

## ABSTRACT

Title of dissertation:      SEARCH FRICTIONS IN  
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This dissertation explores the role of search frictions in macroeconomics and highlights how these frictions influence micro-level decisions which in turn affect aggregated outcomes.

Chapter 1 examines how individuals entering the job market during a recession can suffer persistent wage losses. I document how entering the job market during a recession not only affects wage outcomes but also severely impinges on early between-career changes. I then build a model that shows how entering the job market during a recession hampers early career mobility which is critical towards facilitating learning about one's comparative advantage and accumulating human capital specific to one's ideal career. Consequently, 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. Permanent misallocation also arises when marginal workers who, having accumulated sufficient career-specific human capital, find it too costly to switch careers in the recovery. Persistent wage losses are a result of misallocation and experience gaps, both of which take time to correct.

Chapter 2 looks at how consumer search behavior and the durability of the product affect firms’ strategic pricing decisions. In the model, search is costly and consumers do not get to sample all prices in the market but rather have some positive probability of meeting only one or two sellers. In addition, consumers purchase goods that do not perish immediately and are able to postpone transactions. Firms face two types of customers: loyalists and shoppers. The presence of a customer base and search frictions imply that a firm takes into account the consumer search method when setting prices. Durability of the product and the consumer’s ability to postpone purchases suggest that consumers have greater bargaining power over the maximum price the firm is able to charge. In the numerical exercises, I show that all else equal, 1) the range of prices supported under durable goods is larger than the range of prices supported for non-durables, and 2) money is not neutral once the presence of a customer base is taken into account.

SEARCH FRICTIONS IN  
MACROECONOMICS

by

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# Dedication

*To my family*

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## Chapter 1: Born Under a Bad Sign: The Cost of Entering the Job Market During a Recession

Nearly half of all wage gains accrued to an individual between the age of 18 and 46 occur before age 30, suggesting that the early years of an individual's working life are critical to his overall earnings growth.<sup>1</sup> The recent continuing weakness in the labor market and overall tepid recovery, however, has severely affected the employment prospects for young workers.<sup>2</sup> Existing literature by Kahn (2010), Oreopoulos et al. (2012), Gregg and Tominey (2005) and Oyer (2006) document the persistence of wage losses stemming from economic conditions at the time of entry into the labor market. For the US economy, Kahn (2010) looks at white male college graduates who entered the job market prior to, during and after the 1980s recession and observes that a 1 percentage point increase in the unemployment rate at the time of entry leads to an initial wage loss of 6 to 7 percent. Moreover, she finds that the negative wage effect is persistent and that agents who enter the job market in a bad economy continue to suffer a wage loss of 2.5 percent 15 years after entry.<sup>3</sup> While the

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<sup>1</sup> 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".

<sup>2</sup> 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.

<sup>3</sup> Oreopoulos 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

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 to learning about comparative advantage and to 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 of those who enter during a recession 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 job 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 job changes while within-career job changes remain mostly unscathed.

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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.

Given these facts, I build a dynamic stochastic equilibrium model that demonstrates how reduced opportunities to switch careers early on cause slowdowns in learning about comparative advantage and increased accumulation of ‘irrelevant’ human capital, both of which affects individuals’ subsequent job search behavior and future wage outcomes. I then decompose the wage gap suffered by individuals who enter during recessions and show that diminished opportunities to switch careers early on generate misallocation and experience gaps. These misallocation and experience gaps take time to correct and are the main components driving the persistence in wage loss. In the model, a wage gap of 6 percent continues to persist even after the recessionary shock has dissipated and only fades completely 60 quarters after entry into the labor market.

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

However, learning by itself may not be sufficient 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 accumulation of 'irrelevant' human capital, i.e. experience in tasks at which the individual has comparative disadvantage. 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. Once the economy recovers, a 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 switches careers 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. Poor initial conditions, therefore, can cause persistent wage losses by affecting the individual's ability to climb the wage ladder, as well as by raising the probability of permanent misallocation.



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

While this is not the first paper to examine how poor initial conditions affect long run wage outcomes, the literature has yet to arrive at a consensus on the mechanism explaining these persistent wage losses. Notably, the standard labor search model cannot account for persistent wage scars. In the canonical Diamond-Mortensen-Pissarides (DMP) labor search model, workers and firms split the value of a job. An increase in aggregate productivity raises the value of a job and encourages firms to create more vacancies. Consequently, improvements in the job-finding rate exert upward pressure on wages, resulting in wages recovering with the aggregate state. Hornstein et al. (2007) 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 (2006) incorporates on-the-job search and heterogeneous

workers into the standard labor search model and studies the sullyng 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 therefore his model 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. However, workers can switch to their ideal job once the economy recovers. 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.<sup>4</sup> This mechanism is likely to be most powerful during sluggish recoveries when unemployment remains high and many individuals are unemployed for long spells. The relatively short durations of past recessions and the quick recoveries that accompanied them, however, imply that a high rate of human capital depreciation would be required to generate the persistent wage losses observed in the data.

In a seminal paper, Beaudry and DiNardo (1991) focus on implicit contracts and

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<sup>4</sup> 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.

find that current wages depend heavily on initial economic conditions only when mobility is costly.<sup>5</sup> This implies that a model of wage contracts and past wage premiums alone is 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 demonstrates a channel through which persistent wage losses could arise that 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 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 learning and human capital accumulation of young workers.

The rest of this paper is organized as follows: Section 1.1 reviews the related literature whilst Section 1.2 describes the empirical motivation and data that will be

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<sup>5</sup> 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.

used to calibrate the model. Section 1.3 presents the model. Section 5 lists the calibration process while Section 6 provides results from a numerical simulation. Section 7 concludes.

## *1.1 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. This suggests 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' job change as one which involves a change in both industry and occupation as well as employer, and a 'simple' job change as one which involves a change in employer, but not a change in both occupation and industry, Neal finds that the

early years of an individual's working life are marked by complex job changes while the latter years of an individual's working life tend to involve simple job changes. Using data from the National Longitudinal Survey of Youth 1979 (NLSY79), he finds that at least 70 percent of high school graduates and about 50 percent of college graduates undergo a career change - i.e. a complex change of jobs - after starting their first full-time job. The frequency of complex job changes, however, is decreasing with experience. In contrast, the probability of a simple job change increases as one gains experience in the labor market. Given this evidence, Neal concludes that individuals initially search for a career and only concentrate their search efforts towards finding an employer match once a suitable career has been found.

Pavan (2011) updates the results of Neal (1999) and finds that wage gains from simple and complex job changes are similar in magnitude and account for about 45 percent of 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 var-

ious 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 the facts about 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 search model. In the former, the authors show that the introduction of occupational learning into a labor search model can 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. 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 affect future wage outcomes.

Delacroix and Shi (2006) show how observed concave wage profiles over the life cycle can be explained in a model where 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. Their paper suggests that current wage outcomes may be pegged to past wage premiums. Similar to Delacroix and Shi(2006), this paper also demonstrates that current wage outcomes may be benchmarked by past wages received. However, persistence in wage outcomes in my model is not a product of past wage premiums alone but is also a function of the evolution of relevant human capital. The amount of wage compensation a worker can demand is a function of his effective labor input. The presence of irrelevant human capital impinges on a worker's ability to demand higher wages in a new career. Hence, persistence in wage returns and slow climbing of the wage ladder are outcomes of the evolution of relevant human capital. In addition, a worker who chooses to remain in a career where he has comparative disadvantage also experiences slower growth in specific human capital due to his lack of innate aptitude at

that job. This again gives rise to persistence in wage losses.

Another related paper by Adda et al. (2013) finds that continuously employed young workers who enter the labor market during a recession suffer earnings losses of about 1 to 2 percent in net present value terms over a 15 year horizon. They attribute this loss 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 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 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 among workers who enter in a recession, then these individuals 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.



## 1.2 Data

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

I restrict my focus to white males, of which there are 3790 in the sample in 1979. I exclude 377 individuals who spent 4 or more consecutive years in the military in the early stages of their career.<sup>6</sup> 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 who 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 48232

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<sup>6</sup> While being in the military may be in itself a career choice, individuals who enter into the military tend to be 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.

annual observations in my sample. As wage returns are likely to be affected by the presence of unobservables, I further limit my analysis to a more homogeneous group of individuals. In particular, I focus on two separate sub-samples. The first sub-sample consists of white male college graduates with four year college degrees. This sub-sample consists of 433 individuals and 24350 quarterly observations. The second sub-sample comprises white male high school graduates and consists of 717 individuals and 44023 quarterly observations.

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

### 1.2.1 *Verifying Persistent Wage Losses*

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

$$w_{it} = \alpha_0 + \alpha_1 u_{0,i} + \alpha_2 u_{0,i} * Pot.Exp_{it} + \beta X_{it} + \varepsilon_{it} \quad (1.1)$$

where  $w_{it}$  is the log hourly wage of individual  $i$  at time  $t$  and  $u_{0,i}$  is the main regressor of interest, the national unemployment rate at entry.  $u_{0,i} * Pot.Exp_{it}$  is the interaction of the unemployment rate at entry with potential experience. This variable captures the extent to which initial unemployment rates continue to weigh on current wages. A negative coefficient on  $u_{0,i}$  combined with a positive coefficient on  $u_{0,i} * Pot.Exp_{it}$  implies that entering during a recession generates an initial drop in wages followed by subsequent catch-up 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, the current unemployment rate as well as regional dummies. To account for selection effects and the endogenous timing of labor market entry, Kahn conducts a separate instrumental variables regression (IV) where she instruments for the unemployment rate at entry with the unemployment rate at the modal age of graduation. Similarly, the interaction term  $u_{0,i} * Pot.Exp_{it}$  is instrumented with the product of the unemployment rate at the modal age of graduation and potential experience. Accordingly, the first stage regressions take the form of:

$$u_{0,i} = \pi_0 + \pi_1 u_{m,i} + \pi_2 u_{m,i} * Pot.Exp_{it} + \delta_1 X_{it} + \epsilon_{it} \quad (1.2)$$

$$u_{0,i} * Pot.Exp_{it} = \pi_3 + \pi_4 u_{m,i} + \pi_5 u_{m,i} * Pot.Exp_{it} + \delta_2 X_{it} + \xi_{it} \quad (1.3)$$

where  $u_{m,i}$  refers to the unemployment rate at the modal age of graduation. In the NLYSY79 data, the modal age of college graduation is 22 years. While I replicate

Kahn's empirical exercise, it should be noted that my results differ slightly from Kahn (2010) because that I focus on the hourly wage rate for the individual's main job in a given quarter while the time period in Kahn's analysis is a year.

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

percentage point increase in the unemployment rate at entry lowers the initial wage by about 3 percent. The interaction term of potential experience with the national unemployment rate at entry is positive and significant; the point estimate implies that it takes 56 quarters or 14 years for wage gaps to close.

While it perhaps easy to rationalize why entering the job market during a recession might cause severe initial wage losses, a more pressing issue concerns the recession's impact on future wage growth. One possible explanation for the existence of persistent wage losses may be that individuals who enter the job market in a recession suffer recurrent joblessness. Entering in a recession may cause individuals to be unemployed for longer at the beginning of their working lives. The lack of initial learning and job stability may in turn precipitate recurrent unemployment spells as these individuals continually quit to search for jobs with the best match quality. In this case, wages for individuals who enter during a recession may on average be persistently lower, as these individuals are more likely to experience subsequent unemployment spells and less human capital accumulation. Indeed, Pries (2004) shows how unemployment rates may remain at an elevated level even after a recessionary shock has died off because individuals suffer recurrent joblessness. To examine if this is the main mechanism driving persistent wage losses, I replicate the empirical exercise denoted in equation (1.1) but replace the dependent variable with the probability of being employed. Since wages can only be reported if one is employed, the sample used for the wage regression is a subset of the sample used for the regression on the probability of being employed.

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

Table A.4 demonstrates the analogous results for high school graduates. The OLS specifications in columns (1) and (3) show that a 1 percentage point increase in the national or regional unemployment rate at the time of entry lowers the initial probability of being employed by close to 1 percentage point. However, this coefficient is smaller in magnitude and statistically insignificant in the IV specification. Unlike the result for college graduates, the current unemployment rate is a significant

factor for determining the probability of being employed for high school graduates. Overall, these results show that high unemployment rates at entry do not exert persistent effects on the employability of individuals, especially for college graduates. These results suggest that persistent unemployment is likely not the main vehicle driving persistent wage losses for college graduates.

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

### *1.2.2 Definition of Job Changes*

A key assertion of this paper is that persistent wage losses arise when individuals enter the job market during recessions because of slow learning about comparative advantage and because individuals accumulate irrelevant human capital. While both current voluntary employment-to-employment (EE) transitions and unemployment-to-employment (UE) transitions decline with the advent of a recession, this paper posits that **future** employment-to-employment transitions are also affected when individuals enter the job market during a recession. Throughout this paper, I focus on quarterly transitions, although my results continue to hold at the monthly frequency. An EE transition is recorded whenever an individual who was employed at the start of the previous quarter is matched with a new employer at the start of the

next quarter. Similarly, a UE (EU) transition is recorded when an individual who was unemployed (employed) at the start of the previous quarter becomes employed (unemployed) at the start of the next quarter. A UE (EU) transition probability is therefore defined as the proportion of unemployed (employed) individuals at the start of period  $t - 1$  who became employed (unemployed) at the beginning of period  $t$ . Table A.5 records the average transition probabilities for the samples of college and high school graduates in the NLSY79 over the period 1979 to 2006. On average, the rate at which employed college graduates move from one employer to another is about 5.5% per quarter, while high school graduates move from employer to employer at a rate of 6% per quarter. The rate at which the unemployed find jobs (UE rate) is about 53% per quarter for college graduates, while about 32% of unemployed high school graduates manage to find jobs each quarter. About 5% of employed college and high school graduates enter into unemployment each quarter. These rates are comparable to numbers found by Shimer (2012) and Fallick and Fleischmann (2004) (henceforth referred to as FF(2004)) for the whole labor force.<sup>7</sup>

Since this paper is primarily concerned with individuals' voluntary job changes motivated by the desire to find a career that suits their comparative advantage, I focus on EE transitions. Limiting the focus to EE transitions helps to reduce the number of involuntary job changes in the sample. An individual who is displaced from his current job during a recession may be forced to undertake another job which uses

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



completely different tasks and human capital. However, it is clear that under such a scenario the individual did not switch jobs voluntarily in an attempt to find his comparative advantage but was rather forced to take a new job because of reasons unrelated to learning.

