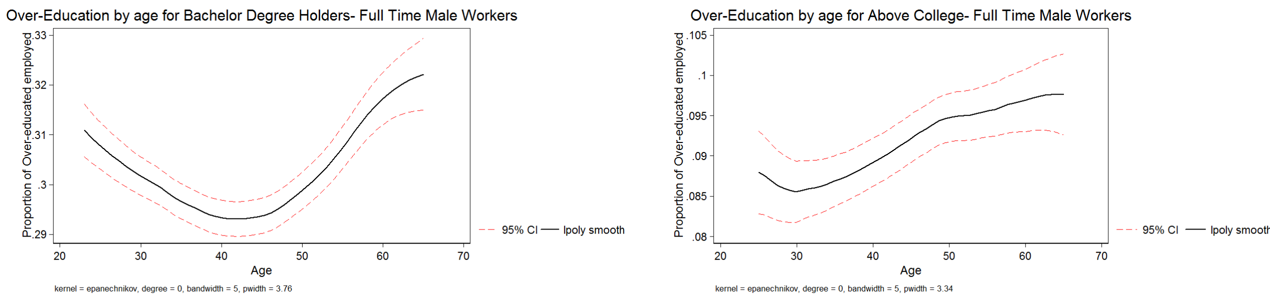
3.4.1 The U-shape of Over-Education for a Restricted Sample

One question that immediately comes to mind is that whether the pattern above is driven by particular demographic groups such as women or part-time workers. 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 first repeat the analysis in the previous section using only the sample of male full time workers. The results are shown in Figure 3. As can be seen the patterns for this restricted group are also very similar to the overall sample across age groups.

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

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 a particular time period. I then report the marginal effects with respect to age which can be interpreted as the residual effect of age

Figure 3: Over-education among Male Full Time Workers



(a) **(b)**

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:

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

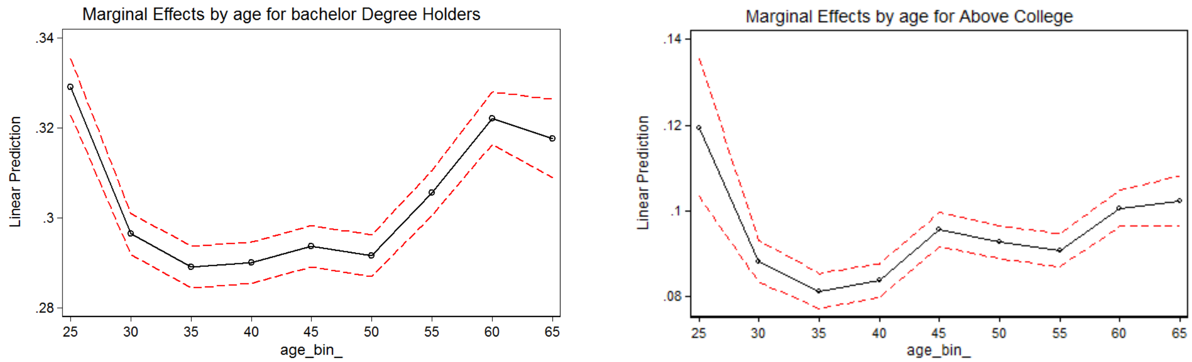
where Y_{ia} is an indicator of over-education which equals 1 if person i is in age group a is over-educated, and D_{ia} is a dummy variable which is 1 if individual i belongs to age group a. Demographic control variables are in the vector X_i which contains dummy variables for gender, marital status, self-employment status and a dummy variable for whether the individual was born in a foreign country. The results of this regression are reported in Appendix B table 1 but here I plot the marginal effect of age on the incidence of over-education in Figure 4. As can be seen that 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. Appendix A contains some additional robustness checks in which I have found similar results after removing immigrants from the sample and after using data from the period before the Great Recession as well.

3.4.3 Evidence from National Survey of College Graduates

To provide corroborating evidence of over-education I use the National Survey of College Graduates (NSCG). The National Survey of College Graduates is conducted by the National Science Foundation and only contains college graduates, i.e., individuals with at least a bachelor's degree. In this survey, 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 ... "

Figure 4: Marginal Effects With Respect to Age



(a) **(b)**

Respondents are given three choices and are asked to mark Yes or No for "each" item.

↪ Engineering, computer science, math or the natural sciences

↪ The social sciences

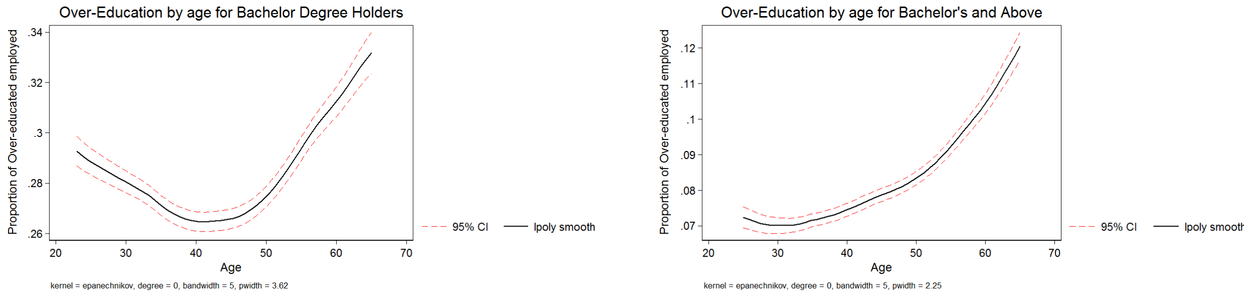
↪ Some other field (e.g., health business or education)-Specify

I classify respondents as over-educated if they answer No to all three items. Notice that this measure should be the same as the one developed above, where I defined some occupations as college jobs and others as non-college jobs and defined over-education as college graduates working in non-college jobs[3].Thus, the lifecycle profile of over-education from this dataset should be the same as documented from the ACS data. I use the NSCG samples from the years 2003, 2008 and 2010 in my empirical analysis.

Figure 5 provides evidence on over-education among college graduates in the NSCG. The results are strikingly similar to the ones documented in Figures 1 and 2. The magnitudes may be smaller but nevertheless the U-shape is still clearly visible. The similarities between Figures 1, 2 and 5 are reassuring that the measure of required education that I have developed above is capturing over-education very well. It addresses two main concerns regarding the findings presented in Section 3.3.1. First, the patterns in Figures 1 and 2 are not driven by the construction of education requirements using the O*NET data. Second, the patterns are not driven by the use of one particular dataset such as the CPS-MORG.

[3]This way of measuring over-education has also been used in past studies (Leuven and Oosterbeek, 2011).

Figure 5: Over-education in the NSCG Sample



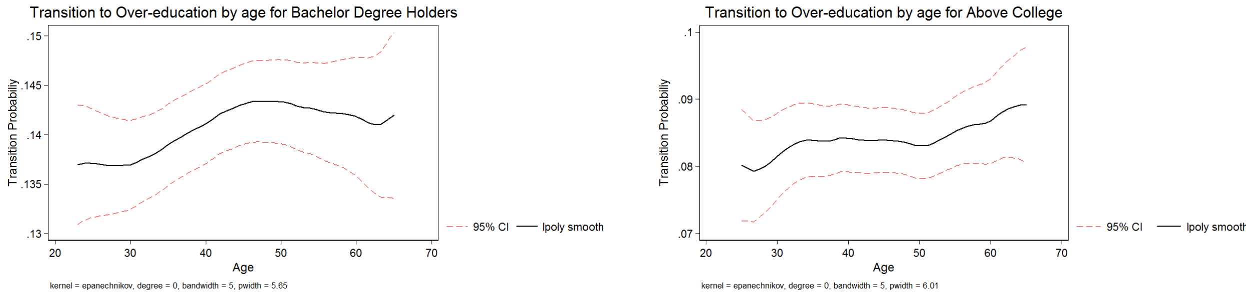
(a) **(b)**

3.4.4 Evidence from Panel Data

In this section I use the panel dimension of CPS-MORG data to investigate the reason behind the rise in over-education at later ages. In particular the aim is to find evidence that workers tend to move towards over-education with age. Using the panel dimension of the CPS-MORG files I construct individual worker transitions into and out of over-education at yearly intervals. Using these individual worker transitions, I again perform a kernel-weighted local polynomial regression of the transition status on the age of a worker conditional on occupation change. Conditioning on occupation change is important because the probability of switching occupations declines with age. The results are shown in Figures 6 and 7.

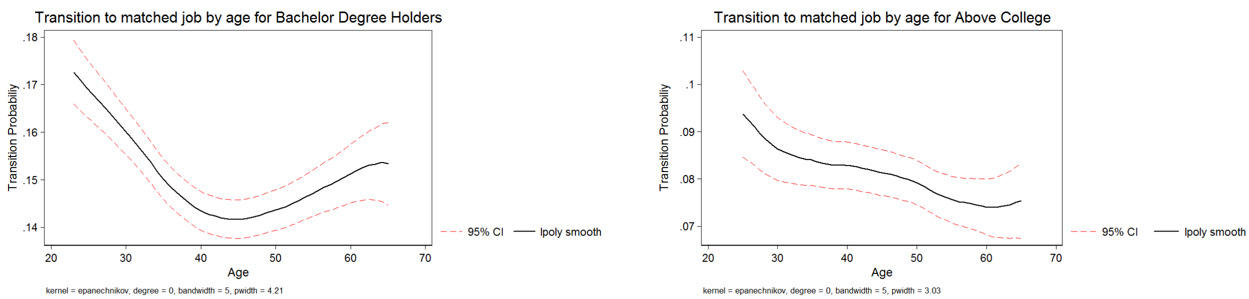
Figure 6 shows that the probability of moving towards over-education increases with age. Panel (a) shows that after the age of 30, workers with a bachelor degree are more likely to move towards over-education than younger workers upon making an occupational switch. Similar patterns can be seen for workers with more than a college degree in panel (b). Figure 7 on the other hand shows that the probability of moving from over-education state to the matched state conditional on changing occupations is declining for most part of the lifecycle. The shapes of these transition profiles would be used as a test of the model in the next section. Overall, these two figures show that workers are more likely to move towards over-education and less likely to move to matched jobs with age. Taken together they 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 6: Transitions to Over-Education by Age Conditional on Occupation Change



(a) **(b)**

Figure 7: Transitions to Matched State by Age Conditional on Occupation Change



(a) **(b)**

3.5 Implications of Over-education for Wages and Experience

Having established that college graduates make transitions to over-educated state during prime working age, this section explores two possible reasons behind these transitions. The literature has already documented that at the individual level, over-education is associated with lower wages. 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 lifecycle and there is no evidence that older over-educated workers are working in jobs that require more exp'erience.

