Born Under a Bad Sign: The Cost of Entering the Job Market During a Recession

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Abstract

Existing literature has highlighted how economic shocks in the early years of an individual's working life can give rise to persistent wage scars. Using data from the National Longitudinal Survey of Youth 1979, I document how entering the job market during a recession not only affects wage outcomes but also severely impinges on between-career changes that are largely concentrated in the early years of an individual's working life. Given these facts, I build a model that shows how entering the job market during a recession hampers early career mobility which is critical towards facilitating learning about one's comparative advantage and accumulating human capital specific to one's ideal career. The combined effect of these two forces implies that individuals who choose to switch careers post-recession are forced to restart at lower wages as they lack 'relevant' career-specific human capital and certainty over their aptitude in their new careers. In addition, poor initial conditions can depress future wage growth by cementing permanent misallocation as marginal workers who have accumulated sufficient specific human capital in their current careers find it too costly to switch careers in the recovery. Persistent wage losses are a result of misallocation and experience gaps, both of which take time to correct even after the initial recessionary shock has disappeared. In the model, a wage gap of 6% continues to persist post-recession and only fades completely 60 quarters after entry into the labor market.

1 Introduction

Nearly half of all wage gains accrued to an individual between the age of 18 and 46 occurs before age 30, suggesting that the early years of an individual's working life are critical to his overall earnings growth.[1] The recent continuing weakness in the labor market and overall tepid recovery, however, has severely affected the employment prospects for young workers.[2] Existing literature by Kahn (2010), Oreopoulous et al (2012), Gregg and Tominey (2005) and Oyer (2006) document the persistence of wage losses stemming from economic conditions at the time of entry into the labor market. For the US economy, Kahn (2010) looks at white male college graduates who entered the job market prior to, during and after the 1980s recession and observes that a 1 percentage point increase in the unemployment rate at the time of entry leads to an initial wage loss of 6 to 7 percent. Moreover, she finds that the negative wage effect is persistent and that agents who entered the job market in a bad economy continue to suffer a wage loss of 2.5

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[#]For the latest version, check, http://econweb.umd.edu/~wee/wee_jmp.pdf

[1]See BLS Economic News Release, 25 Jul 2012 "Number of Jobs Held, Labor Market Activity, and Earnings Growth Among the Youngest Baby Boomers: Results from a Longitudinal Survey Summary".

[2]Elsby et al (2010) note that young workers aged 16-25, less educated workers and workers from ethnic minorities observe sharper increases in joblessness during recessions.

percent 15 years after entry.[3] While the above literature has concentrated on establishing a link between initial entry conditions and future wage outcomes, the primary focus of this paper is on examining the channel through which these persistent wage losses occur. In particular, this paper proposes that weak labor markets inhibit early career transitions which are critical towards advancing the learning of comparative advantage and the accumulation of human capital specific to one's ideal career. The speed of learning and accumulation of specific human capital that is non-transferable across careers are the key factors which keep wages depressed long after the economy has recovered.

I first document how career mobility varies over the life cycle using data from the National Longitudinal Survey of Youth 1979 and show that entering in a recession has a negative impact on career transitions. The early years of an individual's working life are dominated by between-career changes. The frequency of these between-career changes, however, falls sharply with age. In contrast, within-career job changes are less predominant in the early years of one's working life but observe a much gentler decline with age. Importantly, entering the job market during a recession severely impinges on an individual's ability to conduct between-career changes while within-career job changes remain mostly unscathed. Given these facts, I build a dynamic stochastic equilibrium model that demonstrates how reduced opportunities to switch careers early on cause slowdowns in learning about comparative advantage and increased accumulation of 'irrelevant' human capital, the combined effect of which affects individuals' subsequent job search behavior and future wage outcomes. I then decompose the wage gap and show that diminished opportunities to switch careers early on generate misallocation and experience gaps. These misallocation and experience gaps take time to correct and are the main components driving the persistence in wage loss. In the model, a wage gap of 6 percent continues to persist even after the recessionary shock has dissipated and only fades completely 60 quarters after entry into the labor market.

Learning about comparative advantage and accumulating 'relevant' human capital are two key elements that contribute towards wage growth. Intuitively, individuals entering the job market are uncertain about which career is best suited to their abilities. In the early years of their working life, individuals engage in job experimentation to learn more about their comparative advantage. Recessions, however, inhibit early job-to-job transitions and overall job experimentation. As such, even individuals who are continuously employed suffer a slowdown in their learning process, as individuals who discover that they have poor aptitude at their current job are unable to switch careers and learn about their aptitude at an alternative career.

Learning alone, however, may not be sufficient by itself to replicate the degree of persistent wage losses seen in

[3] Oreopoulous et al (2012) focus on Canadian college graduates and find that individuals who enter the job market during a recession suffer an initial wage penalty of 9 percent. These wage losses, though not permanent, only fade 10 years after entry into the labor market. Gregg and Tominey (2005) find that the higher incidence of youth unemployment stemming from entry into a recession has severely persistent negative wage effects. Oyer (2006) looks at PhD economists and observes that even for this subset of the labor market, initial conditions matter for long-term outcomes. Overall, the growing empirical literature points toward the harmful effects that initial economic conditions can have on individuals' wage trajectories.

the data. When the economy recovers, individuals should be able to re-start their job experimentation, learn their aptitude at various careers, and switch into a career at which they have comparative advantage. This implies a rapid catch-up in wages post-recession. Thus, to account for persistent wage scarring effects, I consider how the accumulation of career-specific human capital interacts with individuals' learning processes to affect their job-finding prospects and future wage outcomes. In particular, prolonged weakness in the labor market can lead to an increased incidence of accumulating 'irrelevant' human capital. When labor markets are weak and individuals are prevented from moving into alternative jobs, they remain 'stuck' in their current vocation and as such accumulate experience that may be non-transferable to their next career. This 'irrelevant' human capital, i.e. experience gained at tasks at which the individual has comparative disadvantage, may be underutilized in future alternative careers, causing wage growth to be dampened.

In the recovery, the worker who has learnt that he has poor aptitude in his current career is faced with a discrete choice of discarding all the experience he has gained thus far and switching into a career where he has only a noisy signal of his aptitude, or remaining in his current career. An individual who chooses to switch careers when the economy recovers may be forced to restart at lower rungs of the wage ladder, as his accumulated human capital up to this point is irrelevant towards his new career. Alternatively, an individual who has accumulated significant amounts of career-specific human capital may find it too costly to switch careers and may optimally choose to remain in a career at which he has comparative disadvantage. By staying in a career where he has comparative disadvantage, the worker's weaker productivity at his current career contributes towards his lower wage outcome. Poor initial conditions, therefore, can cause persistent wage losses by affecting the individual's ability to climb the wage ladder, as well as by raising the probability of permanent misallocation.

In addition to its direct impact on a worker's output, the specificity of human capital and lack of certainty about an individual's productivity in his new career also modify an individual's job-finding prospects. High perceived aptitude and the development of relevant experience raise the worker's probability of finding a job as well as the wage compensation he can demand. Intuitively, firms prefer to hire workers who bring more effective labor input into production. By slowing down learning about comparative advantage and by fostering accumulation of irrelevant human capital, recessions adversely affect an individual's future job-finding and retention probabilities, and consequently the wage share that a worker can demand.

While this is not the first paper to examine how poor initial conditions affect long run wage outcomes, the literature has yet to arrive at a consensus on the mechanism explaining these persistent wage losses. Notably, the standard labor search model cannot account for persistent wage scars. In the canonical Diamond-Mortensen-Pissarides (DMP) labor search model, workers and firms split the value of a job. An increase in aggregate productivity raises the value of a job and encourages firms to create more vacancies. Consequently, improvements in the job-finding rate exert upward pressure on wages, resulting in wages recovering with the aggregate state. Hornstein et al (2005) find that the canonical labor search model can only rationalize a very small amount of dispersion in the wage data. Extending the standard labor search model to incorporate on-the-job search does not help to explain persistent wage scars. Barlevy (2002) incorporates on-the-job search and heterogeneous workers into the standard labor search model and studies the sullying effects of a recession. He finds that recessions act toward suppressing worker reallocation and contribute towards a decline in aggregate match quality. Nonetheless, aggregate match quality rebounds with the recovery of the economy in his model and as such, gives rise to little or no persistent wage losses. Moscarini (2001) considers a model where individuals know their comparative advantage but are, however, willing to take jobs where they have comparative disadvantage during a recession as it is costly to wait for the right job. While Moscarini (2001) and Barlevy (2002) are instructive in showing how mismatch can arise in a recession, their models do not focus on explaining how persistent wage losses can arise.

Pissarides (1992) suggests that persistent wage losses may arise if workers' skills depreciate while unemployed.[4] This mechanism is likely to be most powerful during sluggish recoveries when the unemployment rates continually remain high and many individuals are long-term unemployed. The relatively short durations of past recessions and quick recoveries that accompanied them, however, imply that a high rate of human capital depreciation is required to generate such persistent wage losses. In a seminal paper, Beaudry and Dinardo (1991) focus on implicit contracts and find that current wages depend heavily on initial economic conditions only when mobility is costly.[5] This implies that a model of wage contracts and past wage premiums alone are unable to predict persistent wage scars, since agents are able to move across jobs in a recovery and start new wage contracts that depend on economic conditions at the time of hiring.

This paper contributes to the above literature by offering a complementary explanation as to how persistent wage losses may arise from poor entry conditions. By focusing on how recessions affect the learning of one's comparative advantage as well as the accumulation of irrelevant human capital, this paper not only demonstrates the channel through which persistent wage losses could arise but is also consistent with the empirical evidence on career mobility over the life cycle. Incorporating learning as well as career-specific human capital into my model allows me to match the rapid decline in between-career changes with experience, as well as capture the relative prominence of within-career job changes in the latter part of one's working life. As such, my model is able to demonstrate how the life cycle and business cycle aspects of job search behavior can drive persistent wage losses by affecting the amount of initial learning and human capital accumulation of the worker.

[4]More specifically, Pissarides (1992) demonstrates how skill loss can negatively affect the composition of quality among the pool of unemployed workers. Firms create less job openings when the composition of the unemployment pool worsens.

[5]In fact, Beaudry and Dinardo (1991) find that when mobility is costless, current wages are pegged to the lowest unemployment rate since the start of a job.

The rest of this paper is organized as follows: Section 2 reviews the related literature whilst Section 3 describes the empirical motivation and data that will be used to calibrate the model. Section 4 presents the model. Section 5 lists the calibration process while Section 6 provides results from a numerical simulation. Section 7 concludes.

2 Related Literature

The importance of job mobility in the early years of an individual's working life to his overall wage growth has been well documented. Using the Longitudinal Employer-Employee Data (LEED) file for the period spanning 1957Q1 to 1972Q4, Topel and Ward (1992) find that more than half of young workers have held six or more full time jobs ten years after their entry into the labor market. In addition, the average quarterly wage growth associated with a between-job change is about 12 percent for an individual with less than 7 years of working experience, compared to an average 1.75 percent quarterly wage growth within jobs. In contrast, the average quarterly wage growth rate associated with a between-job change is halved for an older worker with more than 7 years of experience, suggesting that early between-job switching is important for wage growth in the first few years of an individual's working life but this effect diminishes as a worker ages. To account for these observations, Neal(1999) posits that workers follow a two-stage search strategy. In his model, a worker must learn about both his career match and his employer match quality. Defining a 'complex' change of jobs as one which involves a change in both industry and occupation as well as employer, and a 'simple' change of jobs as one which involves only a change in employer and not both occupation and industry together, Neal finds that the early years of an individual's working life are marked by complex job changes while the latter years of an individual's working life tend to involve simple job changes. Using data from the National Longitudinal Survey of Youth 1979 (NLSY79), he finds that at least 70 percent of high school graduates and about 50 percent of college graduates undergo a career change - i.e. a complex change of jobs - after starting their first full-time job. The frequency of complex job changes, however, is decreasing with experience. In contrast, the probability of a simple job change increases as one gains experience in the labor market. Given this evidence, Neal concludes that individuals initially search for a career and only concentrate their search efforts towards finding an employer match once a suitable career has been found.

Pavan (2011) updates the results of Neal(1999) and finds that wage gains from simple and complex job changes are similar in magnitude and account for about 45 percent of the total wage growth in the first decade for workers with at least some college education. Importantly, Pavan documents that the accumulation of career-specific human capital (same occupation, same industry) contributes significantly to wage returns. On average, ten years of career-specific tenure gives rise to an increase in log wages by 0.2 points for college graduates. In contrast, Parent (2000) and Kambourov and Manovskii (2009) find that the wage returns from accumulating firm-specific human capital are negligible once one controls for either industry or occupation specific human capital. Conceptually, the transferability of human capital between jobs depends crucially on the similarity of skill sets required at various jobs. Intuitively, jobs within the same career should share many similarities in required skill sets. These empirical findings, therefore, underscore the importance of the career search process and the accumulation of relevant career-specific human capital for maximizing wage returns. This paper attempts to see how both of these drivers of wage growth are affected during a recession. As this study is interested in how recessions affect job shopping and ultimately wage growth paths, I focus on the subset of labor market participants that most actively engage in job-shopping: namely labor market entrants.

Importantly, incorporating learning about one's comparative advantage into the standard labor search model is crucial towards matching life cycle job mobility and wage growth. Recent work by Gervais et al (2011) and Papageorgiou (2013) incorporate learning about one's type into a labor model. In the former, the authors show that the introduction of occupational learning into a labor search model enables them to explain why job separations, and consequently unemployment declines with age. Young workers typically enter into unemployment or change jobs more frequently at a younger age as they learn about their occupational fit or true calling. In the latter, Papageorgiou (2013) demonstrates that learning about one's comparative advantage enables him to match gross workers flows and replicate the declining rate of occupational mobility over one's lifetime. In the same vein, learning in this paper generates a high frequency of between-career changes in the early years of an individual's working life. Felli and Harris (1996) incorporate learning about one's productivity at a job into a model with firm-specific human capital. In their model, workers experience learning-by-doing and accumulate human capital that is specific to the firm rather than to a career. While conceptually similar to this paper, Felli and Harris (1996) focus on the wage determination process, and do not examine how business cycle conditions and search frictions may interact to affect the wage path of an individual. In contrast to the above literature that focuses mainly on wage determination and mobility over the life-cycle, this paper examines how initial business cycle conditions impact life cycle considerations in job-search which in turn play out into future wage outcomes.

Delacroix and Shi (2006) offer an alternative mechanism for observed concave wage profiles and propose that workers conduct on-the-job search and climb the wage ladder one rung at a time. As past wage compensations form a worker's current reservation wage, they show how one can generate wage dispersion in a model as well as attain serial correlation in wage outcomes. An implication of their paper suggests that current wage outcomes may be pegged to past wage premiums. Similar to Delacroix and Shi(2006), this paper also demonstrates current wage outcomes may be benchmarked by past wages received. However, the persistence in wage outcomes here is not a product of past wage premiums alone but is in fact a function of the evolution of relevant human capital. The amount of wage compensation a worker can demand is a function of his effective labor input. The presence of irrelevant human capital impinges on a worker's ability to demand higher wages in a new career. Hence, persistence in wage returns and slow climbing of the wage ladder are outcomes of the evolution of relevant human capital. In addition, a worker who chooses to remain in a career where he has comparative disadvantage also experiences a slower growth in specific human capital due to his lack of innate aptitude at that job. This again gives rise to persistence in wage losses.

Another related paper by Adda, Dustmann, Meghir and Robin (2013) finds that continuously employed young workers suffer earnings losses of about a 1 to 2 percent in net present value terms over a 15 year horizon. They attribute this loss in earnings for continuously employed young workers to the loss of search capital. In their model, workers accumulate firm-specific human capital on the job. Firm-worker match quality is heterogeneous and drawn only when a firm and worker meet. Recessions, however, inhibit both current and future job-to-job transitions as workers accumulate firm-specific human capital while at a job and forego searching for better match quality even after the economy recovers. This paper differs from Adda et al (2013) in two aspects: 1) human capital is firstly career-specific rather than match-specific and 2) individuals must learn about their comparative advantage. These two aspects allow me to match the evidence documented by Neal(1999) that workers continue to conduct simple job changes and change employers later in their working life while agents spend the early part of their working life searching for an appropriate career. If the accumulation of firm-specific human capital was the only factor driving persistently decreased job mobility from entering in a recession, then individuals who enter in a recession would also conduct fewer simple job changes post-recession. However, this is not consistent with the data. In what follows, I will demonstrate that job search strategies related to finding the appropriate career are most affected by the recession while the impact on individuals' job search within the same career is minimal.

3 Data

To observe how job search behavior of labor market entrants varies with the business cycle, I use panel data from National Longitudinal Survey of Youth 1979 (NLSY79). The survey tracks information on the employment and wage histories of a sample of individuals initially aged 14 to 21 years old in 1979 to today. For my analysis, I restrict the sample to the period spanning 1979 to 2006. I do not examine the data for subsequent years, as any declines in wage outcomes in those years could be due to the Great Recession rather than persistent initial conditions. Unemployment rates and layoff rates escalated during the Great Recession. Declines in wages during that period may be due more to the severe decline in demand conditions rather than the initial conditions faced at entry.

I restrict my focus to white males, of which there are 3790 in the sample in 1979. I exclude 377 individuals who spent 4 or more consecutive years in the military in the early stages of their career.[6] If an individual spent less

[6]While being in the military may be in itself a career choice, individuals who enter into the military tend to locked into a military

than 4 consecutive years in the military, I drop the observations for which he was on active duty. I exclude another 146 individuals who displayed weak labor market attachment, i.e. individuals spent more than 15 years out of the labor force. In addition, I delete another 126 individuals who dropped out of the sample and were interviewed fewer than 5 years. Finally, I drop another 14 individuals whose initial labor market attachment cannot be observed. At this point, I have 3246 individuals and 48,232 annual observations in my sample. As wage returns are likely to be affected by the presence of unobservables, I further limit my analysis to a more homogeneous group of individuals. In particular, I focus on two separate sub-samples. The first sub-sample consists of white male college graduates with four year college degrees. This sub-sample consists of 433 individuals and 24350 quarterly observations. The second sub-sample comprises white male high school graduates and consists of 717 individuals and 44023 quarterly observations.

Wages are measured using the usual rate of pay at the time of the interview and are deflated using the Consumer Price Index. A key change in the structure of the NLSY79 is that from 1994 onwards, the survey changed from an annual frequency to being conducted once every two years. Thus, the wage rate reported for each job reflects only the wage reported at the time of the survey period. While an individual may hold more than one job in a given period, I focus on the main job an individual works at for a given quarter. I define a main job as the job at which an individual spends the most hours working within a given quarter.

3.1 Verifying Persistent Wage Losses

As a quick verification, I replicate the exercise in Kahn(2010) and show how initial conditions can exert a lasting impact on wage outcomes. In her paper, Kahn looks at how the unemployment rate at entry affects log hourly wages for white male college graduates. In particular, she conducts the following regression:

$$w_{it} = \alpha_0 + \alpha_1 u_{0,i} + \alpha_2 u_{0,i} * Pot.Exp_{it} + \beta X_{it} + \varepsilon_{it} \tag{1}$$

where w_{it} is the log hourly wage of individual i at time t and $u_{0,i}$ is the main regressor of interest, the national unemployment rate at entry. $u_{0,i} * Pot.Exp_{it}$ is the interaction of the unemployment rate at entry with potential experience. This variable captures the extent to which initial unemployment rates continue to weigh on current wages. A positive coefficient on $u_{0,i} * Pot.Exp_{it}$ implies some form of catch-up in wages over time. X_{it} is a set of control variables which includes the individual's potential experience, the square of potential experience, the AFQT score which acts a proxy for underlying ability, current unemployment rate as well as regional dummies. To account for selection effects and the endogenous timing of labor market entry, Kahn conducts a separate instrumental

career for the length of their contract. Since it is difficult to quantify the relevance of the occupational skills attained while in the military, there are potentially large miscoding errors when these individuals re-enter the labor market and search for jobs. In particular, it is difficult to ascertain the relevant years of specific human capital experience that may apply to private sector jobs for individuals who choose to re-enter the job market after a spell with the military.

variables regression (IV) where she instruments for the unemployment rate at entry with the unemployment rate at the modal age of graduation. Similarly, the interaction term $u_{0,i} * Pot.Exp_{it}$ is instrumented with the product of the unemployment rate at the modal age of graduation and potential experience. Accordingly, the first stage regressions take the form of:

$$u_{0,i} = \pi_0 + \pi_1 u_{m,i} + \pi_2 u_{m,i} * Pot.Exp_{it} + \delta_1 X_{it} + \epsilon_{it} \tag{2}$$

$$u_{0,i} * Pot.Exp_{it} = \pi_3 + \pi_4 u_{m,i} + \pi_5 u_{m,i} * Pot.Exp_{it} + \delta_2 X_{it} + \xi_{it} \tag{3}$$

where $u_{m,i}$ refers to the unemployment rate at the modal age of graduation. In the NLYSY79 data, the modal age of college graduation is 22 years. While I replicate Kahn's empirical exercise, it should be noted that my results differ slightly from Kahn(2010) in the sense that I focus on the hourly wage rate for the individual's main job in a given quarter while the time period in Kahn's set-up is a year.

Table 1 documents the effect of the initial unemployment rate on log wages. Column (1) of Table 1 shows the results from an OLS wage regression while Column (2) presents the results from the IV regression. All regression coefficients are reported in terms of percentage points. Robust standard errors are reported in parentheses. In addition, standard errors in all regressions are clustered by birth cohort year. Similar to the results in Kahn(2010), I find that a one percentage point increase in the initial national unemployment rate leads to decline in log wages of about 5 to 6.5 percentage points. More importantly, the interaction term of potential experience with the initial national unemployment rate suggests that this wage loss does not disappear quickly and is in fact very persistent. Columns(3) and (4) replicate the analysis in the previous two columns and use the geographical variation over Census regions to look at the impact of the regional unemployment rate at entry on log wage outcomes. In this specification, the initial, modal age and current unemployment rates are all at the regional level. A one percentage point increase in the regional unemployment rate at entry leads to an initial wage loss of about 4 to 5 percent. Again the interaction terms of potential experience with initial unemployment rate at entry imply no appreciable catch-up in wages over time. Table 2 repeats the above exercise but for high school graduates. Here, the modal age of graduation is 18 years. For high school graduates, a 1 percentage point increase in the unemployment rate at entry lowers the initial wage by about 3 percent. The interaction term of potential experience with the national unemployment rate at entry implies that it takes 56 quarters or 14 years for wage gaps to close.

While it perhaps easy to rationalize why entering the job market during a recession might cause one to suffer severe initial wage losses, a more pressing issue concerns the recession's impact on future wage growth. One possible explanation for the existence of persistent wage losses may be that individuals who enter the job market in a recession suffer recurrent joblessness. Entering in a recession may cause individuals to be unemployed for longer at the beginning of their working lives. The lack of initial learning and job stability may in turn precipitate recurrent unemployment spells as these individuals continually quit to search for jobs with the best match quality. In this case, wages for individuals who enter during a recession may on average be lower as these individuals are more likely to experience more bouts of unemployment spells and less human capital accumulation. Indeed, Pries (2004) shows how unemployment rates may remain at an elevated level even after the recessionary shock has died off so long as individuals suffer recurrent joblessness. To examine if this is the main mechanism driving wage losses, I replicate the empirical exercise denoted in equation (1) but replace the dependent variable with the probability of being employed. Since wages can only be reported if one is employed, the sample used for the wage regression is a subset of the sample used for the regression on the probability of being employed.

Table 3 demonstrates the results from these regressions. Column (1) and (2) show the effect of the national unemployment rate at entry on the probability of being employed from an OLS and IV regression respectively while Column (3) and (4) show the analogous OLS and IV results for the regional unemployment rate at entry. Importantly, a 1 percentage point increase in either the national or regional unemployment rate at entry causes no significant reduction in the probability of being employed for collage graduates. In fact, Kahn (2010) finds that a 1 percentage point increase in the national unemployment rate at entry raises the probability of being employed for college graduates by about 1 percent at the 10% significance level. This suggests that the main source of wage losses for college graduates does not stem from a lower probability of being employed. This result is perhaps not unsurprising. Intuitively, employers may be more selective in hiring during a recession and may seek to hire individuals who have a better signal of productivity. College individuals, in general, tend to fare better in terms of employment prospects during a recession.

Table 4 demonstrates the analogous results for high school graduates. Column (1) and (3) show that a 1 percentage point increase in the national or regional unemployment rate lowers the probability of being employed by close to 1 percentage point. This result, however, does not hold under the IV specification. Unlike the result for college graduates, the current unemployment rate is a more important factor for determining the probability of being employed for high school graduates. While the current employment rate exerts no significant impact on the probability of being employed for college graduates, a 1 percentage point increase in the current unemployment rate does lower the probability of being employed by about 1 percentage point for high school graduates. Overall, these results show that high unemployment rates at entry do not exert persistent effects on the employability of individuals, especially for college graduates in my sample. These results suggest that persistent unemployment may not be the main vehicle driving lower wage losses for college graduates.