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

accumulated human capital when he becomes sales manager at a firm. Thus, in the following, I focus on how EE transitions between jobs behave over the life cycle and the business cycle.

### *1.2.3 Defining Simple and Complex Job Changes*

Previous literature such as Neal (1999) and Gervais et al (2010) suggests that individuals tend to search for a career in the early stages of their working life while they tend to search for an employer or for match quality in the latter stages of their working life. While Gervais et al (2010) focus on how occupational learning causes unemployment rates to change over the life cycle, I focus on the type of job search the individual undertakes over his working life and how this changes with the business cycle. To distinguish between the types of job search, I follow the framework given in Pavan (2011) and Neal (1999). Using 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) industry code, 2) occupation code and 3) 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 changing jobs within the same career if he only undergoes either one or two of the above three mentioned changes. A within-career job change is recorded whenever the individual 1) changes employers and observes no change in either occupation or industry code, or 2) changes employers and ob-

serves either a change in occupation or industry, but not both. Any within-career job change or between-career job change must observe an employer change. This condition avoids mis-coding promotions at jobs as either a within-career or between-career job change. Having controlled for promotions, I assume that between-career changes reflect an individual's search for a career that fits his comparative advantage, while within-career changes reflect the individual's search for a better match quality in terms of employer. Following the convention established in Neal(1999), I will henceforth use the term 'complex change' when referring to a between-career job change and the term 'simple change' when referring to a within-career job change.

A problem that arises in the data is that many of the job changes recorded in the NLSY79 are actually cycles between two values, from occupation 1 to occupation 2 and then back to occupation 1. These cycles could be due to 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 either 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 (but not both) in period  $t - 1$  are different from the occupation and industry codes in period  $t$  and  $t + 1$ . These

definitions help to reduce any mis-coding of job changes.

A key concern is whether these definitions accurately depict between and within career changes. As a quick check, I use the Dictionary of Occupational Titles to check if a complex (simple) job change entails a more significant (less significant) change in the tasks required to work in that job. In the appendix, I explain 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.

#### *1.2.4 Job Search Strategies over the Life Cycle and Business Cycle*

Central to this paper's focus is how job search strategies vary with both the life cycle and business cycle. To capture the variation over the life-cycle, Figure A.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 A.2 plots the same variation for high school graduates. Dashed lines represent 90% confidence

bands. Notably, individuals engage in more complex job-to-job transitions early on in their working life, reinforcing the notion that individuals initially search for a career. On average, about 3.2% of employed college graduates and 3.9% of employed high school graduates undergo a complex change each quarter. However, the rate of complex job changes declines sharply with age. In contrast, simple job-to-job transitions decline more slowly with age and only exhibit a significant downward decline from age 40 onwards. Hence, I find evidence supportive of the two stage job-search strategy suggested by Neal (1999). The accumulation of career-specific human capital is a leading candidate explanation for the sharp decay in the number of complex job changes over age. Pavan (2011) documents that career-specific tenure contributes to an important part of wage growth; ten years of career-specific human capital raises log wages by 0.2 points. As such, complex job changes should optimally decline as individuals age, as individuals would otherwise lose out on accumulating career-specific human capital essential to later wage growth.

A more interesting question is how these job search strategies may be affected by initial business cycle conditions. Given the life cycle behavior of voluntary job changes, I examine how entering the job market during an expansionary or recessionary period might affect the trajectory of these voluntary job changes. As the NLSY79 follows individuals born between the years of 1958 to 1965, the major recessions faced at the time of entry for college graduates in my sample are the 1980s and 1990s recessions. For high school graduates, the major recessions captured at the time of entry are the 1980s recessions. To overcome the limitations in time-series

variation, I focus on both spatial and time variation in unemployment rates, using data on both the national unemployment rate and unemployment rates across Census regions. To define a recession, I follow the methodology of Hoynes et al. (2012) and define a recession as the trough-to-peak points of the seasonally adjusted unemployment rate. Figure A.3 highlights that the cyclical adjustment of the national unemployment rate tends to lag NBER recession dates, shown in the figure using shaded bars. In general, labor market recoveries tend to lag the recovery in GDP growth. As high search frictions are posited as the main reason why slow learning and an accumulation of irrelevant human capital may occur for workers entering the job market during a recession, my preferred indicator of business cycle turning points is the unemployment rate, as this best proxies for the level of search frictions in the economy. Hence, for the following analyses, the words ‘expansion’ and ‘recession’ will be used to refer loosely to periods marking peak-to-trough and trough-to-peak movement in unemployment respectively.

I conduct two exercises to examine how job search strategies may be affected by initial business cycle conditions. Firstly, I examine the duration before an individual undertakes his first complex (simple) job change. Intuitively, I expect that if search frictions are high, both unemployed and employed workers would face reduced job mobility. Hence, recessions should slow the learning process for individuals and delay their switching into alternative careers or jobs. Secondly, I examine how future mobility in terms of both complex and simple job changes is affected by initial job conditions. This second exercise aims to verify if there is any evidence of

a ‘lock-in’ effect. An individual who was initially unable to switch jobs may observe reduced future job mobility especially in terms of complex job changes, as it is costly to switch careers and discard accumulated career-specific human capital.

### *1.2.5 Results on Initial Job Mobility*

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

individuals who joined the job market during an expansion, while the dashed line highlights the survivor function for individuals who joined the job market during a recession. A comparison of Figure A.4 and Figure A.7 suggests that high school graduates entering during a recession face an even sharper reduction in their ability to switch careers than college graduates. This is consistent with the notion that the 1980s recession was largely a “blue collar recession”.

In contrast, Figure A.8 plots the analogous survivor function for simple job changes and shows the probability that a college graduate has not experienced any simple job change since his initial entry into the labor market. Unlike complex job changes, recessions do not seem to significantly affect the timing of college graduates’ first simple job change. Intuitively, this may be because individuals tend to concentrate on complex job changes early in their working career. Hence, initial conditions are likely to affect only the first complex job change rather than the first simple job change that the individual is able to undertake. Figure A.9 shows the corresponding plot for high school graduates. Unlike the result for college graduates, high school graduates who enter during a recession are more likely to observe a delay in their first simple job change, although this difference is small in magnitude. This in part may be due to the fact that high school graduates are more likely to be unemployed during a recession. Recall from Table (A.4) that the current unemployment rate exerts a negative effect on high school graduates’ probability of being employed. High school graduates who enter during a recession are less likely to be employed and hence may suffer a set-back in terms of overall human capital accumulation.



This lack of human capital accumulation, in turn, affects a high school graduate's future job-finding probabilities within a career as experience adds to an individual's effective labor input. Consequently, even the first simple job change for a high school graduate may be delayed if he enters the labor market during a recession. Notably, Adda et al (2013) argue that the loss in earnings for less-skilled workers who enter during a recession stems largely from low human capital accumulation on the job while the loss in earnings for high-skilled workers stems from a loss of job mobility or search capital.

To investigate whether these differences are sensitive to my definition of a "recession", I estimate a proportional hazards duration model including the national unemployment rate faced at the time of entry, controlling for other individual characteristics such as potential experience, potential experience squared, the AFQT score, the current national unemployment rate and regional dummies. The duration model assumes the standardized Weibull distribution. Table A.6 presents the results from these regressions. Column 1 presents the results of the proportional hazards model of the probability of having no complex job change for college graduates, while Column 3 presents the analogous results for high school graduates. The estimated coefficients are from a regression on the log of the hazard function. Negative coefficients imply lower hazard rates and correspondingly longer durations. Taking the exponent of the regression coefficients, a one percentage point increase in the unemployment rate at entry multiplies the baseline hazard rate of a complex job change for college graduates by a factor of 0.93, or equivalently lowers the hazard

rate by 7%. Similarly, a 1 percentage point increase in the initial unemployment rate faced at entry lowers the hazard rate by about 9 percent for high school graduates. These effects are both significant at the 10% level. Columns 2 and 4 of Table A.6 demonstrate that the initial unemployment rate has no significant impact on the duration before the first simple job change for either college or high school graduates.

One problem with these estimated survival functions is that actual entry into the labor market is endogenous. There may be unobserved systematic differences between individuals who choose to enter during a recession and those who choose to enter during an expansion. To control for potential selection effects, I follow Kahn (2010) and instrument the actual unemployment rate at date of entry with the unemployment rate at the modal age of entry. To do this, I first 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.<sup>8</sup> I then estimate the following regression:

$$Mob_{it}^c = \gamma_0 + \gamma_1 u_{0,i} + \gamma_2 u_{0,i} * Pot.Exp_{it} + \zeta X_{it} + \nu_{ist} \quad (1.4)$$

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. Independent variables are the same as in equation (1.1). Table A.7 reports the results for the probability of conducting a complex job change for college graduates while Table A.8 presents analogous results for simple job changes. For both tables, Columns 1 and 2 show

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

OLS and IV results using the initial national unemployment rate while Columns 3 and 4 present analogous results using the initial regional unemployment rate. Standard errors are robust to heteroskedasticity and are clustered by birth year cohort. Notably, Tables A.7 and A.8 show that increases in potential experience exert significant downward pressure on the probability of a complex job change but have relatively little effect on simple job changes. This is line with the idea that complex job changes involve a loss of career-specific human capital whereas human capital is typically transferable between simple job changes.

From the IV regressions, a one percentage point increase in the initial national unemployment rate lowers the initial probability of a complex job change 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 entry into the job market. The estimated coefficient on the interaction term,  $u_{it} * Pot.Exp_{it}$ , suggests that it takes about 50 quarters or 12 years before the gap in complex job-to-job transition probabilities disappears. Importantly, the first 12 years of an individual's working life form precisely the period when individuals concentrate on finding the right career. In contrast, Columns 1 and 2 of Table A.8 indicate that initial labor market conditions exert little or no impact on the probability of undertaking simple job changes.

Similar findings are obtained using regional unemployment rates. Column 4 of Table A.7 indicates that a one percentage point increase in the regional unemployment rate at the time of entry lowers the initial 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 the local unemployment rate. Recent work by Wozniak (2010) and Cadena and Kovak (2013) suggests that higher-skilled individuals and college graduates are more affected by changing national labor market conditions than lower skilled workers and high school graduates, and are more likely to move to markets with better job opportunities. The more muted impact of the initial regional unemployment rate may arise as a result of college graduates selecting or migrating into local labor markets with better opportunities. In contrast, a more depressed national labor market at entry suggests weak job-finding opportunities overall and hence fewer avenues for college graduates to conduct complex job changes.

Tables A.9 and A.10 present results for high school graduates. Results for complex job changes are qualitatively similar but are smaller in magnitude. About 3.9% of employed high school graduates conduct a complex job-to-job transition every quarter. The IV results in column 2 of Table A.9 suggest that a 1 percentage point increase in the initial national unemployment rate reduces the probability of a complex job change by about 0.1 percentage points, while a 1 percentage point increase

in the initial regional unemployment rate reduces the probability of a complex job change by about 0.2 percentage points. Notably, for high school graduates, the national unemployment rate at entry does not exert a more adverse effect on the probability of a complex job-to-job transition rate relative to the initial regional unemployment rate, in line with previous literature showing that lower skilled workers and high school graduates are more affected by local labor market conditions and are less likely to migrate for better job opportunities. Simple job changes are also adversely affected by an increase in the initial unemployment rate for high school graduates, albeit to a smaller extent than complex changes. A 1 percentage point increase in the national (regional) unemployment rate at entry lowers the probability of a simple job change by about 0.07 (0.1) percentage points.

Overall, college graduates who enter in a weak labor market are less likely to conduct a between-career change not just in the initial years but for a substantial portion of their working life. On average, it takes about 50 quarters or 12 years before the negative effect of a 1 percentage point increase in the unemployment rate at entry on the probability of conducting a complex job change completely wears off. High school graduates, on the other hand, are less likely to conduct both complex and simple job changes over their working life if they enter during a recession. In general, these results suggest that the initial unemployment rate exerts a significant and persistent impact on career mobility, especially for college graduates. Given that early job switching is associated with significant increases in wages, this suggests that early lost opportunities to find the right career can affect future wage outcomes. To

rationalize these findings, I now construct a model that 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.

### *1.3 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 et al. (2012). Specifically I incorporate two new features into the model. First, I embed a learning problem into 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 their previous wage offer.

Secondly, I allow for multi-dimensional 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 accu-

mulated is specific to the career workers are employed in. Finally, my model also deviates from the standard Menzio and Shi (2010) directed search framework, in which 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 assumes spot wage contracts for computational simplicity.

Given these features, I build a general 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 conventions: 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  $\tau$  is used to indicate the worker’s age. The next section details the set-up of the model.

### 1.3.1 Environment

#### Workers

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 workers born into the economy such that there are always  $T$  overlapping generations in the economy. There is no savings in the economy and workers consume all of their wage income. There are  $K$  varieties of goods in the market that individuals can consume. For simplicity, I assume that preferences take the form of a Cobb-Douglas utility function, i.e.

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

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

$$\max \sum_{\tau=0}^T \beta^\tau u(C_\tau) \tag{1.5}$$

where  $\tau$  refers to the age of the individual.

Since workers get equal utility from consuming the same amount of any  $c_k$  for  $k \in [1, K]$ , individuals seek to maximize the expected present discounted value of their wage outcomes in order to maximize their expected lifetime utility. Thus, we can represent the individual's preferences each period in terms of an indirect utility function that is linear in wages. Throughout this paper, I will be working with the



indirect utility function.

### *Human Capital*

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

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

Individuals 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

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<sup>9</sup> This assumption can be relaxed in future versions of the model. One can assume that jobs are multi-dimensional and use more than one task for production. Workers then learn about their aptitudes at many tasks from one job. The rate of learning would be pegged to the intensity with which that task is used for production. This would induce a trade-off between learning about more aptitudes against lower experience gained at each task. Alternatively, one can model a job as having varying informational content. Antonovics and Golan(2012) construct a model of life-cycle job mobility and show that agents would initially engage in job experimentation and take initial wage cuts to work in jobs that provide more informational content.

level of experience in that task:

$$h_{ik} = \mu_{ik}y_{ik} \tag{1.6}$$

where  $\mu_{ik}$  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  $\zeta$  denotes the additional experience gained by working at a particular task. If a worker doesn't use a particular task in his current sector then he gains no experience in that particular task this period.

