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 new facts on 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. I then build a dynamic stochastic general equilibrium model with search and matching frictions to decompose how the effects on early career mobility can impact future wage growth. In particular, I show that 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. In the model, a wage gap of 5% continues to persist post-recession and only fades completely 40 quarters after entry into the labor market.

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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

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[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.

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 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 macro dynamic stochastic general equilibrium model with search and matching frictions. The model 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 calibrate the model to moments observed in the NLSY79 data and decompose the forces that drive tepid wage recoveries. I show that diminished opportunities to switch careers early 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 5 percent continues to persist even after the recessionary shock has dissipated and only fades completely 40 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

[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.

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 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.

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.

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.

[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.

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 job changes 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 allows for on-the-job search and shows how wage outcomes exhibit history dependence. 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. While firms can offer a new wage each period, the retention probability of a worker depends on both his current amount of perceived human capital and the firm's wage offer. A firm must offer a high wage to retain a worker with high effective labor input. Entering the job market during a recession however, slows down the worker's sorting into his "correct" career as well as his accumulation of relevant human capital.

A closely 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.[6]

I restrict my focus to white male college graduates. Appendix A documents the steps taken to derive the sample of white male college graduates with four year college degrees. This sample consists of 433 individuals and 24350 quarterly observations.Throughout this paper I will focus on the results for college graduates although I also find similar results for high school graduates.[7]

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.

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

[6]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.

[7]Results on high school graduates is available upon request

quarterly employment-to-employment (EE) transitions.[8] The median unemployment duration is about 3.2 months in the data. As such, focusing on the quarterly frequency enables me to capture any short-term employment to non-employment to employment (ENE) job changes that are voluntary in nature. Limiting the focus to quarterly 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.

3.1 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. Focusing on the type of job search the individual undertakes over his working life and how this changes with the business cycle, I distinguish between the types of job search using the framework as given in Pavan (2011) and Neal (1999). Firstly, I focus on job changes which involve an employer change, i.e. I focus on between-job transitions rather than on within-job transitions. A within-job transition is observed whenever the individual undergoes a change in occupation or industry 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. Hence, the focus is limited to EE transitions that involve a change of employer.

These EE transitions are further decomposed into between-career changes and within-career changes. 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 changes employers but not both occupation and industry 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

[8] Results continue to hold at the monthly frequency.

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.[9]

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.

3.2 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 **??** 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 onward. Hence, I find evidence supportive of the two stage job-search strategies suggested by Neal (1999).

[INSERT FIGURE 1 HERE]

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 for individuals with some college. To examine the importance of career-specific experience, Table (8) shows how wages change

[9] See Appendix A for details on how complex and simple job changes are coded.

with career-specific human capital and job changes. Focusing on white male college graduates, I find that ten years of career-specific experience raises log wages by 0.32 points. Importantly, complex job changes entail a wage loss on impact. Log wages decline by about 0.1 points at the time of a complex job change. This suggests that complex job changes which by nature involve large lateral jumps in terms of human capital are costly. The positive coefficient on the interaction of complex job changes with potential experience however indicates that complex job changes while costly in the beginning are beneficial in the end since there is significant catch-up in wages over time. Wages catch up six years after a complex job change and continue to grow faster than if the individual did no complex job change. In contrast, simple job changes have no significant effect on wages on impact. This suggests that human capital is largely transferable under simple job changes. Given the costly nature of between-career changes, complex job changes should optimally decline as individuals age, as individuals would lose out on accumulating career-specific human capital essential to later wage growth.

[INSERT TABLE 1 HERE]

3.3 Results on Initial Job Mobility

A more interesting question is how these job search strategies may be affected by initial conditions. A complication that arises when examining how career changes are affected by initial conditions 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. Then I follow the set-up in Kahn (2010) and examine how the unemployment rate at entry affects the probability of conducting a complex (simple) job change over the individual's lifetime. In her paper, Kahn looks at how the unemployment rate at entry affects log hourly wages for white male college graduates. To account for selection effects and the endogenous timing of labor market entry, she instruments for the unemployment rate at entry with the unemployment rate at the modal age of graduation. Using the same set-up but replacing the dependent variable with the mobility indicator, the main regression takes the form of equation (1):

$$Mob_{it}^{c} = \gamma_0 + \gamma_1 u_{0,i} + \gamma_2 u_{0,i} * Pot.Exp_{it} + \zeta X_{it} + \nu_{ist} \tag{1}$$

where Mob_{it}^{c} 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. $c \in \{Complex, Simple\}$. $u_{0,i}$ 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. In a separate instrumental variables regression (IV), the unemployment rate at entry is instrumented 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. In all regressions, robust standard errors are reported and all standard errors are clustered by birth year cohort.

Table 2 documents the regression results for the probability of conducting a complex job change for college graduates while Table 3 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 2 and 3 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.[10] 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.

[INSERT TABLE 2 and 3 HERE]

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

[10] Results for high school graduates can be found in the Appendix. Notably, high school graduates suffer declines in their probability of conducting both complex and simple job changes when the unemployment rate at entry rises by one percentage point.

working life form precisely the period where individuals concentrate on finding the right career. In contrast, results from Columns 1 and 2 of Table 3 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.

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.

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.

4 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.

4.1 Environment

4.1.1 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. Workers are risk-neutral. There is no savings in the economy and individuals consume all of their wage income. Individuals, therefore, seek to maximize the expected present discounted value of their wage outcomes.

4.1.2 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 $\Sigma_\mu = I_{K\times K} \times \sigma_\mu^2$.

Each job in a career 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 careers 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 careers.

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:

$$h_{ik} = \mu_{ik} exp(y_{ik}) \tag{4}$$

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.

4.1.3 Production Technology

There are K number of careers in the economy. A 'career' is defined by the single task it uses for production, implying an equal number of tasks as careers. There exists an infinite number of idle firms in each career. 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 career 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 career 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 career k has the following production technology:

$$q_{ijk} = exp(z + a_j)h_{ik}^{\alpha} \tag{5}$$

where q_{ijk} refers to the output of a firm-worker pair $\{j, i\}$ at task k.[11] 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 normal 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.

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

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.

4.1.4 Labor Market

Idle firms in a career 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 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 career 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 current levels of perceived innate aptitude and experience that a firm requires of a worker respectively.[12] 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.

Since 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

[12] 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.

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 which 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 career k. Thus, $u_\tau(\mu_k, y_k)$ refers only to the unemployed searching in a particular career 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 are searching in a particular career k in a sub-market which requires $\{\mu_k, y_k, \tau\}$ characteristics of a worker. Because searching for a job is costless, all individuals regardless of employment status will always search for a job each period. For each sub-market, we can calculate and distinguish the number of unemployed and employed who apply to that market.