3.5.1 Wage effects

One reason for using the CPS-MORG data files 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 transitions. To get a sense of how wage losses differ with age, I also interact the transition to over-education status with the age variable. More specifically I estimate the following equation:

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

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 [4]. The results of the model are shown in the appendix table A-2 [5] but here I show the marginal effect of age on wage growth for workers making a transition to over-education and those who do not. The results are shown in Figure 8. While wage growth typically declines with age, 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 %.

3.5.2 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 done by over-educated young workers. This would imply a tradeoff between skill and experience in the labor market. To answer this question 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

[4] That is, the equation was not estimated separately for bachelor degree holders and for individuals with more than a college degree.

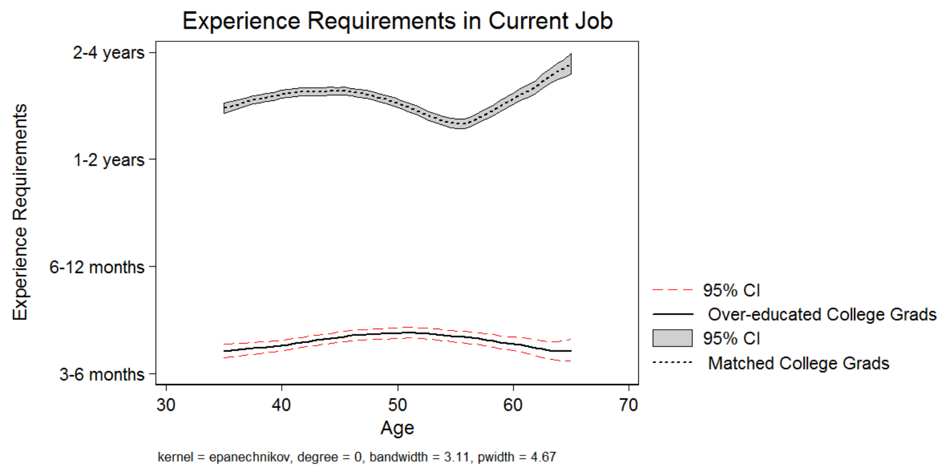
[5] Tables are not in Appendix yet

Figure 8: Wage Growth with Age and Transition status, Source CPS-MORG, 2003-2010

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 can also determine the experience requirements for each occupation and merge it with survey data. I can 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 9. 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 becoming 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 the measure of over-education that I am using has been well constructed. 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. I show that the quality of jobs performed by over-educated college workers are similar to the quality of jobs performed by non-college workers when I look at different measures of occupation quality. For additional details see the discussion in Appendix A.

Figure 9: Experience Requirements in Jobs by Age, Source CPS-MORG, 2003-2010



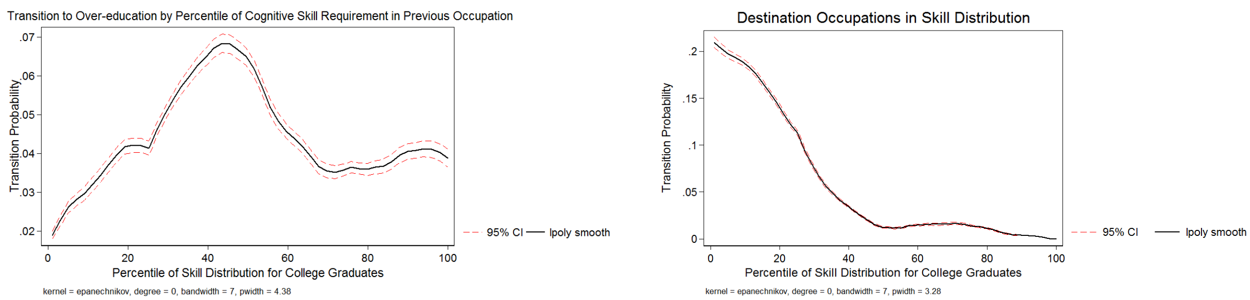
3.6 Who Transitions to Over-education?

To wrap up my empirical evidence I show that the probability of transitioning to over-education is non-monotonic over the skill space. Workers in the middle of the skill distribution are more likely to transition to over-education and this has important implications for the model that I consider in the next section. The measure of skill requirements in a job is taken from Acemoglu and Autor (2011) and it measures the cognitive skills required to perform a job. Acemoglu and Autor (2011) argued that college educated workers are more likely to work in occupations that require more cognitive skills. I then divide the occupations into 100 bins based on this measure. Thus occupations in the 100th bin require the most cognitive skills.

I estimate the probability of transitioning to over-education as a function of the skill requirement in the past job for workers aged 30 and above. The results are shown in Figure 10(a). As can be seen from the figure, workers mostly in the middle of the skill distribution are more likely to transition to over-education. Figure 10(b) shows that their most likely destination is the lower end of the skill distribution which is why they are being classified as making a transition to over-education.

It is also worthwhile exploring the occupations that lie in the middle of the skill distribution. These occupations contain some managerial level jobs such as administrative and service managers, food service managers and general and operations managers. It also contains some financial sector occupations such as loan officers, personal financial advisors and tax preparers. Finally it contains some technical occupations such as optometrists, respiratory therapists, health technologists and health technicians. The occupations that these

Figure 10: Transitions over the skill space



(a) **(b)**

workers move to are mostly clerical and office jobs such as cashiers, secretaries, stenographers, receptionists, book keepers, clerks and health and nursing aides.

4 Model

In this section I present an equilibrium model of life cycle occupation search, with heterogeneous workers and firms, skill accumulation, idiosyncratic uncertainty and vacancy creation. Workers and firms encounter frictions in the matching process as in the canonical DMP model. I present two versions of the model, one without on the job search and one with on the job search. In appendix B I provide a frictionless assignment model which also has similar predictions and the current model builds on that frictionless world.

4.1 Framework

Time is discrete and continues forever. There are a finite number of occupations indexed by $k = 1, 2, ...K$ which differ in terms of their productivity and job finding probabilities. Occupations are ranked in terms of their productivity with p_k being the productivity of the k^{th} occupation and $p_1 < p_2 < p_3 .... < p_{K-1} < p_K$. The job finding rates are estimated directly from the data using the gross flows method as in Shimer (2012).

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 then 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 do not depend on the type of the worker. Within each occupation the labor market has a DMP structure in which workers and firms match, production takes place, surplus is split and continuation decisions are made. Thus the model is similar to directed search models (such as Shi (2009), Menzio and Shi (2010), Menzio and Shi (2011) and Menzio, Telyukova, and Visschers (2015)) in which the labor market is segmented into sub-markets and each sub-market has a DMP structure. However, unlike these papers, in the current setup the sub-markets are not indexed by the type of the worker (or the posted wages and job finding rates) but rather by the productivity of the firms and the job finding rates. A direct consequence is that workers of different types do congest each other in the matching process which does not happen in directed search papers mentioned above.

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 $f(e(x), p_k) \subset R$, where $e(x)$ denotes productivity of a worker of type x. I allow for the possibility that positive value added may require a threshold level of inputs. Thus firms operating in higher productivity occupations might require workers to provide a threshold 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. [6] Furthermore, I allow for complementaries between the worker and firm types, $f_{e,p_k} \geq 0$.

All workers enter the labor market with a starting level of productivity which is exogenously specified. 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 and to production activities $(1-s)$. In particular, a human capital evolution function is specified, $h' = g(s, h)$, which maps current human capital h to future human capital h' based on the investment decision s. The level of worker productivity 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 apposed to learning by doing. The key distinction 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]

[6] Such a restriction on the production technology has been used in the literature previously by Albrecht and Vroman (2002) and Lise and Robin (2014).

[7] Such a setup has previously been formulated in Sanders and Taber (2012).

When unemployed, the workers productivity evolves through an exogenous process.

Matching Each occupation market has the DMP structure. Unemployed workers and vacancies meet each other through a constant returns to scale matching function within each market. The matching technology is assumed to be the same across all labor markets. When a firm and a worker meet, they agree to form the match if the value they derive from forming the match is greater than their outside value. Matches can break-up with exogenous probability δ and can also end if the firm and the worker choose to do so. Once the match ends, the worker becomes unemployed while the firm has to decide to reopen the vacancy. Each occupation's labor market is characterized by free entry of firms which drives ex-ante profits in equilibrium to zero in each market. The vacancy posting cost c_k is allowed to be different across markets.

Reallocation Unemployed workers can reallocate and search for jobs in different occupations. As worker productivity increases, they may find it optimal to search for jobs in high productivity occupations and thus move up the occupation ladder. Similarly a decline in worker productivity can induce the workers to separate from a match and search for a job in the low productivity sub-market. Reallocation does not lead to a loss in the productivity of the worker because human capital is transferable across occupations.

Employed workers can also reallocate if they receive an outside offer from a different occupation. Since the firms within each occupation sub-market are similar I do not allow for on the job search within each occupation. In the case that the worker receives an outside offer, the worker ends up in a match with the highest surplus of the two. The losing firm is left to decide whether to open a new vacancy or not.