Workers and firms can perfectly observe the total amount of experience a worker has accumulated working at a particular task,  $y_{ik}$ . It is imperfect information on an individual's innate aptitude,  $\mu_{ik}$ , that causes workers and firms to have imperfect information on workers' human capital.

### *Production Technology*

The economy has  $K$  'sectors'; each 'sector' is defined by the task it uses for production, implying an equal number of tasks as sectors. Equivalently, a sector in this

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

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

$$q_{ijk} = za_j h_{ik}^\alpha \tag{1.7}$$

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

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<sup>10</sup> Note that since each sector is defined by the task firms use for production,  $k$  corresponds to both the sector and the task.

is no scope for firms to learn about their idiosyncratic productivity next period.

Finally, production is subject to an aggregate shock  $z$  that uniformly affects output at all tasks.  $z$  lies in the set  $Z = \{z_1, z_2, \dots, z_N\}$ , 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 workers observe  $\{q_{ijk}, z, y_{ik}, \tau\}$  while they have imperfect information on  $\{\mu_{ik}, a_j\}$ . Firms and workers also know  $\zeta$  and hence can observe the amount of relevant experience workers will have for the next period,  $y'_{ik}$ . Upon observing output, firms and workers update and form new priors of workers' type,  $\hat{\mu}'_i$ . Firms and workers also update  $\Sigma_{\mu_i, \tau}$ , the variance co-variance matrix of their posterior beliefs.  $\Sigma_{\mu_i, \tau}$  evolves deterministically as a worker accumulates experience and is strictly non-increasing over time. As  $a_j$  is an i.i.d. shock, output today provides no information about idiosyncratic shocks tomorrow.

Both firms and workers form beliefs about  $\mu_i$  in order to form their recruitment and job search decisions. As output is a noisy signal, firms and workers face a signal extraction problem when trying to learn about a worker's type. Information, while imperfect, is symmetric between firms and workers.

## *Labor Market*

Idle firms in a sector  $k$  become recruiting firms when they choose to post a vacancy. As each job consists of a single firm-worker pair, currently matched firms do not post new vacancies. Recruiting firms post spot market wage contracts when creating a vacancy. At the same time, matched firms in each period make new take-it-or-leave-it wage-share offers based on 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 shares to workers they are currently matched with. In addition, search is costless for workers.

Each sector  $k$  is defined by a continuum of submarkets indexed by the tuple  $(x_k, \mu_k, y_k, \tau)$ , where  $\tau$  refers to the age of the worker,  $x_k$  is the share of output a firm promises its worker, and  $\mu_k$  and  $y_k$  are the current levels of perceived innate aptitude and experience that a firm requires of a worker respectively.<sup>11</sup> Notice that beyond specifying the wage share offer, firms are also able to condition on the current perceived value of aptitude and on current experience when posting a job.

Importantly, the amount of career-specific experience affects both the worker's level

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<sup>11</sup> 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 et al. (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.

of human capital and the precision of beliefs about the worker's aptitude at that career. When an individual works at a task, he not only gains career-specific experience but learns about his aptitude at that career. More experienced workers have more certainty over their aptitude at that career. Posting experience requirements implies that firms are also inherently choosing the level of precision they desire in beliefs about a worker's aptitude.

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

Job-finding and job-filling probabilities depend on the labor tightness condition. The probability of finding a job  $p(\theta)$  is assumed twice-differentiable, strictly increasing and concave in  $\theta$  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  $\theta$ ,  $f(0) = 1$  and  $f(\infty) = 0$ . When a firm and a worker meet in sub-market  $(x_k, \mu_k, y_k, \tau)$ , a worker

without the pre-requisite requirements, i.e. a worker whose perceived aptitude, experience and age are not equal to  $(\mu_k, y_k, \tau)$ , 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  $\varphi$  is a function  $n : \mathbb{N} \rightarrow \mathbb{R}_+$  where  $n$  represents the measure of individuals that are entering the labor market for the first time. The second element of  $\varphi$  is a function  $u : \mathbb{N}^3 \rightarrow \mathbb{R}_+$  where  $u(\mu_k, y_k, \tau)$  is the measure of unemployed people of age  $\tau$  who have perceived aptitude  $\hat{\mu}_k = \mu_k$  and experience  $y_k$  in a particular sector  $k$ . Thus,  $u(\mu_k, y_k, \tau)$  refers only to the unemployed searching in a particular sector  $k$  in a sub-market which requires  $\{\mu_k, y_k, \tau\}$  characteristics of a worker. The last element of  $\varphi$  is a function  $e : \mathbb{N}^3 \rightarrow \mathbb{R}_+$ , where  $e(\mu_k, y_k, \tau)$  refers to the measure of employed people of age  $\tau$  who have perceived aptitude  $\mu_k$  and experience  $y_k$ . Hence for each submarket, we can calculate and distinguish the number of unemployed and employed who apply to that market.

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

### 1.3.2 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,  $\omega$ . Denote  $s = \{\hat{\mu}_i, y_i, z\}$ . Hence, currently employed workers begin the period with  $\{s, \omega\}$ .

In the first sub-stage (Entry), an unmatched firm must decide whether to post a vacancy given its observation of aggregate productivity today,  $z$ . If a firm decides to post a vacancy, it incurs a vacancy posting cost of  $\kappa$ . In addition, a firm  $j$  in sector  $k$  that chooses to recruit a worker has to decide which submarket,  $(x_k, \mu_k, y_k, \tau)$ , to post a vacancy in. While all firms like workers to possess high innate aptitude and experience, posting a high requirement of  $\mu_k$  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. However, a low wage share offer 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 the firm's profits. Al-



though 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 sector he is searching in brings higher expected discounted profits to the firm, as he has a lower likelihood of leaving the firm for a job in another sector. Intuitively, workers base their career search decisions on the expected life-time wage earnings they can derive from working in a particular sector. Young workers with poor precision in their beliefs are more liable to switch careers as they learn about their type. Low retention probabilities of such workers imply lower streams of profit to a firm. Nevertheless, while firms like workers with more precise beliefs, higher requirements on a worker's experience (which is a proxy for precision) also reduce the firm's hiring probability.

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

In the second sub-stage (Separation), a firm that is already matched with a worker is exogenously destroyed with probability  $\delta$ . In addition, given their beliefs as summarized by  $s$  and their new wage share offer  $\omega$ , employed workers voluntarily part with firms if the value of being unemployed is higher than the value of staying with

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

the firm. Hence, a firm separates from its worker with probability  $d(\omega) \in \{\delta, 1\}$ .

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

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

which sector to search for a job. A worker finds a job in sector  $k$  in submarket  $\{x_k, \mu_k, y_k, \tau\}$  with probability  $p(\theta(x_k, \mu_k, y_k, \tau, z, \varphi))$ . 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 (1.7).

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

### 1.3.3 Value Functions

As aforementioned, I use  $s = (\hat{\mu}_i, y_i, \tau, z)$  to denote an individual's perception about his aptitude, experience, age 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.

### *Unemployed Worker*

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

$$U(s) = \max\{R_1^{u*}(s), R_2^{u*}(s), \dots, R_K^{u*}(s)\} \quad (1.8)$$

s.t.

$$\begin{aligned} R_k^u(s) = & \max_{x_k} p(\theta(x_k, \mu_k, y_k, \tau, z, \varphi)) \left[ Ex_k q_{ijk} + \beta EV(x'_k, s') \right] \\ & + (1 - p(\theta(x_k, \mu_k, y_k, \tau, z, \varphi))) \left[ b + \beta EU(s') \right] \end{aligned} \quad (1.9)$$

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

As aforementioned, unemployed workers must solve a two-stage optimization problem. In the first stage, an unemployed worker chooses which sub-market to search within a sector. Because a firm's vacancy posting in a sub-market specifies the requirements a worker must have in order to apply for that job, i.e.  $(\mu_k, y_k, \tau)$ , a

worker effectively only chooses  $x_k$  in deciding which sub-market to search. From equation (1.9), an unemployed individual maximizes his search problem in a sector  $k$  by choosing the optimal wage share  $x_k$  from the menu of contracts posted. The first line in equation (1.9) describes the expected return from finding a job in a particular sub-market;  $p(\theta(x_k, \mu_k, y_k, \tau, z, \varphi))$  is the probability that a worker finds a job in sub-market  $(x_k, \mu_k, y_k, \tau)$ , 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 (1.9) denotes the individual's expected current and continuation utility if he fails to find a job in that particular sub-market. The policy function associated with equation (1.9) is  $x_k^u = \operatorname{argmax}_{x_k} R_k^u(s)$ , which is implicitly given by equation (1.10):

$$p_x(\theta_\tau) \left[ E x_k q_{ijk} + \beta EV(x'_k, s') - b - \beta EU(s') \right] + p(\theta) E q_{ijk} = 0 \quad (1.10)$$

where  $p_x(\theta)$  refers to the first derivative of  $p(\theta(x_k, \mu_k, y_k, \tau z, \varphi))$  with respect to  $x_k$  and  $p(\theta)$  refers to  $p(\theta(x_k, \mu_k, y_k, \tau, z, \varphi))$ . 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 (1.10) therefore refers to the expected marginal cost of seeking a job that offers a higher wage share. The second term in equation (1.10) refers to the expected marginal benefit of seeking a job that offers a higher wage share. As firms get to 'reset' their wage share offers every period, the optimal choice of  $x_k$  affects only current period wage outcomes. From equation (1.10), the optimal targeted wage share,  $x_k^u$ , is a function of both the

individual's outside option as well as his own characteristics, including the amount of human capital he has in that sector.

Having solved this first-stage optimization problem, the unemployed individual then chooses which sector  $k$  would provide him the greatest benefit from search. This choice is given by equation (1.8). Because search is costless, unemployed workers search for a job in every period.

### *Employed Workers*

Employed workers enter the period with updated beliefs on their aptitude  $\mu_i$ , observe  $z$  and receive new wage share offers  $\omega$  from their current employers. Hence, each employed worker starts the period prior to vacancy posting with  $(\omega, s)$ . Workers who are currently employed in sector  $l$  solve the following discrete choice problem:

$$V(\omega, s) = \max\{R_1^{e*}(\omega, s), R_2^{e*}(\omega, s), \dots, R_K^{e*}(\omega, s)\} \quad (1.11)$$

where

$$\begin{aligned} R_k^e(\omega, s) &= \max_{x_k} d(\omega) \left[ b + \beta EU(s') \right] \\ &+ (1 - d(\omega)) \left\{ (1 - \lambda^e p(\theta(x_k, \mu_k, y_k, \tau, z, \varphi))) \left[ E\omega q_{ijl} + \beta EV(\omega', s') \right] \right. \\ &+ \left. \lambda^e p(\theta(x_k, \mu_k, y_k, \tau, z, \varphi)) \left[ Ex_k q_{ijk} + \beta EV(x'_k, s') \right] \right\} \end{aligned} \quad (1.12)$$

and

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

$R_k^{e*}(\omega, s)$  for  $k \geq 1$  represents the value from the optimized search problem for each sector. Equation (1.12) highlights the search problem of an employed worker currently in sector  $l$ . Note that  $x_k$  represents the potential wage offer from recruiting firms while  $\omega$  represents the wage offer from the current firm. Similarly,  $\omega'$  is the wage offer from the current firm for next period, while  $x'_k$  is the wage offer from the recruiting firm next period.  $Ex_k q_{ijk}$  in equation (1.12) refers to the expected current wage the worker receives if he finds a new job in the sector  $k$  while  $E\omega q_{ijl}$  refers to the expected wage the worker receives if he remains in his current job in sector  $l$ . Note that  $l$  can be equal to  $k$  if the worker chooses to search within the same sector for his next job.

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

The first line in equation (1.12) refers to the scenario where an employed worker is

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

With probability  $(1 - d(\omega))$ , the worker does not separate from the firm. In this case, the second line of equation (1.12) denotes the case where the worker searches in a particular sub-market  $(x_k, \mu_k, y_k, \tau)$  but is unable to find an alternative job that pays wage share  $x_k$ . With probability  $(1 - d(\omega))(1 - \lambda^e p(\theta))$ , the worker is unable to find an alternative job and he instead enjoys current expected utility  $E\omega q_{ijl}$  and continuation utility  $V(\omega', s')$ . With probability  $(1 - d(\omega))\lambda^e p(\theta)$ , the worker is successful in finding an alternate job that pays current wage share  $x_k$  and with continuation utility  $V(x'_k, s')$ . Similar to the unemployed worker's problem, the policy function associated with equation (1.12) is given by  $x_k^e = \operatorname{argmax}_{x_k} R_k^e(\omega, s)$  which is implicitly given by equation (1.13).

$$(1 - d(\omega)) \left\{ \lambda^e p_x(\theta) \left[ E x_k q_{ijk} + \beta EV(x'_k, s') - E \omega q_{ijl} - \beta EV(\omega', s') \right] + \lambda^e p(\theta) E q_{ijk} \right\} = 0 \quad (1.13)$$



## Operating Firms

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

$$J(s) = \max_{\omega} \left( (1 - d(\omega))(1 - \lambda^e p^*(\theta(x^*, \cdot))) [(1 - \omega)E q_{ijl} + \beta EJ(s')] \right) \quad (1.14)$$

s.t.

$$d(\omega) = \begin{cases} 1 & \text{if } b + U(s') > V(\omega, s), \\ \delta & \text{else.} \end{cases} \quad (1.15)$$

and

$$x^* = x(\omega) \quad (1.16)$$

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

In equilibrium,  $x_k^e = x^*$  and the firm's optimal choice of  $\omega^* = \omega(x^*)$ .

Equation (1.15) represents the individual rationality constraint. Given  $s$ , there is a range of wage shares for which the worker would prefer to be unemployed. Consequently, the firm and the worker would agree to mutually separate with  $d(\omega) = 1$ . With probability  $(1 - d(\omega))(1 - \lambda^e p^*(\theta(x^*)))$ , the worker stays with the firm and the firm receives current and future expected profits of  $((1 - \omega)Eq_{ijl} + \beta EJ(s'))$ . Denote  $\omega^c(s)$  as the critical wage share below which the worker will choose not to voluntarily separate from the firm, which satisfies:

$$b + U(s') = V(\omega^c, s)$$

Then for any wage above  $\omega^c$ , we can use the fact that  $d(\omega) = \delta$ , the exogenous rate of separation. Taking first-order conditions with respect to equation (1.14), one can solve for the firm's optimal wage share offer. Equation (1.17) below 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:

$$(1 - \lambda^e p^*(\theta))Eq_{ijl} = -\lambda^e p_x^*(\theta) \frac{\partial x_k}{\partial \omega} \left[ (1 - \omega)Eq_{ijl} + \beta EJ(s', x'^*) \right] \quad (1.17)$$

Intuitively, the probability of the worker finding another job is decreasing in the matched firm's wage offer, as  $\omega$  implicitly forms an individual's reservation wage.