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

4.2 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 $s = \{\hat{\mu}_i, y_i, z\}$. Both workers and firms also know the distribution of employed and unemployed workers each period, φ. Hence, currently employed workers begin the period with $\{s, \omega, \varphi\}$.

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 career k that chooses to recruit a worker has to decide which sub-market, (x_k, μ_k, y_k, τ), to post a vacancy. 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 career. Intuitively, workers base their career search decisions on the expected life-time wage earnings they can derive from working in a particular career. 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. With free entry and as all recruiting firms are ex-ante homogeneous, the trade-off in hiring probabilities and expected profit makes them indifferent in posting in any market.

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, their new wage share offer ω and the aggregate distribution of workers, 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 $d(\omega, s, \varphi) \in \{\delta, 1\}$. If a worker parts with a firm in this second sub-stage, he must wait one period before he can search for a new job. Hence, all separations in the second sub-stage give us employment to unemployment (EU) transitions.

In the third sub-stage (Search and Matching), a worker (either unemployed since the beginning of the period or employed) chooses which sub-market, (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 have the opportunity to search the labor market for jobs in each period with probability λ^u which for simplicity will be normalized to 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 $\lambda^e \leq 1$.

When a vacancy and a worker meet in sub-market $\{x_k, \mu_k, y_k, \tau\}$, the firm always rejects any worker whose age, experience and perceived innate aptitude differ from the specified levels $\{\mu_k, y_k, \tau\}$. 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 career, and then chooses which career to search for a job. A worker finds a job in career k in sub-market $\{x_k, \mu_k, y_k, \tau\}$ 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 (5).

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 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.

4.3 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.

4.3.1 Unemployed Worker

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

$$U_\tau(s, \varphi) = \max\{R_1^{u*}(s, \varphi), R_2^{u*}(s, \varphi), \ldots, R_K^{u*}(s, \varphi)\} \tag{6}$$

s.t.

$$\begin{aligned} R_k^u(s,\varphi) &= \max_{x_k} p\big(\theta_\tau(x_k,\mu_k,y_k,z,\varphi)\big)\Big[Ex_k q_{ijk} + \beta EV_{\tau+1}(x_k',s',\varphi')\Big] \\ &+ \big(1-p(\theta_\tau(x_k,\mu_k,y_k,z,\varphi))\big)\Big[b+\beta EU_{\tau+1}(s',\varphi')\Big] \end{aligned} \tag{7}$$

where $R_k^{u*}(s,\varphi)$ represents the optimized search problem for each career 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 each career to search for a job. From equation (7), an unemployed individual maximizes his search problem in a career k by choosing the optimal wage share x_k from the menu of contracts posted. The first line in equation (7) 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 (7) 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 (7) is $x_k^u = \underset{x_k}{\operatorname{argmax}}\, R_k^u(s,\varphi)$ which is implicitly given by equation (8):

$$p_x(\theta_\tau)\Big[Ex_k q_{ijk} + \beta EV_{\tau+1}(x_k',s',\varphi') - b - \beta EU_{\tau+1}(s',\varphi')\Big] + p(\theta_\tau)Eq_{ijk} = 0 \tag{8}$$

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 (8) therefore refers to the expected marginal cost of seeking a job that offers a higher wage share. The second term in equation (8) 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 (8), 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 $R_k^{*u}(s,\varphi)$ would provide him the greatest benefit from search. This is given by equation (6).

4.3.2 Employed Workers

Employed workers enter the period with updated beliefs on their aptitude μ_i, observe $\{z, \varphi\}$, 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, φ). Employed workers solve the following discrete choice problem:

$$V_\tau(\omega, s, \varphi) = \max\{R_1^{e*}(\omega, s, \varphi), R_2^{e*}(\omega, s, \varphi), \ldots, R_K^{e*}(\omega, s, \varphi)\} \tag{9}$$

where

$$\begin{aligned} R_k^e(\omega, s, \varphi) &= \max_{x_k} d(\omega, s, \varphi)\Big[b + \beta E U_{\tau+1}(s', \varphi')\Big] \\ &+ (1 - d(\omega, s, \varphi))\Big\{\big(1 - \lambda^e p(\theta_\tau(x_k, \mu_k, y_k, z, \varphi))\big)\Big[E\omega q_{ijl} + \beta E V_{\tau+1}(\omega', s', \varphi')\Big] \\ &+ \lambda^e p(\theta_\tau(x_k, \mu_k, y_k, z, \varphi))\Big[E x_k q_{ijk} + \beta E V_{\tau+1}(x_k', s', \varphi')\Big]\Big\} \end{aligned} \tag{10}$$

and

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

$R_k^{e*}(\omega, s, \varphi)$ for $k \geq 1$ represents the optimized search problem for each career. Equation (10) highlights the search problem of an employed worker within a career. 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. $Ex_k q_{ijk}$ in equation (10) refers to the expected current wage the worker receives if he finds a job in the career k while $E\omega q_{ijl}$ refers to the expected wage the worker receives if he remains in his current job in career l. Note that l can be equivalent to k if the worker chooses to search within the same career 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 career before deciding which career provides them the maximal benefit from search. The employed worker's problem differs from the unemployed individual's problem in two key areas. Firstly, the employed individual faces some probability,d of being separated from his current job. This probability depends on the worker's current wage share offer, his perceived characteristics and the aggregate state of the economy. For expositional purposes, I will refer to the separation probability as d although it should be clear that d is an endogenous object that depends on state variables. Secondly, an employed worker only has the opportunity to search for new jobs with probability $\lambda^e \leq 1$.

The first line in equation (10) refers to the scenario where an employed worker is separated from his job and becomes unemployed. With probability d, 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 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 $(1-d)$, the worker does not separate from the firm. In this case, the second line of equation (10) 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 $(1-d)(1-\lambda^e p(\theta_\tau))$, the worker is unable to find an alternative job and he instead enjoys current expected utility $E\omega q_{ijl}$ and continuation utility $V_{\tau+1}(\omega', s', \varphi')$. With probability $(1-d)\lambda^e p(\theta_\tau)$, the worker is successful in finding an alternate job that pays current wage share x_k and with continuation utility $V_{\tau+1}(x'_k, s', \varphi')$. Similar to the unemployed worker's problem, the policy function associated with equation (10) is given by $x_k^e = \underset{x_k}{\operatorname{argmax}} R_k^e(\omega, s, \varphi)$ which is implicitly given by equation (11).

$$(1-d)\Big\{\lambda^e p_x(\theta_\tau)\Big[Ex_k q_{ijk} + \beta EV_{\tau+1}(x'_k, s', \varphi') - E\omega q_{ijl} - \beta EV_{\tau+1}(\omega', s', \varphi')\Big] + \lambda^e p(\theta_\tau) Eq_{ijk}\Big\} = 0 \tag{11}$$