Timing of Events The timing of events is as follows. At the beginning of the period the current level of worker productivity is revealed, which depends upon the investment decisions made last period and the idiosyncratic shocks to worker productivity. After these realizations the period is sub-divided into four stages: separation, reallocation, matching and production. Wage determination and human capital investment decisions are made during the production stage.

Worker's Problem Consider an unemployed worker characterized by the pair $x = (h, t)$ at the beginning of the production stage. The value function of the worker is given by:

$$U(x) = b + \beta \mathbb{E} \max_{k(x')} \{(\lambda_k W_k(w_u, x') + (1 - \lambda_k) U(x'))\} \tag{1}$$

$$\begin{aligned} h' &= exp(z)(1 - \sigma)h, \quad z\ N(0, \psi) \\ t' &= t + 1 \end{aligned} \tag{2}$$

where λ_k denotes the job finding probability in occupation k, σ is the depreciation rate of human capital and z is the shock to the stock of human capital that is assumed to be iid across individuals and over time.

The value of unemployment consists of the flow value of unemployment benefits and the discounted expected value of being unemployed at the start of next period's reallocation stage. 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 $W_{k,u}(x)$. The subscript k referes to the occupation in which the worker finds the job and the subscript 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. The state variables evolve according to the transition functions in equation (2). I assume that human capital can only depreciate during unemployment spells and the depreciation rate is σ. The stock of worker human capital is also subject to random shocks,z, which are realized at the beginning of the next period. Age of the worker evolves deterministically from one period to the next. There is no direct (an 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 upon an unsuccessful search. The policy 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 Jarosch (2014), I also 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 still renegotiated and the negotiation benchmark becomes unemployment. Unemployment also serves as the negotiation benchmark when the worker is hired out of the unemployed pool of workers.

Define by $S(x, k)$ as the surplus of a match between a worker of type x and a firm of type k. Then the expected value of employment for a worker of type x, matched to a firm of type k with negotiation benchmark i, is given by:

$$W_{k,i}(x) = w_{k,i}(x) + \beta\mathbb{E}\Big\{d(x')U(x') + (1-d(x'))\{\eta_i \mathbf{1}_{\{S(x,i)>S(x,k)\}} W_{i,k}(x') + \eta_i \mathbf{1}_{\{S(x,i)<S(x,k)\}} W_{k,i}(x') + (1-\eta_i) W_{k,u}(x')\}\Big\} \tag{3}$$

$$\begin{aligned} h' &= z\left[A(s(x)\times h)^{\alpha} + (1-\sigma)h\right], \quad z\ N(0,\psi) \\ t' &= t+1 \\ d(x') &= \begin{cases} \delta, & \text{if } S(x',k) > 0 \\ 1, & \text{otherwise} \end{cases} \end{aligned} \tag{4}$$

where δ denotes the exogenous match destruction probability. The match ends endogenously if the match surplus is negative. The job separation decision is thus described by the function $d(x')$. The worker receives outside offers from occupation $i \neq k$ with probability η_i. If $S(x,i) > S(x,k)$ then the worker moves to the firm of type i and firm k becomes the negotiation benchmark. On the other hand if $S(x,i) < S(x,k)$ then the worker stays with his current firm but firm i becomes his negotiation benchmark.

The evolution of worker productivity while employed depends upon the level of chosen investment, s, and the parameters of the human capital production function A, α and σ. The above specification for the human capital accumulation function is widely used in the empirical literature that seeks to explain wage growth over the life-cycle. Here σ refers to the depreciation rate of human capital and A is referred to as the learning ability in the literature.

Firm's Problem Now consider a firm in occupation k employing a worker with type $x = (h,t)$ and negotiation benchmark i. The expected profit of this firm is given by

$$J_{k,i}(x) = f(e(x), p_k) - w_{k,i}(x) + \beta\mathbb{E}[(1-d(x'))\{\eta_i \mathbf{1}_{\{S(x,i)<S(x,k)\}} J_{k,i}(x') + \eta_i \mathbf{1}_{\{S(x,i)>S(x,k)\}} V_k + (1-\eta_i) J_{k,u}(x) + d(x')V_k] \tag{5}$$

$$
\begin{aligned}
h' &= z\left[A(s(x) \times h)^{\alpha} + (1-\sigma)h\right] \\
e(x) &= (1 - s(x))h \\
t' &= t + 1 \\
d(x') &= \begin{cases} \delta, & \text{if } S(x', k) > 0 \\ 1, & \text{otherwise} \end{cases}
\end{aligned}
\tag{6}
$$

where $d(x')$ is the layoff decision of the firm 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 $i \neq k$ and $S(x,i) > S(x,k)$, the worker moves to firm i and firm $k's$ continuation value is given by V_k.

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. The worker and the firm jointly agree upon the level of investment $s(x)$ 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 $e(x) = (1 - s(x))h$.

Wages and Investment Decisions I assume that wages and investment decisions are determined by Nash Bargaining. In the spirit of Dey and Flinn (2005) and Cahuc, Postel-Vinay, and Robin (2006) I assume that when a worker encounters an outside offer his outside option is the total match value with 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. Such bargaining protocols are standard in the literature with on the job search.

Denote by $S_k(x)$ the surplus of the match defined as the sum of the surplus to the worker plus the surplus to the firm of being matched rather than apart:

$$
S_k(x) = W_{k,i}(x) - U(x) + J_{k,i}(x) - V_k \tag{7}
$$

Similarly, denote by $M_k(x)$ the value of the match defined as the sum of the value to the worker plus the value to the worker: Now consider a worker firm match in occupation k with worker type x and negotiation benchmark j that produces a positive surplus. Nash Bargaining implies that the wage, $w(x)$, and investment, $s(x)$ solve

$$
(w_{k,i}(x), s_k(x)) \in \arg\max \left[W_{k,i}(x) - M_i(x)\right]^q \left[J_{k,i}(x) - V_k\right]^{1-q} \tag{8}
$$

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

Lemma 1. *Given the assumption of Nash Bargaining over the surplus to determine the wages and investment in worker productivity, it can be shown that problem (24) reduces to*

$$s_k(x) \in \arg\max S_k(x) \tag{9}$$

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

$$\begin{aligned} W_{k,i}(x) - M_i(x) &= \beta[J_{k,i}(x) + W_{k,i}(x) - M_i(x)] \\ &= \beta[S_k(x) - S_i(x)] \end{aligned} \tag{10}$$

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

$$J_{k,i}(x) = (1-\beta)[S_k(x) - S_i(x)] \tag{11}$$

Substituting equations (27) and (26) into (24), one can solve for the investment function $s_k(x)$. The problem reduces to:

$$\begin{aligned} & s_k(x) \in \arg\max q^q(1-q)^{(1-q)}[S_k(x) - S_i(x)] \\ \iff & s_k(x) \in \arg\max S_k(x) \end{aligned} \tag{12}$$

□

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

$$\begin{aligned} S_k(x) = \max \Big\{ 0, f(e(x), p_k) - b + \beta \mathbb{E}_{x'|x,e}[(1-d(x'))\{\eta_i \mathbf{1}_{\{S_i(x') > S_k(x')\}} q(S_i(x') - S_k(x')) \\ + S_k(x')\} + U(x')] - \beta \mathbb{E}_{x'|x,u}[U(x') + q \max_{j(x')} \lambda_j S_j(x')] \Big\} \end{aligned} \tag{13}$$

where the expectation operator is dependent on the state of the worker as human capital depreciates during unemployment while it evolves according to equation (4) or (8) when the worker is employed. 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 given in equation (17) which can be rewritten as:

$$U(x) = b + \mathbb{E}_{x'|x,u}\left[U(x') + q \max_{k(x')} \lambda_k S_k(x')\right] \tag{14}$$

Equilibrium Now one can define the long run steady state equilibrium in the above economy. In the long run stationary equilibrium of the economy the decisions of the workers are only dependent upon their type and not upon the distribution of workers in various states. 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 long run steady state equilibrium is a set of value functions $U(x), W_k(x), J_k(x)$, worker's policy functions $k(x), d(x)$ (occupation choice and separation decisions respectively), firm's policy functions $\sigma(x)$ (layoff decision), wage and investment functions $w(x), s(x)$, vacancy posting costs c_k and laws of motion for the distribution of employed and unemployed workers over all occupations such that: given the job finding rates in each occupation λ_k; (i) the value functions and the decision rules follow from the worker's and the firm's problem described in equations (1)-(6); (ii) Vacancy posting cost, c_k is consistent with free entry of firms in each occupation sub-market; (iii) wages and investment decisions solve (7); (iv) the distribution of unemployed and employed workers across occupations is stationary and consistent with the policy functions above, the exogenous allocation of productivity across workers before entering the labor market and the shocks to the stock of human capital each period.

4.2 Quantitative Exercise

I assume that there are three occupations with $P_3 > P_2 > P_1$ and label 2 and 3 as college occupations while occupation 1 is referred to as a non-college occupation. 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. I assume that workers with different education levels draw their initial productivity from the same distribution but with different means. I assume that there are three types of workers of equal measure, those without college education (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 a log-normal distribution with mean α_i, such that $\alpha_{mc} > \alpha_b > \alpha_{nc}$, and variance η. The empirical literature has also considered variation in learning ability, A but that is not a feature of the current model.

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. I solve for the steady state and then choose the parameters of the model to match the model moments with the data moments. [8]

Parametrization Value added at the match level in each occupation is parameterized in the following way:

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

where I restrict $\tau_{1,k} = 1$ so that $f_{e,p_k} \geq 0$ and do not place any restriction on $\tau_{0,k}$ which is to be estimated. This is because I want to allow for the possibility that firms with higher p_k may operate with more costly non-labor inputs. In that case only workers above a certain level of productivity would be able to produce enough to cover non-labor costs and deliver positive profits to the firms even if they devote all their time to the production process and not divide it between production and investment in human capital.

A direct consequence of this parametrization is that if $\tau_{0,k}$ is high enough for high productivity occupations then young workers with lower human capital search in low productivity occupations, increase their productivity and then move up the occupation ladder to higher productivity occupations. As workers get older, investment in human capital declines and depreciation leads to a fall in overall worker productivity. Hence workers would find it optimal to separate from their matches in high productivity occupations and search for jobs in low productivity occupations.