An individual will never search in a sub-market in his current career 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  $\omega$ , this implies that worker's job finding rate  $p$  is decreasing in  $\omega$ .

### *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  $\kappa$ . 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,  $f(\theta(x_k, \mu_k, y_k, \tau, z, \varphi))$ , and its expected profits. A firm never creates a vacancy in a submarket that doesn't require the task the firm uses for production, i.e. a firm that uses task  $l$  for production will never advertise in any sub-market in sector  $k \neq l$ . 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. On the other hand, 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:

$$\kappa \geq f(\theta(x_k, \mu_k, y_k, \tau, z, \varphi)) \left( (1 - x_k) E q_{ijk} + \beta E J(s', x'^*) \right) \quad (1.18)$$

and  $\theta \geq 0$  with complementary slackness. Equation (1.18) provides us with the firm's optimal job creation policy. For any submarket that is active with  $\theta > 0$ ,

equation (1.18) holds with equality and firms post vacancies in a submarket up to the point where the benefit is equal to the cost of posting a vacancy. When the benefit of creating a vacancy is strictly less than the cost, no firm creates a vacancy in that submarket. Equation (1.18) is key to the existence of a Block Recursive Equilibrium, which I now define as in Menzio and Shi (2010).

## 1.4 Equilibrium

**Definition 1.** *A Block Recursive Equilibrium (BRE) consists of a market tightness function  $\theta_\tau$ , a value function for the worker's search problem,  $R$ , a value function for the unemployed worker,  $U$ , a corresponding policy function for the unemployed worker's problem,  $x_k^u$ , a value function for the employed worker's problem  $V$ , the corresponding policy function for the employed worker,  $x_k^e$ , a firm's value function  $J$ , and contract policy functions,  $\{\omega, d(\omega)\}$ , for each type of  $(\hat{\mu}_k, y_k, \tau)$  worker searching for a job in sector  $k$ . These functions satisfy the following conditions:*

- 1  $\theta, U, V, R_k^u, R_k^e, J, x_k^u, x_k^e, \omega$ , and  $d(\omega)$  are all independent of  $\varphi$ .
- 2  $\theta$  satisfies equation (1.18) for all values of  $(x_k, \mu_k, y_k, \tau, z, \varphi)$ .
- 3  $U, R_k^u$  and  $x_k^u$  satisfy (1.8) for all  $(x_k, \mu_k, y_k, \tau, z, \varphi)$ .
- 4  $R_k^e$  and  $x_k^e$  satisfy (1.11) for all  $(x_k, \mu_k, y_k, \tau, z, \varphi)$ .
- 5  $J, \omega$  and  $d(\omega)$  satisfy (1.14) for all  $s$  and for all  $\tau = 1 \dots T$ .

The equilibrium is block-recursive, implying that all value functions and corresponding policy functions are independent of  $\varphi$ , the aggregate distribution of workers

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

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

*Proof:* See the appendix. 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 assume that individuals live for a finite number of periods and 2) I assume spot wage contracts instead of long-term dynamic wage contracts. Nonetheless, one can show by back-

ward 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  $T$ . With some abuse of notation, let the labor tightness condition for workers of age  $T$  be denoted as  $\theta_T(\cdot)$ . Also let all other value functions for workers in the last age  $T$  be denoted with a subscript  $T$ . From the free entry condition, it is easy to see that  $\theta_T$  depends only on the vacancy posting cost  $\kappa$ , the promised wage share and the realizations of the worker's human capital and the productivity shocks. Thus,  $\theta_T$  is independent of the aggregate distribution of workers,  $\varphi$ . From equation (1.14), it is clear that if  $\theta_T$  is independent of the aggregate distribution of workers, then  $J_T$  is also independent of  $\varphi$  and the firm's optimal choice of  $\omega$  is independent of  $\varphi$ . Independence of  $\theta_T$  and  $\omega$  from  $\varphi$  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  $\varphi$  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  $\varphi$ , 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  $\theta_{T-1}$  independent of  $\varphi$ . Thus, one can work backwards and repeat the same argument for all prior value functions.

## 1.5 Comparative Statics

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

*Proof* See the appendix. Intuitively, a worker recognizes that a higher innate aptitude implies that he is more productive at a particular task. Highly productive workers are valuable to a firm as they increase output. A worker recognizes that he can demand more compensation when he has higher aptitude. Importantly, more positive beliefs also raise the outside option of the worker. As a worker's search value is increasing in his perceived aptitude, this implies that the value of unemployment is also increasing. Equation (1.15) shows that when the outside option of the worker is increasing, the firm has to offer higher wages in order to retain the worker. Thus, overall, desired wages increase in the optimism of one's belief about his innate aptitude.

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

The monotonicity of desired wages in beliefs has important effects on wage growth and job transitions in this model. In a recession, an individual faces higher search

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

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



the time of entry and long run wage outcomes.

## 1.6 Calibration

Each period in my model is a quarter. In order to calibrate the parameters of my model, I use NLSY79 data on transition rates for white male college graduates across employment states. In particular, I use the UE, EU and EE transition rates reported in Column 1 of Table A.5 to jointly calibrate the vacancy posting cost, the exogenous rate of separation  $\delta$ , and the relative probability of being able to search for a job for employed vs. unemployed workers  $\lambda^e$ . While these targets are taken from the NLSY79 data, they accord well with the monthly probabilities calculated from CPS surveys.<sup>13</sup> Using CPS data, Nagypal (2008) reports that about 0.45% of employed college graduates transition into unemployment every month while 2.42% of college graduates conduct EE transitions every month. These translate into quarterly EU and EE transition rates of 1.3% and 7% respectively. While this EE transition rate accords well with the values reported in FF(2004), the quarterly EU rate is much lower. However, FF(2004)'s reported transition rates refer to all workers, rather than just college graduates. Nagypal(2008) also reports a monthly EU transition rate for all educational categories of 0.89%, which is equivalent to a 2.6% quarterly EU transition rate. This rate falls in the range of the numbers reported by Shimer(2012) and FF(2004). While Nagypal (2008) does not report UE transition rates, Shimer(2012) finds that 32% of all unemployed individuals transition to employment every quarter. Menzio, Telyukova and Visschers, using SIPP data, find

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<sup>13</sup> Quarterly transition probabilities are calculated as  $r_{quarter} = 1 - (1 - r_{monthly})^3$ .

that 25% of the unemployed transition to employment every month, or that 57% of unemployed individuals enter employment every quarter. Given that the transition probabilities in the NLSY79 dataset generally accords with the monthly transition probabilities found in both the CPS and SIPP data, I target the transitional probabilities found in the NLSY79 data to calibrate  $\kappa$ ,  $\delta$ , and  $\lambda^e$ . The unemployed's probability of being able to search for a job,  $\lambda^u$ , is normalized to 1.

In addition, I use NLSY79 data for college graduates on the average quarterly complex job-to-job transition rate to calibrate the value of  $\sigma_\mu$ . 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  $\mu$  is centered around a mean of 1. The gain in experience,  $\zeta$ , is assumed to be 0.25 for each quarter worked; or equivalently a worker gains one year of experience for each year he works at a job.

Since the period in my model is a quarter, I set  $\beta = 0.987$ , which is consistent with an annual interest rate of 5%. Given a modal college graduation age of 22 and assuming an average retirement age of 62 years, I set the lifespan of an individual to  $T = 160$  quarters. To construct the probability transition matrix for aggregate productivity shocks, I use the Tauchen method and set the number of grid points for the shock to be  $N_z = 5$ . I assume that the distribution of shocks is centered around the mean of  $\bar{z} = 1$ . Hagedorn and Manovskii (2013) argue that the appropriate business cycle indicator for labor market search frictions should be the

labor market tightness. Using data from the Job Openings and Labor Turnover Survey (JOLTS) on the number of job openings in the private sector and combining it with information from the BLS on the number of unemployed, I construct the labor tightness measure,  $\theta$ , to be the number of vacancies over the number of unemployed,  $\theta = \frac{v}{u}$ . To identify the cyclical component of  $\theta$ , I take logs and detrend using the Hodrick-Prescott Filter with smoothness parameter 1600. The standard deviation of the cyclical component of the labor tightness condition is roughly equal to 0.274. Results from an AR(1) regression suggest that the quarterly persistence of labor tightness is about 0.92. Setting the persistence of the aggregate shock to be  $\rho_z = 0.92$ , I calibrate the volatility in the aggregate shock,  $\sigma_z$ , such that the implied volatility in  $\theta$  matches its counterpart in the data. This gives me a standard deviation of  $\sigma_z = 0.13$ . I assume that idiosyncratic productivity shocks follow a lognormal distribution with mean 1 and standard deviation  $\sigma_a = 0.1$ . The value of  $\sigma_a$  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.<sup>14</sup>

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

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<sup>14</sup> I find quarterly volatility by calculating  $\sigma_{qtr} = \sigma_{mth} * \sqrt{3}$ .

function exhibits decreasing returns to labor input and set  $\alpha = 0.67$ .

Tables A.11 and A.12 detail the fixed and calibrated parameter values used. Given the finite horizon of the model, I solve the model backwards and compute the value functions at each period accordingly. Figure A.10 shows how closely the model replicates the data in terms of matching the life cycle profile of complex job-to-job transitions. Recall that the calibration exercise only targeted average lifetime transition rates rather than the average transition rate at each age. Similar to the data, the model predicts that the first few years of an individual's life are spent searching for a career. While the model predicts a similar exponential decay in the lifetime path of complex job-to-job transitions, it does slightly underpredict the amount of complex job-to-job transitions in later years. Nonetheless, the model matches the overall life cycle profile of complex job-to-job transitions.

## 1.7 Numerical Simulations

### 1.7.1 Effect of Worker Characteristics on the Job-Finding Probability

I examine how worker characteristics affect the job-finding probabilities of individuals. Throughout this paper, I assume that a recession (boom) is a one standard deviation dip (rise) in aggregate productivity from its mean. Figure A.11 shows the economy in a recession and examines how perceived aptitudes affect job finding probabilities for a new entrant to the labor market. Notably, individuals with high perceived aptitude,  $\hat{\mu}_{ik}$  - defined as a level of aptitude one standard deviation above

the mean and as shown by the dot-dash line - have higher job-finding probabilities than their peers with lower perceived aptitudes at a particular career. Intuitively, firms like workers with higher levels of productivity at the task required for production. As such, more vacancies requiring high aptitude are created, and thus the labor tightness function  $\theta$  and consequently the worker's job finding probability  $p(\theta)$  are increasing in  $\hat{\mu}_{ik}$ . Figure A.11 also demonstrates that the worker's job finding probability is decreasing in  $x_k$ , the posted wage share offer. Firms prefer to create jobs where they can keep a larger share of the rents. Thus, for all levels of aptitude, job finding probabilities increase in markets with lower wage offers.

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

In contrast, job finding probabilities decline with age. Figure A.12 demonstrates

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

Figure A.13 outlines how business cycles affect the job-finding probabilities of labor market entrants. Unsurprisingly, recessions lower the job-finding probability of an individual for all levels of wage offers. This occurs despite the fact that each worker represents an "investment" by the firm, as workers can gain experience specific to that career and contribute to profits in the future.

### *1.7.2 Effect of Aggregate Productivity Shocks*

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

Each individual at time  $t = 0$  draws their  $K \times 1$  vector of true aptitudes  $\mu_i$  from a standard normal distribution. This vector of aptitudes  $\mu_i$  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 prior of their comparative advantage.

Figure A.14 is the analogue of the exercise conducted in Figure A.4 but with the simulated data. The vertical axis denotes the survival probability of staying within the initial career, i.e. no complex job change, while the horizontal axis denotes the quarters since entry. The solid line refers to workers who enter in an expansion while the dashed line refers to workers who enter in a recession. In the model, workers who enter the job market during a recession observe a significant delay in

their first between-career change. Table A.13 highlights the results from estimating a proportional hazards duration model on the simulated data, where the main regressor is a dummy variable indicating whether the worker entered the job market during a recession.<sup>15</sup> Column 1 presents results on the probability of never doing a complex job change while Column 2 looks at the probability of never doing a simple job change. From Column 1, entering the job market during a recession lowers the hazard rate of the first complex job change by 32%. Figure A.15 demonstrates the survival probability of having no simple job change. Compared to the results on complex job changes, entering the job market during a recession has a much more muted impact on the probability of never doing a simple job change. From Column 2 of Table A.13, entering during a recession reduces the hazard ratio by 5%. As in the empirical data, the simulated model demonstrates that recessions impact early between-career changes more strongly than within-career changes.

While Figure A.14 looks at the duration before the first complex job change, Figure A.16 looks at the differences in between-career transition rates over the life cycle for workers who enter in a recession relative to those who enter in a boom. Figure A.16 demonstrates that workers who enter during a recession have muted complex job-to-job transition rates earlier in their working life. This is a direct by-product of the higher search frictions faced during a recession. Weak labor markets impede early job experimentation, which is crucial to learning one's comparative advantage. Notably, there is no subsequent catch-up in complex job-to-job transitions even once

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<sup>15</sup> As before, the duration model assumes the standardized Weibull distribution.



the economy recovers. Intuitively, job experimentation more costly for older workers for two reasons: first, the experience gained in the current sector improves both the individual's job-finding probability and expected wage return within that sector, but is not transferable to a different sector; and second, switching to a new career is a gamble, as the individual not only has less certainty about his skill level at a new sector, but also lacks relevant experience and faces lower job-finding opportunities as he is older and represents a smaller stream of expected future profits to the firm. The lack of precision and relevant experience implies that an individual may be forced to accept a wage cut to improve his job-finding probability if he switches careers when the economy recovers. Because of this, some individuals optimally remain in the same career, resulting in a lock-in effect and consequently no catch-up in complex job-to-job transitions even after the economy has recovered.