While these exercises verify and highlight the existence of persistent wage scars from entering in a recession, it remains unclear the channel through which these initial conditions continue to affect wage outcomes. The rest of the analysis here focuses on how job search strategies may be affected by initial conditions and how these may play a role in fomenting persistent wage losses.

3.2 Definition of Job Changes

A key assumption of this paper is that persistent wage losses arise when individuals enter the job market during recessions because of slow learning and because individuals accumulate irrelevant human capital. While both current voluntary employment-to-employment (EE) transitions and unemployment-to-employment (UE) transitions decline with the advent of a recession, this paper posits that **future** employment-to-employment transitions are also affected when individuals enter the job market during a recession. Throughout this paper, I focus on quarterly transitions, although my results continue to hold at the monthly frequency. An EE transition is recorded whenever an individual who was employed at the start of the previous quarter is matched with a new employer at the start of the next quarter. Similarly, a UE (EU) transition is recorded when an individual who was unemployed (employed) at the start of the previous quarter becomes employed (unemployed) at the start of the next quarter. A UE (EU) transition probability is therefore defined as the proportion of unemployed (employed) individuals at the start of period $t-1$ who became employed (unemployed) at the beginning of period t. Table 5 records the average transition probabilities for the respective samples. On average, the rate at which employed college graduates move from one employer to another is about 5.5% per quarter, while high school graduates move from employer to employer at a rate of 6% per quarter. The rate at which the unemployed find jobs (UE rate) is about 53% per quarter for college graduates, while about 32% of unemployed high school graduates manage to find jobs each quarter. About 5% of employed college and high school graduates enter into unemployment each quarter. These rates are comparable to numbers found by Shimer(2012) and Fallick and Fleischmann (2004) (henceforth referred to as FF(2004)) for the whole labor force.[7]

Since this paper is primarily concerned with individuals' voluntary changes between jobs that may use different types of specific human capital in their attempts to find a career that suits their comparative advantage, I focus on EE transitions. Limiting the focus to EE transitions helps to reduce the number of involuntary job changes in the sample. An individual who is displaced from his current job during a recession may be forced to undertake another job which uses completely different tasks and human capital. However, it is clear that under such a scenario the individual has not switched jobs voluntarily in an attempt to find his comparative advantage but was rather forced to take up a new job because of reasons unrelated to learning.

In addition, I focus on between-job transitions rather than within-job transitions. A between-job transition is

[7] Note that the quarterly equivalents for the monthly transitions rates recorded for FF(2004) are calculated as $r_{quarter} = 1 - (1 - r_{month})^3$.

observed whenever there is a change of employer. A within-job transition is observed whenever the individual undergoes a change in occupation code but **no** change in employer. An individual's work activities at a firm may change as he climbs up the internal labor market ladder; these within-job transitions, however, are not regarded as career changes in the model, as they do not necessarily reflect an individual's effort at job experimentation in order to learn his comparative advantage. Rather, these within-job transitions reflect positional changes at the same firm. In focusing on between-job changes, I control for the fact that individuals may take into account the career progression or promotion prospects at a particular job. For example, an individual may choose to work as a sale representative at a firm, knowing that he may later observe a within-job transition to become a sales manager. In this case, such a transition would resemble a career progression rather than a switch in careers. In general, I treat within-job transitions to be career progressions, as it likely that the human capital gained at a lower position in a particular job is still transferable even as the individual moves up the internal labor market ladder at that job. Continuing the earlier example, an individual who was initially a sales representative is likely to be able to transfer his accumulated human capital when he transitions to become sales manager at a firm. Thus, in the following, I focus on how EE transitions between jobs behave over the life cycle and the business cycle.

3.3 Defining Simple and Complex Job Changes

Previous literature such as Neal (1999) and Gervais et al (2010) have suggested that individuals initially tend to search for a career in the early stages of their working life while they tend to search for an employer or for match quality in the latter stages of their working life. While Gervais et al (2010) focus on how occupational learning causes unemployment rates to change over the life cycle, I focus on the type of job search the individual undertakes over his working life and how this changes with the business cycle. To distinguish between the types of job search, I follow the framework as given in Pavan (2011) and Neal (1999). Using the three-digit Census occupation and industry codes, an individual is defined to have undergone a between-career change if changes are recorded in all of the following three dimensions: 1) a change in industry code, 2) a change in occupation code and 3) a change in employer. Recall that a between-job change only requires a change in employer. Hence, it is important to note that not all between-job changes are between-career changes.

An individual is assumed to be within the same career if he only undergoes either one or two of the above three mentioned changes. A within-career job change is recorded whenever the individual 1) changes employers and observes no change in either occupation or industry code, or 2) changes employers and observes either a change in occupation or industry but not both at the same time. Any within-career job change or between-career job change must observe an employer change. This condition avoids mis-coding promotions at jobs as either a within-career or between-career job change. Having controlled for promotions, I assume that between-career changes reflect an individual's search for a career that fits his comparative advantage, while within-career changes reflect the individual's search for a better match quality in terms of employer. Following the convention established in Neal(1999), I will henceforth use the term 'complex change' when referring to a between-career job change and the term 'simple change' when referring to a within-career job change.

A problem that arises in the data is that many of the job changes recorded in the NLSY79 are actually cycles between two values, from occupation 1 to occupation 2 and then back to occupation 1. These cycles are due to possible mis-coding within the dataset. Following Pavan(2011) and Neal(1999), I infer that a complex job change has occurred if 1) the employer in period t is different from the employer in period $t-1$ and the same as in period $t+1$, and 2) the industry and occupation codes in period $t-1$ are different from the occupation and industry codes in period t and $t+1$. In the same vein, a simple job change is coded if 1) the employer in period t is different from the employer in period $t-1$ and the same as in period $t+1$, and there is no observed change in both occupation and industry codes, or 2) the employer in period t is different from the employer in period $t-1$ and the same as in period $t+1$, and either the industry or occupation codes in period $t-1$ (but not both) are different from the occupation and industry codes in period t and $t+1$. These definitions help to reduce any mis-coding of job changes.

A key concern is whether these definitions of complex and simple job changes accurately capture between and within career changes accurately. As a quick check, I use the Dictionary of Occupational Titles to check if a complex (simple) job change corresponds to a more significant (less significant) change in tasks required to work in that job. Appendix A explains in detail how I construct a measure of task distance using information from the Dictionary of Occupational Titles. A higher task distance for an observed job change is associated with less transferability of human capital between jobs. In general, I find that about 85 per cent of simple job changes observed in my sample have a task distance below the mean task distance observed for all job changes. In contrast, 45 per cent of complex job changes in my sample have a task distance above the mean task distance. These findings suggest that complex job changes are more strongly associated with non-transferability of specific human capital, while simple job changes seem to preserve human capital accumulated and are less likely to represent between-career changes.

4 Job Search Strategies over the Life Cycle and Business Cycle

Central to this paper's focus is how job search strategies vary with both the life cycle and business cycle. To observe the variation over the life-cycle, Figure 1 plots the probabilities of complex and simple EE transitions exhibited by each age group of white male college graduates in the labor force, while Figure 2 plots the same variation for high school graduates. Dashed lines represent 90% confidence bands. Notably, individuals engage in more complex job-to-job transitions early on in their working life, reinforcing the notion that individuals initially search for a career. On average, about 3.2% of employed college graduates and 3.9% of employed high school graduates undergo a complex change each quarter. However, the rate of complex job changes declines sharply with age. In contrast, simple job-to-job transitions decline more slowly with age and only exhibit a significant downward decline from age 40 onwards. Hence, I find evidence supportive of the two stage job-search strategies suggested by Neal (1999). The accumulation of career-specific human capital is a leading candidate explanation for the sharp decay in the number of complex job changes over age. Pavan(2011) documents that career-specific tenure contributes to an important part of wage growth; ten years of career-specific human capital raises log wages by 0.2 points. As such, complex job changes should optimally decline as individuals age, as individuals would otherwise lose out on accumulating career-specific human capital essential to later wage growth.

A more interesting question is how these job search strategies may be affected by initial conditions. Given the life cycle behavior of voluntary job changes, I examine how entering the job market during an expansionary or recessionary period might affect the trajectory of these voluntary job changes. As the NLSY79 follows individuals born between the years of 1958 to 1965, the major recessions faced at the time of entry for college graduates in my sample are the 1980s and 1990s recessions. For high school graduates, the major recession captured at the time of entry is the 1980s recession. To overcome the limitations in time-series variation, I focus on both spatial and time variation in unemployment rates, using data on both the national unemployment rate and unemployment rates across Census regions. To define a recession, I follow the methodology of Hoynes et al (2012) and define a recession as the trough-to-peak points of the seasonally adjusted unemployment rate. Figure 3 highlights that the cyclical adjustment of the national unemployment rate tends to lag NBER recession dates, shown in the figure using shaded bars. In general, labor market recoveries tend to lag the recovery in GDP growth. As high search frictions are posited as the main reason why slow learning and an accumulation of irrelevant human capital may occur for workers entering the job market during a recession, my preferred indicator of business cycle turning points is the unemployment rate, as this best proxies for the level of search frictions in the economy. Hence, for the following analyses, the words ‘expansion’ and ‘recession’ will be used to refer loosely to periods marking peak-to-trough and trough-to-peak unemployment respectively.

I conduct two exercises to examine how job search strategies may be affected by initial business cycle conditions. Firstly, I examine the duration before an individual undertakes his first complex (simple) job change. Intuitively, I expect that if search frictions are high, both unemployed and employed workers would face reduced job mobility. Hence, recessions should slow the learning process for individuals and delay their switching into alternative careers or jobs. Secondly, I examine how future mobility in terms of both complex and simple job changes are affected by initial job conditions. This second exercise aims to verify if there is any evidence of a ‘lock-in’ effect. An individual who was initially unable to switch jobs may observe reduced future job mobility especially in terms of complex job changes, as it is costly to switch careers and discard accumulated career-specific human capital.

4.1 Results on Initial Job Mobility

In the following figures, individuals in the sample were divided into two groups, 1) individuals who entered the job market in a recession vs. 2) those who entered in an expansion. Recall that a recession is defined as the trough-to-peak periods of the unemployment rate. Unless otherwise mentioned, all analyses are conducted at a quarterly frequency. Figure 4 plots the Kaplan - Meier estimate of the survivor function and outlines the probability that a college graduate remains in the same career since his initial entry into the labor market. Dotted lines refer to 90% confidence intervals. Figure 4 is indicative of the duration before a college graduate undertakes his first complex job change. Notably, individuals who entered the labor market during a recession experience a lower hazard rate and are less likely to conduct a complex job change. This delay in early career changes holds even when the analysis is restricted to individuals who managed to find a job and were employed within the first quarter of entry into the job market, i.e. when the survival probability conditional on being employed is plotted as in Figure 5. These results continue to apply at a higher frequency of job-to-job transitions. Figure 6 uses monthly data and again shows that individuals entering during a recession have a lower probability of conducting a complex job change. Figure 7 plots the analog to Figure 4 but for high school graduates. The solid line highlights the survivor function for individuals who joined the job market during an expansion, while the dashed line highlights the survivor function for individuals who joined the job market during a recession. A comparison of Figure 4 and Figure 7 suggests that high school graduates entering during a recession face an even sharper reduction in their ability to switch careers than college graduates. This is consistent with the notion that the 1980s recession was largely a "blue collar recession".

In contrast, Figure 8 plots the analogous survivor function for simple job changes and shows the probability that a college graduate has not experienced any simple job change since his initial entry into the labor market. Unlike complex job changes, recessions do not seem to significantly affect the timing of college graduates' first simple job change. Intuitively, this may be because individuals tend to concentrate on complex job changes early in their working career. Hence, initial conditions are likely to affect only the first complex job change rather than the first simple job change that the individual is able to undertake. Figure 9 shows the corresponding result for high school graduates. Unlike the result for college graduates, high school graduates who enter during a recession are more likely to observe a delay in their first simple job change, although this difference is small in magnitude. This in part may be due to the fact that high school graduates are more likely to be unemployed during a recession. Recall from Table (4) that the current unemployment rate exerts a negative effect on high school graduates' probability of being employed. High school graduates who enter during a recession when unemployment rates are high, are less likely to be employed and hence may suffer a set-back in terms of overall human capital accumulation. This lack of human capital accumulation, in turn, affects a high school graduate's future job-finding probabilities within a career as experience gained adds to an individual's effective labor input. Consequently, even the first simple job change for a high school graduate may be delayed if he enters the labor market during a recession. Notably, Adda et al (2013) argue that the loss in earnings for less-skilled workers who enter during a recession stems largely from low human capital accumulation on the job while the loss in earnings for high-skilled workers stems from a loss of job mobility or search capital.

To test that these differences are not sensitive to my definition of a "recession", I run a proportional hazards duration model against the national unemployment rate faced at the time of entry, controlling for other individual characteristics such as potential experience, potential experience squared, the AFQT score, the current national unemployment rate and regional dummies. The duration model assumes the standardized Weibull distribution. Table 6 presents the results from these regressions. Column 1 presents the results of the proportional hazards model on the probability of having no complex or between career change for college graduates while Column 3 presents the analogous results for high school graduates. Coefficient estimated are from a regression on the log of the hazard function. Negative coefficients imply lower hazard rates and correspondingly longer durations. Taking the exponent of the regression coefficients, a one percentage point increase in the unemployment rate at entry increases the baseline hazard rate for college graduates by a factor of 0.93, i.e. a one percentage point increase in the unemployment rate at entry lowers the hazard rate by 7%. Similarly, a 1 percentage point increase in the initial unemployment rate faced at entry lowers the hazard ratio by about 9 percent for high school graduates. These effects are both significant at the 10% significance level. Column 2 and 4 of Table 6 demonstrates that the initial unemployment rate has no significant impact on the duration before the first simple job change for either college or high school graduates.

One problem with the above reported survival functions is that actual entry into the labor market is endogenous. There may be unobserved systematic differences between individuals who choose to enter during a recession and those who choose to enter during an expansion. To control for potential selection effects, I conduct the following exercise. First, I construct a mobility indicator which takes the value of 1 if the individual undergoes a complex (simple) job change in a particular period and zero otherwise.[8] I repeat the empirical exercise in equation (1) but replace the dependent variable with the mobility indicator. In particular, the main regression takes the form of equation (4):

$$Mob^c_{it} = \gamma_0 + \gamma_1 u_{0,i} + \gamma_2 u_{0,i} * Pot.Exp_{it} + \zeta X_{it} + \nu_{ist} \tag{4}$$

where Mob^c_{it} is the mobility indicator for individual i in period t and the superscript c refers to either a Complex or Simple job change, i.e. $c \in \{Complex, Simple\}$. Independent variables are the same as in equation (1). Again, robust standard errors are reported and all standard errors are clustered by birth year cohort. Table 7 documents

[8]Note that because complex job changes can only be calculated for those who are employed, the sample used here is the same as the sample used for the wage regressions.

the regression results for the probability of conducting a complex job change for college graduates while Table 8 presents the results for the probability of conducting a simple job change for college graduates. For both tables, Columns 1 and 2 show OLS and IV results using the initial national unemployment rate while Columns 3 and 4 present analagous results using the initial regional unemployment rate. Notably, Tables 7 and 8 show that increases in potential experience significantly exert downward pressure on the probability of a complex job change but exert almost no significant effect on simple job changes. This is line with the earlier hypothesis that complex changes involve a loss of career-specific human capital whereas human capital is typically transferable between simple job changes.

From the IV regressions, a one percentage point increase in the initial national unemployment rate lowers the probability of complex changes by 1.35 percentage points for a new college graduate. Given that on average, 3.2% of employed individuals conduct a complex job-to-job transition every quarter, this suggests that a one percentage point increase in the unemployment rate reduces the initial complex employment-to-employment transition probability by about a third. Moreover, this effect seems to persist for some years after the college graduate has entered the job market. The interaction term, $u_{it} * Pot.Exp_{it}$, suggests that it takes about 50 quarters or 12 years before the gap in complex job-to-job transition probabilities disappears. Importantly, the first 12 years of an individual's working life form precisely the period where individuals concentrate on finding the right career. In contrast, results from Columns 1 and 2 of Table 8 indicate that initial labor market conditions do not seem to exert any impact on the probability of undertaking simple job changes.

Similar findings are obtained using regional unemployment rates. Here, a one percentage point increase in the regional unemployment rate at the time of entry lowers the average probability of a complex job-to-job transition by about 0.54 percentage points, implying that the probability of conducting a complex change is reduced by about 15 percent when an individual enters the job market during a recession. Interestingly, these results suggest that the national unemployment rate at entry exerts a stronger adverse effect on the probability of a complex job change than local unemployment rate. Recent work by Wozniak (2010) and Cadena and Kovak (2013) suggests that higher-skilled individuals and college graduates are more affected by changing national labor market conditions than lower skilled workers and high school graduates, and are more likely to move to markets with better job opportunities. The more muted impact of the initial regional unemployment rate may arise as a result of college graduates selecting or migrating into local labor markets with better opportunities. In contrast, a more depressed national labor market at entry suggests weak job-finding opportunities overall and hence fewer avenues for college graduates to conduct complex job changes.

Tables 9 and 10 present results for high school graduates. Results for complex job changes are qualitatively similar but are smaller in magnitude. About 3.9% of employed high school graduates conduct a complex job-to-job transition every quarter. The IV results in column 2 of Table 9 suggest that a 1 percentage point increase in the initial national unemployment rate reduces the probability of a complex job-to-job transition by about 0.1 percentage points while a 1 percentage point increase in the initial regional unemployment rate reduces the probability of a complex job-to-job transition by about 0.2 percentage points. Notably, for high school graduates, the national unemployment rate at entry does not exert a more adverse effect on the probability of a complex job-to-job transition rate relative to the initial regional unemployment rate. This is perhaps not surprising since previous literature has found that lower skilled workers and high school graduates are more affected by local labor market conditions and are less likely to migrate for better job opportunities. Simple job-to-job transitions are also adversely affected by an increase in the initial unemployment rate for high school graduates, albeit to a smaller extent. A 1 percentage point increase in the national (regional) unemployment rate at entry lowers the probability of a simple job change by about 0.07 (0.1) percentage points. As aforementioned, high school graduates were more likely than college graduates to be unemployed during periods of high unemployment. The lack of early human capital accumulation could dampen future employability and consequently the potential for future simple job-to-job transitions.

Overall, college graduates who enter in a weak labor market are not only less likely to conduct a between-career change in the early years of their working life but they also exhibit a lower propensity to conduct a complex job change over their entire working life. On average, it takes about 50 quarters or at least 12 years before the negative effect of a 1 percentage point increase in the unemployment rate at entry on the probability of conducting a complex job change completely wears off. High school graduates, on the other hand, are less likely to conduct both complex and simple job changes over their working life. This difference stems from the possible variation in the amounts of human capital accumulated on the job between high school and college graduates.

In general, these results suggest that the initial unemployment rate exerts a significant and persistent impact on career mobility, especially for college graduates. Entering the job market during a recession decreases job mobility in terms of complex changes not only initially but throughout the subsequent years of one's working life. In contrast, the results suggest no significant impact of initial unemployment rates on simple job changes for college graduates. Overall, the striking result of a lower propensity to switch careers for college graduates who enter the job market during a recession suggests that the early years of one's working life are critical towards finding the right career. Given how early job switching is associated with significant increases in wages, this suggests that early lost opportunities to find the right career can extend into future wage outcomes. To rationalize these findings, I now construct a model which outlines how initial business cycle conditions can affect complex (between-career) job changes and show how these effects on job search strategies may factor into wage outcomes.

5 Model

To examine how initial conditions, learning and specific human capital can interact to affect long-term wage outcomes, this paper builds upon the directed search framework of Menzio and Shi(2010), and the extension of that model with human capital accumulation outlined in Menzio, Telyukova, and Visschers (2012). Specifically I incorporate two new features into the model. First, I embed a learning problem in the standard Menzio and Shi(2010) directed search framework. Individuals are ex-ante heterogeneous and have differing aptitudes at different careers. As individuals have imperfect knowledge about their comparative advantage and do not know which career maximizes their type, they must work at different careers to learn about their set of aptitudes. Individuals, upon observing output, update priors about their comparative advantage and direct their search according to their perceived type and known characteristics rather than just based on their previous wage offer.

Secondly, I consider multi-dimensional skill set or aptitudes and introduce specific human capital into the set-up of Menzio, Telyukova and Visschers(2012). The latter paper assumes that workers only possess general human capital. In my model, workers gain experience through on-the-job learning-by-doing. However, experience accumulated is specific to the career workers are employed in. Finally, my model also deviates from the standard Menzio and Shi(2010) directed search framework where firms post lifetime expected utility contracts, by assuming that firms post spot wage contracts. As agents in my model learn about their aptitudes through working at a job, downward revisions in perceived capabilities are possible. Spot wage contracts prevent a firm from being locked-into an unsavory contract with a worker who is later discovered to be a "lemon" at that particular career. Alternatively, one could introduce a state-contingent contract where wages evolve with the perceived and known characteristics of the worker. Since such long-term state-contingent contracts would need to take into account the possible evolution of the worker's type, this paper assume spot wage contracts for computational simplicity.

Given these features, I build a partial equilibrium model to consider how learning and accumulation of human capital, and consequently wage growth, are affected by the initial state of the business cycle. The notation throughout this paper observes the following convention: all current period (time t) objects are listed as x, while all next period objects are denoted with a prime, x'. All forecast terms are denoted with a hat, $\hat{x}$, and all terms that are signals are denoted with a tilde, $\tilde{x}$. The subscript τ is used to indicate the worker's age. The rest of this paper details the set-up of the simplest version of the model.

5.1 Environment

5.1.1 Individuals

Time is discrete and continues forever. In a single cohort, there is a unit measure of individuals who live for T periods. In every period, there is a new generation of individuals born into the economy such that there are always T overlapping generations in the economy. There is no savings in the economy and individuals consume all of their wage income. There are K varieties of goods in the market that individuals can consume. For simplicity, I assume that preferences take the form of a Cobb-Douglas utility function,i.e.

$$u(C) = \Pi_{k=1}^{K} c_k^{\frac{1}{K}}$$

where C is taken to be an aggregate consumption good and c_k is the amount of consumption good from each sector. Thus, each individual seeks to maximize the following:

$$\max \sum_{\tau=0}^{T} \beta^{\tau} u(C_{\tau}) \tag{5}$$

where τ refers to the age of the individual.

As individuals consume all of their income, individuals seek to maximize the expected present discounted value of their wage outcomes in order to maximize their expected lifetime utility. Thus, we can represent the individual's preferences each period in terms of an indirect utility function that is linear in wages. Throughout this paper, I will be working with the indirect utility function.

5.1.2 Human Capital

Individuals are ex-ante heterogeneous and are each endowed with different aptitudes at picking up K variety of tasks, where $K \geq 2$. Denote μ_i as the time-invariant vector that characterizes individual i's aptitude at learning different tasks. Specifically, μ_i is a $K \times 1$ vector with $\mu_i = [\mu_{i1}, \mu_{i2}, \ldots, \mu_{iK}]'$. μ_i is log-normally distributed with mean $\bar{\mu}_{K\times 1}$ and variance $\Sigma_\mu = I_{K\times K} \times \sigma_\mu^2$.

I assume that each job in a sector k uses task k to produce variety k. Thus, each career is a single-task job. Individuals entering the job market for the first time have imperfect information about their aptitudes at different tasks. A worker learns about his aptitude at a particular task by working at a job that uses that task for production. The current job, however, does not reveal the worker's aptitude at other jobs that utilize different tasks. As such, searching and working only at jobs within a sector does not reveal a worker's aptitude at jobs in other sectors.[9]

[9] This assumption can be relaxed in future versions of the model. One can assume that jobs are multi-dimensional and use more than one task for production. Workers then learn about their aptitudes at many tasks from one job. The rate of learning would be pegged

Individuals can also learn on the job and accumulate task-specific experience. Human capital at a task k, h_{ik}, is a product of both the individual's innate aptitude and his level of experience at such an activity:

$$h_{ik} = \mu_{ik} y_{ik} \tag{6}$$

where μ_{ik} refers to the innate and unknown aptitude that an individual i has at task k, while y_{ik} refers to the amount of experience individual i has accumulated at task k. Labor market experience at a task evolves in the following manner:

$$y'_{ik} = \begin{cases} y_{ik} + \zeta & \text{if worked at task } k \text{ today} \\ y_{ik} & \text{else} \end{cases}$$

where ζ denotes the additional experience gained by working at a particular task. If a task is not used in production, then there is no experience gained in working at that particular task.