Calibration Some parameters of the model are calibrated independently. In particular, the discount factor is set to 0.99 which implies an annual rate of approximately 3%. The job finding probabilities for each occupation, λ_k, are calculated from the CPS data using the flows based approach of Shimer (2012). However, to find 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

[8]For the current calibration, I do not introduce exogenous shocks to worker productivity.

each occupation.

In order to measure job finding probabilities from the CPS data for each occupation I use two approaches. In the first approach I condition on the unemployed workers' reported occupation and find the monthly probability of working in the three occupations in the next period. The results of this exercise are reported below in table 1. According to the table, workers who were last working in a non-college occupation are more likely to find their next job in the same occupation. Similar results hold for workers who were working in occupation 2 and 3, which require at least a college degree.

The table also shows that the job finding rate in occupation 3 for workers last employed in occupation 3 is higher than the comparable number for occupation 2. If these numbers were interpreted as job finding rates for these occupations and used in the model along with the assumption that the $P_2 < P_3$ then the market for occupation 2 would not exist as no one would choose to search in occupation 2. As mentioned above, the assignment of occupation to unemployed workers based on their last occupation means that these numbers can not be interpreted as the true job finding probabilities in each occupation. To circumvent this issue, I proxy the job finding rate in occupation 2 by using the average job finding probability of occupation 2 and the average job finding probability of occupation 3 among all workers which implies that $\lambda_2 > \lambda_3$.

In another approach to find the job finding probability of each occupation, I found the job finding probability of each occupation by education groups. The crucial assumption being that most non-college workers search in non-college occupations and college educated workers search in college occupations. Using this approach also gave me the same result as above,i.e. $\lambda_2 > \lambda_3$. Using both approaches I find that $\lambda_1 > \max\{\lambda_2, \lambda_3\}$. Thus the overall relationship between the job finding probabilities that I use in the calibration exercise is $\lambda_1 > \lambda_2 > \lambda_3$. Moreover, it is always the case that non-college jobs are more easier to find than all college jobs.

Table 1: Monthly Transition Rates

Occupation when Unemployed in period t	Employed in Non-College Occ (O_1) in $t+1$	Employed in Bachelor Degree Occ (O_2) in $t+1$	Employed in higher than Bachelor Degree Occ (O_3) in $t+1$
Non-College Occ, O_1	0.213	0.0175	0.0028
Bachelor Degree Occ, O_2	0.092	0.1161	0.0093
Higher than Bachelor Occ, O_3	0.0729	0.052	0.1342

The rest of the parameters of the model are chosen to match the moments from the data. Table 2 shows the fit of the model and table 3 shows the remaining parameters of the model that were estimated using the Simulated Method of Moments (SMM)technique. The moments I choose from the data are the proportion of male over-educated workers with a Bachelors' degree. The counterpart of this statistic in the model is the proportion of workers who enter the labor market as bachelor degree holders and are working in occupation 1. As can be seen from table 2, the model does a very good job of matching the qualitative shape of the life-cycle profile of over-education observed in the data. However, it does over-predict the fraction of older over-educated workers and under-predicts the fraction of over-educated workers in the age group 40-49.

Table 2: Fit of the Model: Proportion of Over-educated college workers

Age	Model	Data
25-29	0.3834	0.318
30-34	0.3449	0.2996
35-39	0.2815	0.301
40-44	0.2173	0.3016
45-49	0.1750	0.2898
50-54	0.2007	0..3092
55-69	0.3583	0.3285
60-64	0.4926	.332

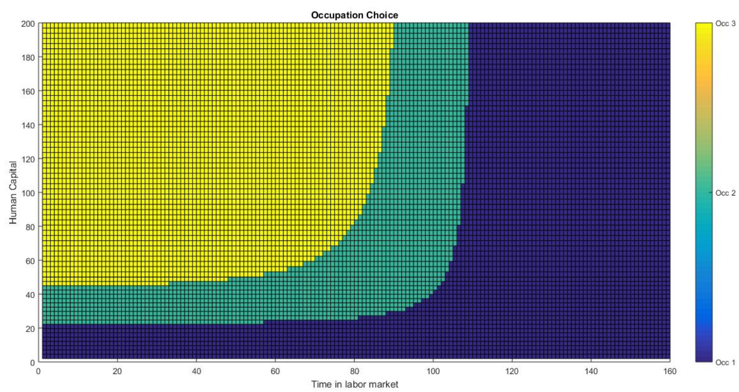
The only heterogeneity assumed in the model is the level of initial worker human capital and over time the productivity of the workers converges because there are only three occupations in which individuals work and accumulate human capital. Introducing shocks to the stock of productivity would lead to more heterogeneity in worker outcomes over the life-cycle.

Table 3 shows the values of the estimated parameters. The value of bargaining power perimeter is within the range of values estimated in the literature without on the job search (e.g see Papageorgiou (2013)). Similarly the human capital transition function parameters, η, A, ϕ are close to values estimated by the empirical literature on life-cycle wage growth (see Sanders and Taber (2012)). 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 5% which is close to the average unemployment rate for the time period 2003-2010. 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

Table 3: Calibrated Parameters

Parameter	Value	Parameter	Values
P_1	1.377	δ	0.01
P_2	1.642	α_{nc}	0.5
P_3	1.709	α_b	3.4
τ_1	0	α_{mc}	4.2
τ_2	10	η_{nc}	0.5
τ_3	25	η_b	0.9
q	0.33	η_{mc}	0.5
σ	0.013	A	0.68
ϕ	0.13		

Figure 11: Job Search Decisions

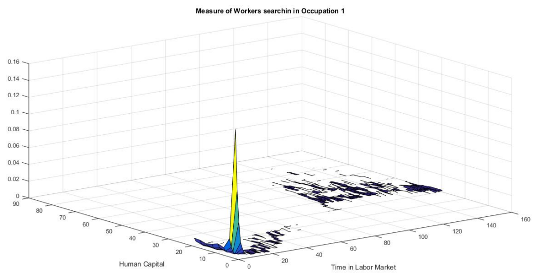


unemployment rate would be higher for any given value of δ.

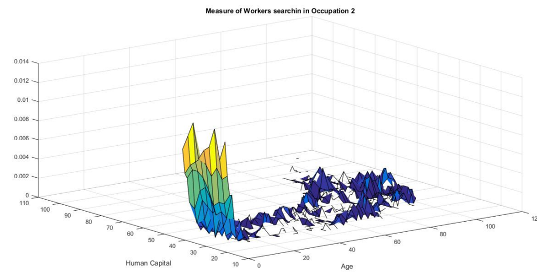
Discussion of Results The calibrated values of the production function cannot be compared with any previous estimate. These values along with the job finding probability in each occupation play an important role in the search strategies of workers across the age and productivity dimension. This interplay between the two can be seen in Figure 11 below. Young workers with low levels of human capital search in lower productivity occupations where the jobs are easier to find. As their productivity evolves over the course of their careers, they start searching in 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 each occupation shrinks and the job search decision is driven by the differences in job finding rates which are constant across age in the model.

As noted before these are the job search strategies of the workers if they were to lose

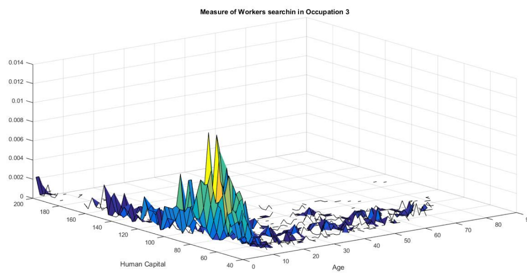
Figure 12: Job Search Decisions in the Steady State: Age on the X-Axis



(a) Occupation 1



(b) Occupation 2



(c) Occupation 3

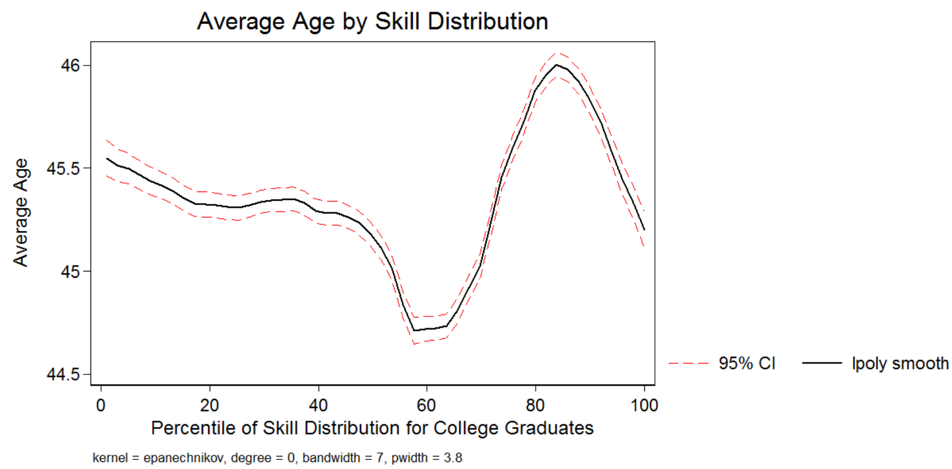
a job and not the search behavior of the workers that actually materializes in the model because the job destruction shock is exogenous and random across workers and time. Figure 12 shows the measures of workers searching in each occupation across the age and human capital dimension in the steady state of the model. Workers searching in occupation 1 are either low productivity young workers or those who lose their jobs in the latter part of their career. Similarly workers searching in occupation 2 and 3 are either young high productivity workers or middle aged workers who lose their jobs [9].

Average Age by Occupation Skill level An implication of the model is that older workers are being replaced by young more productive workers in their occupations. This would imply that the average age should be lower in occupations from where older workers are being replaced. In section 3.6, I showed that older workers over the age of 30 are more likely to be replaced from occupations in the middle of the skill distribution. If the general equilibrium model of occupation choice and human capital investment is to be believed then the average age in these occupations should be lower than the rest of the distribution.