Figure A.17 illustrates how the lock-in effect can occur. Consider an individual with the set of true aptitudes and initial priors as given in Table A.14. The individual has comparative advantage in sector 1. However, at the time of entry, he believes that he has highest aptitude at sector 2. As such, the individual initially chooses sector 2. This is true for both expansions and recessions. The "X"s and "O"s in the figure represent the sector the individual searches in each period after entering during a recession and expansion respectively, while the solid line and dashed line represent the sector the individual winds up in at the end of each period. Upon working in sector 2, the individual revises his belief of his aptitude in sector 2 and seeks a job in his next best guess, sector 6. However, due to the persistence of the

aggregate shock, the individual who entered during a boom is able to move to sector 6 immediately while the individual who entered during a recession is ‘unlucky’ and unable to move. The individual who entered during a boom, upon working in sector 6, revises down his prior and moves to his next best guess, sector 1. Subsequently, this individual continues to work and search within sector 1 as that is where his true comparative advantage lies. In contrast, the individual who was ‘stuck’ during the recession in sector 2 stops seeking to switch sectors after quarter 5, as he has accumulated enough experience such that it is no longer worth switching to sector 6.

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

This wage loss persists even after the economy recovers. The aggregate shock disap-

pears after about 5 years. The wage gap, in contrast, is only closed after 60 quarters (15 years). There is significant catch-up in wages as the economy recovers; by the 20th quarter, the wage loss is about 6 per cent. This rapid catch up is largely due to the recovery in the aggregate shock. However, wage losses continue as individuals are working in sectors that do not maximize their comparative advantage. These wage losses are not permanent, as individuals are able to conduct simple job changes and move up the wage ladder once the economy recovers. Over time, comparative advantage 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 at which they have comparative advantage. However, their lack of relevant human capital depresses the wage outcomes of individuals who re-start their careers.

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

specific experience early on than their counterparts who enter in a recession.

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

to misallocation.

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

It is important to note that these gaps in career-specific experience and aptitude have both a direct and indirect effect on wage outcomes. Firstly, lower levels of aptitude and career-specific experience directly translate into lower output at a job. This in turn causes wages to fall. Secondly, aptitude and career-specific experience factor into the wage shares that workers can demand. Recall that a currently matched firm chooses the wage share to offer a worker at the start of the period

based on his revised estimate of the worker's type as well as the worker's experience. A worker with low perceived aptitude may be offered a low wage share since he is not as productive as previously expected. As in equation (1.13), the worker's expected utility from staying with the current firm forms the worker's outside option, which in turn influences the optimal sub-market that a worker would choose to search for a new 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. It is the combination of the direct effects of human capital and its indirect effects through the wage share that causes the 6% wage gap observed even after the aggregate economy has recovered 20 quarters after initial entry.

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

### 1.7.3 *Comparison of Benchmark Model with Other Alternatives*

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

that wages converge once the economy has recovered.

The model with only specific human capital and no learning thus is the least able to explain persistent wage losses. In this model, there is no misallocation, the only difference between the two cohorts aside from the direct effect of the aggregate shock itself comes from the amount of experience accumulated. Because cohorts who enter in a recession face an unemployment rate that is about 5 percentage points higher, this leads to differences in human capital accumulation. However, because each individual knows his aptitude perfectly, individuals always direct their search towards the sector at which they have comparative advantage. The difference in career-specific experience is thus small in the model with only specific human capital and no learning. Figure A.21 shows that there is no significant misallocation in the model with no learning, and less than half a period's difference in career-specific experience. As such, the wage losses evaporate with the recovery of the economy.

Compared to the model with specific human capital and no learning, the model with learning and general human capital does better in generating persistent wage losses. Similar to the benchmark model, the difference in misallocation widens for a few years after entry into the labor market and reaches its zenith at around 26 quarters. The widening in 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, individuals who enter in a recession face a delay in their learning. However, the percentage difference in aptitudes in the model



with learning and general human capital is much smaller than that observed in the benchmark model. This is because the presence of specific human capital raises the cost of switching careers. Individuals who enter in a recession and who start in the wrong career find it easier to switch jobs once the economy recovers when human capital is general, as experience gained at one's current career is completely transferable to another career. Workers are therefore not penalized for switching careers. In addition, as an individual works at his current job, he gains experience that is relevant to all other careers. With general human capital, the increase in experience contributes towards improving the worker's job-finding rate at all careers. As such, there is less misallocation in a model with learning and general human capital, as experience gained 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.

#### *1.7.4 Comparison of Model with Linear Wage Regression*

A key remaining question concerns how well the mechanism in the model explains the timing and magnitude of 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 implied my simulated model to the data, I use the estimated linear wage regression coefficients from Equation (1.1) to calculate the predicted wage loss if individuals experienced the same aggregate shock process as in my simulated model. In particular, I plug in the sequence of unemployment rates as implied by the aggregate shock process in my simulated model. I assume that all individuals have the same AFQT score. Holding all else constant, this implies the following predicted wage loss calculation:

$$\Delta \ln(w_t) = \hat{\alpha}_1 \Delta u_0 + \hat{\alpha}_2 \Delta u_0 * Pot.Exp_t + \hat{\beta}_1 \Delta u_t \quad (1.19)$$

where the  $\Delta$  refers to the difference between a cohort that entered in a recession versus a boom. As aforementioned, a recession in the simulated model assumes an aggregate shock such that there is a difference of 5.2 percentage points in the unemployment rate for the entering cohorts. Thus, the difference in unemployment rate at entry,  $\Delta u_0$ , is fixed at 5.2 in the predicted wage loss calculation.  $\Delta u_t$  captures how the difference in unemployment rates in the simulated model varies over time. Notably, the difference in unemployment rates narrows very quickly with the recovery of economy. Differences in the unemployment rate are negligible by the 8th quarter.<sup>16</sup>

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

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

In general, the simulated wage loss closely matches the predicted wage loss from the linear regression model in the first 10 quarters, but deviates significantly thereafter. This is because differences in unemployment rates are negligible by period 10 although the aggregate shock has not completely recovered yet as shown in the top panel of Figure A.23. From the 10th quarter onwards, the predicted wage loss from

the linear regression model is completely driven by the difference in unemployment rate at entry and the catch-up implied by the interaction term. In contrast, the simulated model shows faster catch-up and a non-linear recovery in wages. This non-linear catch-up in wages is not surprising. Recall that wages in the model 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 the worker's estimate of his aptitude, his 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. I leave estimating the structural parameters of the model to future work.

### 1.7.5 *Mature Workers*

While the model is able to generate persistent wage losses for labor market entrants, recessions in this model do not create persistent wage losses for older workers. This is mainly due to the fact that mature workers are more likely to have already identified their ideal careers. There are therefore no losses stemming from a decline in job experimentation or from accumulating irrelevant experience. Figure A.24 shows the time path of percentage wage losses for a mature worker who experiences a recession 40 quarters after his entry into the labor market. The top panel again highlights the path of the path aggregate shock while the lower panel highlights the percentage wage difference between individuals who experienced a recession 40

quarters after entry and individuals who experienced an expansion 40 quarters after entry. Figure A.24 highlights that for mature workers, the wage gap closely tracks the recovery in the economy. The wage gap closes by 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 would need to be extended to incorporate differential sectoral shocks. This will be left for future work.

## 1.8 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

## Chapter A: Appendix for Chapter 1

### *A.1 Data*

#### *A.1.1 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.

### *A.1.2 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)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  $3 \times 1$  vector of occupation  $o$  and  $B$  be the  $3 \times 1$  vector of occupation  $o'$ . Then the angular separation

of  $o$  and  $o'$  is:

$$\text{Angular Separation}_{oo'} = \frac{A \cdot B}{\|A\| \|B\|} \quad (\text{A.1.1})$$

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

$$\text{Distance}_{oo'} = 1 - \text{Angular Separation}_{oo'} \quad (\text{A.1.2})$$

Equation (A.1.1) 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.

## A.2 Proofs

### A.2.1 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,  $\varphi$ . This independence from the aggregate distribution of workers allows us to solve the model in a block recursive manner.

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

$$\theta_T = f^{-1}\left(\frac{\kappa}{(1 - x_k)Eq_{ijk}}\right) \tag{A.2.1}$$

Note that  $\theta_T$  depends only on parameters and the expected share of output the recruiting firm gets to keep. From equation (1.7), it is clear that output depends on the aggregate state only through  $z$ , aggregate productivity for that period. In addition, the expected output of the worker is in no way affected by the aggregate

distribution of workers as the firm is able to specify exactly what kind of worker he desires. In particular, the human capital requirements of  $\{\mu_k, y_k\}$  are specified whenever a firm posts a vacancy. By posting the level of experience required,  $y_k$ , the firm also implicitly determines the probability distribution of  $\mu_k$  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  $\mu_k$  levels of aptitude is independent of the aggregate distribution of workers. Hence,  $\theta_T$  is entirely independent of the aggregate distribution of workers,  $\varphi$ .

Given the independence of  $\theta_T$  from  $\varphi$ , it follows that  $p^*(\theta_T)$  from equation (1.14) does not depend on  $\varphi$  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 (1.17) for a firm attached to a worker in the last period of his life:

$$(1 - \lambda^e p^*(\theta_T))Eq_{ijl} = -\lambda^e p_x^*(\theta_T) \frac{\partial x_k}{\partial \omega} (1 - \omega)Eq_{ijl} \quad (\text{A.2.2})$$

From equation (A.2.2), it clear that  $\omega$  is depends on  $\theta_T$ ,  $\lambda^e$  and expected output. Since  $Eq_{ijl}$  and  $\theta_T$  do not depend on  $\varphi$ ,  $\omega$  does not depend on  $\varphi$ .

Turning to the search problem of an employed worker at age  $T$ , notice that we can

re-write  $R_k^e$  as:

$$R_k^e(\omega, s) = \max_{x_k} d(\omega)b + (1 - d(\omega))[\lambda^e p(\theta_T) E x_k q_{ijk} + (1 - \lambda^e p(\theta_T)) E \omega q_{ijl}] \quad (\text{A.2.3})$$

From equation (A.2.3), it is clear that independence of  $\theta_T$ ,  $\omega$  and  $E q_{ijk}$  from  $\varphi$  implies that  $R_k^e$  is independent of the aggregate distribution of workers. Analogously,  $R_k^u$  is also independent of  $\varphi$ . Since  $\{R_k^u, R_k^e\}$  are independent of  $\varphi$  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  $\varphi$ , 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 :

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

Since  $J_T$  is independent from  $\varphi$ , the above equation implies that  $\theta_{T-1}$  is also independent of this period's aggregate distribution of workers. Since all  $T - 1$  value functions depend on  $\theta_{T-1}$  and on  $T$  value functions, and since  $\theta_{T-1}$  and  $T$  value functions are independent of  $\varphi$ , 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  $\tau = 1$ .

### A.2.2 Proof of Monotonicity in Wages in Beliefs

Since the search problem of the unemployed worker and employed worker is similar, I demonstrate only the proof for the employed worker's problem. Differentiating equation (1.13) with respect to  $\hat{\mu}_{ik}$  and using the property that  $p_{x,\mu} = \frac{\partial p_x}{\partial x} \frac{\partial x}{\partial \hat{\mu}} = p_{xx} \frac{\partial x}{\partial \hat{\mu}}$ , one can show that the desired compensation,  $x_k$  is rising in the optimism of one's belief about  $\hat{m}u_{ik}$ :

$$\frac{\partial x_k}{\partial \hat{\mu}_{ik}} = \frac{p_x(\theta_\tau)B + p(\theta_\tau) \frac{\partial E q_{ijk}}{\partial \hat{\mu}_{ik}} + p_\mu(\theta_\tau) E q_{ijk}}{A} \quad (\text{A.2.4})$$

where

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

and

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

I first focus on the numerator in equation (A.2.4). Note that the job-finding probability of a worker is decreasing in the desired compensation,  $p_x < 0$ , while the job-finding probability of a worker is increasing in his level of perceived aptitude,  $\mu_k$ . As workers like high-pay, many workers would flood a vacancy offering a high wage share offer  $x_k$ , causing congestion to arise and  $p(\theta_\tau)$  to decline in  $x_k$ . In contrast,

firms like to post vacancies requiring high perceived aptitude, while not many workers may satisfy such a requirement. Hence, a worker with high perceived aptitude has a higher chance of finding a job, hence  $p_\mu > 0$ . Expected income is increasing in higher perceived aptitude as demonstrated by  $\frac{\partial E q_{ijk}}{\partial \hat{\mu}_{ik}} > 0$ , as a higher aptitude at one's job naturally translates into higher output. Notably, since no individual will search for a job which offers less expected utility than the current job, i.e. an individual would only apply to a job with  $E(x_k q_{ijk} + \beta V_{\tau+1}(x'_k, s')) \geq E(\omega q_{ijl} + \beta V_{\tau+1}(\omega', s'))$ , it must be that  $\frac{\partial E(x_k q_{ijk} + \beta V_{\tau+1}(x'_k, s'))}{\partial \hat{\mu}_{ik}} \leq \frac{\partial E(\omega q_{ijl} + \beta V_{\tau+1}(\omega', s'))}{\partial \hat{\mu}_{ik}}$ . In addition, concavity of the production function in  $\mu_{ik}$  implies that the marginal expected life-time utility is declining in  $\hat{\mu}_{ik}$ . Thus, the term  $B$  is strictly non-positive, implying that  $p_x(\theta_\tau)B$  is strictly non-negative. Hence, it is clear that the numerator of equation (A.2.4) is strictly positive.

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

### A.2.3 Proof of Monotonicity of Wages in Belief of TFP

Differentiating (1.13) with respect to  $z$ , and using the property that  $p_{x,z} = \frac{\partial p_x}{\partial x} \frac{\partial x}{\partial z} = p_{xx} \frac{\partial x}{\partial z}$ , we get:

$$\frac{\partial x_k}{\partial z} = \frac{p_x(\theta)D + p(\theta)\frac{\partial E q_{ijk}}{\partial z} + p_z(\theta)E q_{ijk}}{A} \quad (\text{A.2.5})$$

where

$$D = \left[ \frac{\partial E(x_k q_{ijk} + \beta V(x'_k, s'))}{\partial z} - \frac{\partial E(\omega q_{ijl} + \beta V(\omega', s'))}{\partial z} \right]$$

Equation (A.2.5) is analogous to equation (A.2.4). Note that the job finding probability is directly increasing in  $z$ , i.e.  $p_z > 0$  and expected utility from income is also increasing in the perceived level of aggregate productivity,  $\frac{\partial E q_{ijk}}{\partial z} > 0$ . In addition, as  $z$  is persistent, this implies that expected lifetime utility  $\frac{\partial E(x_k q_{ijk} + \beta V(x'_k, s'))}{\partial z}$  from searching for a job is also positive. Given concavity of the production function in  $z$ , marginal expected life-time utility is decreasing in  $z$ . Thus,  $\frac{\partial E(x_k q_{ijk} + \beta V(x'_k, s'))}{\partial z} \leq \frac{\partial E(\omega q_{ijl} + \beta V(\omega', s'))}{\partial z}$  and the numerator in equation (A.2.5) is strictly positive and  $\frac{\partial x_k}{\partial z}$  is also strictly positive.