An individual can perfectly observe the total amount of experience he has accumulated working at a particular task, y_{ik}. It is imperfect information on an individual's innate aptitude, μ_{ik}, that causes an individual to have imperfect information on his human capital.

5.1.3 Production Technology

The economy has K 'sectors'; each 'sector' is defined by the task it uses for production, implying an equal number of tasks as sectors. Equivalently, a sector in this model is the same as a career since each task is tied to one career. There always exists an infinite number of idle firms in each sector. However, not all existing firms operate in the economy at the same time. In every period, an "unrestricted" mass of firms optimally chooses to enter or exit the market. Given free entry, the zero profit condition determines the number of firms in operation in each sector at any period in time. Each job consists of a single firm-worker pair. When a firm separates from a worker, it leaves the labor market and shuts down. Firms that shut down are replaced automatically by new idle firms in the market.

All firms that operate in a sector k possess the same production technology but are subject to idiosyncratic productivity shocks in addition to an aggregate productivity shock. A firm j that chooses to operate and that is matched with a worker i in sector k has the following production technology:

$$q_{ijk} = z a_j h_{ik}^{\alpha} \tag{7}$$

to the intensity with which that task is used for production. This would induce a trade-off between learning about more aptitudes against lower experience gained at each task. Alternatively, one can model a job as having varying informational content. Antonovics and Golan(2012) construct a model of life-cycle job mobility and show that agents would initially engage in job experimentation and take initial wage cuts to work in jobs that provide more informational content.

where q_{ijk} refers to the output of a firm-worker pair $\{j, i\}$ at task k.[10] h_{ik} refers to individual i's human capital at task k. Each firm j that is currently in operation in the market is faced with an i.i.d idiosyncratic productivity shock, a_j, which is drawn from a lognormal distribution with mean $\bar{a}$ and variance σ_a. I assume that firms do not know their true idiosyncratic productivity, a_j, although they do know the distribution it is drawn from.

Finally, production is subject to an aggregate shock z that uniformly affects output at all tasks. z lies in the set $Z = \{z_1, z_2, \ldots, z_N\}$, where N is a positive integer, and z follows a Markov process. At the beginning of each period, nature draws the aggregate productivity, z, from the probability distribution $\Phi(z|z_{-1})$. All firms and workers are able to observe z at the start of each period.

Firms and individuals observe $\{q_{ijk}, z, y_{ik}, \tau\}$ while they have imperfect information on $\{\mu_{ik}, a_j\}$. Individuals also know ζ and hence can observe the amount of relevant experience they will have for the next period, y'_{ik}. Upon observing output, individuals update and form new priors of their type, $\hat{\mu}'_i$. Individuals also update the variance of their posterior distribution of beliefs. As such, individuals also know $\Sigma_{\mu_i,\tau}$, the variance co-variance matrix of their posterior beliefs. $\Sigma_{\mu_i,\tau}$ evolves deterministically as an individual accumulates experience and is strictly non-increasing. As a_j is an i.i.d. shock, output today provides no information about idiosyncratic shocks tomorrow.

Both firms and individuals have to forecast μ_i in order to form their recruitment and job search decisions. As output is a noisy signal, individuals face a signal extraction problem when trying to learn about their type. Information, while imperfect, is symmetric between firm and worker. Hence, what the individual learns about himself is also shared with the firm.

5.1.4 Labor Market

Idle firms in a sector k become recruiting firms when they choose to post a vacancy. As each job consists of a single firm-worker pair, currently matched firms do not post new vacancies. Recruiting firms post spot market wage contracts when creating a vacancy. At the same time, matched firms in each period make new take-it-or-leave-it wage-share offers based on realized or updated guesses of their worker's type. While recruiting firms incur a vacancy posting cost whenever they create a vacancy and post a wage offer, matched firms do not incur any vacancy posting cost as they are merely offering new wage share offers to workers they are currently matched with. In addition, search is costless for workers.

Each K sector is defined by a continuum of submarkets indexed by the tuplet (x_k, μ_k, y_k, τ) where τ refers to the age of the worker, x_k is the share of output a firm promises its worker, and μ_k and y_k are the cuurent levels of perceived

[10]Note that since each sector is defined by the task firms use for production, k corresponds to both the sector and the task.

innate aptitude and experience that a firm requires of a worker respectively.[11] Notice that beyond specifying the wage share offer, firms are also able to condition on the current perceived values of aptitude and on current levels of experience when posting a job. Importantly, the amount of career-specific experience affects both the worker's level of human capital and the precision of beliefs about the worker's aptitude at that career. When an individual works at a task, he not only gains career-specific experience but learns about his aptitude at that career. More experienced workers have more certainty over their aptitude at that career. Posting experience requirements implies that firms are also inherently choosing the level of precision they desire in beliefs about a worker's aptitude.

Submarkets differ in the terms of trade offered by firms; a submarket (x_k, μ_k, y_k, τ) consists of firms offering wage share x_k to a worker of age τ with experience y_k and perceived innate aptitude μ_k. This implies that θ, the labor market tightness condition in each submarket within a sector, is a function of (x_k,μ_k,y_k,τ). The labor tightness condition θ - defined as the ratio of vacancies to the number of applicants - is also affected by the aggregate state of the economy given by $\{z, \varphi\}$, where φ refers to the aggregate distribution of workers in the economy. As shown by Menzio and Shi (2010), under a block-recursive equilibrium, the labor tightness condition will depend on the aggregate economy only through the value of aggregate productivity z, as will be elaborated further below.

Job-finding and job-filling probabilities depend on the labor tightness condition. The probability of finding a job $p(\theta)$ is twice-differentiable, strictly increasing and concave in θ with boundary conditions $p(0) = 0$ and $p(\infty) = 1$. A firm fills a job with probability $f(\theta) = \frac{p(\theta)}{\theta}$, where $f(\theta)$ is strictly decreasing in θ, $f(0) = 1$ and $f(\infty) = 0$. When a firm and a worker meet in sub-market (x_k, μ_k, y_k, τ), a worker without the pre-requisite requirements, i.e. a worker whose perceived aptitude, experience and age are not equal to (μ_k, y_k, τ), is automatically rejected. A worker who meets the criteria of a job and chooses to accept the offer begins production within the same period.

At the beginning of every period, the aggregate distribution of workers can be summarized by the tuple $\varphi = (n, u, e)$. The first element of φ is a function $n : \mathbb{N} \to \mathbb{R}_+$ where n represents the measure of individuals that are entering the labor market for the first time. The second element of φ is a function $u : \mathbb{N}^3 \to \mathbb{R}_+$ where $u_\tau(\mu_k, y_k)$ is the measure of unemployed people of age τ who perceive that they have aptitude $\hat{\mu}_k = \mu_k$ and experience y_k in a particular sector k. Thus, $u_\tau(\mu_k, y_k)$ refers only to the unemployed searching in a particular sector k in a sub-market which requires $\{\mu_k, y_k, \tau\}$ characteristics of a worker. The last element of φ is a function $e : \mathbb{N}^3 \to \mathbb{R}_+$, where $e_\tau(\mu_k, y_k)$ refers to the measure of employed people of age τ who perceive that they have aptitude μ_k and experience y_k.

[11] While it may seem odd that firms can condition so precisely on a worker's type, this version of the model allows for this assumption for tractability reasons, as submarkets are continuous and information is symmetric. This assumption can be relaxed by assuming that information is still symmetric but there exists regulation that allows firms to only specify requirements in "blocks". In this case, firms specify minimum requirements or alternatively, trait sets. In addition, it is not uncommon in the search literature for firms to condition on experience, age and ability. Relevant examples include Burdett, Carrillo-Tudela and Coles (2011) who allow contracts to depend on applicants' skill and experience (but not their employment state), and Menzio, Telyukova, and Visschers (2012) who allow firms to write contracts that depend on age and experience.

Hence for each submarket, we can calculate and distinguish the number of unemployed and employed who apply to that market.

Since a sector is defined by a task or skill that it uses for production, implicitly one can think of job-to-job transitions across sectors as complex job changes, while a job-to-job transition within the same sector but to a different submarket can be represented as a simple job change. Notably, experience, y_k, is not transferable across sectors but is transferable within a sector across different submarkets.

5.2 Timing

Each period is divided into five sub-stages: 1) entry, 2) separation, 3) search and matching, 4) production and finally 5) learning.

At the end of the last period, firms and workers observe the posterior belief on the worker's vector of aptitudes. Hence, both firms and workers start each new period with the updated guess of the worker's comparative advantage. At the beginning of a period, both firms and workers also observe the new draw of aggregate productivity z. Upon observing z and the updated guess on the worker's type, currently matched firms make a new 'take-it-or-leave-it' wage share offer, ω. Denote $s = \{\hat{\mu}_i, y_i, z\}$. Hence, currently employed workers begin the period with $\{s, \omega\}$.

In the first sub-stage (Entry), an unmatched firm must decide whether to post a vacancy given its observation of aggregate productivity today, z. If a firm decides to post a vacancy, it incurs a vacancy posting cost of κ. In addition, a firm j in sector k that chooses to recruit a worker has to decide which submarket, (x_k, μ_k, y_k, τ), to post a vacancy in. While all firms like workers to possess high innate aptitude and experience, posting a high requirement of μ_k or y_k reduces the probability of finding a worker. Similarly, firms would prefer to post a low wage share offer to workers as this increases their profits. A low wage share offer to a worker, however, lowers the firm's hiring probability. In the same vein, firms prefer workers who have high precision on their type, as this reduces the uncertainty with regards to firm's profits. Although firms are risk-neutral, the precision of a worker's beliefs matters for a firm's expected lifetime profits. A worker who has a more precise belief that he has high aptitude in the current sector he is searching in, brings higher discounted profits to the firm as he has a lower likelihood of leaving the firm for a job in another sector. Intuitively, workers base their career search decisions on the expected life-time wage earnings they can derive from working in a particular sector. Young workers with poor precision in their beliefs are more liable to switch careers as they learn about their type. Low retention probabilities of such workers imply lower streams of profit to a firm. Nevertheless, while firms like workers with more precise beliefs, higher requirements on a worker's experience (which is a proxy for precision) also reduces the firm's hiring probability.

Thus, the firm's hiring probability, $f(\theta_\tau(x_k, \mu_k, y_k, z, \varphi))$, is increasing in x_k, the wage share offer to workers, and decreasing in μ_k and y_k. As all recruiting firms are ex-ante homogeneous, the trade-off in hiring probabilities and expected profit makes them indifferent in posting to any market.[12].

In the second sub-stage (Separation), a firm that is already matched with a worker is exogenously destroyed with probability δ. Given their beliefs as summarized by s and their new wage share offer ω, employed workers voluntarily part with firms if the value of being unemployed is higher than the value of staying with the firm. Hence, a firm separates from its worker with probability $d(\omega) \in \{\delta, 1\}$.

In the third sub-stage (Search and Matching), a worker (either unemployed or employed) chooses which submarket, (x_k, μ_k, y_k, τ), to search for a job based on his beliefs of his type and of aggregate TFP. Individuals who are unemployed at the beginning of the period (before the first sub-stage) have the opportunity to search the labor market for jobs in each period with probability $\lambda^u = 1$. Individuals who were employed at the beginning of the period and who were not separated from their jobs in the second sub-stage have the opportunity to search the market for alternative jobs with probability $\lambda^e \leq 1$. Individuals who were employed at the beginning of the period but were separated in the second sub-stage cannot search immediately but must wait until the next period to look for a job. This follows the convention of Menzio and Shi(2010).

When a vacancy and a worker meet in submarket $\{x_k, \mu_k, y_k, \tau\}$, the firm always rejects any worker whose age, experience and perceived innate aptitude differ from the specified levels $\{\mu_k, y_k, \tau\}$. Thus, the firm's posting of $\{\mu_k, y_k, \tau\}$ constrains the types of workers that can qualify for the job. As such, an individual that does not meet the posted requirements will never search for a job in that sub-market as his probability of getting the job will be zero. Effectively, this implies that within a sector, an individual only has choice over his desired wage share x_k. Given his vectors of perceived aptitudes and experience, the worker conducts a two-stage job search strategy. The worker first optimizes which sub-market to visit in each sector, and then chooses which sector to search for a job. A worker finds a job in sector k in submarket $\{x_k, \mu_k, y_k, \tau\}$ with probability $p(\theta_\tau(x_k, \mu_k, y_k, z, \varphi))$. In equilibrium, workers always accept a job when they meet a firm since they have already optimized which market to search for a job.

In the fourth sub-stage (Production), matched firm-worker pairs produce output according to equation (7).

Finally, in the last sub-stage (Learning), matched firm-worker pairs observe their output at each task. Matched firms and workers update their guess on the matched worker's aptitude at a job by using the information from their

[12]This claim is no longer true if idiosyncratic productivity is persistent. In that case, there would be sorting by both firms and workers. However, functional forms and parameters would determine whether positive sorting results.

own private output and the public signal. I assume that individuals solve a Kalman Filtering problem to update their guess on their type.

At the end of the period, matched workers consume the promised share, ω, of output and matched firms receive $(1-\omega)$ share of output as profits. Unemployed individuals receive benefit b, which for simplicity can be assumed to be financed by a lump sum tax that is levied on all individuals.

5.3 Value Functions

As aforementioned, I use $s = (\hat{\mu}_i, y_i, z)$ to denote an individual's perception about his aptitude, experience and aggregate productivity today. Since production occurs after separation and search, individuals at the beginning of a period do not know for certain the amount of income they will receive in the current period. Instead, individuals form expectations over the likely income they will receive in both current and future periods.

5.3.1 Unemployed Worker

At the start of a period, an unemployed individual, given s, must solve the following discrete choice problem:

$$U_\tau(s) = \max\{R_1^{u*}(s), R_2^{u*}(s), \ldots, R_K^{u*}(s)\} \tag{8}$$

s.t.

$$\begin{aligned} R_k^u(s) &= \max_{x_k} p\big(\theta_\tau(x_k, \mu_k, y_k, z, \varphi)\big)\Big[Ex_k q_{ijk} + \beta EV_{\tau+1}(x_k', s')\Big] \\ &+ \big(1 - p(\theta_\tau(x_k, \mu_k, y_k, z, \varphi))\big)\Big[b + \beta EU_{\tau+1}(s')\Big] \end{aligned} \tag{9}$$

where $R_k^{u*}(s)$ represents the optimized search problem for each sector k and b is the unemployment compensation the worker receives if he is unemployed at the end of the period.

As aforementioned, unemployed individuals must solve a two-stage optimization problem. In the first stage, an unemployed individual chooses which sub-market within a sector to search for a job. Because a firm's vacancy posting in a sub-market specifies the requirements a worker must have in order to apply for that job, i.e. (μ_k, y_k, τ), a worker effectively only chooses x_k in deciding which sub-market to search. From equation (9), an unemployed individual maximizes his search problem in a sector k by choosing the optimal wage share x_k from the menu of contracts posted. The first line in equation (9) describes the expected return from finding a job in a particular sub-market; $p(\theta_\tau(x_k, \mu_k, y_k, z, \varphi))$ is the probability that a worker finds a job in sub-market (x_k, μ_k, y_k, τ) while the second term refers to the expected current and continuation utility an individual would receive if he finds a job in that sub-market. The second line in equation (9) denotes the individual's expected current and continuation utility if he fails to find a job in that particular sub-market. The policy function associated with equation (9) is $x_k^u = \underset{x_k}{\operatorname{argmax}}\, R_k^u(s)$ which is implicitly given by equation (10):

$$p_x(\theta_\tau)\Big[Ex_kq_{ijk} + \beta EV_{\tau+1}(x_k', s') - b - \beta EU_{\tau+1}(s')\Big] + p(\theta_\tau)Eq_{ijk} = 0 \tag{10}$$

where $p_x(\theta_\tau)$ refers to the first derivative of $p(\theta_\tau(x_k, \mu_k, y_k, z, \varphi))$ with respect to x_k and $p(\theta_\tau)$ refers to $p(\theta_\tau(x_k, \mu_k, y_k, z, \varphi))$. Recall that p_x is negative, as higher postings of x_k erode a firm's take-home profit for that period and as such decrease the job-finding rate of the worker. The first term in equation (10) therefore refers to the expected marginal cost of seeking a job that offers a higher wage share. The second term in equation (10) refers to the expected marginal benefit of seeking a job that offers a higher wage share. As firms get to 'reset' their wage share offers every period, the optimal choice of x_k affects only current period wage outcomes. From equation (10), the optimal targeted wage share, x_k^u, is a function of both the individual's outside option as well as his own characteristics, including the amount of human capital he has in that sector.

Having solved this first-stage optimization problem, the unemployed individual then chooses which sector $R_k^{*u}(s)$ would provide him the greatest benefit from search. This is given by equation (8). Because search is costless, unemployed workers search for a job in every period.

5.3.2 Employed Workers

Employed workers enter the period with updated beliefs on their aptitude μ_i, observe z and receive new wage share offers ω from their current employers. Hence, each employed worker starts the period prior to vacancy posting with (ω, s). Employed workers solve the following discrete choice problem:

$$V_\tau(\omega, s) = \max\{R_1^{e*}(\omega, s), R_2^{e*}(\omega, s), \ldots, R_K^{e*}(\omega, s)\} \tag{11}$$

where

$$\begin{aligned} R_k^e(\omega, s) &= \max_{x_k} d(\omega)\Big[b + \beta EU_{\tau+1}(s')\Big] \\ &+ (1 - d(\omega))\Big\{\big(1 - \lambda^e p(\theta_\tau(x_k, \mu_k, y_k, z, \varphi))\big)\Big[E\omega q_{ijl} + \beta EV_{\tau+1}(\omega', s')\Big] \\ &+ \lambda^e p(\theta_\tau(x_k, \mu_k, y_k, z, \varphi))\Big[Ex_kq_{ijk} + \beta EV_{\tau+1}(x_k', s')\Big]\Big\} \end{aligned} \tag{12}$$

and

$$l \in \{1, \ldots, K\}, k \in \{1, \ldots, K\}$$

$R_k^{e*}(\omega, s)$ for $k \geq 1$ represents the optimized search problem for each sector. Equation (12) highlights the search problem of an employed worker within a sector. Note that x_k is used to distinguish the potential wage offer from recruiting firms while ω represents the wage offer from the current firm. Similarly, ω' is the wage offer from the matched firm for next period, while x_k' is the wage offer from the recruiting firm next period. Ex_kq_{ijk} in equation (12) refers to the expected current wage the worker receives if he finds a job in the sector k while $E\omega q_{ijl}$ refers to the expected wage the worker receives if he remains in his current job in sector l. Note that l can be equivalent to k if the worker chooses to search within the same sector for his next job.

Similar to their unemployed counterparts, employed individuals solve a two-stage optimization problem. Employed individuals first choose which sub-market to search within a sector before deciding which sector provides them the maximal benefit from search. The employed worker's problem differs from the unemployed individual's problem in two key areas: 1) The employed individual faces some probability of being separated from his current job, $d(\omega)$, and 2) an employed worker only has the opportunity to search for new jobs with probability $\lambda^e \leq 1$.

The first line in equation (12) refers to the scenario where an employed worker is separated from his job and becomes unemployed. With probability $d(\omega)$, the worker separates from the firm and enters into unemployment. In this case, the employed individual receives current utility b and continuation utility $U_{\tau+1}$. The worker may separate from the firm for either exogenous or endogenous reasons depending on the wage share ω offered by their current firm. I will elaborate on the properties of $d(\omega)$ when I discuss the firm's problem. Briefly, however, it is clear that the level of wage share offer ω affects the benefit of staying with a current firm. Endogenous separations arise when the worker perceives that he is better off being unemployed given the current wage share offer, and chooses to voluntarily leave the firm.

With probability $(1 - d(\omega))$, the worker does not separate from the firm. In this case, the second line of equation (12) denotes the case where the worker searches in a particular sub-market (x_k, μ_k, y_k, τ) but is unable to find an alternative job that pays wage share x_k. With probability $(1 - d(\omega))(1 - \lambda^e p(\theta_\tau))$, the worker is unable to find an alternative job and he instead enjoys current expected utility $E\omega q_{ijl}$ and continuation utility $V_{\tau+1}(\omega', s')$. With probability $(1 - d(\omega))\lambda^e p(\theta_\tau)$, the worker is successful in finding an alternate job that pays current wage share x_k and with continuation utility $V_{\tau+1}(x_k', s')$. Similar to the unemployed worker's problem, the policy function associated with equation (12) is given by $x_k^e = \underset{x_k}{\operatorname{argmax}}\, R_k^e(\omega, s)$ which is implicitly given by equation (13).

$$(1 - d(\omega))\Big\{\lambda^e p_x(\theta_\tau)\Big[Ex_kq_{ijk} + \beta EV_{\tau+1}(x_k', s') - E\omega q_{ijl} - \beta EV_{\tau+1}(\omega', s')\Big] + \lambda^e p(\theta_\tau) Eq_{ijk}\Big\} = 0 \tag{13}$$

5.3.3 Operating Firms

Prior to the first sub-stage of vacancy posting, matched firms make new wage share offers ω to their current workers, given z and their updated guess of their worker's aptitude. A firm j in sector l solves the following problem:

$$J_\tau(s, x^*) = \max_{\omega} \Big((1 - d(\omega))(1 - \lambda^e p^*(\theta_\tau)) \big[(1-\omega) E q_{ijl} + \beta E J_{\tau+1}(s', x'^*) \big] \Big) \tag{14}$$

s.t.

$$d(\omega) = \begin{cases} 1 & \text{if } b + U_{\tau+1}(s') > V_\tau(\omega, s), \\ \delta & \text{else.} \end{cases} \tag{15}$$

where $p^*(\theta_\tau)$ refers to the optimal value derived from the worker's search problem. Implicitly, the firm internalizes the worker's search problem and takes into account that his offer of ω affects the optimal submarket and sector the worker would choose to search, as well as his decision to quit to unemployment. Explicitly, this means that worker's optimal choice of x is a function of the firm's wage offer. Hence, $x^* = x(\omega)$. The firm takes this relationship between x^* and the current wage offer ω as given and therefore takes into account the worker's probability of contacting an alternate offer $\lambda^e p^*(\theta_\tau(x^*, \cdot))$ when choosing the optimal current wage share to offer. In equilibrium, $x_k^e = x^*$ and the firm's optimal choice of $\omega^* = \omega(x^*)$.

Equation (15) represents the individual rationality constraint. Given s, there is a range of wage shares for which the worker will find it sub-optimal to stay with the current firm. Hence, if the wage share is too low, the worker would prefer to be unemployed. Consequently, the firm and the worker would agree to mutually separate with $d(\omega) = 1$. With probability $(1 - d(\omega))(1 - \lambda^e p^*(\theta_\tau))$, the worker stays with the firm and the firm receives current and future expected profits of $\big((1-\omega)Eq_{ijl} + \beta E J_{\tau+1}(s', x'^*)\big)$. Denote $\omega^c_\tau(s)$ as the critical wage share below which the worker will choose not to voluntarily separate from the firm, which satisfies:

$$b + U_{\tau+1}(s') = V_\tau(\omega^c, s)$$

Then for any wage above ω^c, we can use the fact that $d(\omega) = \delta$, the exogenous rate of separation. Taking first-order conditions with respect to equation (14), one can solve for the firm's optimal choice of wage share to offer the worker. Equation (16) states that the optimal wage is chosen such that the marginal expected cost of offering a higher wage share in terms of forgone profits is exactly equal to the expected marginal benefit of retaining that worker:

Assuming that the optimal $\omega \geq \omega^c$, we have:

$$(1 - \lambda^e p^*(\theta_\tau))Eq_{ijl} = -\lambda^e p_x^*(\theta_\tau)\frac{\partial x_k}{\partial \omega}\Big[(1-\omega)Eq_{ijl} + \beta E J_{\tau+1}(s', x'^*)\Big] \tag{16}$$

Intuitively, the probability of the worker finding another job is decreasing in the matched firm's wage offer, as ω implicitly forms an individual's reservation wage. Within a sector, an individual will never search in a sub-market in sector k that offers compensation $x_k < \omega$, as he is better off staying in a job which offers him a higher wage share. As the worker's desired wage compensation, x_k^e, is increasing in ω, this implies that worker's job finding rate p is decreasing in ω.