Figure 13 shows that this is indeed the case. Furthermore the average age in occu-

[9] Note that the x-axis for occupation 2 and occupation 3 ends age 90 and age 120 respectively while the x-axis for occupation 1 is till age 160

Figure 13: Average Age in Occupations



pations starts rising after the 60th percentile when the probability of transitioning to over-education also declines. There are some occupations at the very top of the skill distribution that have a lower average age as well. These occupations are mostly the ones that require a doctoral degree, for example space scientists and economists are some occupations part of that group. The evidence presented in Figure 13 shows that the mechanism present in the model is possibly behind the U-shape pattern of over-education.

5 Model Extensions and Conclusion

In this paper, I document a new stylized fact; workers tend to move towards lower productivity occupations in the middle of their careers. I then build a life-cycle occupational search model with skill accumulation to explain the empirical fact. 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 move 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 thus we see a rise in the rate of over-educated workers with age. The model does a good job of matching the empirical facts with minimal theory.

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. It can be used to evaluate the role of policies that increase labor market mobility on the careers of the workers. It can also be used to test the implications of an increased supply of college educated workers in the labor market. In a partial equilibrium model an increased supply of college educated workers would lead to higher levels of over-education, a concern that is repeatedly raised in public policy discussions around the issue of affordable higher education. However, in an equilibrium this is not necessarily true. If there are more productive workers in the labor market, then high productivity firms would also post more vacancies and over-education might actually go down.

Finally, the model can be used to analyze how workers of different skills and demographics cope with a structural shock to the labor market. As a thought experiment, consider a change in the relative productivity of one occupation with respect to the others. If that occupation becomes more productive then workers would try to reach that occupation and this could have significant impact on the careers of the workers along the transition path.

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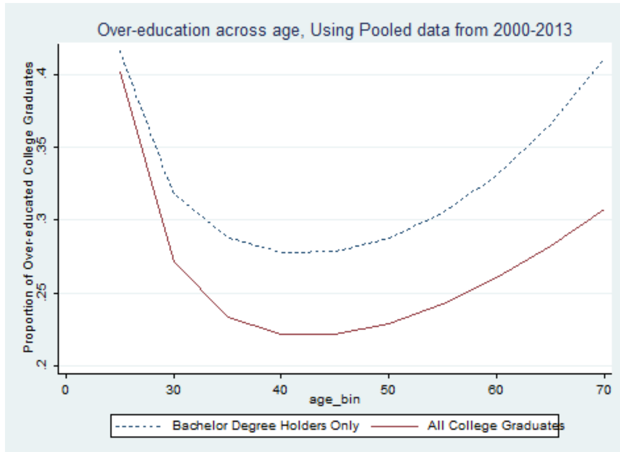
Figure A1: Over-Education across Age Groups among College Graduates, Source Pooled ACS 2000-2013



Appendix A Further Robustness Checks

Appendix A.1 The U-shape of Over-Education Across Years and Over the Business Cycle

One possible concern could be that the U-shaped pattern is only present in the year 2010 and not otherwise, perhaps because of bad overall labor market conditions. To address this concern, I combine data from 2000-2013 American Community Survey and check if the U-shaped pattern in Figures 1 and 2 exists in the pooled data. The resulting age profiles can be seen in Figure 4. As can be seen, the U-shape still persists and is more prominent at later ages for people who just have a bachelor's degree.

Furthermore, I check if the pattern changes with the labor market conditions and whether the U-shape becomes more/less steep with overall labor market tightness. To analyze this question I pool data from different years since 2000 and divide them into expansion, recession and recovery periods and then plot over-education profiles for bachelor degree holders and for all college graduates in Figure 5 and 6. Perhaps surprisingly there seems to be no cyclical component to the measure of over-education.

Appendix A.2 Over-education for a Restricted Sample

Here I show that if I restrict the sample to men who usually work full-time in their jobs (40 hours or more), worked for at least 26 weeks in the past year and are not receiving any retirement income, the U-shape of over-education still exists and is in fact more pronounced.

Figure A2: Over-Education across Age Groups among Bachelor Degree holders, Source ACS 2002-2013

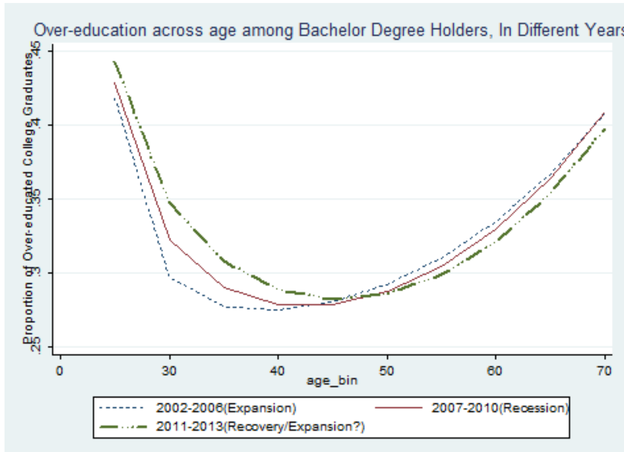
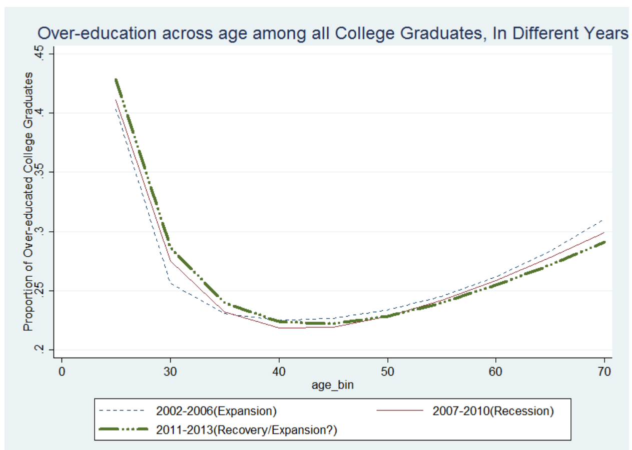


Figure A3: Over-Education across Age Groups among all College Graduates (Bachelor's Degree and Higher), Source ACS 2002-2013



The over-education profile for this restricted sample is shown in Figure A4. This Figure thus shows that the women or part-time workers who are more likely to be over-educated are not driving the aggregate U-shape in the data.

Appendix A.3 Wages and Experience Requirements

Figure A5 shows the wage premium in cross-sectional data. The wage premium for over-educated college graduates is virtually non-existent, specially at younger and older ages. Another striking feature of this figure is that the overall 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 no premium on

Figure A4: Over-Education across Age Groups among Bachelor Degree Holders in the Restricted Sample, Source ACS 2010

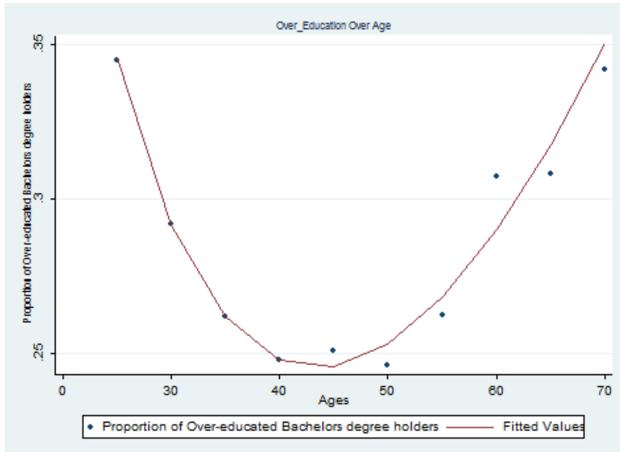
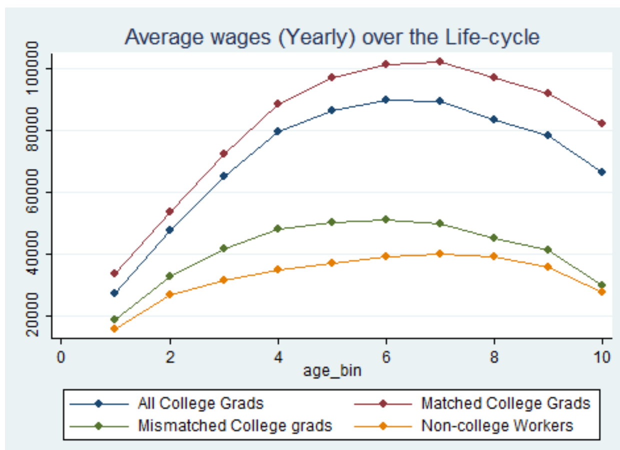


Figure A5: Wage Premium over Age across Different Groups, Source ACS 2010



their investment. This figure shows that if indeed the overall profile of over-education is rising at later ages through transitions into over-education then these transitioning workers should suffer substantial wages losses, a hypothesis that is tested using panel data from SIPP.

Figure A6 shows the resulting profile of experience requirements over the course of the lifecycle. 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. Compare this result to the two other groups in the figure, matched college workers and matched non-college workers. Workers in both these groups are working in jobs that require higher experience at older ages.