### A.3 Tables and Figures

Tab. A.1: Impact of Initial Unemployment Rate on Log Wages of College Graduates

Variable	National		Regional	
	1	2	3	4
	OLS	IV	OLS	IV
$u_{0,i}$	-6.358*** (1.085)	-4.982** (2.074)	-4.657** (1.587)	-4.391* (2.504)
Pot. Exp * $u_{0,i}$	0.035 (0.037)	0.077 (0.184)	0.008 (0.054)	0.021 (0.113)
$u_{it}$	-3.815*** (0.361)	-4.130*** (0.431)	-2.670*** (0.635)	-2.725*** (0.450)
AFQT	0.335*** (0.090)	0.298*** (0.056)	0.340*** (0.092)	0.329*** (0.072)
Potential Experience	1.569*** (0.356)	1.255 (1.375)	1.837*** (0.464)	1.739** (0.860)
Potential Experience <sup>2</sup>	-0.012*** (0.002)	-0.012*** (0.002)	-0.012*** (0.002)	-0.012*** (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 (1.2) while "F-stat (1st stage: Pot. Exp \* $u_{0,i}$ )" refers to the F-test associated with equation (1.3). Significance levels: \* : 10% \*\* : 5% \*\*\* : 1%

Tab. A.2: Impact of Initial Unemployment Rate on Log Wages of High School Graduates

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

Dependent variable is log wage. IV first stage regression includes the unemployment rate at age 18, and the unemployment rate at 18\*potential experience. Columns 1 and 2 look at the effect of the national unemployment rate at entry on log wages of high school graduates, Columns 3 and 4 look at the effect of the regional unemployment rate at entry. Coefficients reported in terms of percentage points. All regressions include region dummies. Robust standard errors are reported and all standard errors are clustered by birth year. "F-stat (1st stage:  $u_{0,i}$ )" refers to the F-test associated with equation (1.2) while "F-stat (1st stage: Pot. Exp \* $u_{0,i}$ )" refers to the F-test associated with equation (1.3). Significance levels: \*: 10% \*\*: 5% \*\*\* : 1%

Tab. A.3: Probability of Being Employed (College Graduates)

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

Dependent variable is the probability of being employed. IV first stage regression includes the unemployment rate at age 22, and the unemployment rate at 22\*potential experience. Columns 1 and 2 look at the effect of the national unemployment rate at entry on log wages of college graduates, Columns 3 and 4 look at the effect of the regional unemployment rate at entry. Coefficients reported in terms of percentage points. All regressions include region dummies. Robust standard errors are reported and all standard errors are clustered by birth year. "F-stat (1st stage:  $u_{0,i}$ )" refers to the F-test associated with equation (1.2) while "F-stat (1st stage: Pot. Exp \* $u_{0,i}$ )" refers to the F-test associated with equation (1.3). Significance levels: \* : 10% \*\* : 5% \*\*\* : 1%

Tab. A.4: Probability of Being Employed (High School Graduates)

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

Dependent variable is the probability of being employed. IV first stage regression includes the unemployment rate at age 18, and the unemployment rate at 18\*potential experience. Columns 1 and 2 look at the effect of the national unemployment rate at entry on the employability of high school graduates while columns 3 and 4 look at the effect of the regional unemployment rate at entry. Coefficients reported in terms of percentage points. All regressions include region dummies. Robust standard errors are reported and all standard errors are clustered by birth year. "F-stat (1st stage:  $u_{0,i}$ )" refers to the F-test associated with equation (1.2) while "F-stat (1st stage: Pot. Exp \* $u_{0,i}$ )" refers to the F-test associated with equation (1.3). Significance levels: \*: 10% \*\*: 5% \*\*\* : 1%

Tab. A.5: Transition Probabilities

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

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

Tab. A.6: Results from Proportional Hazards Model

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

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

Tab. A.7: College Graduates: Probability of Complex Job Change

Variable	National		Regional	
	1	2	3	4
	OLS	IV	OLS	IV
$u_{0,i}$	-0.531*** (0.084)	-1.373* (0.741)	-0.469*** (0.079)	-0.536** (0.223)
Pot. Exp * $u_{0,i}$	0.008*** (0.001)	0.027 (0.016)	0.006*** (0.001)	0.013 (0.010)
$u_t$	-0.307*** (0.086)	-0.226*** (0.080)	-0.286*** (0.078)	-0.235*** (0.071)
AFQT	-0.015*** (0.003)	-0.015*** (0.003)	-0.016*** (0.003)	-0.016*** (0.003)
Potential Experience	-0.188*** (0.030)	-0.322** (0.131)	-0.170*** (0.026)	-0.224** (0.087)
Potential Experience <sup>2</sup>	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (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 (1.2) while "F-stat (1st stage: Pot. Exp \* $u_{0,i}$ )" refers to the F-test associated with equation (1.3). Significance levels: \* : 10% \*\* : 5% \*\*\* : 1%

Tab. A.8: College Graduates: Probability of Simple Job Change

Variable	National		Regional	
	1	2	3	4
	OLS	IV	OLS	IV
$u_{0,i}$	-0.167 (0.099)	-0.266 (0.168)	-0.201** (0.083)	-0.173 (0.137)
Pot. Exp * $u_{0,i}$	0.000 (0.002)	0.009 (0.008)	0.002 (0.002)	0.010* (0.005)
$u_t$	-0.102 (0.066)	-0.112** (0.051)	-0.113** (0.036)	-0.125*** (0.033)
AFQT	0.003 (0.002)	0.000 (0.006)	0.003 (0.003)	-0.002 (0.005)
Potential Experience	-0.009 (0.017)	-0.075 (0.054)	- 0.025 (0.015)	-0.082** (0.037)
Potential Experience <sup>2</sup>	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 (1.2) while "F-stat (1st stage: Pot. Exp \* $u_{0,i}$ )" refers to the F-test associated with equation (1.3). Significance levels: \* : 10% \*\* : 5% \*\*\* : 1%



Tab. A.9: High School: Probability of a Complex Job Change

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

Dependent variable is the probability of a complex job change. IV first stage regression includes the unemployment rate at age 18, and the unemployment rate at 18\*potential experience. Sample limited to white male high school graduates. Columns 1 and 2 look at the effect of the national unemployment rate at entry while columns 3 and 4 look at the effect of regional unemployment rates at the time of entry. All regressions include region dummies. Robust standard errors are reported and all standard errors are clustered by birth year. "F-stat (1st stage:  $u_{0,i}$ )" refers to the F-test associated with equation (1.2) while "F-stat (1st stage: Pot. Exp \* $u_{0,i}$ )" refers to the F-test associated with equation (1.3). Significance levels: \*: 10% \*\*: 5% \*\*\* : 1%

Tab. A.10: High School: Probability of a Simple Job Change

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

Dependent variable is the probability of a simple job change. IV first stage regression includes the unemployment rate at age 18, and the unemployment rate at 18\*potential experience. Sample limited to white male high school graduates. Columns 1 and 2 look at the effect of the national unemployment rate at entry while columns 3 and 4 look at the effect of regional unemployment rates at the time of entry. All regressions include region dummies. Robust standard errors are reported and all standard errors are clustered by birth year. "F-stat (1st stage:  $u_{0,i}$ )" refers to the F-test associated with equation (1.2) while "F-stat (1st stage: Pot. Exp \* $u_{0,i}$ )" refers to the F-test associated with equation (1.3). Significance levels: \* : 10% \*\* : 5% \*\*\* : 1%

Tab. A.11: Parameter Space: Fixed

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

Tab. A.12: Parameter Space: Calibrated

Variable	Value	Data target	Model Generated
$\delta$	0.01	mean EU: 0.048	0.043
$\lambda^e$	0.37	mean EE: 0.055	0.072
$\kappa$	17	mean UE: 0.532	0.538
$\sigma_\mu$	2.06	mean Complex EE: 0.032	0.029
$\sigma_z$	0.13	$\sigma_\theta$ : 0.274	0.279

Note: calibrated values are determined jointly in the model.

*Tab. A.13: Survival Probability: Simulated Data*

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

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

*Tab. A.14: Example: Worker's True Aptitudes and Initial Priors*

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

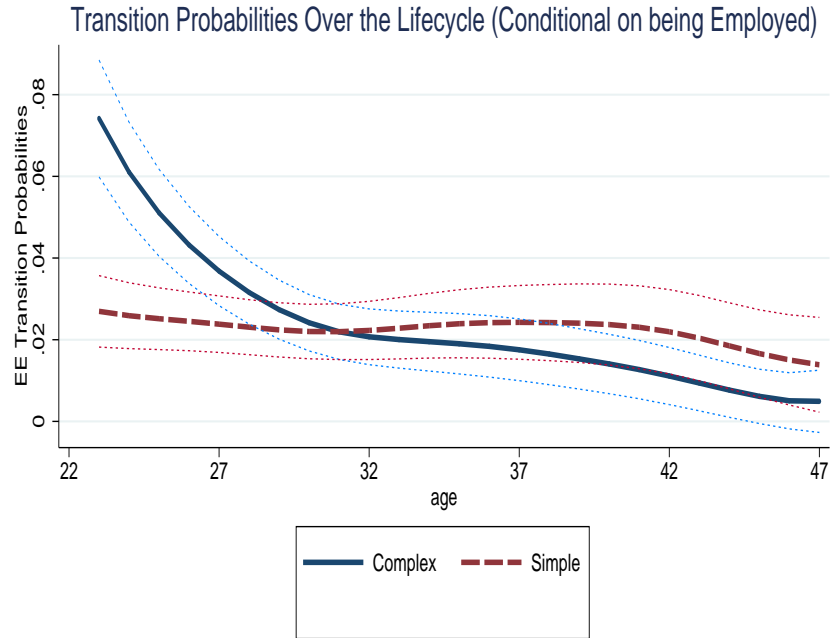


Fig. A.1: EE transitions over the Life-Cycle (College Grads)

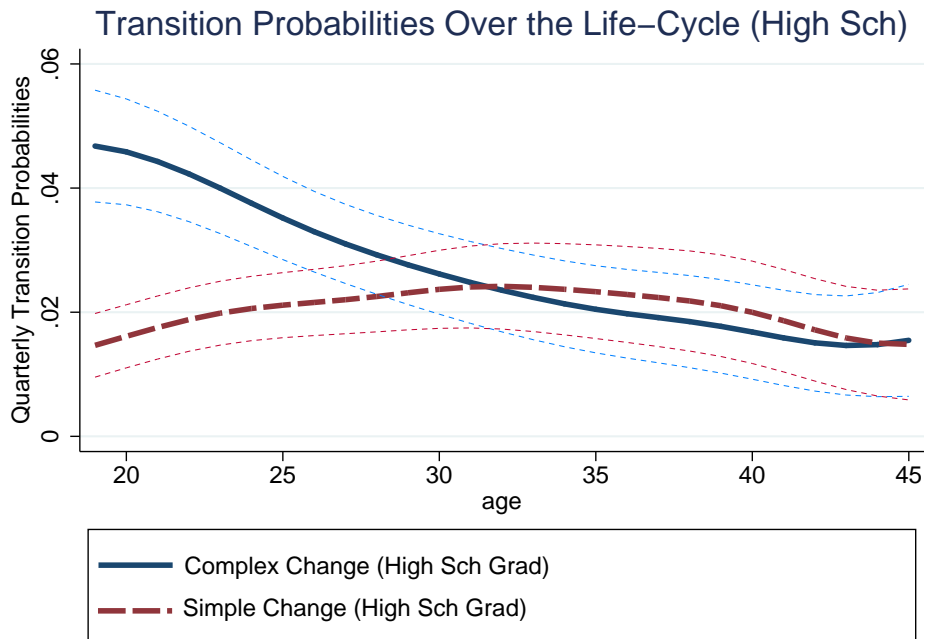


Fig. A.2: EE transitions over the Life-Cycle (High School Grads)