5.3.4 Recruiting Firms

All idle firms that decide to recruit at the start of a period are considered new firms in that period. A firm that seeks to recruit a worker incurs vacancy posting cost κ for each vacancy created. The firm's benefit to creating a vacancy in sub-market $\{x_k, \mu_k, y_k, \tau\}$ in sector k is a product of its hiring probability, $f(\theta_\tau(x_k, \mu_k, y_k, z, \varphi))$, and its expected profits. A firm never creates a vacancy in a market which doesn't require worker characteristics in the task he uses for production, i.e. a firm who uses task l for production will never advertise in any sub-market in sector k since the worker will not necessarily have any human capital relevant to his production needs. In addition, a firm never creates a vacancy in any sub-market where the cost of creating a vacancy exceeds the benefit of creating the job. If the benefit exceeds the cost of creating a vacancy, the firm would seek to open as many vacancies as possible in that sub-market. With free entry of firms, the following condition must therefore hold for any submarket that is visited by a positive number of applicants:

$$\kappa \geq f(\theta_\tau(x_k, \mu_k, y_k, z, \varphi))\Big((1-x_k)Eq_{ijk} + \beta E J_{\tau+1}(s', x'^*)\Big) \tag{17}$$

and $\theta_\tau \geq 0$ with complementary slackness. Equation (17) provides us with the firm's optimal job creation policy. For any submarket that is active with $\theta_\tau > 0$, equation (17) holds with equality and firms post vacancies in a submarket up to the point where the benefit is equal to the cost of posting a vacancy. When the benefit of creating a vacancy is strictly less than the cost, no firm creates a vacancy in that submarket. The free entry/job creation condition is key to the existence of a Block Recursive Equilibrium. With these value functions, I now define a Block Recursive Equilibrium as in Menzio and Shi (2010).

6 Equilibrium

Definition 1. *A Block Recursive Equilibrium (BRE) consists of a market tightness function θ_τ, a value function for the worker's search problem, R, a value function for the unemployed worker, U_τ, a corresponding policy function* *for the unemployed worker's problem, x_k^u, a value function for the employed worker's problem V_τ, the corresponding policy function for the employed worker, x_k^e, a firm's value function J, and contract policy functions, $\{\omega, d(\omega)\}$, for each $\tau = 1, \ldots, T$ age worker. These functions satisfy the following conditions:*

1 $\theta_\tau, U_\tau, V_\tau, R_k^u, R_k^e, J, x_k^u, x_k^e, \omega,$ *and* $d(\omega)$ *are all independent of* φ.

2 θ_τ *satisfies equation (17) for all values of* $(x_k, \mu_k, y_k, z, \varphi)$ *and for* $\tau = 1 \ldots T$.

3 U_τ, R_k^u *and* x_k^u *satisfy (8) for all* $(x_k, \mu_k, y_k, z, \varphi)$ *and for* $\tau = 1 \ldots T$.

4 R_k^e *and* x_k^e *satisfy (11) for all* $(x_k, \mu_k, y_k, z, \varphi)$ *and for* $\tau = 1 \ldots T$.

5 J, ω *and* $d(\omega)$ *satisfy (14) for all* s *and for all* $\tau = 1 \ldots T$.

The equilibrium is block-recursive, implying that all value functions and corresponding policy functions are independent of φ, the aggregate distribution of workers across age, experience, perceived aptitude, precision and employment states. Importantly, it is the self-selection by workers into specific submarkets that allows value functions and policy functions to be formulated and solved independent of the aggregate distribution of workers. When workers optimally self-select into markets, firms know that they will only meet a particular kind of worker when posting vacancies. As such, firms do not worry about the distribution of workers when deciding where to post vacancies. This stands in contrast to models of random search where firms do not know which worker they will meet and the distribution of workers across perceived aptitudes and experience affects workers' outside options, and consequently their wage outcomes. In a model of random search, workers would have to forecast the evolution of the distribution of workers across their perceived aptitudes and experience to compute their optimal bargaining wage. This problem is potentially computationally burdensome and is avoided in a model with directed search.

Proposition 1. *There exists a block recursive equilibrium (BRE) and the unique recursive equilibrium is block-recursive.*

Proof: See appendix B. The proof of existence and uniqueness of a Block Recursive Equilibrium is similar to Menzio and Shi (2009, 2010) and to Menzio, Telyukova and Visschers (2012). However, the proof is slightly different as 1) I consider that individuals live for a finite number of periods and 2) spot wage contracts are assumed instead of long-term dynamic wage contracts. Nonetheless, one can show by backward induction that all value functions and policy functions are independent of the aggregate distribution of workers. Importantly, output, q_{ijk}, is independent of the aggregate distribution of workers. Consider the problem of a recruiting firm that seeks to post a vacancy for a worker of age T. From the free entry condition, it is easy to see that θ_T depends only on the vacancy posting cost κ, the promised wage share and the realizations of the worker's human capital and the productivity shocks. Thus, θ_T is independent of the aggregate distribution of workers, φ. From equation (14), it is clear that if θ_T is independent of the aggregate distribution of workers, then J_T is also independent of φ and the firm's optimal choice of ω is independent of φ. Independence of θ_T and ω from φ implies that the search problems for a worker in the last period of his life, either R_k^u or R_k^e, are also independent of the aggregate distribution of workers. Since R_k^u and R_k^e are independent of φ for a worker in the last period of his life, U_T and V_T are also independent of the aggregate distribution of workers. Given independence of $\{U_T, V_T, J_T\}$ from φ, one can work backwards and show that the free entry condition for a recruiting firm that seeks to post a vacancy for a worker of age $T-1$ also has θ_{T-1} independent of φ. Thus, one can work backwards and repeat the same argument for all prior value functions.

7 Comparative Statics

Proposition 2. *Desired wages, x_k, are increasing in perceived aptitude and in the aggregate state, i.e. $\frac{\partial x_k}{\partial \hat{\mu}_{ik}} > 0$ and $\frac{\partial x_k}{\partial z} > 0$.*

Proof See Appendix C. Intuitively, a worker recognizes that a higher innate aptitude implies that he is more productive at a particular task. Highly productive workers are valuable to a firm as they increase output. A worker recognizes that he can demand more compensation when he has higher innate aptitude. Importantly, more positive beliefs of innate aptitude also raise the outside option of the worker. As a worker's search value is increasing in his perceived aptitude, this implies that the unemployment value of the worker is also increasing. Equation (15) shows that when the outside option of the worker is increasing, the firm has to offer higher wages in order to retain the worker. Thus, overall, desired wages increase in the optimism of one's belief about his innate aptitude.

Desired compensation is also increasing in the level of aggregate productivity. Higher aggregate productivity raises the expected profitability of firms and causes more firms to post vacancies. As a result, the increase in vacancies causes the job finding probability to rise. As it becomes easier to find jobs in all submarkets, workers will choose to demand higher wage compensation.

The monotonicity of desired wages in the optimism of one's beliefs has important effects on wage growth and job transitions in this model. In a recession, an individual faces higher search frictions, and optimally chooses to search in a sub-market with lower compensation so as to raise his job-finding rate, $\frac{\partial x_k}{\partial z} > 0$. As such, recessions are times when individuals are willing to take wage cuts. If a worker stays at a job at which he has comparative disadvantage, his perceived aptitude after observing output and updating will be low. This in turn causes him to search in markets with lower compensation if he chooses to stay in the same sector. Importantly, job finding probabilities are increasing with task-specific experience. This is because increased experience makes the worker valuable to the firm through two channels. First, workers with relevant accumulated task-specific experience contribute more to production. Second, higher experience implies more precision over the worker's aptitude at a job. Because job-finding probabilities are affected by the amount of relevant experience and because specific experience contributes to output, an individual may choose to remain in the same sector if he has accumulated many years of task-specific experience despite not having a particularly high aptitude in that career. This implies that recessions together with slow recoveries can act to lower wage growth by decreasing the desired wage compensation through two channels: 1) increased search frictions cause individuals to optimally trade off wage shares with higher job-finding rate; and 2) initial wrong choices and slow learning of one's true type can cause agents to stay in sectors where they have a comparative disadvantage even after they have realized their true aptitude in that sector. This latter effect is due in part to the specificity of human capital.

In what follows, I calibrate model parameters to match certain data moments. I solve the model numerically and perform various exercises to explore whether the model can generate quantitatively significant interactions between cyclical conditions at the time of entry and long run wage outcomes.

8 Calibration

Each period in my model is a quarter. In order to calibrate the parameters of my model, I use NLSY79 data on transition rates for white male college graduates across employment states. In particular, I use the UE, EU and EE transition rates reported in Column 1 of Table 5 to jointly calibrate the vacancy posting cost, the exogenous rate of separation δ, and the relative probability of being able to search for a job for employed vs. unemployed workers λ^e. While these targets are taken from the NLSY79 data, they accord well with the monthly probabilities calculated from CPS surveys.[13] Using CPS data, Nagypal (2007) reports that about 0.45% of employed college graduates transition into unemployment every month while 2.42% of college graduates conduct EE transitions every month. These translate into quarterly EU and EE transition rates of 1.3% and 7% respectively. While this EE transition rate accords well with the values reported in FF(2004), the quarterly EU rate is much lower. However, FF(2004)'s reported transition rates refer to all workers, rather than just college graduates. Nagypal(2007) also reports a monthly EU transition rate for all educational categories of 0.89%, which is equivalent to a 2.6% quarterly EU transition rate. This rate falls in the range of the numbers reported by Shimer(2012) and FF(2004). While Nagypal (2007) does not report UE transition rates, Shimer(2012) finds that 32% of all unemployed individuals transition to employment every quarter. Menzio, Telyukova and Visschers, using SIPP data, find that 25% of the unemployed transition to employment every month, or that 57% of unemployed individuals enter employment every quarter. Given that the transition probabilities in the NLSY79 dataset generally accords with the monthly transition probabilities found in both the CPS and SIPP data, I target the transitional probabilities found in the NLSY79 data to calibrate κ, δ, and λ^e. The unemployed's probability of being able to search for a job, λ^u, is normalized to 1.

[13] Quarterly transition probabilities are calculated as $r_{quarter} = 1 - (1 - r_{monthly})^3$.

In addition, I use NLSY79 data for college graduates on the average quarterly complex job-to-job transition rate to calibrate the value of σ_μ. The rate of complex job-to-job transitions in the model is strongly affected by how dispersed or noisy beliefs are about one's comparative advantage. I assume that the distribution of μ is centered around a mean of 1. The gain in experience, ζ, is assumed to be 0.25 for each quarter worked; or equivalently a worker gains one year of experience for each year he works at a job.

Since the period in my model is a quarter, I set $\beta = 0.987$, which is consistent with an annual interest rate of 5%. Given a modal college graduation age of 22 and assuming an average retirement age of 62 years, I set the lifespan of an individual to $T = 160$ quarters. To construct the probability transition matrix for aggregate productivity shocks, I use the Tauchen method and set the number of grid points for the shock to be $N_z = 5$. I assume that the distribution of shocks is centered around the mean of $\bar{z} = 1$. Hagedorn and Manovskii(2013) argue that the appropriate business cycle indicator for labor market search frictions should be the labor market tightness. Using data from the Job Openings and Labor Turnover Survey (JOLTS) on the number of job openings from the private sector and combining it with information from the BLS on the number of unemployed, I construct the labor tightness measure, θ, to be the number of vacancies over the number of unemployed, $\theta = \frac{v}{u}$. To identify the cyclical component of θ, I take logs and detrend using the Hodrick Prescott Filter with smoothness parameter 1600. The standard deviation of the cyclical component of the labor tightness condition is roughly equal to 0.274. Results from an AR(1) regression suggest that the quarterly persistence of labor tightness is about 0.92. Setting the persistence of the aggregate shock to be $\rho_z = 0.92$, I calibrate the volatility in the aggregate shock, σ_z, such that the implied volatility in θ matches its counterpart in the data. This gives me a standard deviation of $\sigma_z = 0.13$. I assume that idiosyncratic productivity shocks follow a lognormal distribution with mean 1 and standard deviation $\sigma_a = 0.1$. The value of σ_a is the quarterly analogue of the value in Hagedorn and Manovskii(2013), who use a monthly standard deviation of 0.054 for idiosyncratic productivity shocks faced by the firm.[14]

As in Shimer(2005), I set $b = 0.4$ for the unemployment benefit. As per the related literature (e.g. Menzio and Shi (2010), Shimer(2005), Mortensen and Nagypal(2007)), $p(\theta)$ takes the form of $p(\theta) = \min\{\theta^{\frac{1}{2}}, 1\}$. Since Topel and Ward(1992) suggest that individuals hold 6 to 7 jobs within the first ten years of their working life, I set the number of sectors to be $K = 10$. In addition, I assume that the production function exhibits decreasing returns to labor input and set $\alpha = 0.67$.

Tables 11 and 12 detail the fixed and calibrated parameter values used. Given the finite horizon of the model, I solve the model backwards and compute the value functions at each period accordingly. Figure 10 shows how closely the

[14] I find quarterly volatility by calculating $\sigma_{qtr} = \sigma_{mth} * \sqrt{3}$.

model replicates the data in terms of matching the life cycle profile of complex job-to-job transitions. Recall that the calibration exercise only targeted average lifetime transition rates rather than the average transition rate at each age. Similar to the data, the model predicts that the first few years of an individual's life are spent searching for a career. While the model predicts a similar exponential decay in the lifetime path of complex job-to-job transitions, it does slightly underpredict the amount of complex job-to-job transitions in later years. Nonetheless, the model matches the overall life cycle profile of complex job-to-job transitions.

9 Numerical Simulations

9.1 Effect of Worker Characteristics on the Job-Finding Probability

I examine how worker characteristics affect the job-finding probabilities of individuals. Throughout this paper, I assume that a recession (boom) is a one standard deviation dip (rise) in aggregate productivity from its mean. Figure 11 shows the economy in a recession and examines how perceived aptitudes affect job finding probabilities for a new entrant to the labor market. Notably, individuals with high perceived aptitude, $\hat{\mu}_{ik}$ - defined as a level of aptitude one standard deviation above the mean and as shown by the dot-dash line - have higher job-finding probabilities than their peers with lower perceived aptitudes at a particular career. Intuitively, firms like workers with higher levels of productivity at the task required for production. As such, more vacancies requiring high aptitude are created, and thus the labor tightness function θ and consequently the worker's job finding probability $p(\theta)$ are increasing in $\hat{\mu}_{ik}$. Figure 11 also demonstrates that the worker's job finding probability is decreasing in x_k, the posted wage share offer. Firms prefer to create jobs where they can keep a larger share of the rents. Thus for all levels of aptitude, job finding probabilities increase whenever workers search in markets with lower wage offers.

Age and experience also affect individuals' job finding probabilities. Similar to findings in Menzio, Telyukova and Visschers(2012), job finding probabilities increase in relevant experience but decrease with age. Figure 12 shows an economy in a recession and holds constant the level of aptitude required at $\mu_k = 1$. The dot-dash line highlights the job-finding probability for an individual with five years (20 quarters) of relevant experience in the sector and who has completed 5 years of his working life. The dashed line shows the job-finding probability of a labor market entrant. Noticeably, experience improves the worker's job-finding probability at all levels of the wage offer. This is due to the fact that experience adds to the worker's human capital and hence enhances the profits a firm can attain from matching with that worker. In addition, experience implies that the worker has greater precision over this perceived aptitude.

In contrast, job finding probabilities decline with age. Figure 12 demonstrates that a worker in the last 5 years of his working life has a much lower job finding probability than a worker with the same amount of experience but with 35 more years to his working life. Intuitively, older workers bring a lower stream of expected profits to the firm compared to a young worker of comparable experience and aptitude, because older workers are likely to exit the labor market sooner. Hence, age acts against a worker's job finding opportunities. It is this tension between experience and age that acts towards creating a lock-in effect for workers who accumulate a lot of experience in a field to which they are not well suited. Because older workers represent a lower stream of expected future profits for firms, firms are averse to hiring older workers with little experience. Thus, it is important to find a career that maximizes one's comparative advantage in the earlier years.

Figure 13 outlines how business cycles affect the job-finding probabilities of labor market entrants. Unsurprisingly, the effect of a recession is to lower the job-finding probability of an individual over all levels of wage offers. The decline in job-finding probabilities during a recession arises despite the fact that each worker represents an "investment" by the firm as workers can gain experience specific to that career and contribute to profits in the future.

9.2 Effect of Aggregate Productivity Shocks

In the following simulations, I examine how long-run labor market outcomes are affected by initial conditions. To do this, I assume that there are two "twin cohorts", one which enters during a recession, and another which enters during a boom. I assume that there are $N = 500$ heterogeneous individuals in an economy and simulate the model for $T = 160$ quarters for 200 economies. For 100 of these economies, I assume that the economy starts in a recession, in which z is two standard deviations below the mean, and for the other 100 economies, I assume that the economy starts in an expansion, in which z is initially two standard deviations above the mean. This gives rise to a difference of about 5.2 percentage points in the unemployment rate for the entering cohorts. Notably, the unemployment rate during the 1980s recession rose by close to 5 percentage points from 5.9 percent in 1979Q4 to 10.7 percent in 1982Q4. Thus, the size of the aggregate productivity drop in this simulation exercise gives rise to an increase in the unemployment rate that is consistent with the increase in unemployment in the 1980s recession.

Each individual at time $t = 0$ draws their $K \times 1$ vector of true aptitudes μ_i from a standard normal distribution. This vector of aptitudes μ_i is unknown to each individual. Individuals observe a noisy initial signal of their true vector of aptitudes, denoted as $\hat{\mu}_{i,0}$, where $\hat{\mu}_{i,0} = \mu_i + \epsilon$, which forms their initial priors of their comparative advantage.

Figure 14 is the analogue of the exercise conducted in Figure 4 but with the simulated data. The vertical axis denotes the survival probability of staying within the same career, i.e. no complex job change, while the horizontal axis denotes the quarters since entry. The solid line refers to workers who enter in an expansion while the dashed line refers to workers who enter in a recession. Unlike Figure 4, a recession here is associated with a 5 percentage point increase in the unemployment rate. In the model, workers who enter the job market during a recession observe a significant delay in their first between-career change. Table 13 highlights the results from a a proportional hazards duration model where the main regressor is dummy variable indicating whether the worker entered the job market during a recession.[15] Column 1 presents the results on how entering the job market during a recession affects the probability of never doing a complex job change while Column 2 looks at its impact on the probability of never doing a simple job change. From Column 1, entering the job market during a recession severely impinges on the individual's ability to conduct his first career change and lowers his hazard rate by 32%. This implies that workers who enter during a recession have a much lower probability of leaving their current career. Figure 15 demonstrates the survival probability of never doing a simple job change. Unlike the impact on complex job changes, the effect of entering the job market during a recession has a much more muted impact on the probability of never doing a simple job change. Individuals who enter during a recession observe a lower hazard ratio of 5%. Similar to the results found in the empirical data, the simulated model demonstrates that recessions impact early between-career changes more strongly than within-career changes.

While Figure 14 looks at the duration before the first complex job change, Figure 16 looks at the differences in complex employment-to-employment transition probabilities over the life cycle for workers who enter in a recession relative to those who enter in a boom. Figure 16 demonstrates that workers who enter during a recession have muted complex job-to-job transition rates earlier in their working life. This is directly a by-product of the higher search frictions faced during a recession. Early weak labor markets impede early job experimentation, which is crucial to figuring out the career that maximizes one's comparative advantage. Notably, there is no subsequent pick-up in complex job-to-job transitions even once the economy recovers. Intuitively, job experimentation at a later stage in one's working career is more costly for two reasons: first, the experience gained in the current sector helps to improve both the individual's job-finding probability and expected wage return within that sector, but is not transferable to a job in a different sector; and second, switching to a new career implies a gamble, as the individual not only has less certainty about his skill level at a new sector, but he also lacks relevant experience and faces lower job-finding opportunities as he is older and represents a smaller stream of expected future profits to the firm. The lack of precision and relevant experience implies that an individual may be forced to accept a wage cut to improve his job-finding probability if he switches careers when the economy recovers. Because of this, some individuals choose optimally to remain in the same career, resulting in a lock-in effect and consequently no observed pick up in complex job-to-job transitions even after the economy has recovered.

Figure 17 illustrates how the lock-in effect can occur. Consider an individual with the set of true aptitudes and intial priors as given in Table 14. The individual has comparative advantage in sector 1. However, at the time of

[15] As before, the duration model assumes the standardized Weibull distribution.

entry, he believes that he has highest aptitude at sector 2. As such, the individual initially chooses sector 2. This is true for both expansions and recessions. The "X"s and "O"s in the figure represent the sector the individual searches in each period after entering during a recession and expansion respectively, while the solid line and dashed line represent the sector the individual winds up in at the end of each period. Upon working in sector 2, the individual revises his belief of his aptitude in sector 2 and seeks a job in his next best guess, sector 6. However, due to the persistence of the aggregate shock, the individual who entered during a boom is able to move to sector 6 immediately while the individual who entered during a recession is 'unlucky' and unable to move. The individual who entered during a boom, upon working in sector 6, revises down his prior and moves to his next best guess, sector 1. Subsequently, this individual continues to work and search within sector 1 as that is where his true comparative advantage lies. In contrast, the individual who was 'stuck' during the recession in sector 2 stops seeking to switch sectors after quarter 5, as he has accumulated enough experience such that it is no longer worth switching to sector 6.

This decline in early job experimentation plays out in future wage outcomes. Figure 18 shows how the model-generated wage loss gap evolves for cohorts of individuals entering at different points over the business cycle. The percentage wage loss is calculated as the percentage difference in take-home wages between individuals who entered during a recession and individuals who entered during a boom, conditional on being employed. The top panel shows how long it takes for the economy to escape a recession in terms of output growth while the bottom panel shows how long wages take to recover. The initial wage loss conditional on being employed is about 44% in the model. This significant loss comes from two sources. Firstly, the aggregate shock lowers the average output and consequently the average wage return. Secondly, there are fewer vacancies open during a recession offering a higher wage share. As such, workers accept lower wage share offers during recessions in order to raise their probability of getting a job.

This wage loss persists even after the economy recovers. The aggregate shock disappears by about the 20th quarter, about 5 years after the initial shock. The wage gap, in contrast, is only closed after 60 quarters (15 years) after initial entry. There is significant catch-up in wages as the economy recovers; by the 20th quarter, the wage loss is about 6 per cent. This rapid catch up is largely due to the recovery in the aggregate shock. As output rises with increases in aggregate productivity, a large part of the improvement in wages stems from improvements in the aggregate state. However, wage losses continue as individuals are working in sectors that do not maximize their comparative advantage. These wage losses are not permanent, as individuals are able to conduct simple job changes in a recovery and move up the wage ladder. Over time, comparative advantage of the individual plays a smaller role in human capital formation and wage returns as experience accumulates. At the same time, some individuals conduct complex job changes when the economy recovers and move into careers with which they have comparative advantage. Their lack of relevant human capital, however, continues to act toward depressing the wage outcomes of individuals who re-start their careers.

Figure 19 breaks down the sources of persistent wage differences by showcasing the differences in career-specific experience accumulated as well as the extent of misallocation. The upper panel of Figure 19 highlights the difference in the average amounts of career-specific experience between individuals who entered during a recession and those who entered in a boom. Note that in the first five years, differences in relevant career-specific experience are negligible despite the unemployment rate being higher for an individual who entered in a recession. This lack of difference arises because individuals who enter during a boom spend the first few years searching for their ideal career. As experience is not transferable across careers, individuals who enter during a boom do not gain significantly more relevant career-specific experience early on than their counterparts who enter in a recession.

However, individuals who enter in a boom are quicker to find careers that match their comparative advantage. The bottom panel of Figure 19 depicts the average difference in log aptitude at the current job between individuals who entered in a boom and individuals who entered in a recession. While there is little difference in relevant career-specific experience initially between individuals who enter in a boom and a recession, the percentage difference in aptitude at the current job widens in the first few years, with individuals who enter a recession observing consistently lower aptitudes at their current job. When individuals first enter the job market, the amount of misallocation amongst the two 'twin' cohorts is about the same, as individuals do not initially know their comparative advantage. Within the first five years (20 quarters), however, individuals who enter the job market during a boom quickly conduct complex job changes and move into careers at which they have comparative advantage. In contrast, high search frictions prevent individuals who enter during a recession from experimenting and moving into careers where they might have comparative advantage. As such, the percentage difference in aptitudes between individuals who enter in a recession and those who enter in a boom becomes sharply negative in the first five years. This difference reaches its peak at 24 quarters. At this point, the proportion of individuals working in the "wrong" sector is 10% higher for those who entered in a recession than for those who entered in a boom. The corresponding average percentage difference in aptitudes is about 4%. The majority of the 6 percent wage gap observed after 20 quarters is thus due to misallocation.

When the economy has recovered, some of the individuals who entered in a recession conduct complex changes in order to find careers that suit their comparative advantage. This can be seen from the narrowing difference in log aptitudes after 24 quarters. However, because a complex job change requires a sacrifice of experience earlier accumulated, the convergence in aptitudes is accompanied by a rising difference in career-specific experience accumulated between individuals who enter in a recession and a boom. After 24 quarters, individuals who entered in a recession start to record lower amounts of career-specific experience on average than their counterparts who entered in a boom. By the time the wage gap is roughly closed at about 60 quarters, the proportion of individuals working in the wrong career is still about 2% higher for the cohort that entered in a recession than the cohort that entered in a boom. The corresponding percentage difference in aptitude is about 1% while the difference in career-specific experience amounts to over three-quarters of a period.