Figure A6: Experience Requirements over Age across Different Groups, Source Pooled ACS 2010

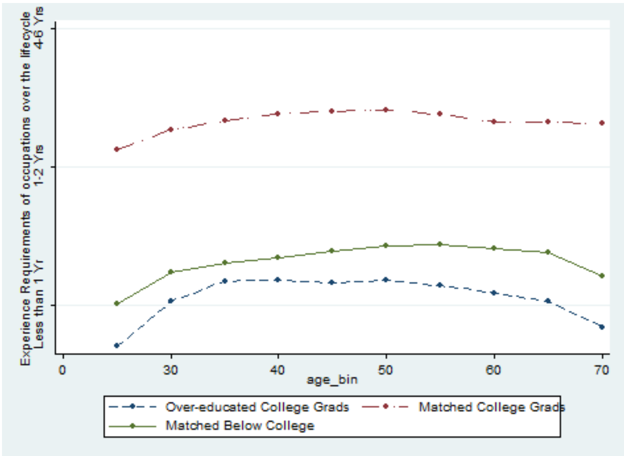
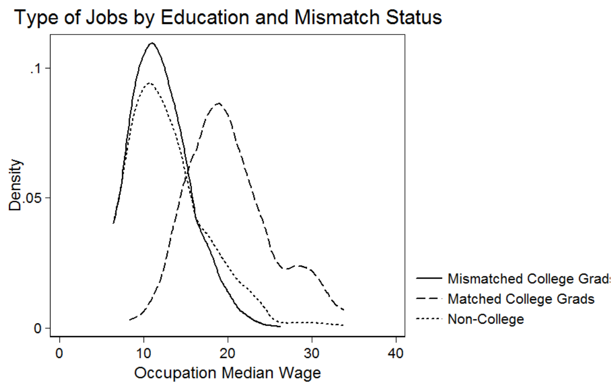


Figure A7: Occupation Median Wage for Jobs done by various groups



Appendix A.4 How well does the over-education measure perform?

Figure A8: Cognitive Skills for Jobs done by various groups

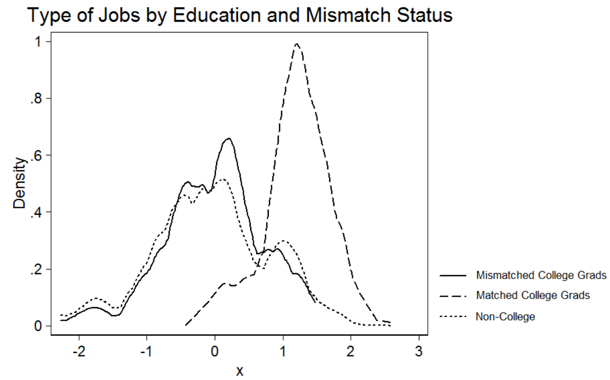
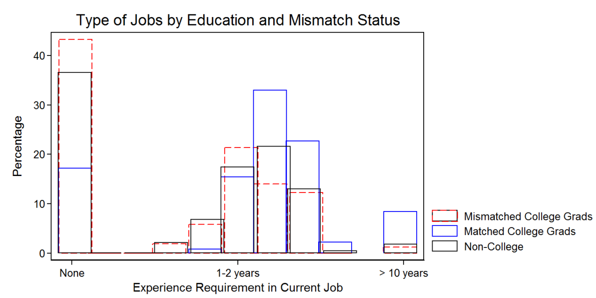


Figure A9: Experience Requirements for Jobs done by various groups



Appendix B A Frictionless Model of Occupation Choice and Human Capital

In this section I present a simple model of occupational choice that aims to capture the U-shape of over-education. The model follows the setup in Groes, Kircher, and Manovskii (2014) with workers and occupations differing in their productivities and provides a theoretical background for the model presented in section 5. I follow the literature on lifecycle wage growth (see Rubinstein and Weiss (2006)) and allow for workers to make active human capital investment decisions. This combination leads to a matching model in which the attributes of the workers evolve over time due to the occupation that they choose.

Appendix B.1 Setup

Workers are assumed to be risk neutral and discount the future at with the discount factor β. Each worker stays in the labor market for T periods. Each period the cohort that leaves the labor market is replaced by a new cohort with $t = 1$. Workers chose employment in different occupations over time to maximize their lifetime earnings and simultaneously choose the investment in human capital. A worker , who has spent t time periods in the labor market and has accumulated a stock of human capital,h_t, has productivity given by $Y_t = (1 - s_t)H_t$. Here s_t is the investment made by the workers in general human capital. Workers know perfectly the process with which their ability evolves over time given their investment choice. Thus, there is no role for learning one's ability in the current setup of the model.

Occupations are ranked in terms of their productivity with P_k being the productivity of the k-th occupation and $P_1 < P_2 < P_3 .... < P_{K-1} < P_K$. The production function in an occupation and worker match, $f(P_k, Y)$, is assumed to be supermodular in P_k and Y and I assume a particular functional form for this function. In particular I assume that a worker with productivity Y produces the following output in a match with occupation k.

$$Q(k, Y) = P_k Y$$

The consequence of this assumption is that all workers produce more in higher ranked occupations. Finally it is assumed there that are a fixed number of jobs, γ_k in each occupation. I start by considering an economy without any matching frictions between the workers and jobs.[10] I even abstract from informational frictions because the worker's actual ability is known. In such a setting, wages are typically assumed to be output-contingent contracts that specify different wages for different outputs realized within a match. In particular the wage for a worker with productivity Y, working in occupation k will be given by:

$$W(k, Y) = P_k Y - \Pi_k$$

where Π_k is the share of the output that goes to the firms in occupation k. This object is determined in equilibrium to satisfy the feasibility constraint. The workers' problem then becomes twofold. He first chooses the occupation to work in and then the level of investment in human capital. The investment in human capital depends not only on the current match of the worker but also on the chances that the worker can move to a better match in the future with that investment. The dynamic problem of the worker can be written as:

$$V_t(h_t) = \max_{k_t \in k_1, k_2, ...k_k} \left\{ \max_{s_t} \left(P_k(1 - s_t)h_t - \Pi_k + \beta V_{t+1}(h_{t+1}) \right) \right\}$$

Human capital evolves according to the following function.

[10] I relax this assumption in the next section.

$$h_{t+1} = A(s_t h_t)^{\phi} + (1-\eta)h_t$$

The above specification for the human capital accumulation function is widely used in the empirical literature that seeks to explain wage growth over the life-cycle and σ refers to the depreciation rate of human capital. There are two policy functions associated with the above problem, $k_t(h_t)$, which defines the occupation choice of the worker and $s_t(h_t, k_t(h_t))$ which defines the investment choice of the worker given the occupation choice and the current stock of human capital

To introduce heterogeneity in the model I assume variation in initial human capital and that workers with different education levels draw their initial human capital from different distributions. The empirical literature has also considered variation in learning ability, A, but that is not a feature of the current model. I consider the long run stationary equilibrium of the economy in which the decisions of the workers are only dependent upon their time spent in the labor market and the endogenous share of output for the firms in each occupation are constant over time [11].

Equilibrium An equilibrium is a vector of payoffs to the firms such that $\sum_i \sum_t k_{it}(H_{it}) = \gamma_k$, the number of jobs in each occupation.

Appendix B.2 Some Qualitative Results from the Model

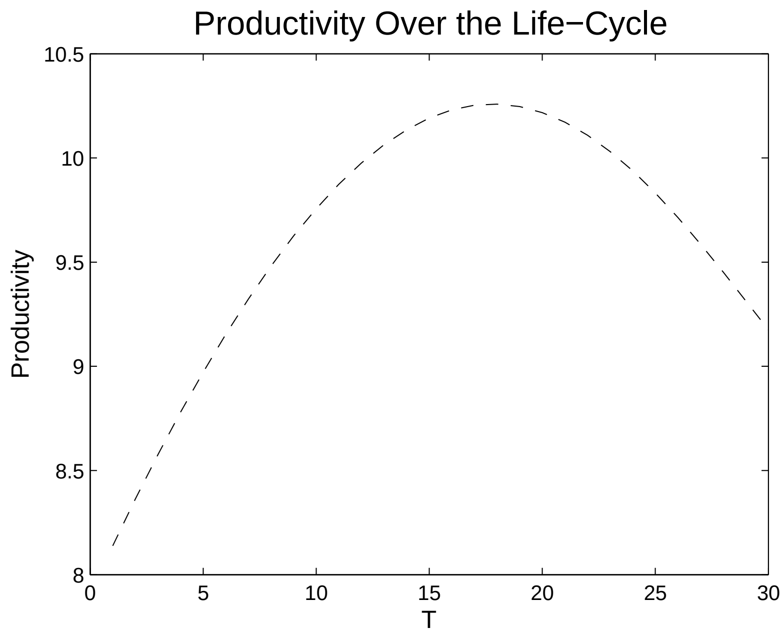
I now take the basic model outlined above and try to match the over-education profile observed in the data. The aim of this exercise is not to perform a serious calibration but to judge if the above model can deliver the patterns in the data qualitatively. It will also provide a useful starting point for further additions to the model that will be required to match the life-cycle moments quantitatively.

I assume that there are three occupations namely P_1, P_2 and P_3 with $P_3 > P_2 > P_1$. I call P_2 and P_3 as college occupations while P_1 is referred to as a non-college occupation. On the worker side I assume that there are three types of workers of equal measure, those without college education (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 a log-normal distribution with mean α_i, such that $\alpha_{mc} > \alpha_b > \alpha_{nc}$, and variance σ. I also assume that workers stay for 30 time periods in the labor market.