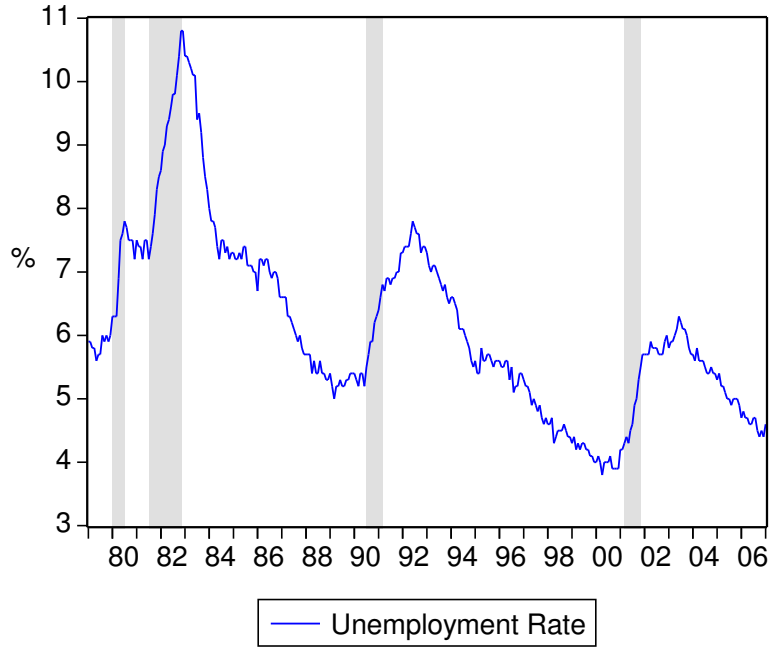


Fig. A.3: Unemployment lags the recovery in GDP

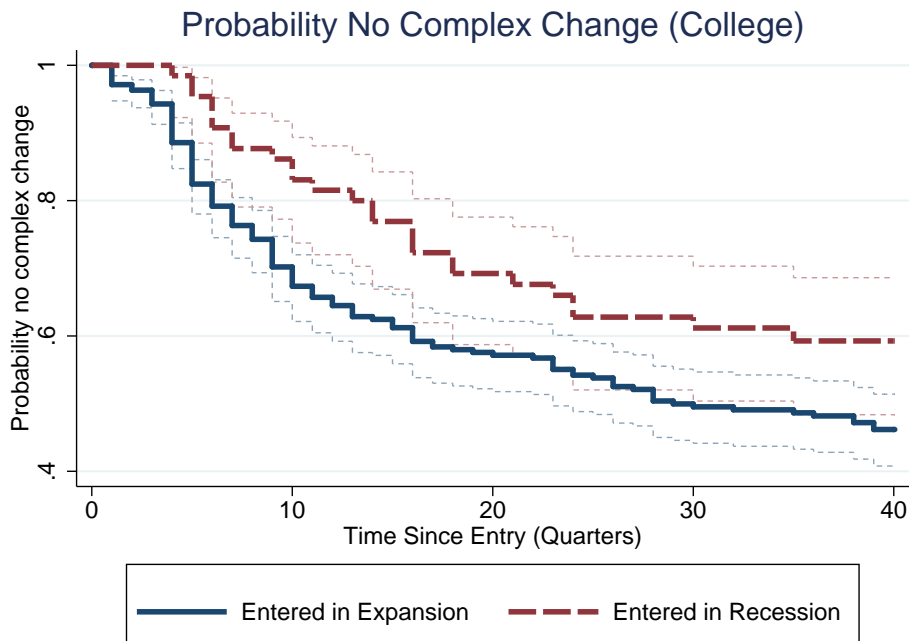


Fig. A.4: Probability No Complex Change Undertaken (College Graduates)

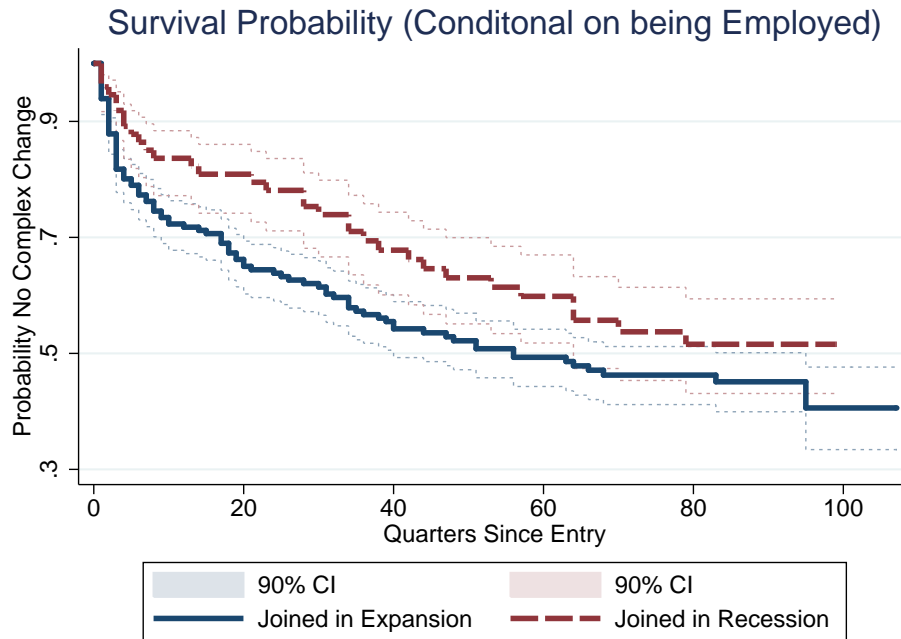


Fig. A.5: Probability No Complex Change Undertaken Conditional on Being Employed (College Graduates)

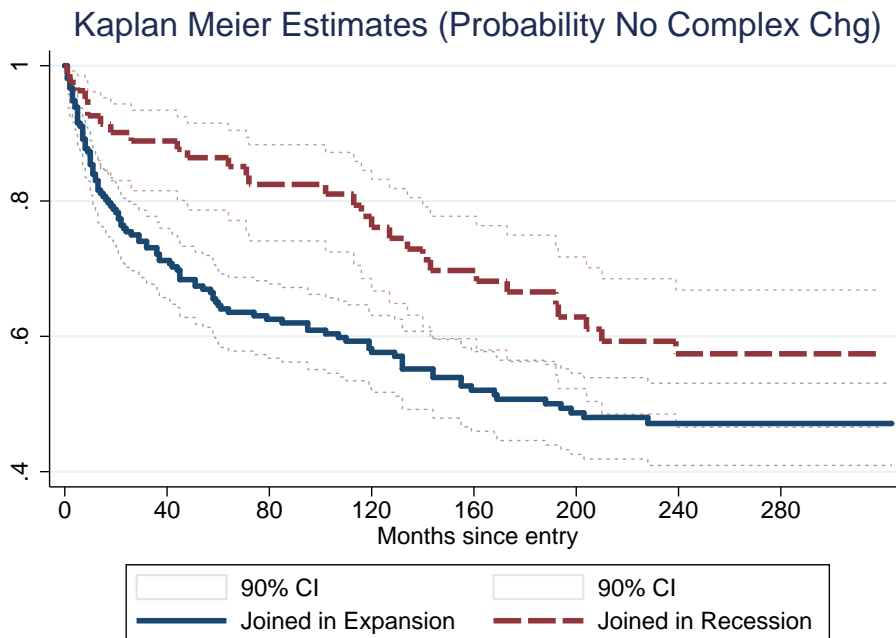


Fig. A.6: Probability No Complex Change Undertaken Conditional on Being Employed (College Graduates, Monthly)

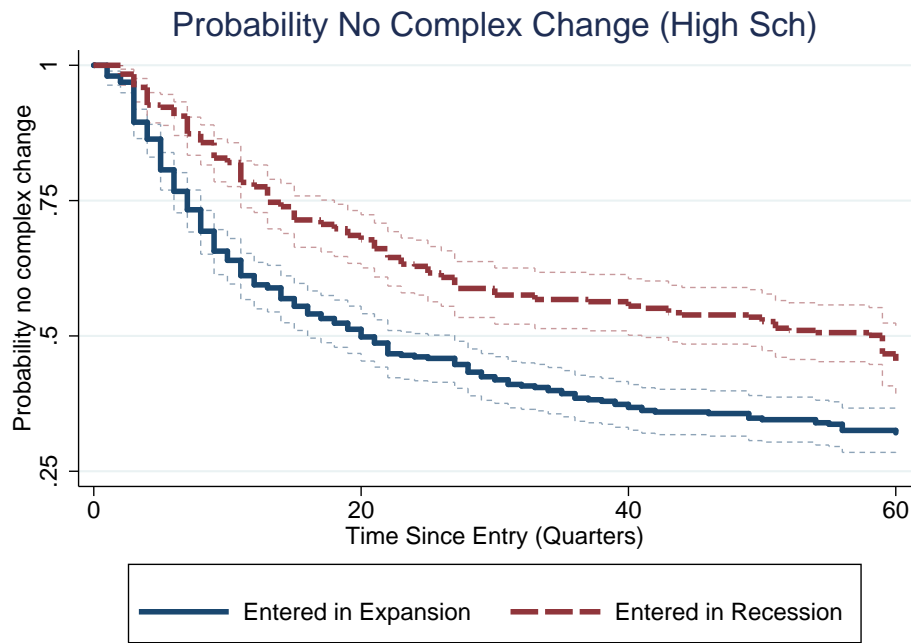


Fig. A.7: Probability No Complex Change Undertaken (High School Graduates)

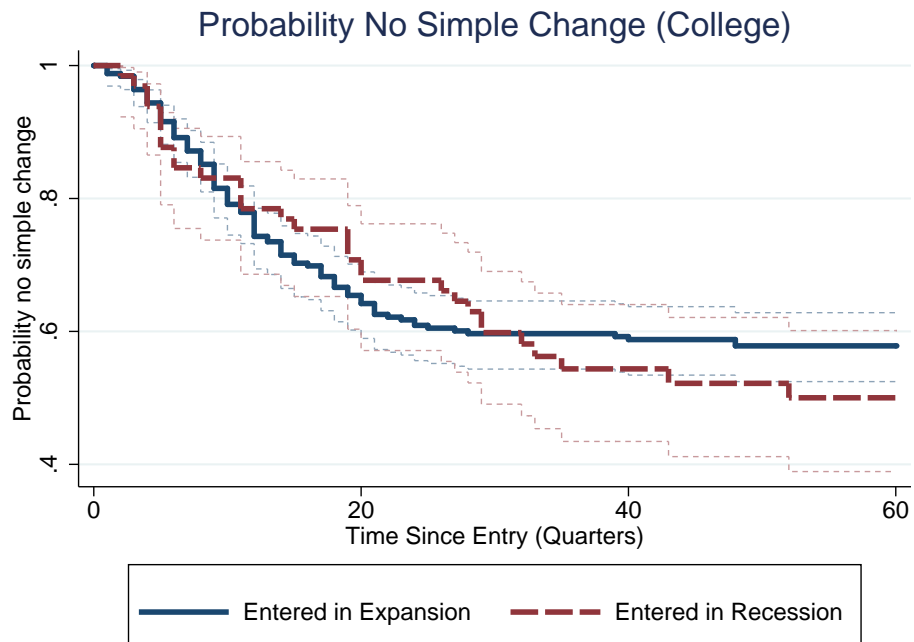


Fig. A.8: Probability No Simple Change Undertaken (College Graduates)



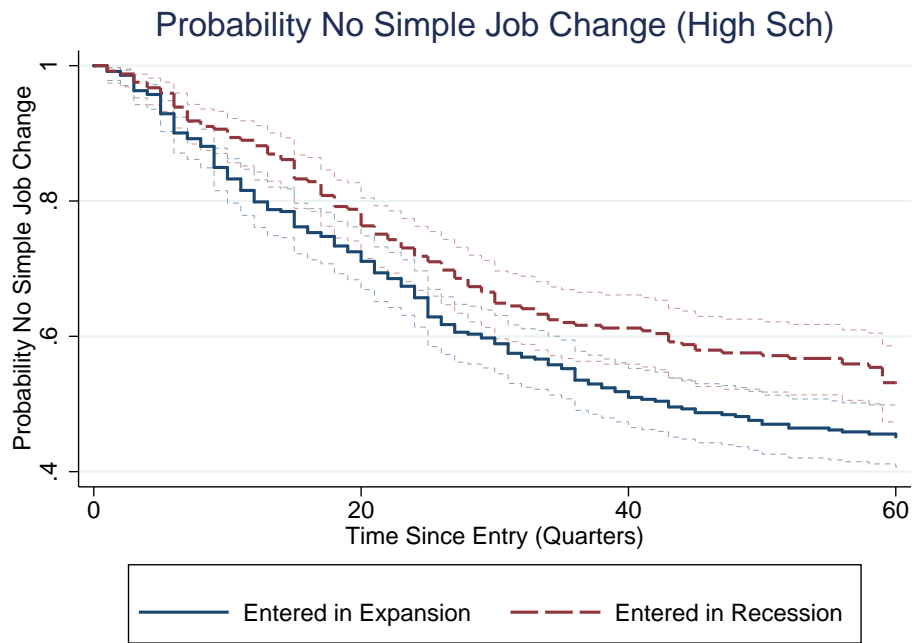


Fig. A.9: Probability No Simple Change Undertaken (High School Graduates)