It is important to note that these gaps in career-specific experience and aptitude have both a direct and indirect effect on wage outcomes. Firstly, lower levels of aptitude and career-specific experience directly translate into lower output at a job. This in turn causes wages to fall. Secondly, aptitude and career-specific experience factor into the wage shares that workers can demand. Recall that a currently matched firm chooses the wage share to offer a worker at the start of the period based on his revised estimate of the worker's type as well as the worker's experience. A worker with low perceived aptitude may be offered a low wage share since he is not as productive as previously expected. As in equation (13),the worker's expected utility from staying with the current firm forms the worker's outside option, which in turn influences the optimal sub-market that a worker would choose to search for a job. Lower wage share offers from the worker's current firm put downward pressure on the wage share offer, x_k, that a worker targets in his search. In addition, the worker's experience in other sectors also affects his ability to find a job in an alternative career, and consequently affects the wage share he can demand from a new sector. Thus, the level of perceived aptitude and relevant experience also interact with the wage share offer of a worker. It is the combination of the direct effects of human capital and its indirect effects through the wage share that causes the 6% wage gap observed even after the aggregate economy has recovered 20 quarters after initial entry.

Although the difference in log aptitudes never completely vanishes and the difference in career-specific experience stabilizes at around one period, the wage gap disappears by the 60th quarter. Percentage differences in wage outcomes become negligible as workers gain more experience. By 60 quarters, workers have roughly close to 14 years of experience. Any persistent misallocation or differences in experience at this point are too small in percentage terms to have any significant impact on wages. Overall, the model predicts a present value wage loss of 3.7% over fifteen years. Approximately a quarter of these losses is due to misallocation or working at a job where the worker is less productive, while another one-fifth of the present value wage losses is due to the differences in career-specific experience gained.

9.3 Comparison of Benchmark Model with Other Alternatives

This paper has assumed that both learning and specific human capital are essential towards explaining persistent wage losses experienced by workers entering the labor market in a recession. In this section, I compare my benchmark model to two simpler alternatives. First, I consider a model where agents have to learn their comparative advantage but there is no specific human capital. Instead, experience gained is transferable between any job. Differences in aptitude merely imply that an individual is more productive in one particular career over another. Second, I consider a model in which there is specific human capital but individuals have perfect knowledge of their comparative advantage.

Figure 20 shows the evolution of the percentage wage gap in the three model specifications from quarters 10 to 70. The vertical line at 20 quarters marks the point where the aggregate shock has disappeared and the economy has recovered. The solid line refers to the benchmark model with both learning and specific human capital. The dash-dot line represents the model with general human capital and learning only while the dashed line represents the model with specific human capital and no learning. Compared to the benchmark model where the wage gap closes in 60 quarters, Figure 20 shows that the model with only learning and general human capital closes the wage gap at 44 quarters while there is almost no persistent wage loss in the model with only specific human capital in the sense that wages converge once the economy has recovered.

The model with only specific human capital does poorly in explaining persistent wage losses. In this model, there is no misallocation, thus the only difference between the two cohorts is in terms of the amount of experience accumulated. Because cohorts who enter in a recession face an unemployment rate that is about 5 percentage point higher, this leads to differences in human capital accumulation. However, because each individual knows their aptitudes perfectly, individuals at entry direct their search towards the sector with which they have comparative advantage. The difference in career-specific experience is thus small in the model with only specific human capital accumulation. Figure 21 shows that there is no significant misallocation in the model with no learning and less than half a period's difference in career-specific experience. As such, the wage losses evaporate with the recovery of the economy.

In contrast to the model with only specific human capital, the model with learning and general human capital does better in generating persistent wage losses. Similar to the benchmark model, the difference in misallocation widens for a few years after entry into the labor market and reaches its zenith at around 26 quarters. The widening in the percentage difference in aptitudes comes from the fact that individuals who enter in a boom are able to conduct complex job changes early and find careers where they have comparative advantage. In contrast, indivduals who enter in a recession face a delay in their learning. This can be seen from the narrowing in the percentage difference in aptitudes starting after 26 quarters, as shown in Figure22. Notably, the percentage difference in aptitudes in the model with learning and general human capital is much lower than that observed in the benchmark model. This is because the presence of specific human capital raises the cost of switching careers. Individuals who enter in a recession and who start in the wrong career find it easier to switch jobs when human capital is general, as experience gained at one's current career is completely transferable to another career. Workers are therefore not penalized for switching careers. In addition, as an individual works at his current job, he gains experience that is relevant to all other careers. With general human capital, the increase in experience contributes towards improving the worker's job-finding rate at all careers. As such, there is less misallocation in a model with learning and general human capital, as experience gained while working contributes to improving one's job finding prospects and makes it easier for workers to conduct complex job changes. Consequently, the overall wage gap in a model with learning and general human capital is smaller than that observed in the benchmark model.

9.4 Comparison of Model with Linear Wage Regression

A key question concerns how well the mechanism in the model explains the wage losses observed in the data. An important point to note is that the calculated wage loss in the simulated data is conditional on the fact that the only difference between the two twin cohorts is their initial entry conditions. In the actual data, however, it is likely that there exists other observable and unobservable differences between each cohort that enters the market. In addition, the data-generating process for aggregate shocks in the simulated model is unlikely to be exactly the same as the aggregate shock process that hits the real economy. As such, I conduct the following exercise to compare the simulated wage loss from my model to the data.

To compare the wage loss generated from my simulated model to the data, I use the estimated linear wage regression coefficients from Equation (1) to calculate the predicted wage loss if individuals experienced the same aggregate shock process as in my simulated model. In particular, I plug in the sequence of unemployment rates as implied by the aggregate shock process in my simulated model. I assume no differences in the AFQT score. Holding all else constant, this implies the following predicted wage loss calculation:

$$\Delta ln(w_t) = \hat{\alpha}_1 \Delta u_0 + \hat{\alpha}_2 \Delta u_0 * Pot.Exp_t + \hat{\beta}_1 \Delta u_t \tag{18}$$

where the Δ refers to the difference between a cohort that entered in a recession vs. a boom. As aforementioned, a recession in the simulated model assumes an aggregate shock such that there is a difference of 5.2 percentage points in the unemployment rate for the entering cohorts. Thus, the difference in unemployment rate at entry, Δu_0, is fixed at 5.2 in the predicted wage loss calculation. Δu_t captures how the difference in unemployment rates in the simulated model varies over time. Notably, the difference in unemployment rates narrows very quickly with the recovery of economy. Differences in the unemployment rate are negligible by the 8th quarter.[16]

Figure 23 shows the predicted wage loss from the linear regression model given the same sequence in unemployment rates as the simulated model. The red solid line documents the simulated wage loss from the benchmark model

[16] This result is perhaps unsurprising since we needed to introduce a very large aggregate shock in the economy to have an increase in the unemployment rate by 5 percentage points.

while the grey line dotted with triangles shows the predicted wage loss implied by the linear regression model given the same sequence of difference in unemployment rates. The top panel of Figure 23 again shows the path of the aggregate shock over time. In Figure 23, the predicted wage loss using the linear regression coefficients suggests that an increase in the unemployment rate at entry by 5 percentage points gives rise to an initial wage loss of about 42 percent. This wage gap narrows to 15% by the 20th quarter and completely fades by the 63rd quarter. Note that the predicted wage loss using the linear regression coefficients shows that the wage losses turn into wage gains after the 63rd quarter. This result is somewhat mechanical and occurs as the positive coefficient on the interaction term of $u_0 * Pot.Exp_t$ implies a constant gain to wages. As such, Figure 23 is truncated at 80 quarters since any difference between the predicted wage loss implied by the linear regression model and the simulated wage loss after the 64th quarter are due to this mechanical result.

In general, the simulated wage loss closely matches the predicted wage loss from the linear regression model in the first 10 quarters, but deviates significantly thereafter. This is because differences in unemployment rates are negligible by this period although the aggregate shock has not completely recovered yet as shown in the top panel of Figure 23. From the 10th quarter onwards, the predicted wage loss from the linear regression model is completely driven by the difference in unemployment rate at entry and the catch-up implied by the interaction term. In contrast, the simulated model shows faster catch-up and a non-linear recovery in wages. This non-linear catch-up in wages is not surprising. Recall that wages are affected by both the aggregate shock, a worker's aptitude and experience as well as the wage share that he can demand. Since the wage share that a worker can demand is increasing in both the worker's estimate of his aptitude, experience and the aggregate state, this suggests that simulated wage paths should be non-linear and history-dependent. Overall, these results are suggestive of how much the proposed mechanism in the simulated model can account for wage losses relative to the predicted wage loss from a linear regression model. In future work, I focus on estimating the structural parameters of the model.

9.5 Mature Workers

While the model is able to generate persistent wage losses for labor market entrants, recessions in this model do not create persistent wage losses for older workers. This is mainly due to the fact that mature workers are more likely to have already identified their ideal careers. There are therefore no losses stemming from a decline in job experimentation or from accumulating irrelevant experience. Figure 24 shows the time path of percentage wage losses for a mature worker who experiences a recession 40 quarters after his entry into the labor market. The top panel again highlights the path of the path aggregate shock while the lower panel highlights the percentage wage difference between individuals who experienced a recession 40 quarters after entry and individuals who experienced an expansion 40 quarters after entry. Figure 24 highlights that for mature workers, the wage gap closely tracks the recovery in the economy. The wage gap closes quarter 60, which is about the same time required for the negative aggregate shock to disappear. This is largely because mature workers have already identified their ideal sector and continue to accumulate relevant experience during the recession. Wages catch up rapidly when the economy recovers, as mature workers can easily conduct simple job changes to re-climb the wage ladder. This quick recovery in wages is similar to the recovery seen in the model with only specific human capital and no learning, another case in which recessions do not cause workers to waste time in suboptimal sectors.

The model results for mature workers are at odds with the empirical literature on displaced workers and persistent earnings losses. This may be because a recession in the model uniformly affects all sectors in the economy. This is not necessarily true in reality. Recessions may affect some sectors more than others, and in certain cases may coincide with permanent sectoral decline. The loss of a sector or a particular career in the labor market can leave mature workers with accumulated irrelevant experience. In this case, wage losses for mature workers may persist long after the economy recovers as mature workers are forced to 're-start' in new careers or sectors where they 1) do not have comparative advantage and 2) do not have relevant experience. In the worst case scenario, long-term unemployment may also result, given that the worker's age, low aptitude and lack of experience in other sectors severely hinder his job-finding probability. To observe how this can occur, the basic model has to be extended to incorporate differential sectoral shocks. This, however, will be left for future research work.

10 Conclusion

This paper investigates a possible channel for why individuals who enter the job market during a recession suffer persistent wage losses. In particular, this paper suggests that early search frictions impact how individuals learn their comparative advantage and slow down the accumulation of relevant human capital. I show using NLSY79 data that job search strategies over the life cycle are affected by initial business cycle conditions and build a model to explain these empirical findings.

While this paper has focused exclusively on aggregate shocks, future work will incorporate how the interaction of aggregate and sectoral shocks may affect the wage losses of both new entrants and mature workers. In particular, one can embed sector-specific shocks in the model and show how sectoral trends would affect individuals' search decisions. In some cases, an individual may forego searching according to comparative advantage if a recession coincides with permanent sectoral shifts.

References

Adda, Jerome, Christian Dustmann, Costas Meghir, and Jean-Marc Robin, ""Career Progression, Economic Downturns, and Skills"," *NBER Working Papers*, 2013, (18832).

Barlevy, Gadi, ““The Sullying Effect of Recessions”,” *Review of Economic Studies*, 2006, (1), 65–96.

Beaudry, Paul and John DiNardo, ““The Effect of Implicit Contracts on the Movement of Wages over the Business Cycle: Evidence from Micro Data”,” *Journal of Political Economy*, 1991, (4), 665–688.

Cadena, Brian C. and Brian K. Kovak, ““Immigrants Equilibrate Local Labor Markets: Evidence from the Great Recession”,” *NBER Working Paper*, August 2013, (19272).

Delacroix, Alain and Shouyong Shi, ““Directed Search On The Job And The Wage Ladder”,” *International Economic Review*, 2006, (2), 651–699.

Fallick, Bruce and C.A. Fleischmann, ““Employer-to-Employer Flows in the US Labor Market: The Complete Picture of Gross Worker Flows”,” *FEDS Working Paper, Washington DC*, 2004, (34).

Felli, Leonardo and Christopher Harris, ““Learning, Wage Dynamics, and Firm-Specific Human Capital”,” *Journal of Political Economy*, aug 1996, *104* (4), 838–868.

Gathmann, Christina and Uta Schonberg, ““How General is Human Capital? A Task-Based Approach”,” *Journal of Labor Economics*, January 2010, *28* (1), 1–49.

Gervais, Martin, Nir Jaimovich, Henry Siu, and Yaniv Yedid-Levi, ““What Should I Be When I Grow Up? Occupations and Employment over the Life Cycle and Business Cycle”,” *Society for Economic Dynamics Meeting Papers*, 2011, (893).

Gregg, Paul and Emma Tominey, ““The Wage Scar From Male Youth Unemployment”,” *Labour Economics*, August 2005, *12* (4), 487–509.

Hagedorn, Marcus and Iourii Manovskii, ““Job Selection and Wages over the Business Cycle”,” *American Economic Review*, April 2013, *103* (2), 771–803.

Hornstein, Andreas, Per Krussell, and Giovanni Violante, ““Frictional Wage Dispersion in Search Models: A Quantitative Assessment”,” *NBER Working Paper*, December 2007, (13674).

Kahn, Lisa B., ““The long-term labor market consequences of graduating from college in a bad economy”,” *Labor Economics*, April 2010, *17* (2), 303–316.

Kambourov, Gueorgui and Iourii Manovskii, ““Occupational Specificity Of Human Capital”,” *International Economic Review*, 2009, *50* (1), 63–115.

Menzio, Guido and Shouyong Shi, ““Directed Search on the Job,Heterogeneity and Aggregate Fluctuations”,” *American Economic Review: Papers and Proceedings*, May 2010, *100*, 327–332.

— , **Irina Telyukova, and Ludo Visschers**, ""Directed Search Over the Life Cycle"," *NBER Working Paper*, January 2012, (17746).

Mortensen, Dale and Eva Nagypal, ""More on Unemployment and Vacancy Fluctuations"," *Review of Economic Dynamics*, 2007, *10* (3), 327–347.

Moscarini, Giuseppe, ""Excess Worker Reallocation"," *Review of Economic Studies*, July 2001, (3), 593–612.

Neal, Derek, ""The Complexity of Job Mobility among Young Men"," *Journal of Labor Economics*, April 1999, *17* (2), 237–261.

Oreopoulos, Philip, Till von Wachter, and Andrew Heisz, ""The Short- and Long-Term Career Effects of Graduating in a Recession"," *American Economic Journal: Applied Economics*, January 2012, *4* (1), 1–29.

Oyer, Paul, ""Initial Labor Market Conditions and Long-Term Outcomes for Economists"," *Journal of Economic Perspectives*, July 2006, *20* (3), 143–160.

Papageorgiou, Theodore, ""Learning Your Comparative Advantages"," *Society for Economic Dynamics Meeting Papers*, 2009, (1150).

Parent, Daniel, ""Industry-Specific Capital and the Wage Profile: Evidence from the National Longitudinal Survey of Youth and the Panel Study of Income Dynamics"," *Journal of Labor Economics*, April 2000, (2), 306–323.

Pavan, Ronni, ""Career Choice and Wage Growth"," *Journal of Labor Economics*, July 2011, *29* (3), 549–587.

Pissarides, Christopher A., ""Loss of Skill during Unemployment and the Persistence of Employment Shocks"," *The Quarterly Journal of Economics*, November 1992, *107* (4), 1371–91.

Pries, Michael J., ""Persistence of Employment Fluctuations: A Model of Recurring Job Loss"," *Review of Economic Studies*, 2004, *71* (1), 193–215.

Shimer, Robert, ""The Cyclical Behavior of Equilibrium Unemployment and Vacancies"," *American Economic Review*, March 2005, *95* (1), 25–49.

— , ""Reassessing the Ins and Outs of Unemployment"," *Review of Economic Dynamics*, April 2012, *15* (2), 127–148.

Topel, Robert H. and Michael P. Ward, ""Job Mobility and the Careers of Young Men"," *Quarterly Journal of Economics*, 1992, *107*, 439–479.

Wozniak, Abigail, ""Are College Graduates More Responsive to Distant Labor Market Opportunities? "," *Journal of Human Resources*, 2010, *45* (4), 944–970.

Appendix A

Overlap of Between and Within Career Changes with Complex and Simple Job Definitions

As a quick check on whether complex job changes coincide with the notion of a career change, I use the Dictionary of Occupation Titles to check if a complex job change overlaps with a significant change in tasks required to work in that career. One caveat about using the Dictionary of Occupational Titles (DOTs) is that the DOTs data by design, only provides information on the tasks performed in each occupation. There is thus no correspondence to industry codes. If a career involves some level of industry-specific knowledge, the DOTs data would not be able to capture this specificity of human capital. Nonetheless, the DOTs data provides a preliminary check on whether the suggested measure of complex and simple job changes capture between and within career changes respectively. To this end, I calculate a measure of task-distances involved in each occupation change observed in the data and measure the overlap with complex and simple job changes.

While the DOTs data classifies occupations along many dimensions, I use the most basic classification of tasks involved in occupations to construct the measure of task distances. The primary classification for occupations is the requirements for working with “Data,” “People,” and “Things.” The category “Data” relates to the necessity of processing and using information. Individuals are ranked from a score of 1 to 6, with the lowest number coding for the most complex task (for e.g. synthesizing data), and the highest number relates to the simplest task (e.g. copying data). The other two categories, “People” and “Things”, are ranked in the same order with most complex tasks in that category being given the lowest number (i.e. 1). The category “People” looks at the necessity of relating to others in one’s occupation, while “Things” looks at the ability to use and manipulate physical objects. As a starting point, I use the information from “Data”, “People” and “Things” to look at the task differences between occupations.

Measure of Distance between Occupations

Because this paper looks at multi-dimensional skill sets, an important questions surrounds how we should quantify the differences between occupations. From the previous section, the task complexity involved in each occupation can be coded as a three-dimensional vector. This three-dimensional vector can be thought as describing a position in the task space. Following Gathmann and Schonberg(2010), I measure the distance between two occupations (o and o') as one minus the angular separation in task space. Let A be the 3×1 vector of occupation o and B be the 3×1 vector of occupation o'. Then the angular separation of o and o' is:

$$\text{Angular Separation}_{oo'} = \frac{A \cdot B}{\|A\|\|B\|} \tag{19}$$

and accordingly, the distance between occupations o and o' is given by:

$$\text{Distance}_{oo'} = 1 - \text{Angular Separation}_{oo'} \tag{20}$$

Equation (19) defines the distance between two occupations as the cosine angle between their positions in vector space. Following Gathmann and Schonberg (2010), defining distance as one minus the angular separation provides us with a simple monotonic single-dimensional index to look at the distance between occupations. The measure is bounded between zero and one inclusive; the measure is zero for occupations that employ identical tasks and one if the two occupations use completely different tasks. Hence, by looking at the angular separation of jobs in the task space, we can collapse multidimensional vectors into a measurable single dimensional index.

The distribution of occupational changes in the dataset is positively skewed, most occupation changes involve small differences between tasks, suggesting that individuals tend to stay within jobs that are similar. The maximum distance between occupation changes observed in the NLSY79 data was about 0.82. The mean task distance between occupations was 0.12 and the median task distance was about 0.06. About 85 per cent of our measure of simple job changes are captured as having a task distance below the mean of 0.12. In contrast, 45 per cent of our measure of complex job changes have a task distance above the mean of 0.12.

Appendix B

Proof of Existence of BRE

In this section, I prove that a Block Recursive Equilibrium (BRE) exists by backward induction. The proof is similar to that of Menzio, Telyukova and Visschers (2012). In what follows, I show that the value functions, policy functions and labor market tightness condition for each sub-market is independent of the aggregate distribution of workers, φ. This independence from the aggregate distribution of workers allows us to solve the model in a block recursive manner.

Given that each individual lives for only T periods, consider a firm that posts a vacancy for an individual of age $\tau = T$. Re-arranging the free-entry condition for $\theta_T > 0$, we have:

$$\theta_T = f^{-1}\left(\frac{\kappa}{(1 - x_k)Eq_{ijk}}\right) \tag{21}$$

Note that θ_T depends only on parameters and the expected share of output the recruiting firm gets to keep. From equation (7), it is clear that output depends on the aggregate state only through z, aggregate productivity for that period. In addition, the expected output of the worker is in no way affected by the aggregate distribution of workers as the firm is able to specify exactly what kind of worker he desires. In particular, the human capital requirements of $\{\mu_k, y_k\}$ are specified whenever a firm posts a vacancy. By posting the level of experience required, y_k, the firm also implicitly determines the probability distribution of μ_k as there exists a one-for-one mapping between career-specific experience and the precision of the worker's type. Thus, the probability that the worker truly has μ_k levels of aptitude is independent of the aggregate distribution of workers. Hence, θ_T is entirely independent of the aggregate distribution of workers, φ.

Given the independence of θ_T from φ, it follows that $p^*(\theta_T)$ from equation (14) does not depend on φ and therefore, the firm's maximization problem, J_T, is also independent of the aggregate distribution of workers. Consequently, the optimal wage share to offer is also independent from the aggregate distribution of workers. This can be seen by re-writing equation (16) for a firm attached to a worker in the last period of his life:

$$(1 - \lambda^e p^*(\theta_T))Eq_{ijl} = -\lambda^e p^*_x(\theta_T)\frac{\partial x_k}{\partial \omega}(1 - \omega)Eq_{ijl} \tag{22}$$

From equation (22), it clear that ω is depends on θ_T , λ^e and expected output. Since Eq_{ijl} and θ_T do not depend on φ, ω does not depend on φ.

Turning to the search problem of an employed worker at age T, notice that we can re-write R^e_k as:

$$R^e_k(\omega, s) = \max_{x_k} d(\omega)b + (1 - d(\omega))\left[\lambda^e p(\theta_T)Ex_k q_{ijk} + (1 - \lambda^e p(\theta_T))E\omega q_{ijl}\right] \tag{23}$$

From equation (23), it is clear that independence of θ_T, ω and Eq_{ijk} from φ implies that R^e_k is independent of the aggregate distribution of workers. Analogously, R^u_k is also independent of φ. Since $\{R^u_k, R^e_k\}$ are independent of φ for all k for individuals for age T, it follows that V_T and U_T are also independent of the aggregate distribution of workers.

Given that J_T is independent of φ, we can return to the problem of a recruiting firm that seeks to hire a worker of age $T - 1$. In this case, the free entry condition is equal to :

$$\kappa = f(\theta_{T-1})\left[E(1 - x_k)q_{ijk} + \beta E J_T(s', x'^*)\right)$$

Since J_T is independent from φ, the above equation implies that θ_{T-1} is also independent of this period's aggregate distribution of workers. Since all $T - 1$ value functions depend on θ_{T-1} and on T value functions, and since θ_{T-1} and T value functions are independent of φ, it follows that all $T - 1$ value functions are also independent of the aggregate distribution of workers. One can continuously repeat this argument to all prior periods until $\tau = 1$.