4.3.3 Operating Firms

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

$$J_\tau(s,\varphi) \quad = \quad \max_{\omega} \Big((1-d(\omega,s,\varphi))(1-\lambda^e p^*(\theta_\tau))\big[(1-\omega)Eq_{ijl} + \beta EJ_{\tau+1}(s',\varphi')\big]\Big) \tag{12}$$

s.t.

$$d(\omega,s,\varphi) = \begin{cases} 1 & \text{if } b + U_{\tau+1}(s'.,\varphi') > V_\tau(\omega,s,\varphi), \\ \delta & \text{else.} \end{cases} \tag{13}$$

and

$$x^* = x(\omega) \tag{14}$$

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 sub-market and career 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 thus takes into account the worker's probability of contacting

an alternate offer $\lambda^e p^*(\theta_\tau)$ 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 (13) 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 $d = 1$. With probability $(1-d)(1-\lambda^e p^*(\theta_\tau))$, the worker stays with the firm and the firm receives current and future expected profits of $\big((1-\omega)Eq_{ijl} + \beta E J_{\tau+1}(s', \varphi')\big)$. Denote $\omega_\tau^c(s)$ as the critical wage share below which the worker will choose not to voluntarily separate from the firm, which satisfies:

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

Then for any wage above ω^c, we can use the fact that $d(\omega, s, \varphi) = \delta$, the exogenous rate of separation. Taking first-order conditions with respect to equation (12), one can solve for the firm's optimal choice of wage share to offer the worker. Equation (15) 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:

$$(1-\lambda^e p^*(\theta_\tau))Eq_{ijl} = -\lambda^e p_x^*(\theta_\tau)\frac{\partial x_k}{\partial \omega}\Big[(1-\omega)Eq_{ijl} + \beta E J_{\tau+1}(s', \varphi')\Big] \tag{15}$$

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.

4.3.4 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:

$$\kappa \geq f(\theta_\tau(x_k, \mu_k, y_k, z, \varphi))\Big((1 - x_k)Eq_{ijk} + \beta E J_{\tau+1}(s', \varphi')\Big) \tag{16}$$

and $\theta_\tau \geq 0$ with complementary slackness. Equation (16) provides us with the firm's optimal job creation policy. For any sub-market that is active with $\theta_\tau > 0$, equation (16) holds with equality and firms post vacancies in a sub-market 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 sub-market. 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).

4.4 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, $\{\omega, d\}$, 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 are all independent of φ.

2 θ_τ satisfies equation (16) 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 (6) 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 (9) for all $(x_k, \mu_k, y_k, z, \varphi)$ and for $\tau = 1 \ldots T$.

5 J, ω and d satisfy (12) 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 sub-markets 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 (12), 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.

5 Calibration

Each period in my model is a quarter. Given this frequency, I set $\beta = 0.987$, which is consistent with an annual interest rate of 5%. I set the lifespan of an individual to $T = 120$ quarters, or a working life of 30 years. 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 $N_z = 9$. I assume that the distribution of shocks is centered around the mean of $\bar{z} = 0$. 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. 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 about $\sigma_z = 0.1$. I assume that idiosyncratic productivity shocks follow a lognormal distribution with mean 1 and standard deviation $\sigma_a = 0.093$. 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.[13]

As per the related literature, $p(\theta)$ takes the form of $p(\theta) = \theta(1+\theta^\gamma)^{\frac{1}{\gamma}}$. I set γ to be 0.5. 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 $K = 10$ which acts like an upper bound on the total number of between-career changes an individual undertakes. On average, college graduates undertake about 2 complex job changes. In addition, I assume that the production function exhibits decreasing returns to labor input and set $\alpha = 0.7$.

[INSERT TABLE 4 HERE]

In order to calibrate the key parameters in 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. 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.[14] While this EE transition rate accords well with the values reported in FF(2004), the quarterly EU rate is much lower. However, the reported transition rates in FF(2004) are for all workers, rather than just college graduates.[15] While Nagypal (2007) does not report UE transition rates, Shimer(2012) finds that 32% of all unemployed individuals transition to employment every quarter. Given that the transition probabilities in the NLSY79 dataset generally accords with the monthly transition probabilities found in the CPS 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] I find quarterly volatility by calculating $\sigma_{qtr} = \sigma_{mth} * \sqrt{3}$.
[14] Quarterly transition probabilities were calculated using the following formula: $r_{quarter} = 1 - (1 - r_{month})^3$.
[15] 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).

[INSERT TABLE 5 HERE]

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. To calibrate the contribution of career-specific experience to wage returns, I use my earlier results that ten years of career-specific tenure contributes 0.32 points to log wages. Using simulated wage data from my model and running the same regression, I calibrate the gain in career-specific experience to be $\zeta = 0.014$.

Following Shimer(2005), I assume an income replacement rate of 40% and calibrate the unemployment benefit to be forty percent of average lifetime wages. This gives me $b = 0.2$.

[INSERT TABLE 6 HERE]

Tables 4 and 6 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 2 shows how closely the model replicates the data in terms of matching the life cycle profile of complex job-to-job transitions. While the calibration exercise only targeted average lifetime transition rates rather than the average transition rate at each age, the model predicts similar life-cycle patterns. Similar to the data, the model predicts that the first few years of an individual's life are spent searching for a career. The model also predicts a similar exponential decay in the lifetime path of complex job-to-job transitions.

[INSERT FIGURE 2 HERE]

6 Numerical Simulations

6.1 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 a cohort and simulate the model for $T = 120$ quarters. 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. I then simulate 100 economies of these identical cohorts. For 50 of these economies, I assume that the economy starts in a recession, in which z_0 is three standard deviations below the mean, and for

the other 50 economies, I assume that the economy starts in an expansion, in which z_0 is initially set at its mean. This gives rise to a difference of about 2 percentage points in the unemployment rate for the entering cohorts. This increase in unemployment rate is roughly consistent with the observed increase in unemployment rate in more moderate recessions. Because of the flexibility in wages, a large shock is required to generate moderate unemployment outcomes. To mimic the unemployment rate outcomes of the 1980s and the Great Recession, one would have to impose an even larger aggregate shock to the economy.

Table (7) demonstrates how the probability of complex job changes are affected by initial conditions. In this regression, the probability of a complex job change is regressed against the simulated unemployment rate at entry, u_0, the interaction term of unemployment at entry and years in the labor market, $u_0 * t$, current unemployment rate,u_t, years in the labor market, t, and years in the labor market squared, t^2, as well as underlying aptitude in that career μ_{ik}, career tenure and career-tenure squared. With the exception of the last two variables, this specification is similar to the earlier regression exercises. Because the relevant experience in the model is career-specific experience, I add the last two variables to show how career tenure affects the probability of a complex job change. In addition, t, the number of years in the labor market, acts as the analogue to potential experience. On average, a one percentage point increase in the unemployment rate at entry lowers the probability of a complex job change by 7 percent. This effect takes 36 quarters or 9 years to dissipate. The regression results also demonstrate that accumulation of career-specific experience reduces the probability of a complex job change. A percentage point increase in career-specific experience reduces the probability of a complex job change by 2 per cent.