I then solve this 3 worker type and 3 occupation model using occupational productivity

[11]In fact I am already assuming stationarity when I wrote statement of the problem for the worker

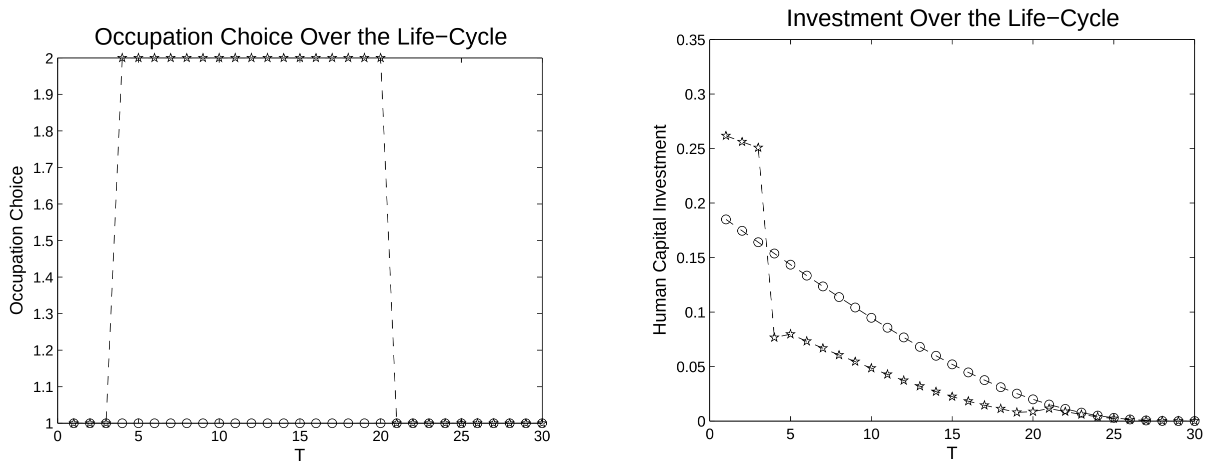
Figure B10: Output from the Model



parameters from Groes, Kircher, and Manovskii (2014) and using human capital production function parameters from Sanders and Taber (2012). The basic human capital model produces the well known hump shaped productivity profile shown in Figure 11. In the current model with vertically differentiated occupations, it would imply that workers with low productivity will choose a low occupation and invest in human capital to increase their productivity in the future. As their productivity increases, they will choose a higher productivity occupation and similarly later on in their career they will choose a lower type occupation. Firms operating in higher productivity occupations have higher profits in equilibrium and thus take a higher share of match output. Thus workers on the declining part of the productivity profile find it optimal to switch to a lower occupation in which the share of match surplus that goes to the firms is lower.

Another feature of the model, the fixed number of jobs in each occupation, prevents every worker from moving up the occupation ladder. This has important implications for the investment decisions of the workers. Figure 12(a) shows two simulated workers in the model. One worker is stuck in the first occupation throughout the lifecycle while the second worker is able to move up the occupation ladder for some part of his career but eventually moves down. The second worker however, has a higher initial human capital. Panel (b) of the figure shows the human capital investment decisions of the same workers. While both workers were in occupation 1, the one with the higher initial human capital is investing more until he makes the switch to the second occupation. In the second occupation his investment

Figure B11: Output from the Model



(a) **(b)**

levels decline because the opportunity cost of investment is higher.

I now show that the model can replicate the U-shape of over-education qualitatively. As mentioned before the model has 3 occupations and 3 types of workers. I assumed that the workers draw their initial human capital from a log-normal distribution and that workers with more education have a higher mean. The variance across education groups is assumed to be the same for now. To calculate the over-education statistic in the model, I estimate the proportion of bachelor degree holders who are working in occupation 1. The results from the model can be seen in Figure 13. The model can indeed predict a U-shape of over-education with age. The human capital depreciation parameter is important for this result as setting it equal to 0 gives a monotonically decreasing pattern with age.

Appendix B.3 Transition profiles

I also assess how the current model performs on other dimensions such as the transition profiles over the lifecyle. The qualitative predictions of the model along these two profiles are shown in Figure 14 and Figure 15. The profiles from the data are calculated conditional on an occupation change while the profiles from the model are not. This is because in the model every worker can choose a new occupation every period.

As can be seen in Figure 14, the model does a good job of matching the shape of transition profile from matched employment to over-education. This provides support for the suggested mechanism of skill obsolescence behind the U-shape of over-education over the lifecycle. Figure 15 shows that the model completely matches the shape of the transition

Figure B12: Output from the Model

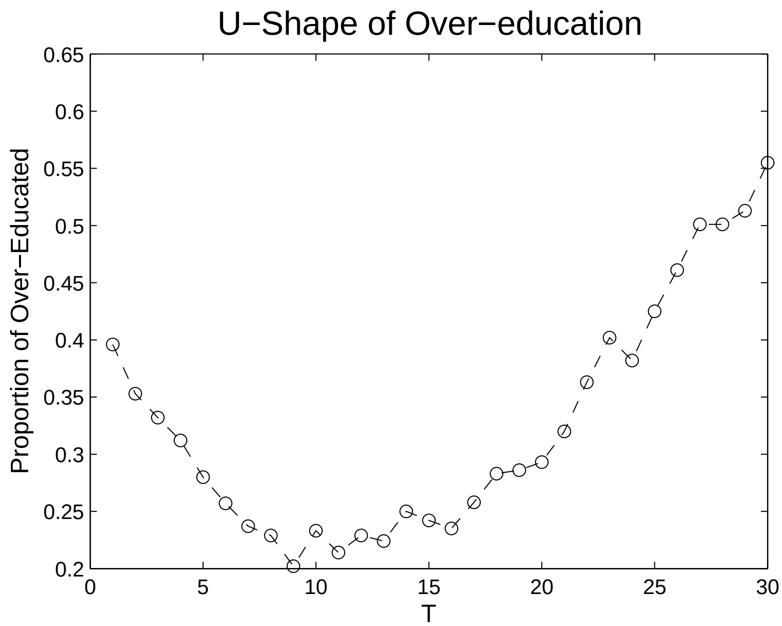
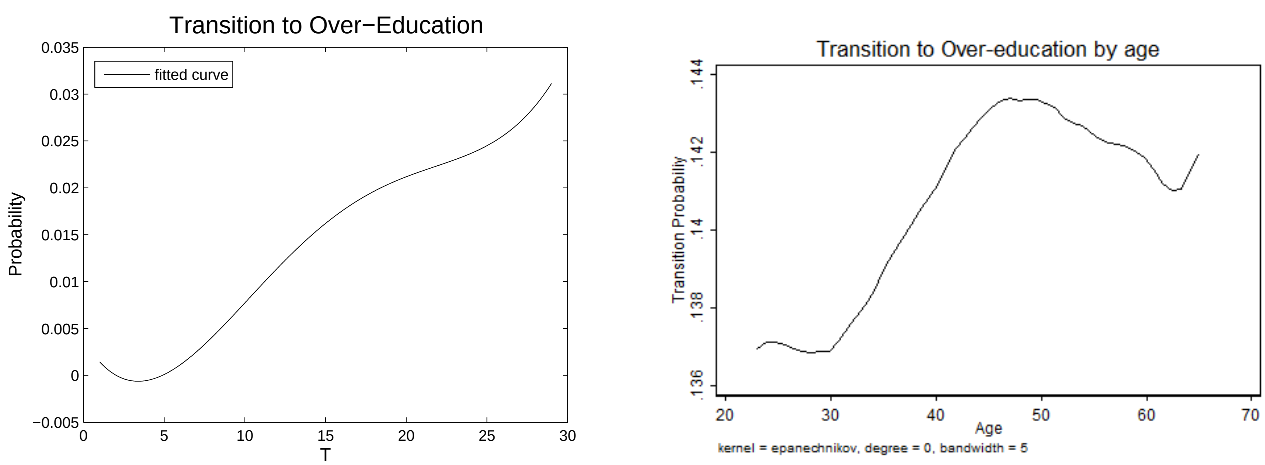


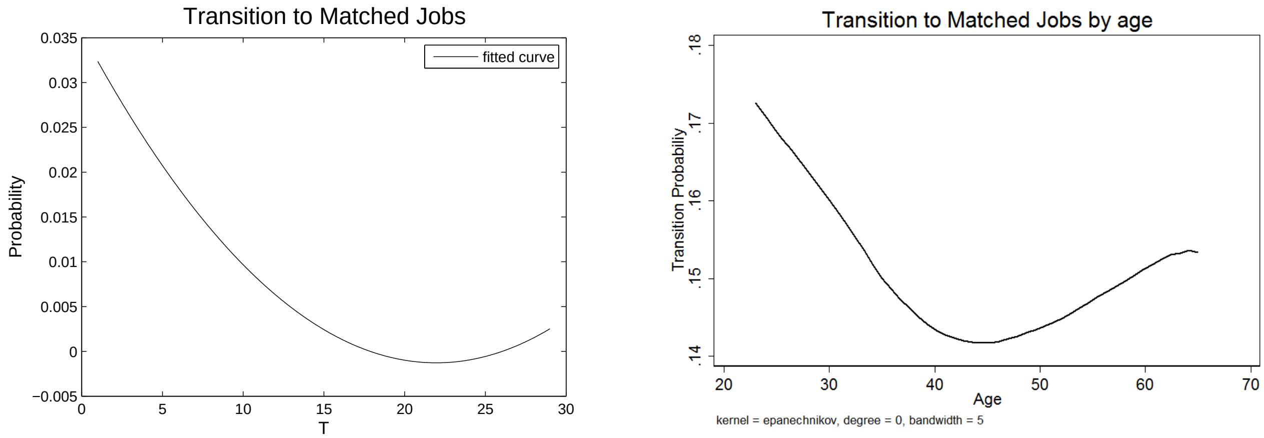
Figure B13: Transition Profiles to Over-education from the Model and the Data



(a) (b)

profile from over-education to matched employment. However, the difference in magnitude between the model and the data show that skill obsolescence is not the only force at play here. Another caveat to keep in mind is that there is no cost for switching occupations in the model and that implies another well known empirical fact, declining occupational mobility with age, can not be matched. Introducing occupation specific human capital accumulation would probably solve this problem.