Appendix C

Proof of Monotonicity in Wages in Beliefs

Since the search problem of the unemployed worker and employed worker is similar, I demonstrate only the proof for the employed worker's problem. Differentiating equation (13) with respect to $\hat{\mu}_{ik}$ and using the property that $p_{x,\mu} = \frac{\partial p_x}{\partial x}\frac{\partial x}{\partial \hat{\mu}} = p_{xx}\frac{\partial x}{\partial \hat{\mu}}$, one can show that the desired compensation, x_k is rising in the optimism of one's belief about $\hat{mu}_{ik}$:

$$\frac{\partial x_k}{\partial \hat{\mu}_{ik}} = \frac{p_x(\theta_\tau)B + p(\theta_\tau)\frac{\partial E q_{ijk}}{\partial \hat{\mu}_{ik}} + p_\mu(\theta_\tau)Eq_{ijk}}{A} \tag{24}$$

where

$$A = -\Big(2p_{xx}(\theta_\tau)\big[E(xq_{ijk} + \beta V_{\tau+1}(x'_k, s')) - E(\omega q_{ijl} + \beta V_{\tau+1}(\omega', s'))\big] + p_x(\theta_\tau)Eq_{ijk}\Big)$$

and

$$B = \Big[\frac{\partial E(x_k q_{ijk} + \beta V_{\tau+1}(x'_k, s'))}{\partial \hat{\mu}_{ik}} - \frac{\partial E(\omega q_{ijl} + \beta V_{\tau+1}(\omega', s'))}{\partial \hat{\mu}_{ik}}\Big]$$

I first focus on the numerator in equation (24). Note that the job-finding probability of a worker is decreasing in the desired compensation, $p_x < 0$, while the job-finding probability of a worker is increasing in his level of perceived aptitude, μ_k. As workers like high-pay, many workers would flood a vacancy offering a high wage share offer x_k, causing congestion to arise and $p(\theta_\tau)$ to decline in x_k. In contrast, firms like to post vacancies requiring high perceived aptitude, while not many workers may satisfy such a requirement. Hence, a worker with high perceived aptitude has a higher chance of finding a job, hence $p_\mu > 0$. Expected income is increasing in higher perceived aptitude as demonstrated by $\frac{\partial E q_{ijk}}{\partial \hat{\mu}_{ik}} > 0$, as a higher aptitude at one's job naturally translates into higher output. Notably, since no individual will search for a job which offers less expected utility than the current job, i.e. an individual would only apply to a job with $E(xq_{ijk} + \beta V_{\tau+1}(x'_k, s')) \geq E(\omega q_{ijl} + \beta V_{\tau+1}(\omega', s'))$, it must be that $\frac{\partial E(x_k q_{ijk} + \beta V_{\tau+1}(x'_k, s'))}{\partial \hat{\mu}_{ik}} \leq \frac{\partial E(\omega q_{ijl} + \beta V_{\tau+1}(x'_k, s'))}{\partial \hat{\mu}_{ik}}$. In addition, concavity of the production function in μ_{ik} implies that the marginal expected life-time utility is declining in $\hat{\mu}_{ik}$. Thus, the term B is strictly non-positive, implying that $p_x(\theta_\tau)B$ is strictly non-negative. Hence, it is clear that the numerator of equation (24) is strictly positive.

Focusing on the denominator A, we first note that concavity of p implies that $p_{xx} < 0$. As aforementioned, an individual never looks for a job that offers him less expected benefit than his current offer, hence $(Ex_k q_{ijk} + \beta EV_{\tau+1}(x'_k, s') - E\omega q_{ijl} - \beta EV_{\tau+1}(\omega', s')) > 0$. Expected output is always non-negative and p_x is aforementioned strictly less than zero. As the whole equation is multiplied by (-1), this implies that A is strictly greater than zero and hence, desired wage compensations are increasing in the optimism of one's belief about his aptitude, $\frac{\partial x_k}{\partial \hat{\mu}_{ik}} > 0$.

Proof of Monotonicity of Wages in Belief of TFP

Differentiating (13) with respect to z , and using the property that $p_{x,z} = \frac{\partial p_x}{\partial x}\frac{\partial x}{\partial z} = p_{xx}\frac{\partial x}{\partial z}$, we get:

$$\frac{\partial x_k}{\partial z} = \frac{p_x(\theta_\tau)D + p(\theta_\tau)\frac{\partial Eq_{ijk}}{\partial z} + p_z(\theta_\tau)Eq_{ijk}}{A} \tag{25}$$

where

$$D = \Big[\frac{\partial E(x_k q_{ijk} + \beta V_{\tau+1}(x'_k, s'))}{\partial z} - \frac{\partial E(\omega q_{ijl} + \beta V_{\tau+1}(\omega', s'))}{\partial z}\Big]$$

Equation (25) is analogous to equation (24) . Note that the job finding probability is directly increasing in z, i.e. $p_z > 0$ and expected utility from income is also increasing in the perceived level of aggregate productivity, $\frac{\partial Eq_{ijk}}{\partial z} > 0$. In addition, as z is persistent, this implies that expected lifetime utility $\frac{\partial E(x_k q_{ijk}+\beta V_{\tau+1}(x'_k,s'))}{\partial z}$ from searching for a job is also positive. Given concavity of the production function in z, marginal expected life-time utility is decreasing in z. Thus, $\frac{\partial E(x_k q_{ijk}+\beta V_{\tau+1}(x'_k,s'))}{\partial z} \leq \frac{\partial E(\omega q_{ijl}+\beta V_{\tau+1}(\omega',s'))}{\partial z}$ and the numerator in equation (25) is strictly positive and $\frac{\partial x_k}{\partial z}$ is also strictly positive.

Appendix D

Table 1: Impact of Initial Unemployment Rate on Log Wages of College Graduates

Variable	National 1 OLS	 2 IV	Regional 3 OLS	 4 IV
$u_{0,i}$	-6.358***	-4.982**	-4.657**	-4.391*
	(1.085)	(2.074)	(1.587)	(2.504)
Pot. Exp $*u_{0,i}$	0.035	0.077	0.008	0.021
	(0.037)	(0.184)	(0.054)	(0.113)
u_{it}	-3.815***	-4.130***	-2.670***	-2.725***
	(0.361)	(0.431)	(0.635)	(0.450)
AFQT	0.335***	0.298***	0.340***	0.329***
	(0.090)	(0.056)	(0.092)	(0.072)
Potential Experience	1.569***	1.255	1.837***	1.739**
	(0.356)	(1.375)	(0.464)	(0.860)
Potential Experience^2	-0.012***	-0.012***	-0.012***	-0.012***
	(0.002)	(0.002)	(0.002)	(0.002)
F-stat (1st stage: $u_{0,i}$)	-	26.91	-	26.88
F-stat (1st stage: Pot. Exp $*u_{0,i}$)	-	923.54	-	752.35
N	22109	22109	22053	22053

Dependent variable is log wage. IV first stage regression includes the unemployment rate at age 22, and the unemployment rate at 22*potential experience. Columns 1 and 2 look at the effect of the national unemployment rate at entry on the probability of being employed for college graduates, Columns 3 and 4 look at the effect of the regional unemployment rate at entry. Coefficients reported in terms of percentage points. All regressions include region dummies. Robust standard errors are reported and all standard errors are clustered by birth year. "F-stat (1st stage: $u_{0,i}$)" refers to the F-test associated with equation (2) while "F-stat (1st stage: Pot. Exp $*u_{0,i}$)" refers to the F-test associated with equation (3). Significance levels: $*$: 10% $**$: 5% $***$: 1%

Table 2: Impact of Initial Unemployment Rate on Log Wages of High School Graduates

Variable	National 1 OLS	 2 IV	Regional 3 OLS	 4 IV
$u_{0,i}$	-1.834	-2.841**	-1.883	-2.782***
	(1.188)	(1.225)	(0.958)	(0.823)
Pot. Exp $*u_{0,i}$	0.032	0.048***	0.029	0.062**
	(0.020)	(0.015)	(0.020)	(0.027)
u_{it}	-2.169***	-2.275***	-1.877***	-1.889***
	(0.267)	(0.345)	(0.447)	(0.275)
AFQT	0.345***	0.343***	0.344***	0.345***
	(0.035)	(0.033)	(0.034)	(0.035)
Potential Experience	1.045***	0.899***	1.060***	0.760***
	(0.162)	(0.134)	(0.183)	(0.228)
Potential Experience^2	-0.007***	-0.007***	-0.007***	-0.007***
	(0.000)	(0.000)	(0.000)	(0.000)
F-stat (1st stage: $u_{0,i}$)	-	59.44	-	72.63
F-stat (1st stage: Pot. Exp $*u_{0,i}$)	-	961.06	-	1072.48
N	42065	42065	41402	41402

Dependent variable is log wage. IV first stage regression includes the unemployment rate at age 18, and the unemployment rate at 18*potential experience. Columns 1 and 2 look at the effect of the national unemployment rate at entry on log wages of high school graduates, Columns 3 and 4 look at the effect of the regional unemployment rate at entry. Coefficients reported in terms of percentage points. All regressions include region dummies. Robust standard errors are reported and all standard errors are clustered by birth year. "F-stat (1st stage: $u_{0,i}$)" refers to the F-test associated with equation (2) while "F-stat (1st stage: Pot. Exp $*u_{0,i}$)" refers to the F-test associated with equation (3). Significance levels: $*$: 10% $**$: 5% $***$: 1%

Table 3: Probability of Being Employed (College Graduates)

Variable	**National**		**Regional**	
	1	**2**	**3**	**4**
	OLS	**IV**	**OLS**	**IV**
$u_{0,i}$	-0.459	1.021	-0.434	0.585
	(0.552)	(2.702)	(0.310)	(1.402)
Pot. Exp $*u_{0,i}$	0.008	-0.044	0.005	-0.031
	(0.008)	(0.052)	(0.006)	(0.024)
u_t	-0.561	-0.648	-0.362	-0.502
	(0.377)	(0.571)	(0.288)	(0.405)
AFQT	0.005	0.015	0.009	0.017
	(0.021)	(0.016)	(0.019)	(0.015)
Potential Experience	0.345^{**}	0.725^{*}	0.379^{***}	0.637^{***}
	(0.129)	(0.398)	(0.086)	(0.191)
Potential Experience^2	-0.004^{***}	-0.004^{***}	-0.004^{***}	-0.004^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
F-stat (1st stage: $u_{0,i}$)	-	33.79	-	32.04
F-stat (1st stage: Pot. Exp $*u_{0,i}$)	-	964.52	-	807.23
N	24350	24350	24150	24150

Dependent variable is the probability of being employed. IV first stage regression includes the unemployment rate at age 22, and the unemployment rate at 22*potential experience. Columns 1 and 2 look at the effect of the national unemployment rate at entry on log wages of college graduates, Columns 3 and 4 look at the effect of the regional unemployment rate at entry. Coefficients reported in terms of percentage points. All regressions include region dummies. Robust standard errors are reported and all standard errors are clustered by birth year. "F-stat (1st stage: $u_{0,i}$)" refers to the F-test associated with equation (2) while "F-stat (1st stage: Pot. Exp $*u_{0,i}$)" refers to the F-test associated with equation (3). Significance levels: $*$: 10% $**$: 5% $***$: 1%

Table 4: Probability of Being Employed (High School Graduates)

Variable	**National**		**Regional**	
	1	**2**	**3**	**4**
	OLS	**IV**	**OLS**	**IV**
$u_{0,i}$	-0.946^{*}	-0.405	-0.705^{**}	-0.628
	(0.372)	(1.026)	(0.241)	(0.942)
Pot. Exp $*u_{0,i}$	0.012	-0.008	0.005	-0.012
	(0.014)	(0.014)	(0.010)	(0.007)
u_t	-1.562^{***}	-1.574^{***}	-0.769^{**}	-0.873^{***}
	(0.241)	(0.203)	(0.243)	(0.125)
AFQT	0.075^{**}	0.073^{***}	0.075^{**}	0.083^{***}
	(0.027)	(0.023)	(0.027)	(0.021)
Potential Experience	0.554^{***}	0.721^{***}	0.666^{***}	0.808^{***}
	(0.082)	(0.141)	(0.054)	(0.089)
Potential Experience^2	-0.005^{***}	-0.005^{***}	-0.005^{***}	-0.005^{***}
	(0.000)	(0.000)	(0.001)	(0.001)
F-stat (1st stage: $u_{0,i}$)	-	78.94	-	80.63
F-stat (1st stage: Pot. Exp $*u_{0,i}$)	-	431.44	-	328.34
N	44023	44023	44023	44023

Dependent variable is the probability of being employed. IV first stage regression includes the unemployment rate at age 18, and the unemployment rate at 18*potential experience. Columns 1 and 2 look at the effect of the national unemployment rate at entry on the employability of high school graduates while columns 3 and 4 look at the effect of the regional unemployment rate at entry. Coefficients reported in terms of percentage points. All regressions include region dummies. Robust standard errors are reported and all standard errors are clustered by birth year. "F-stat (1st stage: $u_{0,i}$)" refers to the F-test associated with equation (2) while "F-stat (1st stage: Pot. Exp $*u_{0,i}$)" refers to the F-test associated with equation (3). Significance levels: $*$: 10% $**$: 5% $***$: 1%

Table 5: Transition Probabilities

Variable	**Data (College)**	**Data (High School)**	**Shimer (2012)**	**FF(2004)**	**FF***
UE	0.532	0.317	0.321	0.283	0.631
	(0.193)	(0.086)	(0.050)	(0.029)	
EU	0.048	0.052	0.020	0.013	0.038
	(0.042)	(0.041)	(0.003)	(0.001)	
EE	0.055	0.060	-	0.026	0.076
	(0.021)	(0.021)	-	(0.001)	
Complex EE	0.032	0.039			
	(0.016)	(0.015)			
Simple EE	0.027	0.025			
	(0.010)	(0.010)			

All transition probabilities are at the quarterly frequency. FF report monthly transition probabilities. Quarterly numbers (denoted as FF*) for FF calculated as $r_{quarter} = 1 - (1 - r_{month})^3$.

Table 6: Results from Proportional Hazards Model

Variable	**College Complex**	**College Simple**	**High Sch Complex**	**High Sch Simple**
$u_{0,i}$	-0.074*	-0.050	-0.088*	-0.013
	(0.041)	(0.080)	(0.045)	(0.032)
Potential Experience	-0.347**	-0.061	-0.481***	-0.172
	(0.142)	(0.271)	(0.059)	(0.204)
Potential Experience^2	0.006	-0.022	0.012***	0.000
	(0.010)	(0.023)	(0.003)	(0.008)
u_t	-0.111**	-0.058	-0.073**	-0.050
	(0.052)	(0.050)	(0.029)	(0.075)
AFQT	0.001	-0.001	0.001	0.001
	(0.004)	(0.004)	(0.003)	(0.001)
N	7424	8327	17238	20926
Log-likelihood	-397.595	-344.357	-836.61	-726.397

Dependent variable is the log of the hazard function. Columns 1 and 2 report results for college graduates while columns 3 and 4 report results for high school graduates. All regressions include region dummies. Standard errors clustered by birth year. Significance levels: $*$: 10% $**$: 5% $***$: 1%

Table 7: College Graduates: Probability of Complex Job Change

Variable	National 1 OLS	National 2 IV	Regional 3 OLS	Regional 4 IV
$u_{0,i}$	-0.531***	-1.373*	-0.469***	-0.536**
	(0.084)	(0.741)	(0.079)	(0.223)
Pot. Exp $*u_{0,i}$	0.008***	0.027	0.006***	0.013
	(0.001)	(0.016)	(0.001)	(0.010)
u_t	-0.307***	-0.226***	-0.286***	-0.235***
	(0.086)	(0.080)	(0.078)	(0.071)
AFQT	-0.015***	-0.015***	-0.016***	-0.016***
	(0.003)	(0.003)	(0.003)	(0.003)
Potential Experience	-0.188***	-0.322**	-0.170***	-0.224**
	(0.030)	(0.131)	(0.026)	(0.087)
Potential Experience^2	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
F-stat (1st stage: $u_{0,i}$)	-	26.91	-	26.88
F-stat (1st stage: Pot. Exp $*u_{0,i}$)	-	923.54	-	752.35
N	22109	22109	22053	22053

Dependent variable is the probability of a complex job change. IV first stage regression includes the unemployment rate at age 22, and the unemployment rate at 22*potential experience. Sample limited to white male college graduates. Columns 1 and 2 look at the effect of the national unemployment rate at entry while columns 3 and 4 look at the effect of regional unemployment rates at the time of entry. Coefficients reported in terms of percentage points. All regressions include region dummies. Robust standard errors are reported and all standard errors are clustered by birth year. "F-stat (1st stage: $u_{0,i}$)" refers to the F-test associated with equation (2) while "F-stat (1st stage: Pot. Exp $*u_{0,i}$)" refers to the F-test associated with equation (3). Significance levels: $*$: 10% $**$: 5% $***$: 1%

Table 8: College Graduates: Probability of Simple Job Change

Variable	National 1 OLS	National 2 IV	Regional 3 OLS	Regional 4 IV
$u_{0,i}$	-0.167	-0.266	-0.201**	-0.173
	(0.099)	(0.168)	(0.083)	(0.137)
Pot. Exp $*u_{0,i}$	0.000	0.009	0.002	0.010*
	(0.002)	(0.008)	(0.002)	(0.005)
u_t	-0.102	-0.112**	-0.113**	-0.125***
	(0.066)	(0.051)	(0.036)	(0.033)
AFQT	0.003	0.000	0.003	-0.002
	(0.002)	(0.006)	(0.003)	(0.005)
Potential Experience	-0.009	-0.075	- 0.025	-0.082**
	(0.017)	(0.054)	(0.015)	(0.037)
Potential Experience^2	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
F-stat (1st stage: $u_{0,i}$)	-	26.91	-	26.88
F-stat (1st stage: Pot. Exp $*u_{0,i}$)	-	923.54	-	752.35
N	22109	22109	22053	22053

Dependent variable is the probability of a simple job change. IV first stage regression includes the unemployment rate at age 22, and the unemployment rate at 22*potential experience. Sample limited to white male college graduates. Columns 1 and 2 look at the effect of the national unemployment rate at entry while columns 3 and 4 look at the effect of regional unemployment rates at the time of entry. Coefficients reported in terms of percentage points. All regressions include region dummies. Robust standard errors are reported and all standard errors are clustered by birth year. "F-stat (1st stage: $u_{0,i}$)" refers to the F-test associated with equation (2) while "F-stat (1st stage: Pot. Exp $*u_{0,i}$)" refers to the F-test associated with equation (3). Significance levels: $*$: 10% $**$: 5% $***$: 1%

Table 9: High School: Probability of a Complex Job Change

Variable	National		Regional	
	1	2	3	4
	OLS	IV	OLS	IV
$u_{0,i}$	-0.125***	-0.095**	-0.118*	-0.205**
	(0.016)	(0.038)	(0.045)	(0.088)
Pot. Exp $*u_{0,i}$	0.001	-0.001***	0.001	0.001
	(0.001)	(0.000)	(0.001)	(0.001)
u_t	-0.392**	-0.397***	-0.281***	-0.409***
	(0.088)	(0.083)	(0.030)	(0.085)
AFQT	-0.007**	-0.008***	-0.007**	-0.008***
	(0.003)	(0.002)	(0.003)	(0.003)
Potential Experience	-0.022**	-0.006*	-0.015	-0.02***
	(0.007)	(0.003)	(0.013)	(0.009)
Potential Experience^2	1e-04*	2e-04**	2e-04*	1e-04***
	(5e-05)	(5e-05)	(8e-05)	(3e-05)
F-stat (1st stage: $u_{0,i}$)	-	59.44	-	72.63
F-stat (1st stage: Pot. Exp $*u_{0,i}$)	-	961.06	-	1072.48
N	42065	42065	41402	41402

Dependent variable is the probability of a complex job change. IV first stage regression includes the unemployment rate at age 18, and the unemployment rate at 18*potential experience. Sample limited to white male high school graduates. Columns 1 and 2 look at the effect of the national unemployment rate at entry while columns 3 and 4 look at the effect of regional unemployment rates at the time of entry. All regressions include region dummies. Robust standard errors are reported and all standard errors are clustered by birth year. "F-stat (1st stage: $u_{0,i}$)" refers to the F-test associated with equation (2) while "F-stat (1st stage: Pot. Exp $*u_{0,i}$)" refers to the F-test associated with equation (3). Significance levels: $*$: 10% $**$: 5% $***$: 1%

Table 10: High School: Probability of a Simple Job Change

Variable	National		Regional	
	1	2	3	4
	OLS	IV	OLS	IV
$u_{0,i}$	-0.075	-0.072**	-0.068	-0.096*
	(0.069)	(0.034)	(0.060)	(0.057)
Pot. Exp $*u_{0,i}$	0.000	0.001	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
u_t	-0.194**	-0.192***	-0.166**	-0.196***
	(0.050)	(0.044)	(0.044)	(0.045)
AFQT	-0.001	-0.001	-0.001	-0.001
	(0.003)	(0.003)	(0.003)	(0.003)
Potential Experience	0.011	0.009	0.014	0.008
	(0.015)	(0.010)	(0.014)	(0.009)
Potential Experience^2	2e-04**	2e-04***	2e-04**	2e-04***
	(6e-05)	(4e-05)	(6e-05)	(4e-05)
F-stat (1st stage: $u_{0,i}$)	-	59.44	-	72.63
F-stat (1st stage: Pot. Exp $*u_{0,i}$)	-	961.06	-	1072.48
N	42065	42065	41402	41402

Dependent variable is the probability of a simple job change. IV first stage regression includes the unemployment rate at age 18, and the unemployment rate at 18*potential experience. Sample limited to white male high school graduates. Columns 1 and 2 look at the effect of the national unemployment rate at entry while columns 3 and 4 look at the effect of regional unemployment rates at the time of entry. All regressions include region dummies. Robust standard errors are reported and all standard errors are clustered by birth year. "F-stat (1st stage: $u_{0,i}$)" refers to the F-test associated with equation (2) while "F-stat (1st stage: Pot. Exp $*u_{0,i}$)" refers to the F-test associated with equation (3). Significance levels: $*$: 10% $**$: 5% $***$: 1%

Table 11: Parameter Space: Fixed

Variable	Value	Description	Source/Target
T	160	40 years of working Life	-
β	0.987	Discount Factor	5% interest rate
b	0.4	Unemployment Compensation	Shimer(2005)
K	10	Number of Sectors	-
ζ	0.25	Experience Gain	1 year of experience
$\bar{a}$	1	Mean of Idiosyncratic Shock	-
σ_a	0.1	Variance of Idiosyncratic Shock	Hagedorn & Manovskii(2013)
α	0.67	Labor share	-
$\bar{\mu}$	1	Unconditional Mean of Aptitude	-
$\bar{z}$	1	Mean of Aggregate Shock	-
ρ_z	0.92	Persistence of Aggregate Shock	JOLTS data

Table 12: Parameter Space: Calibrated

Variable	Value	Data target	Model Generated
δ	0.01	mean EU: 0.048	0.043
λ^e	0.37	mean EE: 0.055	0.072
κ	17	mean UE: 0.532	0.538
σ_μ	2.06	mean Complex EE: 0.032	0.029
σ_z	0.13	σ_θ: 0.274	0.279

Note: calibrated values are determined jointly in the model.