[INSERT TABLE 7 HERE]

Initial conditions affect the ability to conduct complex job changes over the life-cycle which in turn affect the evolution of wage outcomes. Figure 3 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 27% 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, workers optimally search in markets with lower wage share offers during recessions in order to raise their probability of getting a job.

[INSERT FIGURE 3 HERE]

There is rapid catch-up in wages as the economy recovers. As wages are a share of output, the rapid catch-up

in wages is initially mainly due to the recovery in aggregate productivity. Nonetheless, wage losses continue to persist even after the economy has recovered and there is no difference in aggregate productivity between the twin cohorts. The aggregate shock disappears by about the 24th quarter, 6 years after the initial shock. The wage gap, in contrast, becomes negligible after 40 quarters (10 years) after initial entry.

Wage losses are about 5 per cent by the 24th quarter. At this point in time, the differences in wages is entirely due to their evolution of perceived human capital. Here, the wage losses arise from the fact that individuals are either working in careers where they have comparative disadvantage or they have less relevant experience on average. 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 4 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 4 highlights the percentage difference in the average amounts of career-specific experience between individuals who entered during a recession and those who entered in a boom. In the first few quarters, career-specific experience is initially lower due to the lower job-finding rate of individuals during recessions. Subsequently, however, within the first 24 quarters, 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.

[INSERT FIGURE 4 HERE]

However, individuals who enter in a boom are quicker to find careers that match their comparative advantage. The bottom panel of Figure 4 depicts the percentage difference in 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 six years (24 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 six years. This difference reaches its peak at 24 quarters. The average percentage difference in aptitudes is about 4%. The majority of the 5 percent wage gap observed after 24 quarters is initially 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. Noticeably, the trend observed in career-specific experience lags the recovery in misallocation. By the time the wage gap is roughly closed at about 40 quarters, the percentage difference in aptitude is about 0.5% while the difference in career-specific experience amounts to about 0.5%.

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 (11),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 5% wage gap observed even after the aggregate economy has recovered 24 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 40th quarter. Percentage differences in wage outcomes become negligible as workers gain more experience. By 40 quarters, workers have roughly close to 9 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 about 6% over fifteen years.

6.2 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 5 shows the evolution of the percentage wage gap in the three model specifications from quarters 0 to 70. The vertical line at 24 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 long-dashed line represents the model with general human capital and learning only while the short-dashed line represents the model with specific human capital and no learning. Compared to the benchmark model where the wage gap closes at around 40 quarters, Figure 5 shows that the model with only learning and general human capital closes the wage gap at 30 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.

[INSERT FIGURE 5 HERE]

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 2 percentage points 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 career 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 6 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.

[INSERT FIGURE 6]

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 15 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 15 quarters, as shown in Figure7. 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. When human capital is general, experience gained in one's career is completely transferable to another career. Because a worker's effective labor input grows so long as he is working, workers are not penalized for switching 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.

[INSERT FIGURE 7 HERE]

6.3 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 replicate the IV regression in Kahn (2010) and use the estimated wage regression coefficients 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:

$$\Delta ln(w_t) = \hat{\alpha}_1 \Delta u_0 + \hat{\alpha}_2 \Delta u_0 * Pot.Exp_t + \hat{\beta}_1 \Delta u_t \tag{17}$$

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 about 2 percentage points in the unemployment rate for the entering cohorts. Thus, the difference in unemployment rate at entry, Δu_0, is fixed at about 2 in the predicted wage loss calculation. Δu_t captures how the difference in unemployment rates in the simulated model varies over time.

Figure 8 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 while the grey line dotted with triangles shows the predicted wage loss implied by the iv regression model given the same sequence of difference in unemployment rates. The top panel of Figure 8 again shows the path of the aggregate shock over time. In Figure 8, the predicted wage loss using the linear regression coefficients suggests that an increase in the unemployment rate at entry by 2 percentage points gives rise to an initial wage loss of about 20 percent. This wage gap narrows to 8% by the 24th quarter and completely fades by the 50th quarter. Note that the predicted wage loss using the linear regression coefficients shows that the wage losses turn into wage gains after the 50th 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.

[INSERT FIGURE 8 HERE]

From the IV regression model, the wage loss narrows from 20% to 10% by the first ten quarters. This is similar to the rapid catch-up observed in the simulated model. 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 8. 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.

6.4 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 9 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 9 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.

7 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.

Appendix A: Data

Data Sample

The data used in this paper is taken from the publicly available National Longitudinal Survey on Youth 1979 database. I focus on white males 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.[16] If an individual spent less 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 looks only at individuals with 16 years of schooling, i.e. individuals with four year college degrees. The second sub-sample comprises white male with only high school degrees. There are 717 individuals and 44023 quarterly observations in this sample.

Coding Complex vs. Simple Job Changes

I focus on between-job transitions rather than within-job transitions. A between-job transition is 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.Within-job transitions are treated here as 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. In the following, I further decompose EE transitions into

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

between-career changes and within-career changes.

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.

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:

$$\text{Angular Separation}_{oo'} = \frac{A \cdot B}{\|A\|\|B\|} \tag{18}$$

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

$$\text{Distance}_{oo'} = 1 - \text{Angular Separation}_{oo'} \tag{19}$$

Equation (18) 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:

$$\theta_T = f^{-1}\Big(\frac{\kappa}{(1-x_k)Eq_{ijk}}\Big) \tag{20}$$

Note that θ_T depends only on parameters and the expected share of output the recruiting firm gets to keep. From equation (5), 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 (12) 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 (15) for a firm attached to a worker in the last period of his life:

$$(1-\lambda^e p^*(\theta_T))Eq_{ijl} = -\lambda^e p_x^*(\theta_T)\frac{\partial x_k}{\partial \omega}(1-\omega)Eq_{ijl} \tag{21}$$

From equation (21), 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_k^e as:

$$R_k^e(\omega, s) = \max_{x_k} db + (1-d)\big[\lambda^e p(\theta_T) E x_k q_{ijk} + (1 - \lambda^e p(\theta_T)) E\omega q_{ijl}\big] \tag{22}$$

From equation (22), it is clear that independence of θ_T, ω and Eq_{ijk} from φ implies that R_k^e is independent of the aggregate distribution of workers. Analogously, R_k^u is also independent of φ. Since $\{R_k^u, R_k^e\}$ 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 :

$$\kappa = f(\theta_{T-1})\big[E(1-x_k)q_{ijk} + \beta E J_T(s')$$

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 $\tau = 1$.