Figure B14: Transition Profiles to Matched Jobs from the Model and the Data



(a) **(b)**

Appendix C Occupation Categories

Non-College Occupations

Non-College Occupations	
Actors	Control and valve installers and repairers
Adhesive bonding machine operators and tenders	Cooks
Agricultural inspectors	Counter and rental clerks
Air traffic controllers and airfield operations specialists	Counter attendants, cafeteria, food concession, and coffee shop
Aircraft mechanics and service technicians	Couriers and messengers
Aircraft structure, surfaces, rigging, and systems assemblers	Court, municipal, and license clerks
Ambulance drivers and attendants, except emergency medical technicians	Crane and tower operators
Animal control workers	Credit authorizers, checkers, and clerks
Animal trainers	Crossing guards
Appraisers and assessors of real estate	Crushing, grinding, polishing, mixing, and blending workers
Automotive and watercraft service attendants	Cutting workers
Automotive body and related repairers	Cutting, punching, and press machine setters, operators, and tenders, metal and plastic
Automotive glass installers and repairers	Dancers and choreographers
Automotive service technicians and mechanics	Data entry keyers
Avionics technicians	Dental assistants
Baggage porters, bellhops, and concierges	Dental hygienists
Bailiffs, correctional officers, and jailers	Derrick, rotary drill, and service unit operators, oil, gas, and mining
Bakers	Detectives and criminal investigators
Barbers	Diagnostic related technologists and technicians
Bartenders	Dining room and cafeteria attendants and bartender helpers
Bill and account collectors	Dishwashers
Billing and posting clerks	Dispatchers
Boilermakers	Door-to-door sales workers, news and street vendors, and related workers
Bookkeeping, accounting, and auditing clerks	Dredge, excavating, and loading machine operators
Brickmasons, blockmasons, and stonemasons	Drilling and boring machine tool setters, operators, and tenders, metal and plastic
Broadcast and sound engineering technicians and radio operators	Driver/sales workers and truck drivers
Bus and truck mechanics and diesel engine specialists	Drywall installers, ceiling tile installers, and tapers
Bus drivers	Earth drillers, except oil and gas
Butchers and other meat, poultry, and fish processing workers	Electric motor, power tool, and related repairers
Cabinetmakers and bench carpenters	Electrical and electronics repairers, industrial and utility
Cargo and freight agents	Electrical power-line installers and repairers
Carpenters	Electrical, electronics, and electromechanical assemblers
Carpet, floor, and tile installers and finishers	Electricians
Cashiers	Electronic equipment installers and repairers, motor vehicles
Cement masons, concrete finishers, and terrazzo workers	Electronic home entertainment equipment installers and repairers
Chefs and head cooks	Elevator installers and repairers
Chemical processing machine setters, operators, and tenders	Eligibility interviewers, government programs
Chemical technicians	Embalmers and funeral attendants
Childcare workers	Emergency medical technicians and paramedics
Cleaners of vehicles and equipment	Engine and other machine assemblers
Cleaning, washing, and metal pickling equipment operators and tenders	Etchers and engravers
Coin, vending, and amusement machine servicers and repairers	Explosives workers, ordnance handling experts, and blasters
Combined food preparation and serving workers, including fast food	Extruding and drawing machine setters, operators, and tenders, metal and plastic
Computer control programmers and operators	Extruding, forming, pressing, and compacting machine setters, operators, and tenders
Computer operators	Fence erectors
Computer support specialists	File clerks
Computer, automated teller, and office machine repairers	Fire inspectors
Construction and building inspectors	Firefighters
Construction laborers	First-line supervisors of construction trades and extraction workers
	First-line supervisors of correctional officers
First-line supervisors of farming, fishing, and forestry workers	Insurance claims and policy processing clerks
First-line supervisors of fire fighting and prevention workers	Interviewers, except eligibility and loan
First-line supervisors of food preparation and serving workers	Janitors and building cleaners
First-line supervisors of gaming workers	Jewelers and precious stone and metal workers
First-line supervisors of housekeeping and janitorial workers	Laborers and freight, stock, and material movers, hand
First-line supervisors of landscaping, lawn service, and groundskeeping workers	Lathe and turning machine tool setters, operators, and tenders, metal and plastic
First-line supervisors of mechanics, installers, and repairers	Laundry and dry-cleaning workers
First-line supervisors of personal service workers	Library assistants, clerical
First-line supervisors of police and detectives	Licensed practical and licensed vocational nurses
First-line supervisors of production and operating workers	Lifeguards and other recreational, and all other protective service workers
First-line supervisors of retail sales workers	Loan interviewers and clerks
Fishers and related fishing workers	Locksmiths and safe repairers
Flight attendants	Locomotive engineers and operators
Food and tobacco roasting, baking, and drying machine operators and tenders	Logging workers
Food batchmakers	Machine feeders and offbearers
Food cooking machine operators and tenders	Machinists
Food preparation workers	Maids and housekeeping cleaners
Food processing workers, all other	Mail clerks and mail machine operators, except postal service
Food servers, nonrestaurant	Maintenance and repair workers, general
Food service managers	Maintenance workers, machinery
Forging machine setters, operators, and tenders, metal and plastic	Manufactured building and mobile home installers
Furnace, kiln, oven, drier, and kettle operators and tenders	Massage therapists
Furniture finishers	Medical assistants
Gaming cage workers	Medical records and health information technicians

Gaming managers	Medical transcriptionists
Gaming services workers	Medical, dental, and ophthalmic laboratory technicians
Glaziers	Metal furnace operators, tenders, pourers, and casters
Graders and sorters, agricultural products	Meter readers, utilities
Grinding, lapping, polishing, and buffing machine tool setters, operators, and tenders, metal and plastic	Millwrights
Grounds maintenance workers	Mining machine operators
Hairdressers, hairstylists, and cosmetologists	Miscellaneous agricultural workers
Hazardous materials removal workers	Miscellaneous assemblers and fabricators
Health practitioner support technologists and technicians	Miscellaneous construction and related workers
Healthcare support workers, all other, including medical equipment preparers	Miscellaneous entertainment attendants and related workers
Heat treating equipment setters, operators, and tenders, metal and plastic	Miscellaneous health technologists and technicians
Heating, air conditioning, and refrigeration mechanics and installers	Miscellaneous legal support workers
Heavy vehicle and mobile equipment service technicians and mechanics	Miscellaneous personal appearance workers
Helpers, construction trades	Miscellaneous plant and system operators
Helpers--installation, maintenance, and repair workers	Miscellaneous vehicle and mobile equipment mechanics, installers, and repairers
Helpers--production workers	Model makers and patternmakers, metal and plastic
Highway maintenance workers	Models, demonstrators, and product promoters
Hoist and winch operators	Molders and molding machine setters, operators, and tenders, metal and plastic
Home appliance repairers	Molders, shapers, and casters, except metal and plastic
Hosts and hostesses, restaurant, lounge, and coffee shop	Morticians, undertakers, and funeral directors
Hotel, motel, and resort desk clerks	Motion picture projectionists
Human resources assistants, except payroll and timekeeping	New accounts clerks
Industrial and refractory machinery mechanics	Nonfarm animal caretakers
Industrial truck and tractor operators	Nursing, psychiatric, and home health aides
Inspectors, testers, sorters, samplers, and weighers	Occupational therapy assistants and aides
Insulation workers	Office clerks, general
Office machine operators, except computer	Respiratory therapists
Operating engineers and other construction equipment operators	Retail salespersons
Opticians, dispensing	Riggers
Order clerks	Rolling machine setters, operators, and tenders, metal and plastic
Other extraction workers	Roofers
Other installation, maintenance, and repair workers	Sailors and marine oilers
Packaging and filling machine operators and tenders	Sales and related workers, all other
Packers and packagers, hand	Sawing machine setters, operators, and tenders, wood
Painters, construction and maintenance	Secretaries and administrative assistants
Painting workers	Security and fire alarm systems installers
Paper goods machine setters, operators, and tenders	Security guards and gaming surveillance officers
Paperhangers	Sewing machine operators
Parking enforcement workers	Sheet metal workers
Parking lot attendants	Ship and boat captains and operators
Parts salespersons	Shipping, receiving, and traffic clerks
Paving, surfacing, and tamping equipment operators	Shoe and leather workers and repairers
Payroll and timekeeping clerks	Shoe machine operators and tenders
Personal care aides	Small engine mechanics
Pest control workers	Stationary engineers and boiler operators
Pharmacy aides	Stock clerks and order fillers
Phlebotomists	Structural iron and steel workers
Photographers	Structural metal fabricators and fitters
Physical therapist assistants and aides	Subway, streetcar, and other rail transportation workers
Pipelayers, plumbers, pipefitters, and steamfitters	Supervisors of transportation and material moving workers
Plasterers and stucco masons	Surveying and mapping technicians
Plating and coating machine setters, operators, and tenders, metal and plastic	Switchboard operators, including answering service
Police and sheriff's patrol officers	Tailors, dressmakers, and sewers
Postal service clerks	Tax preparers
Postal service mail carriers	Taxi drivers and chauffeurs
Postal service mail sorters, processors, and processing machine operators	Teacher assistants
Power plant operators, distributors, and dispatchers	Telecommunications line installers and repairers
Precision instrument and equipment repairers	Telemarketers
Prepress technicians and workers	Telephone operators
Pressers, textile, garment, and related materials	Tellers
Printing press operators	Textile cutting machine setters, operators, and tenders
Private detectives and investigators	Textile knitting and weaving machine setters, operators, and tenders
Procurement clerks	Textile winding, twisting, and drawing out machine setters, operators, and tenders
Production workers, all other	Tire builders
Production, planning, and expediting clerks	Tool and die makers
Pumping station operators	Tool grinders, filers, and sharpeners
Radiation therapists	Tour and travel guides
Radio and telecommunications equipment installers and repairers	Transportation attendants, except flight attendants
Rail-track laying and maintenance equipment operators	Transportation inspectors
Railroad brake, signal, and switch operators	Transportation security screeners
Railroad conductors and yardmasters	Travel agents
Real estate brokers and sales agents	Upholsterers
Receptionists and information clerks	Ushers, lobby attendants, and ticket takers
Refuse and recyclable material collectors	Veterinary assistants and laboratory animal caretakers
Reinforcing iron and rebar workers	Waiters and waitresses
Reservation and transportation ticket agents and travel clerks	Water and wastewater treatment plant and system operators
	Weighers, measurers, checkers, and samplers, recordkeeping
	Welding, soldering, and brazing workers
	Wholesale and retail buyers, except farm products
	Woodworking machine setters, operators, and tenders, except sawing
	Word processors and typists