Table 13: Survival Probability: Simulated Data

Variable	Complex	Simple
Recession	-0.320***	-0.054***
	(0.006)	(0.007)
Log-likelihood	-144231	-106140

Dependent variable in Column 1 is the survival probability of not ever doing a complex job change while the dependent variable in Column 2 is the survival probability of not ever doing a simple job change. Entering in a recession is associated with a 5 percentage point increase in the unemployment rate. Significance levels: $*$: 10% $**$: 5% $***$: 1%

Table 14: Example: Worker's True Aptitudes and Initial Priors

Sector	μ_i	$\hat{\mu}_{i0}$
1	2.27	0.84
2	1.05	1.64
3	0.40	0.11
4	0.31	0.01
5	1.28	0.56
6	0.09	1.32
7	1.56	0.27
8	0.12	0.69
9	0.02	0.47
10	0.73	0.03

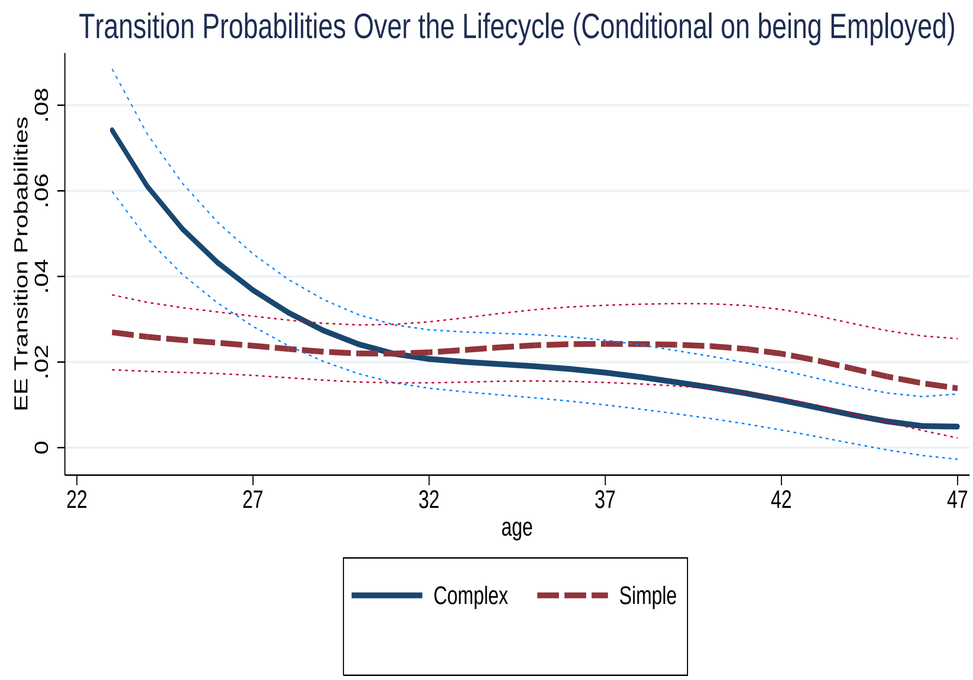

Figure 1: EE transitions over the Life-Cycle (College Grads)

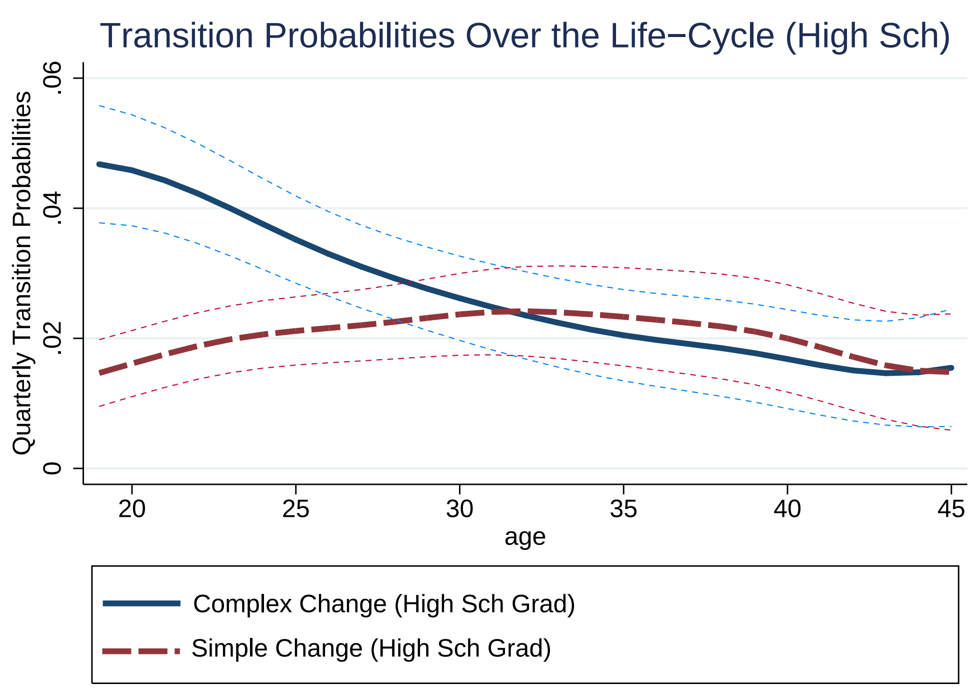

Figure 2: EE transitions over the Life-Cycle (High School Grads)

Figure 3: Unemployment lags the recovery in GDP

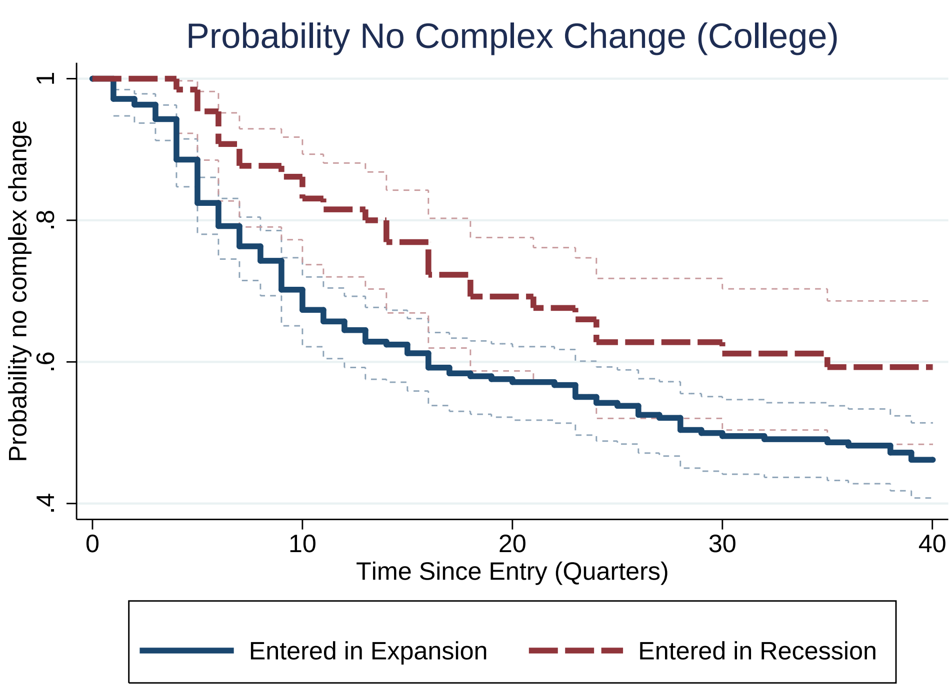

Figure 4: Probability No Complex Change Undertaken (College Graduates)

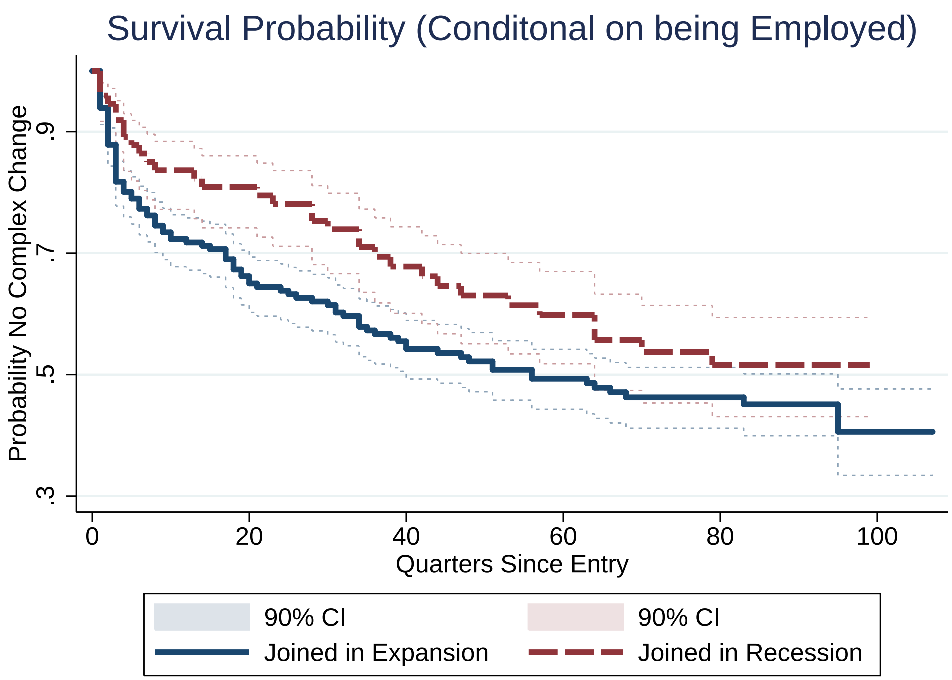

Figure 5: Probability No Complex Change Undertaken Conditional on Being Employed (College Graduates)

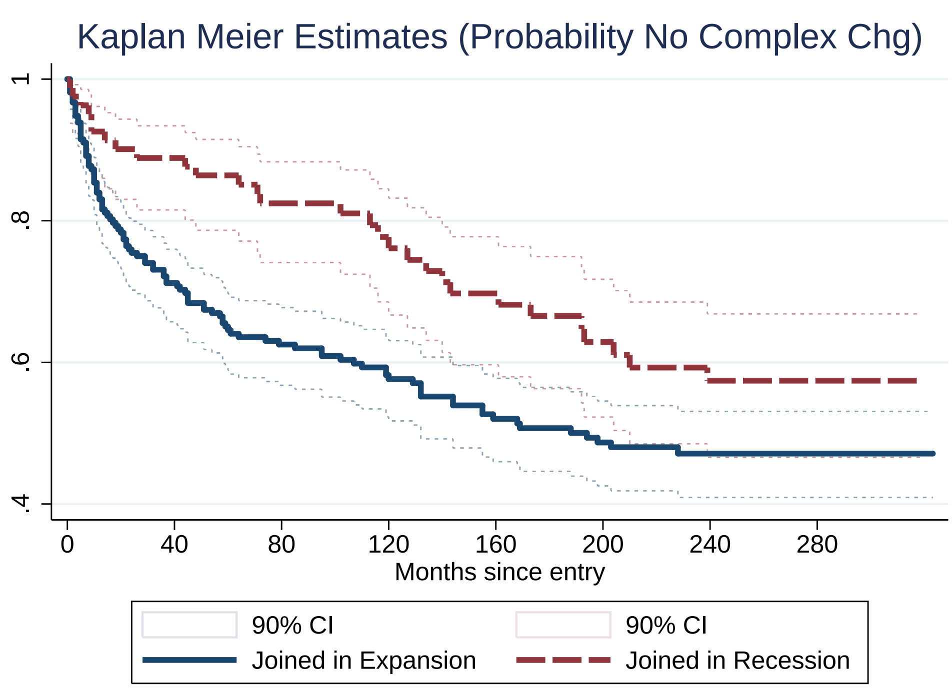

Figure 6: Probability No Complex Change Undertaken Conditional on Being Employed (College Graduates, Monthly)

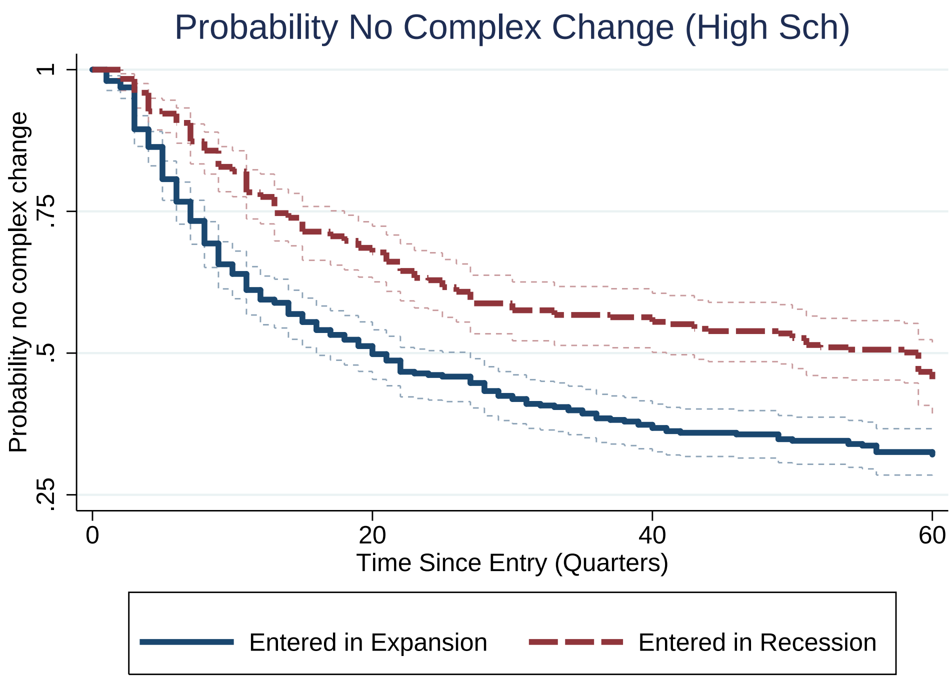

Figure 7: Probability No Complex Change Undertaken (High School Graduates)

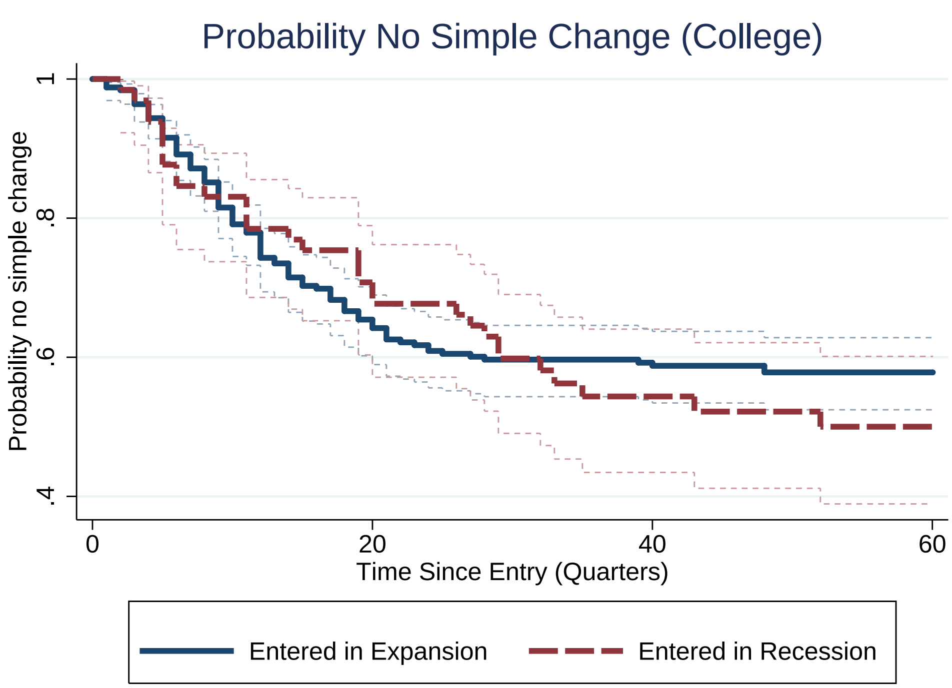

Figure 8: Probability No Simple Change Undertaken (College Graduates)

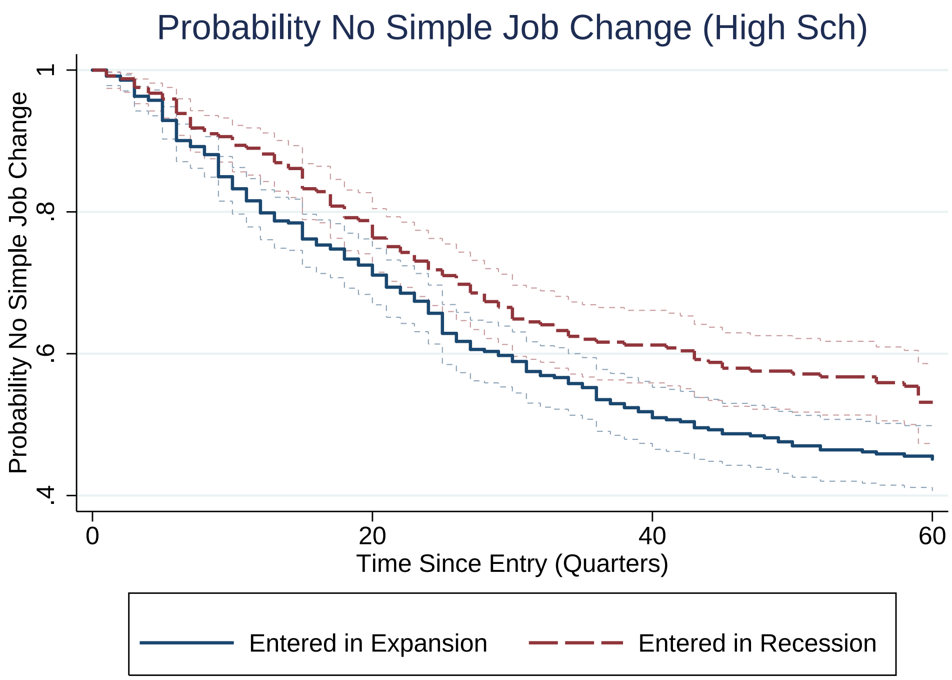

Figure 9: Probability No Simple Change Undertaken (High School Graduates)