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Tables and Figures

Table 1: Impact on Log Wages (College Graduates)

Variable	**1**	**2**	**3**	**4**
Career Tenure	0.008**	-	-	-
	(0.001)	-	-	-
Career Tenure^2	-0.0001**	-	-	-
	(0.000)	-	-	-
Complex	-	-0.100†	-	-0.100†
	-	(0.054)	-	(0.054)
Complex * Pot.Exp	-	0.006	-	0.006
	-	(0.005)	-	(0.005)
Simple	-	-	-0.070	-0.064
	-	-	(0.067)	(0.067)
Simple * Pot.Exp	-	-	0.013**	0.013**
	-	-	(0.005)	(0.005)
N	22109	22109	22109	22109
R^2	0.254	0.256	0.257	0.257

Dependent variable is log wage. Control variables include potential experience, potential experience squared and AFQT score. The variables "Complex" and "Simple" refer to between-career and within-career job changes. "Complex *Pot.Exp" is the interaction term between complex job changes and potential experience. This term captures how fast wages grow after a complex job change. Similarly, "Simple * Pot.exp" is the interaction term between simple job changes and potential experience. Standard errors reported in parentheses. Significance levels: $*$: 10% $**$: 5% $***$: 1%

Table 2: College Graduates: Probability of Complex Job Change

	National		**Regional**	
Variable	**1**	**2**	**3**	**4**
	OLS	**IV**	**OLS**	**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 3: College Graduates: Probability of Simple Job Change

	National		**Regional**	
Variable	**1**	**2**	**3**	**4**
	OLS	**IV**	**OLS**	**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 4: Parameter Space: Fixed

Variable	**Value**	**Description**	**Source/Target**
T	120	30 years of working Life	-
α	0.7	Labor share	-
β	0.987	Discount Factor	5% interest rate
K	10	Number of Sectors	Topel & Ward (1992)
$\bar{a}$	0	Mean of Idiosyncratic Shock	-
σ_a	0.093	Standard deviation of Idiosyncratic Shock	Hagedorn & Manovskii(2013)
$\bar{\mu}$	1	Unconditional Mean of Aptitude	-
$\bar{z}$	0	Mean of Aggregate Shock	-
ρ_z	0.92	Persistence of Aggregate Shock	JOLTS data

Table 5: Transition Probabilities

Variable	**Data (College)**	**Shimer(2012)**	**Nagypal(2007)***	**FF(2004)***
UE	0.532	0.45	-	0.283
	(0.193)	(0.067)	-	(0.029)
EU	0.048	0.034	0.005	0.013
	(0.042)	(0.005)	-	(0.001)
EE	0.055	-	0.024	0.026
	(0.021)	-	-	(0.001)
Complex EE	0.032	0.039		
	(0.016)	(0.015)		
Simple EE	0.027	0.025		
	(0.010)	(0.010)		

FF(2004)* refer to Fallick and Fleischman (2004). Terms with an asterisk denote monthly transition reported by those authors. Terms without an asterisk refer to quarterly transition probabilities. For transition probabilities reported in the column "Shimer (2012)", quarterly transition probabilities were calculated using the data constructed by Robert Shimer. For additional details, please see Shimer (2012). EU transition rates in Shimer (2012) refer to employment exit probabilities.

Table 6: Parameter Space: Calibrated

Variable	**Value**	**Data target**	**Model Generated**
δ	0.04	mean EU: 0.048	0.043
λ^e	0.21	mean EE: 0.055	0.086
κ	0.327	mean UE: 0.532	0.528
σ_μ	1.16	mean Complex EE: 0.032	0.029
ζ	0.014	Experience Gain: 0.0083	0.009
b	0.2	Unemployment benefit	40% of average lifetime wage
σ_z	0.1	0.274	0.212

Note: calibrated values are determined jointly in the model.

Table 7: Probability of Complex Job Change: Simulated Data

Variable	**Coefficient**	**(Std. Err.)**
u_t	-0.548**	(0.014)
u_0	-0.072†	(0.043)
$u_0 * t$	0.002**	(0.001)
μ_{ik}	0.003**	(0.001)
Career Tenure	-0.020**	(0.000)
Career Tenure^2	0.000**	(0.000)
t	0.002**	(0.000)
t^2	0.000**	(0.000)

Dependent variable is Probability of a Complex Job Change. Main regressors of interest are the unemployment rate at entry, u_0; the unemployment rate at entry multiplied by years in the labor market, $u_0 * t$. Control variables include current unemployment rate u_t, years in the labor market t, and its associated squared term,t^2, as well as underlying true aptitude in that career, μ_{ik}, career tenure and the square of career tenure. Significance levels: $*$: 10% $**$: 5% $***$: 1%

Table 8: Impact of Initial Unemployment Rate on Log Wages of College Graduates

	National		**Regional**	
Variable	**1**	**2**	**3**	**4**
	OLS	**IV**	**OLS**	**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%

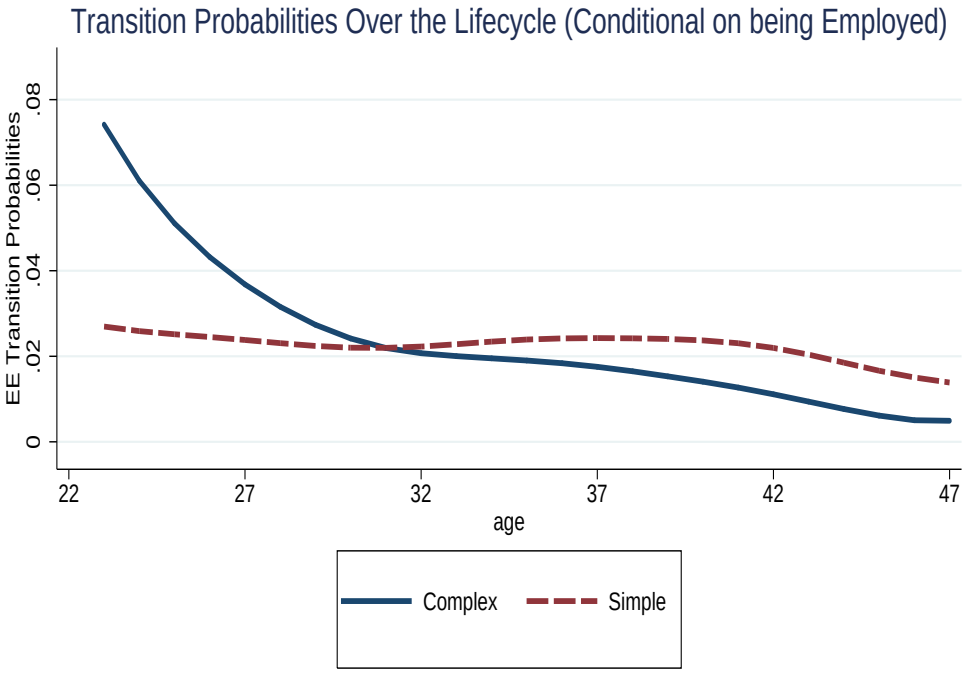

Figure 1: EE transitions over the Life-Cycle (College Grads)