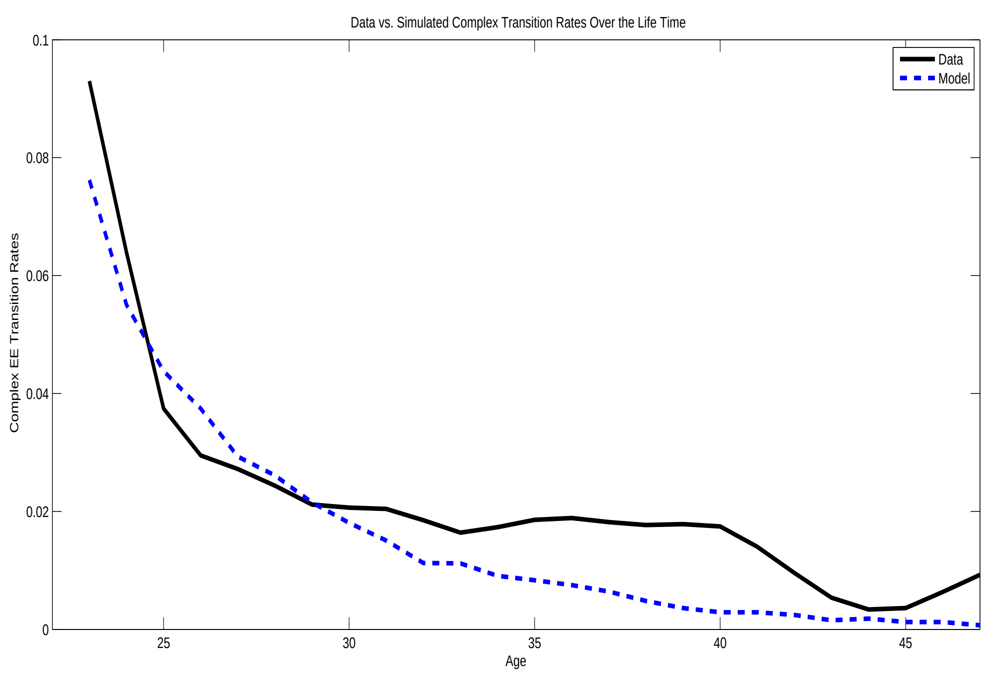

Figure 10: Data vs. Model Simulated Lifecycle Complex EE transition rates

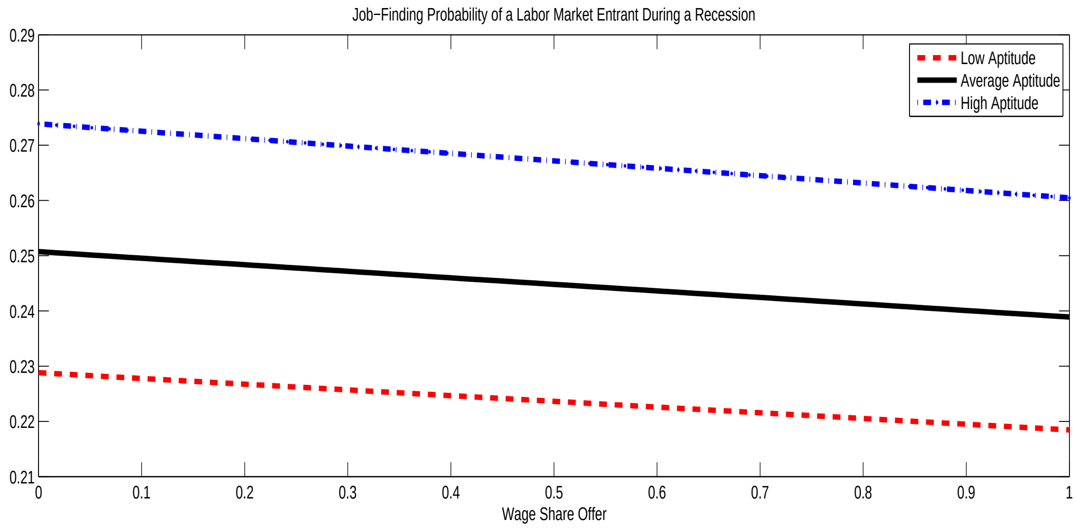

Figure 11: Job Finding Probability Rises with Aptitude

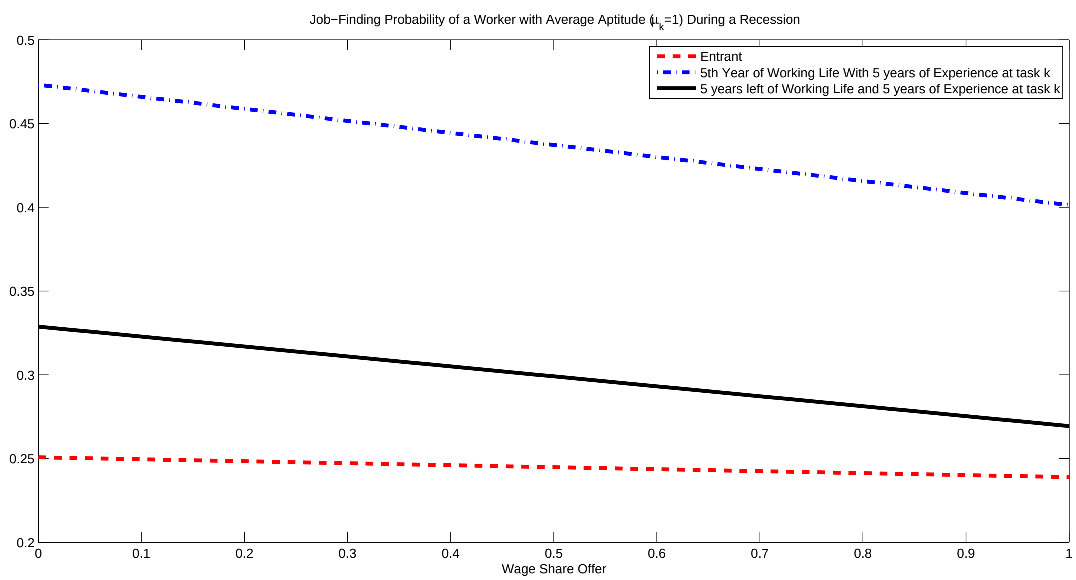

Figure 12: Job Finding Probability Rises with Experience, Declines with Age

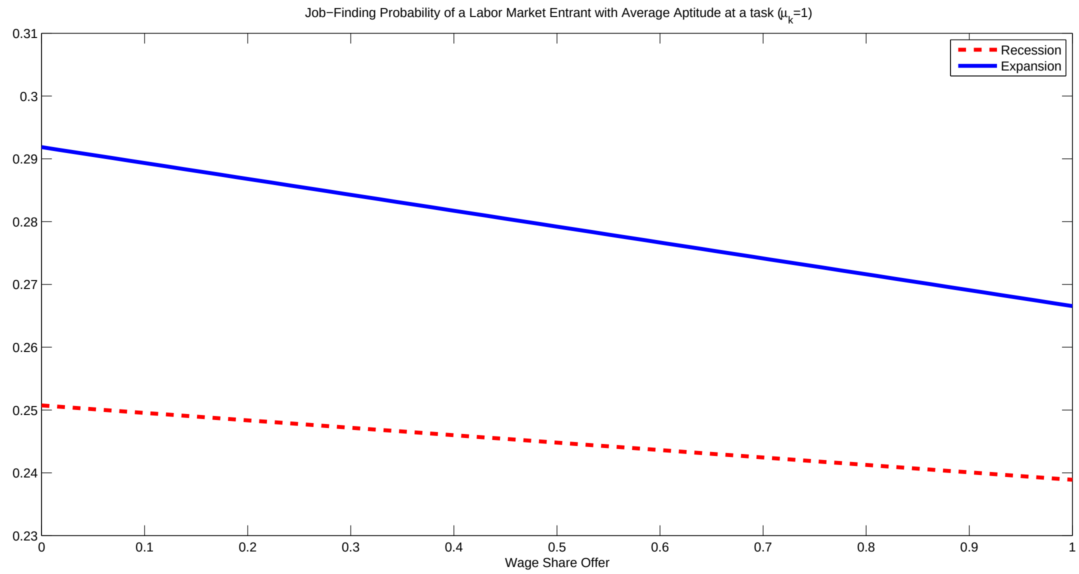

Figure 13: Job Finding Probability Drops in Recessions

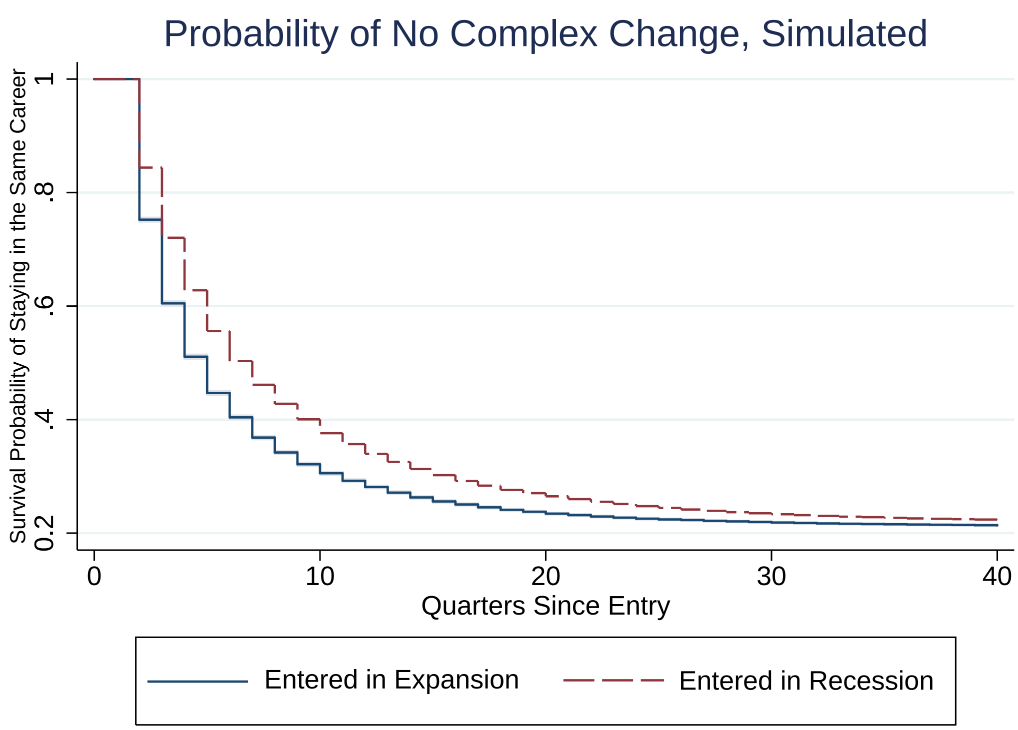

Figure 14: Simulated Survival Probabilities of Staying in the Same Career

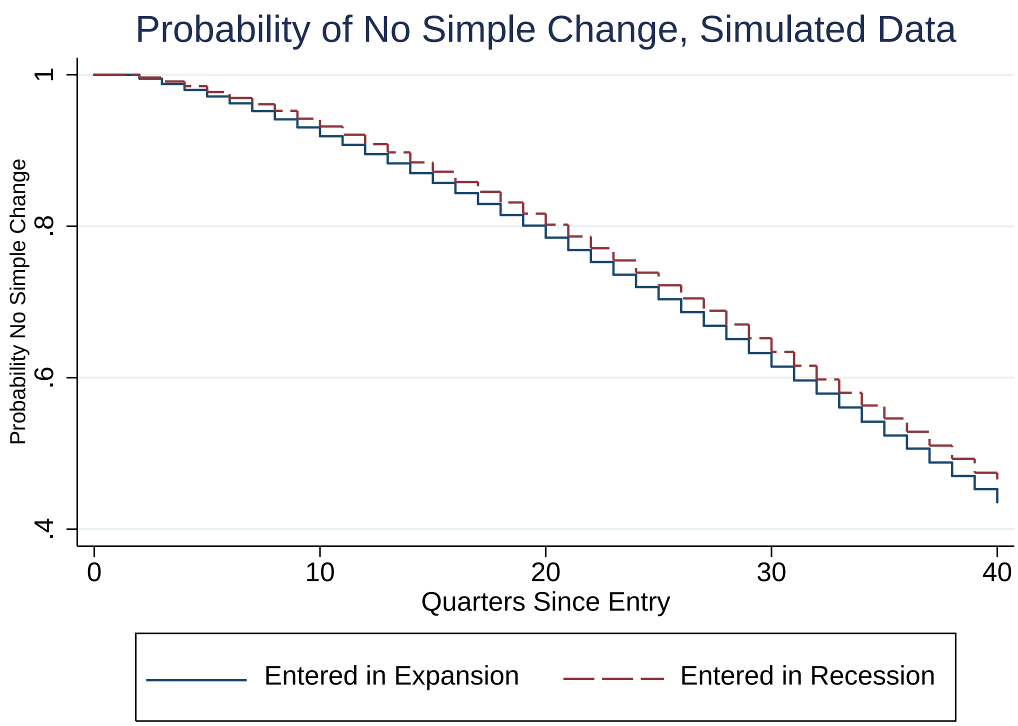

Figure 15: Simulated Survival Probability of Not Ever Doing a Simple Job Change

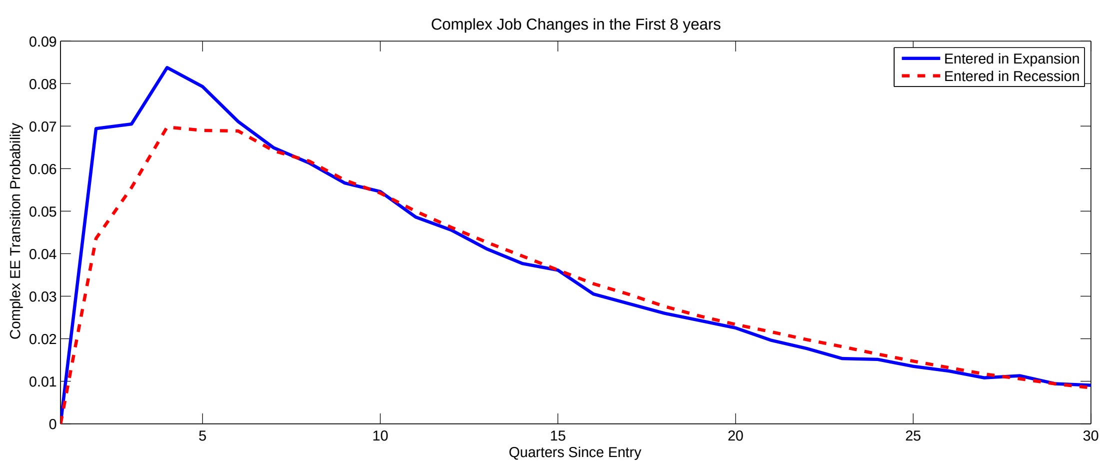

Figure 16: Differences in Complex EE between Recession and Boom

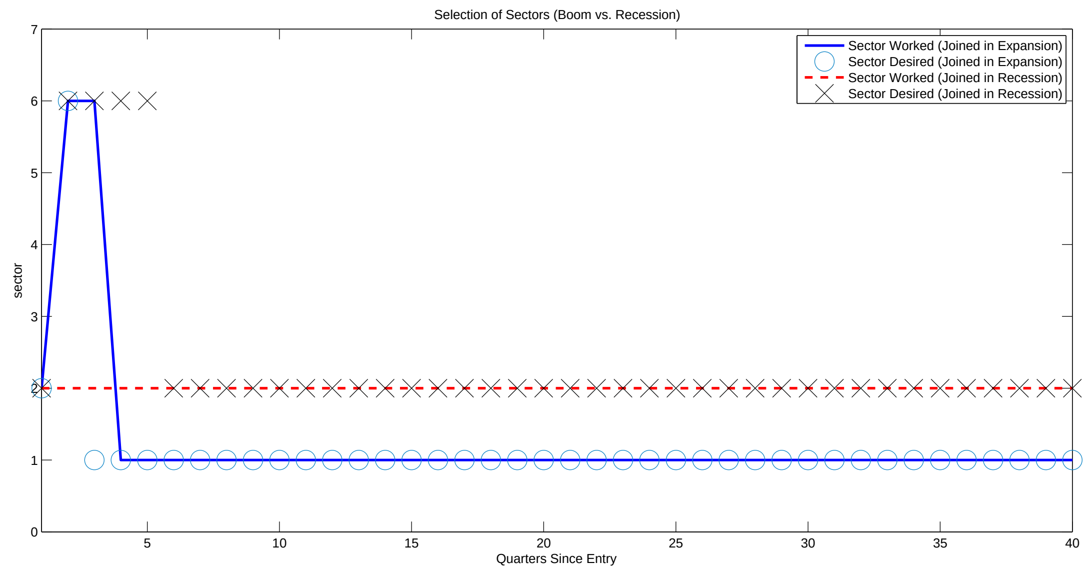

Figure 17: Example of Sector 'Lock-in'

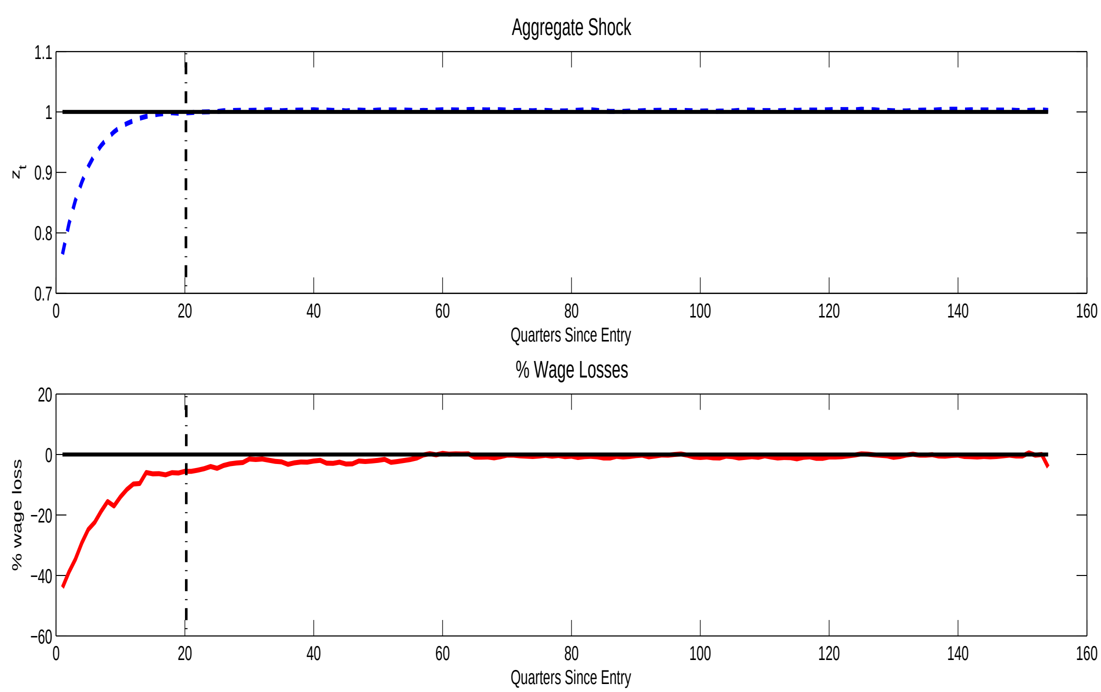

Figure 18: Wage Loss between Entering in Booms vs. Recessions

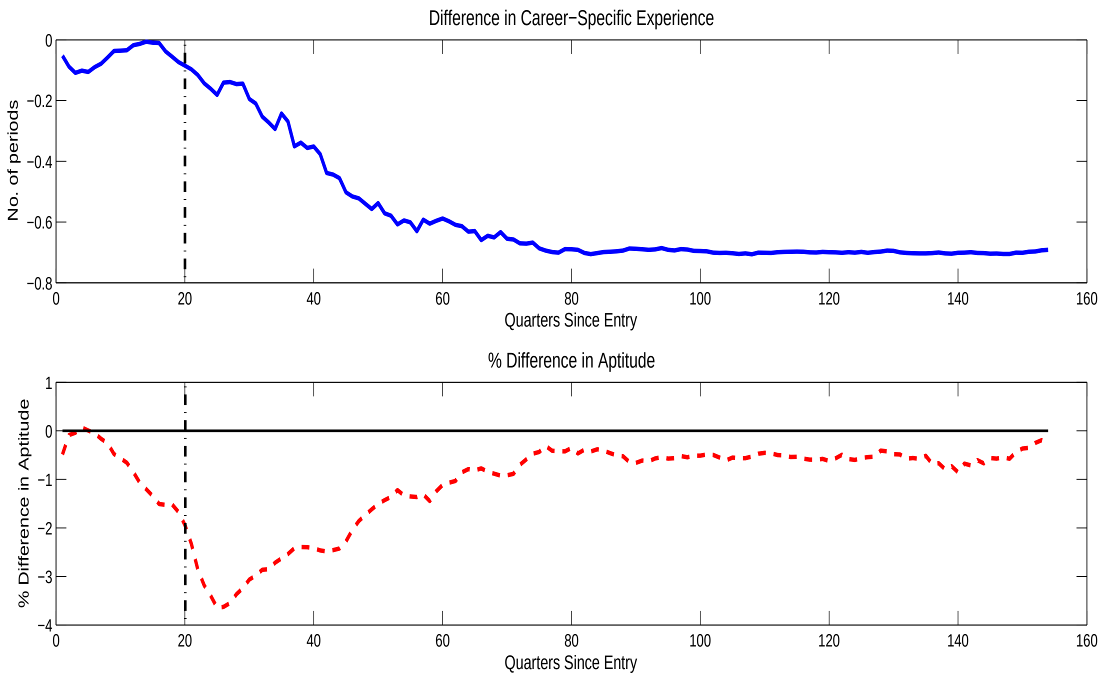

Figure 19: Differences in Levels of Experience and Aptitude at Current Job

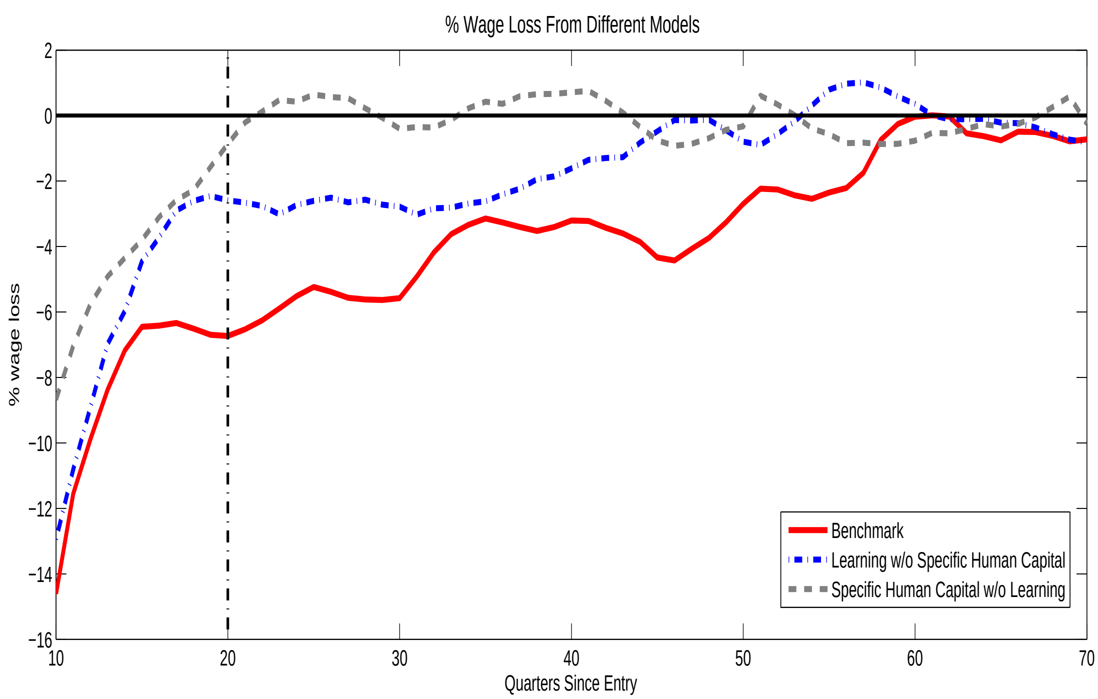

Figure 20: Percentage Wage Losses in Different Model Specifications

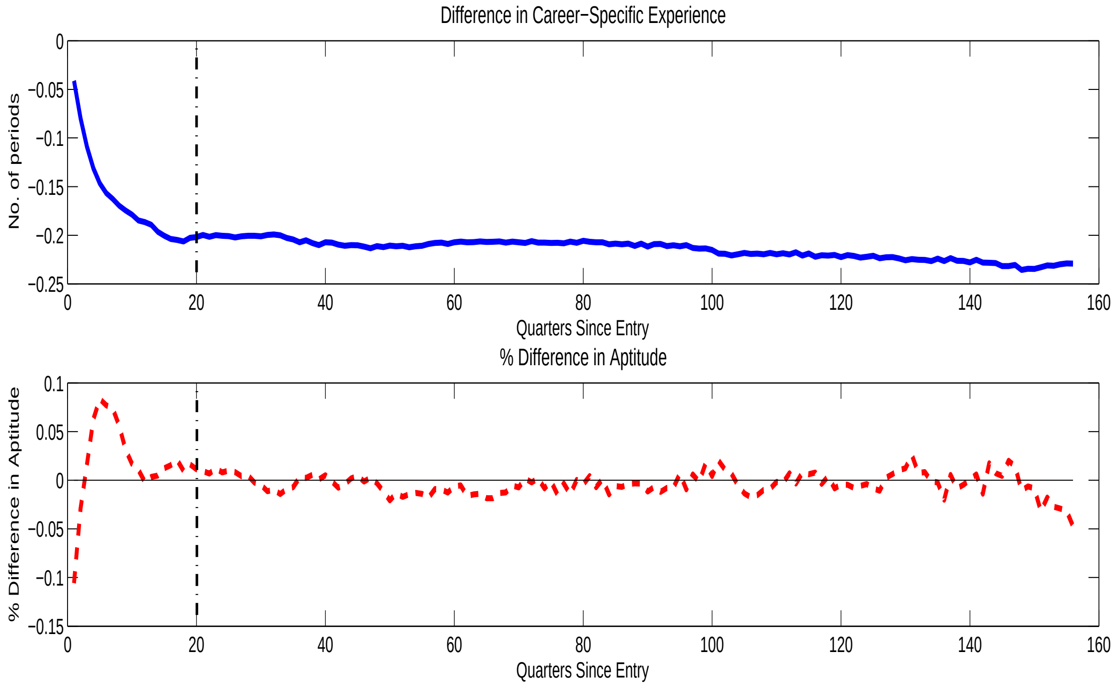

Figure 21: Differences in Levels of Experience and Aptitude at Current Job (No Learning)

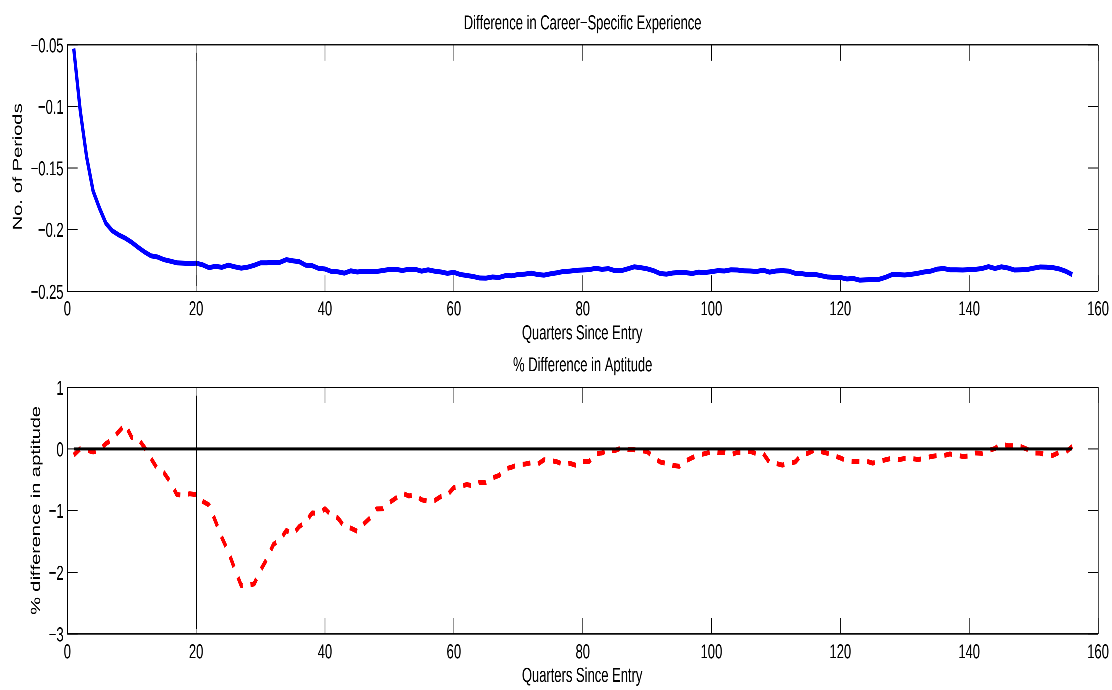

Figure 22: Differences in Levels of Experience and Aptitude at Current Job (No Specific Human Capital)

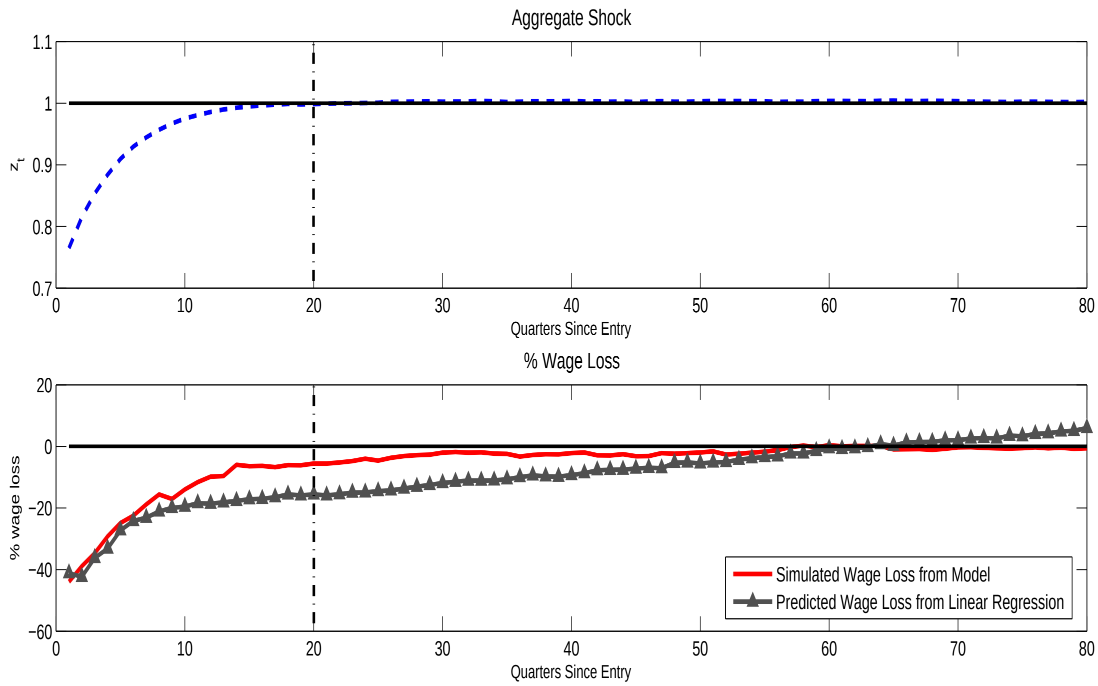

Figure 23: Percentage Wage Losses in Simulated Data and Linear Regression Model

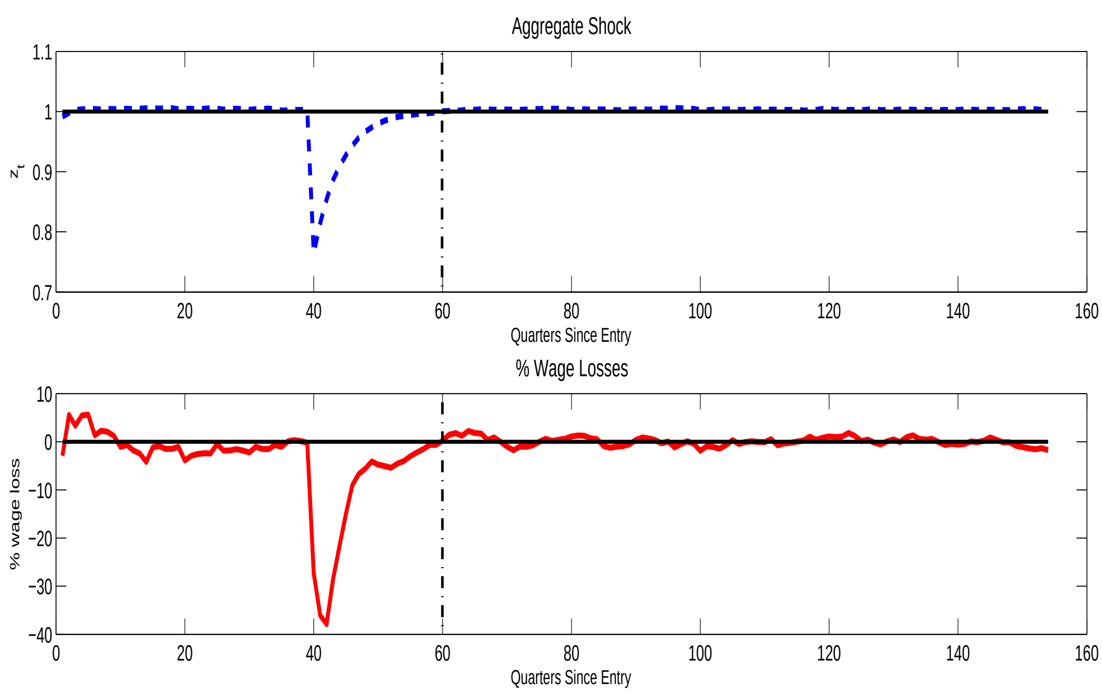

Figure 24: Wage Loss for Mature Workers in Booms vs. Recessions