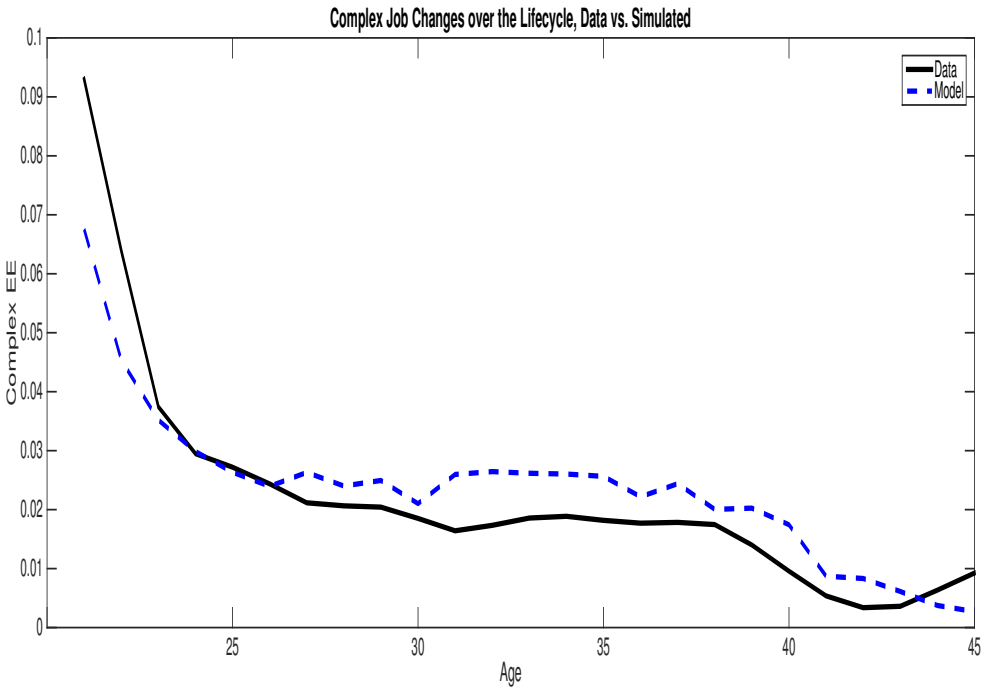

Figure 2: Data vs. Model Simulated Lifecycle Complex EE transition rates

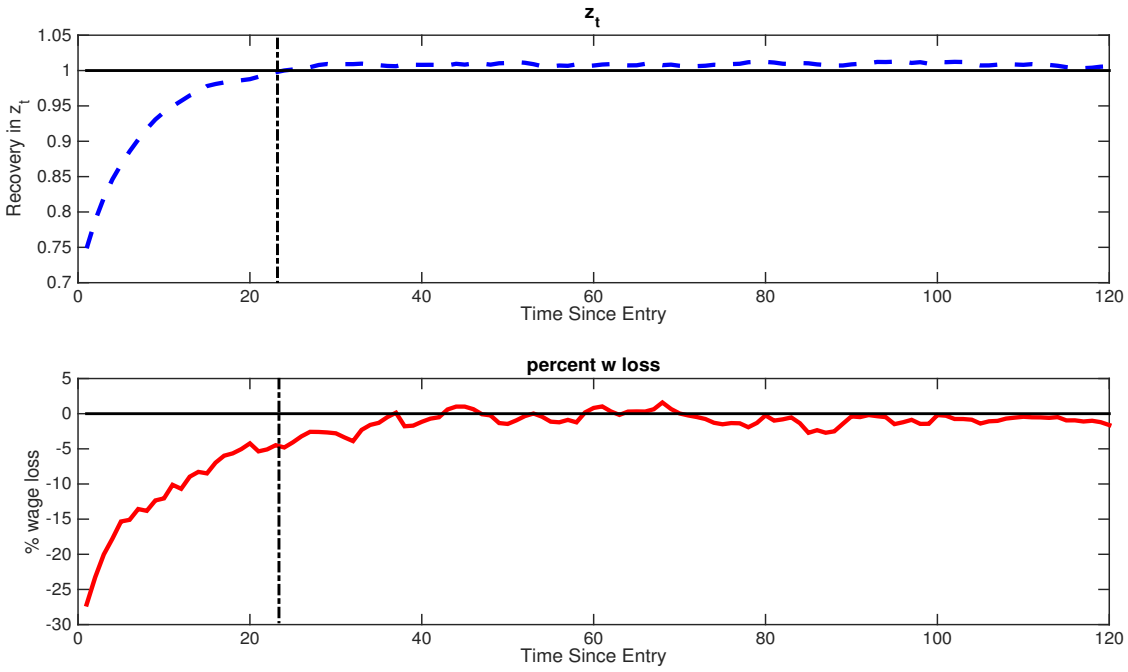

Figure 3: Wage Loss between Entering in Booms vs. Recessions

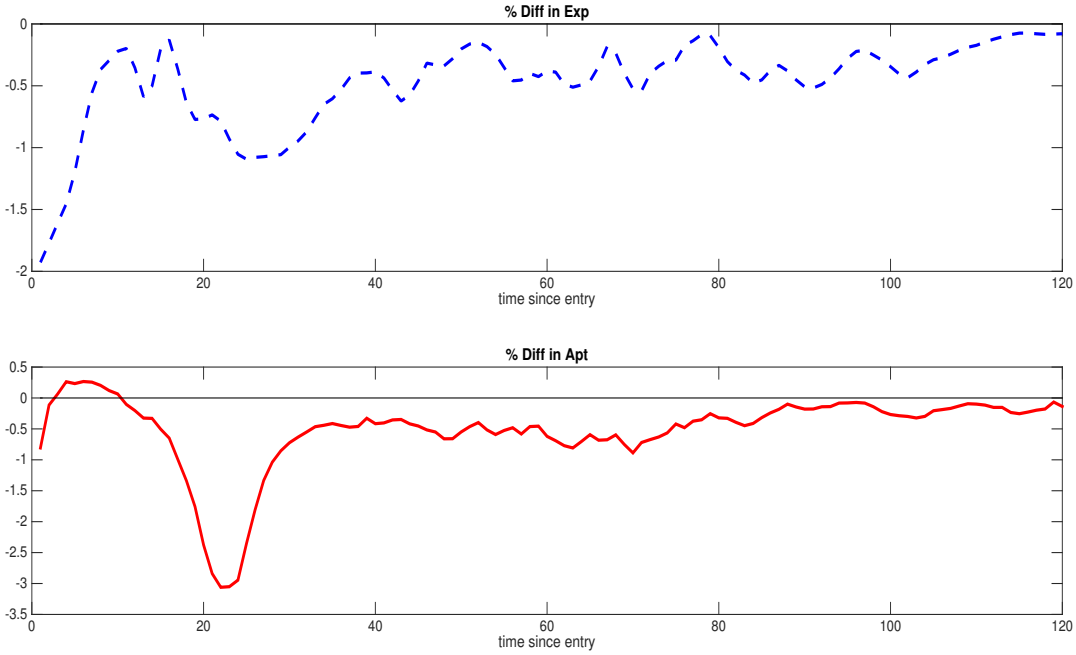

Figure 4: Differences in Levels of Experience and Aptitude at Current Job

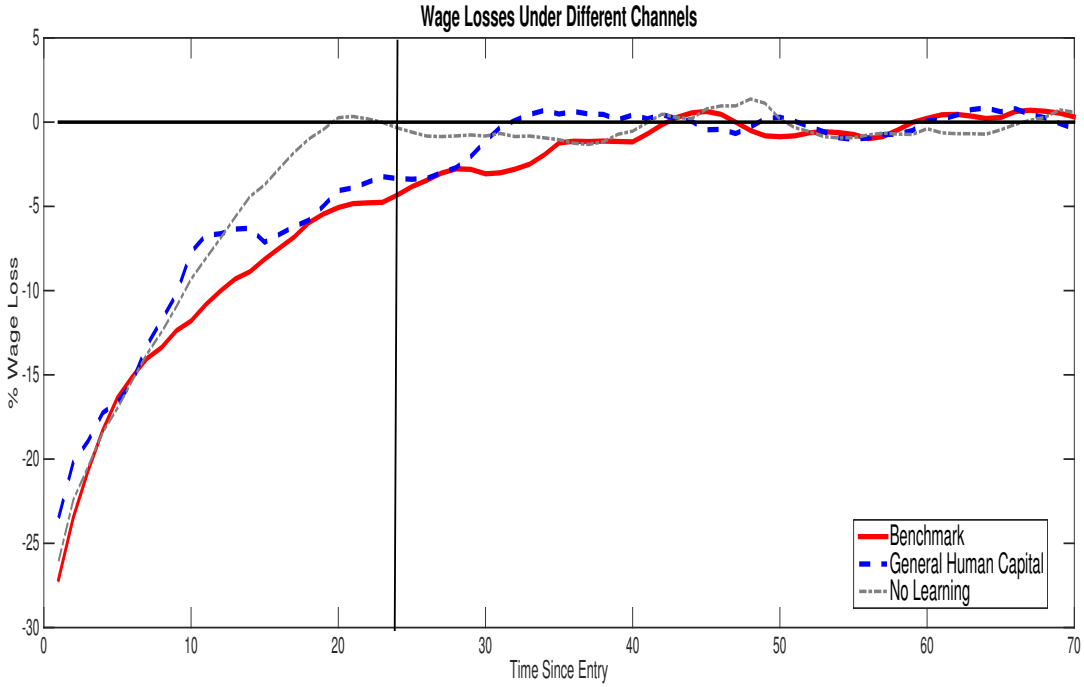

Figure 5: Percentage Wage Losses in Different Model Specifications

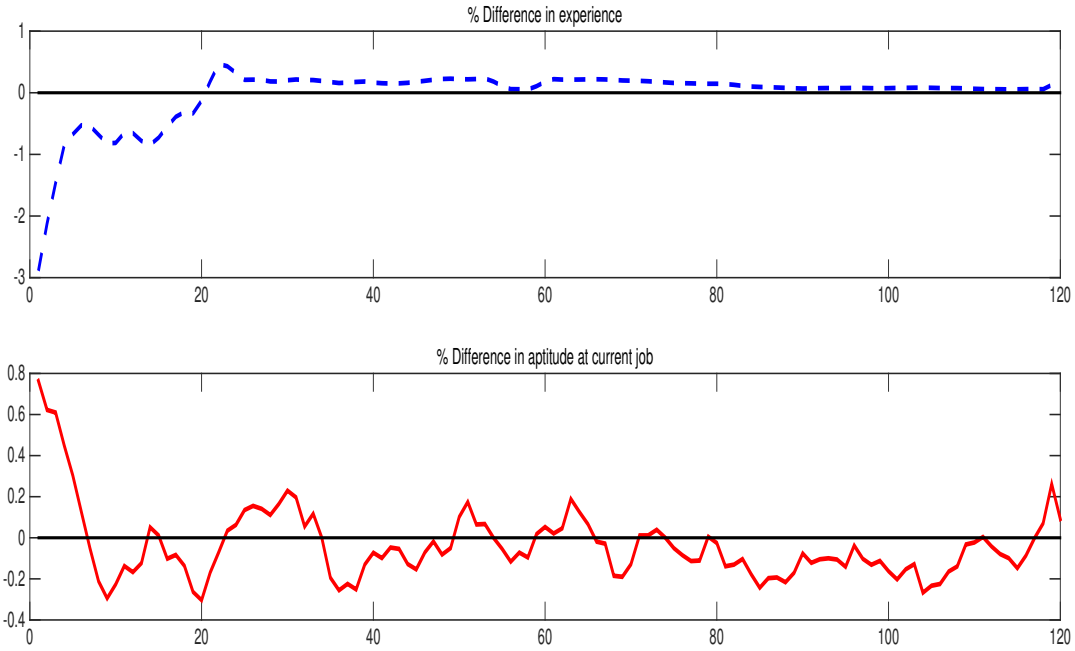

Figure 6: Differences in Levels of Experience and Aptitude at Current Job (No Learning)

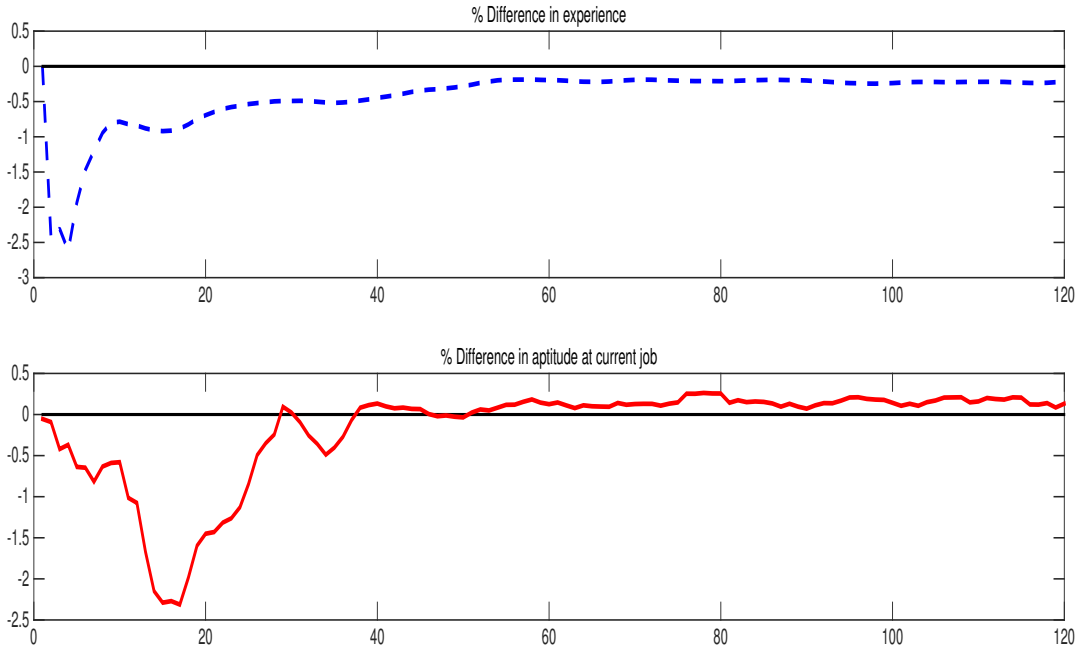

Figure 7: Differences in Levels of Experience and Aptitude at Current Job (No Specific Human Capital)

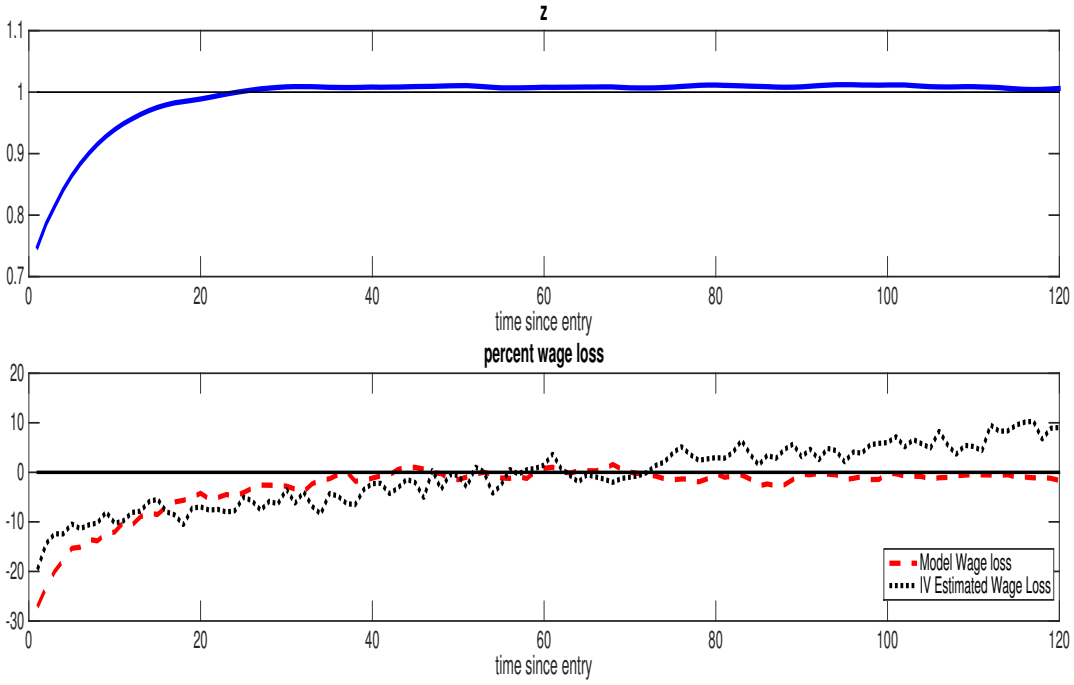

Figure 8: Percentage Wage Losses in Simulated Data and IV Regression Model

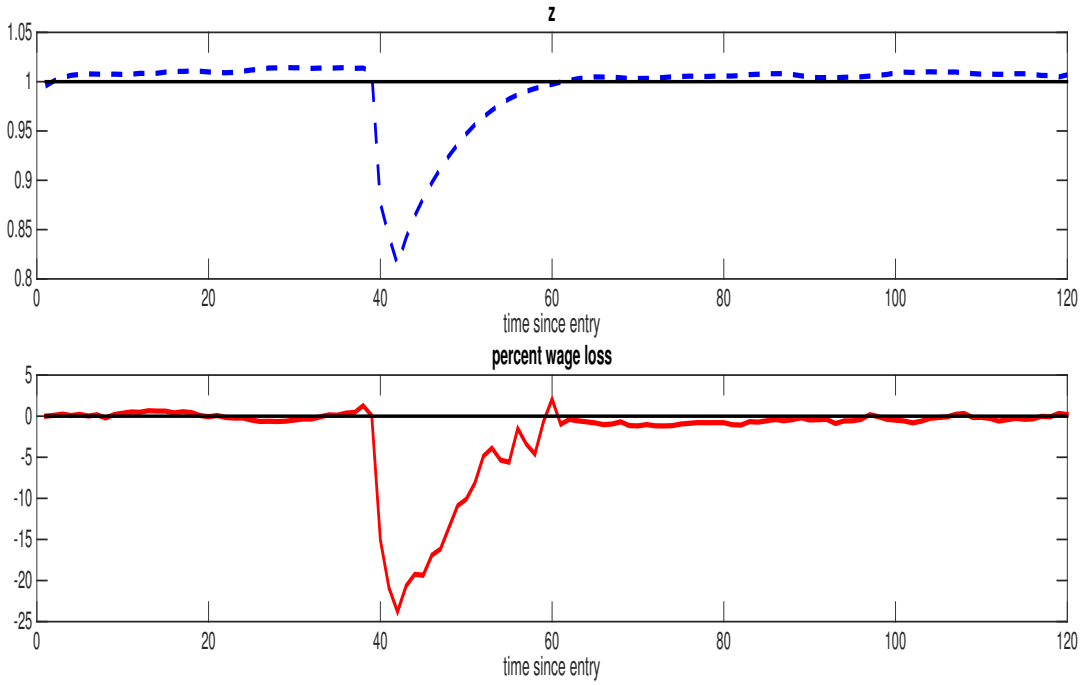

Figure 9: Wage Loss for Mature Workers in Booms vs. Recessions