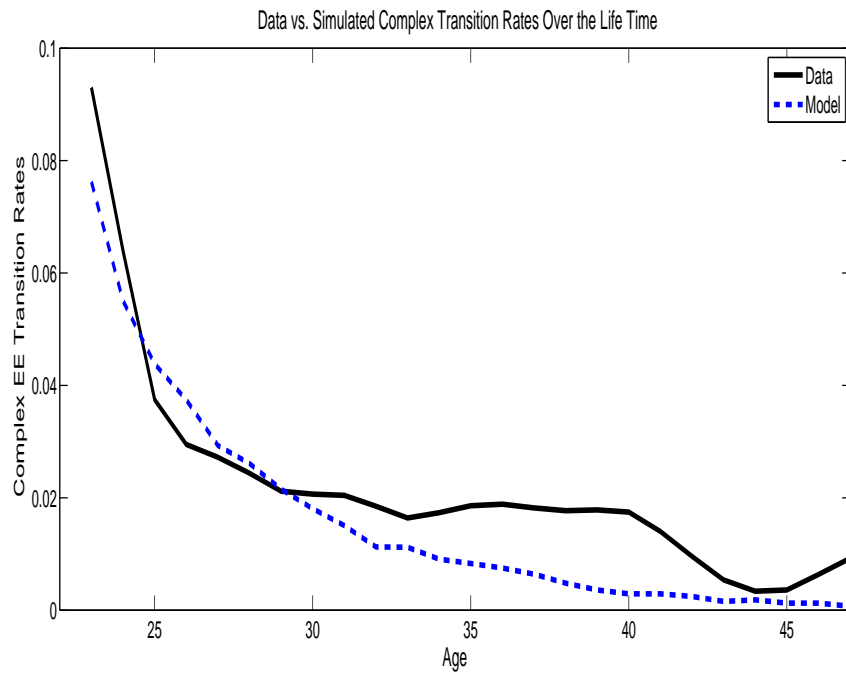


Fig. A.10: Data vs. Model Simulated Lifecycle Complex EE transition rates

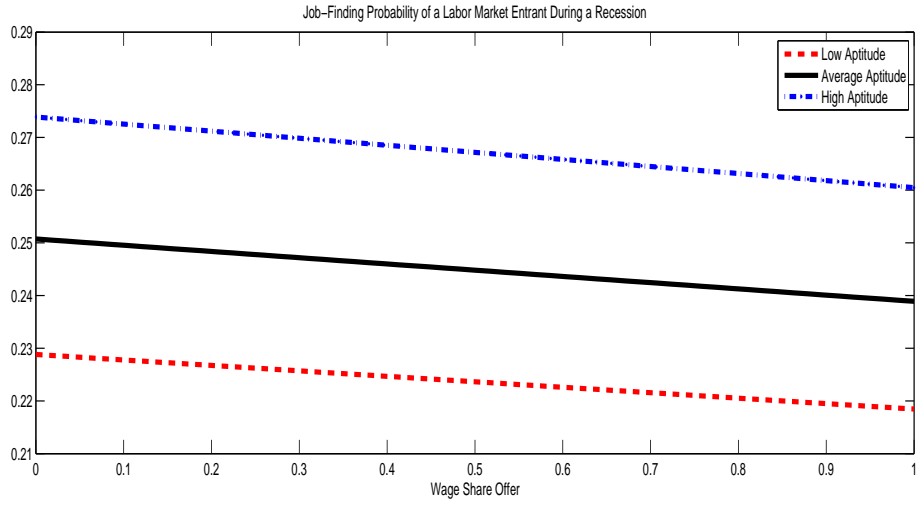


Fig. A.11: Job Finding Probability Rises with Aptitude

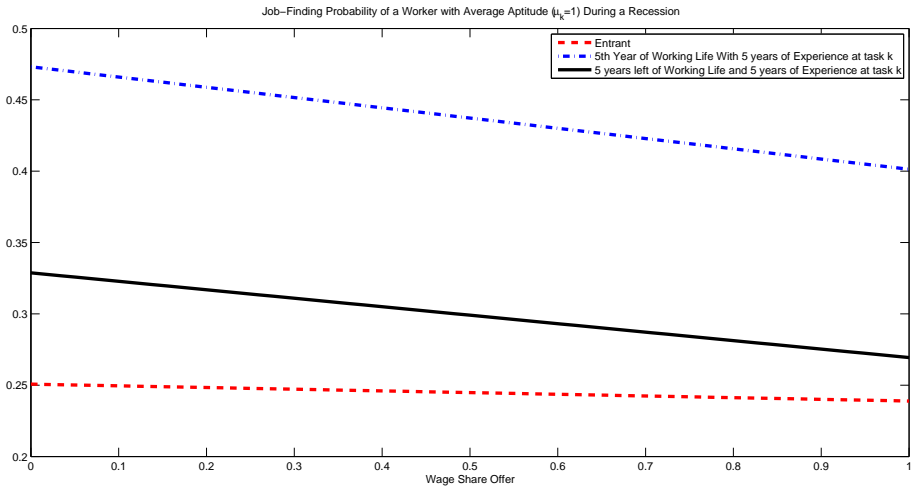


Fig. A.12: Job Finding Probability Rises with Experience, Declines with Age

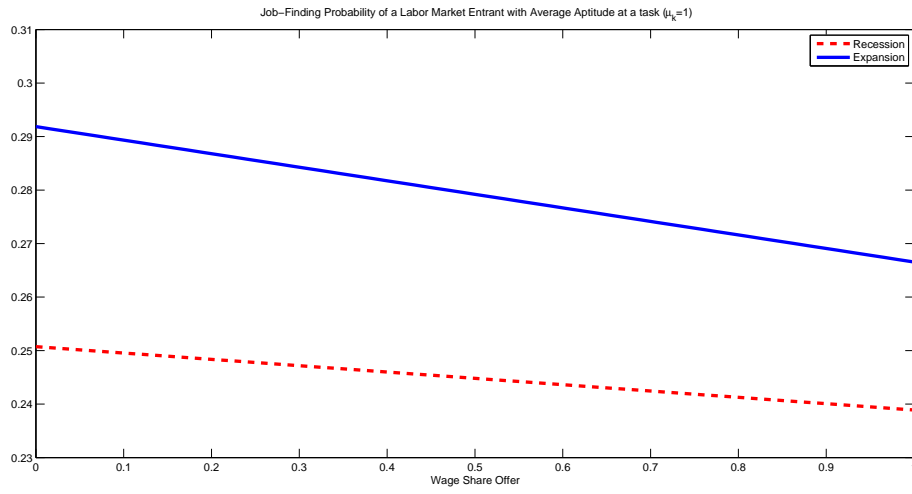


Fig. A.13: Job Finding Probability Drops in Recessions

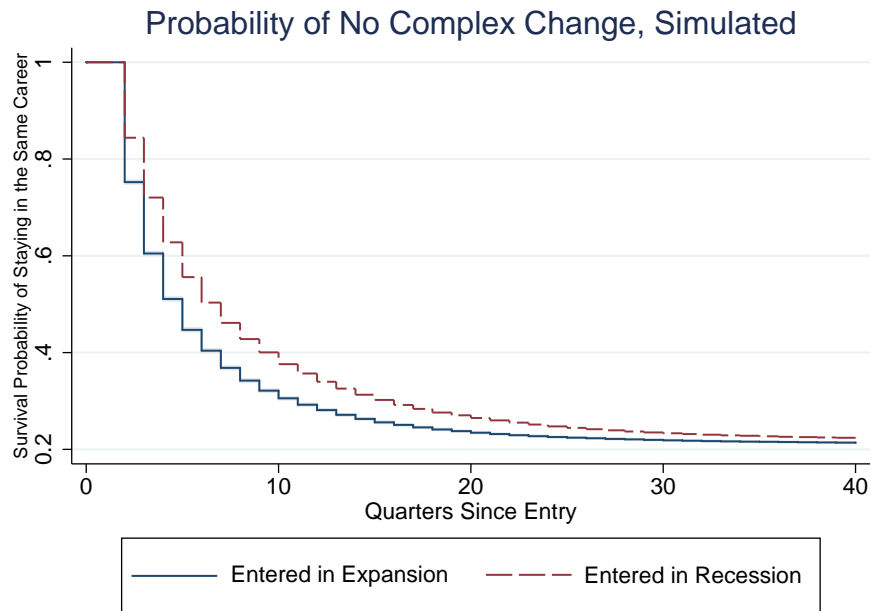


Fig. A.14: Simulated Survival Probabilities of Staying in the Same Career

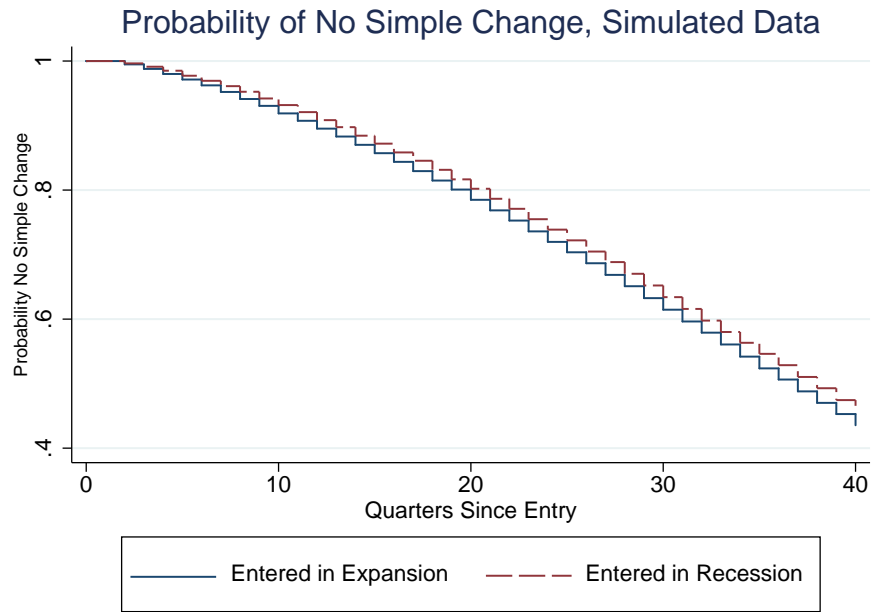


Fig. A.15: Simulated Survival Probability of Not Ever Doing a Simple Job Change

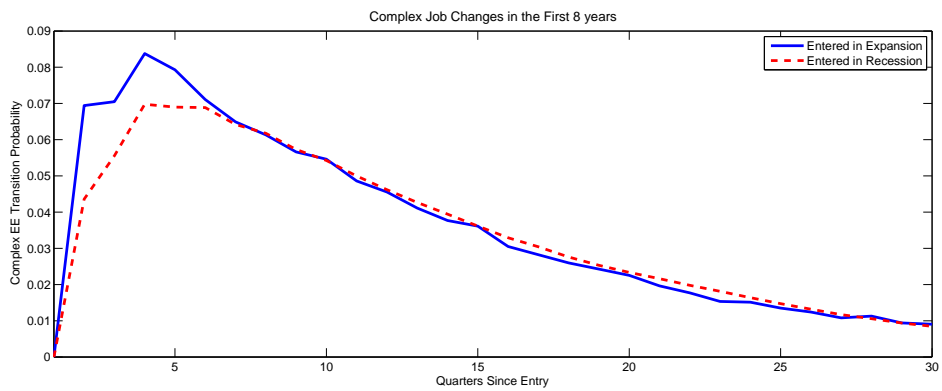


Fig. A.16: Differences in Complex EE between Recession and Boom

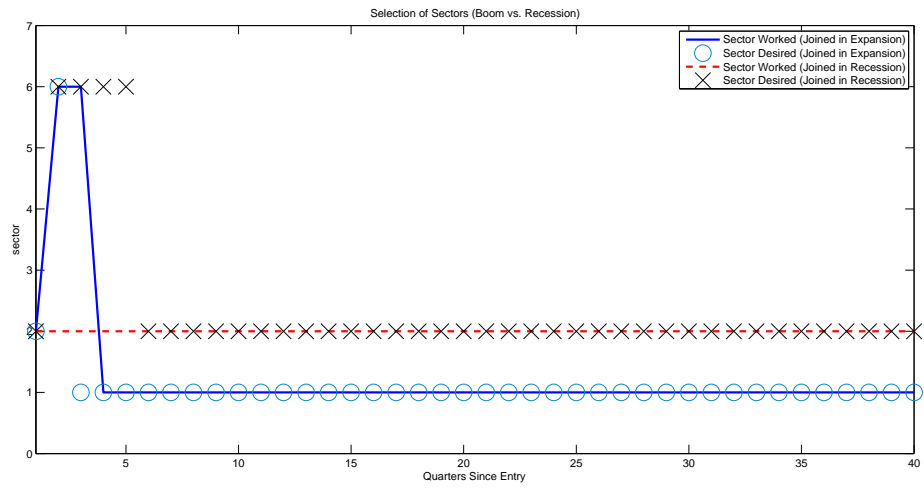


Fig. A.17: Example of Sector ‘Lock-in’

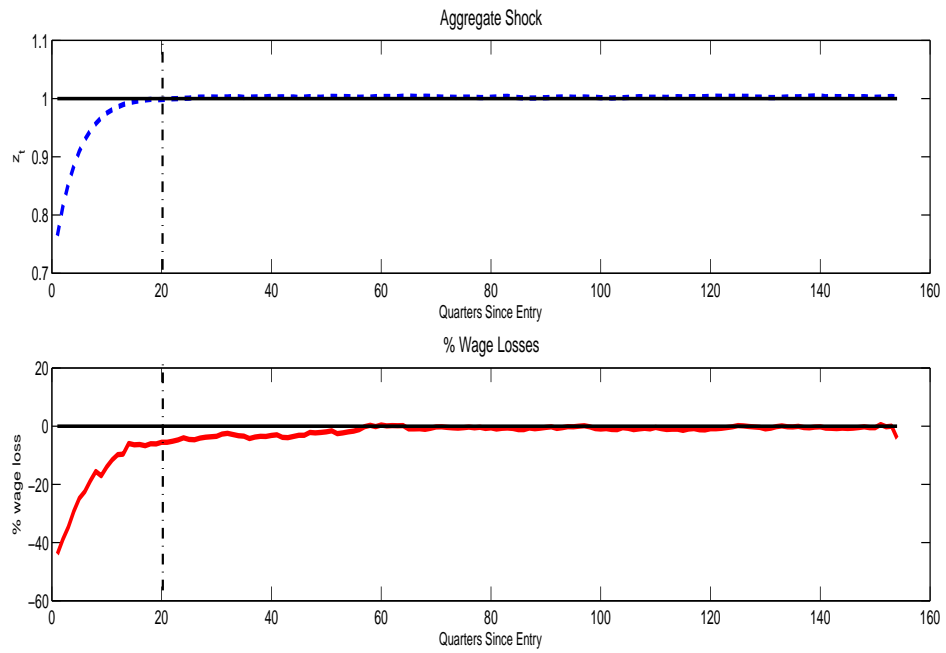


Fig. A.18: Wage Loss between Entering in Booms vs. Recessions

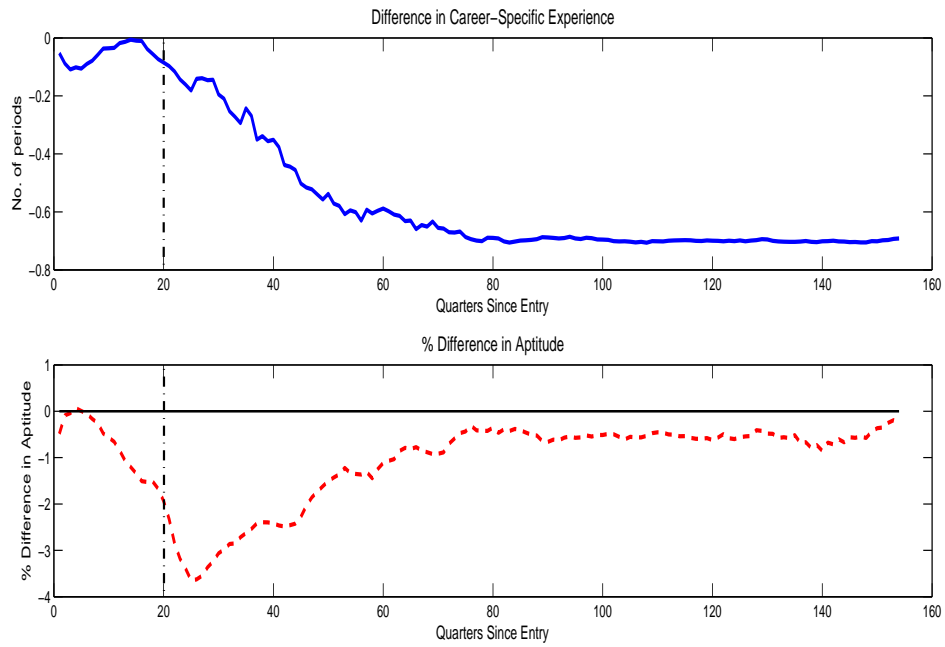


Fig. A.19: Differences in Levels of Experience and Aptitude at Current Job

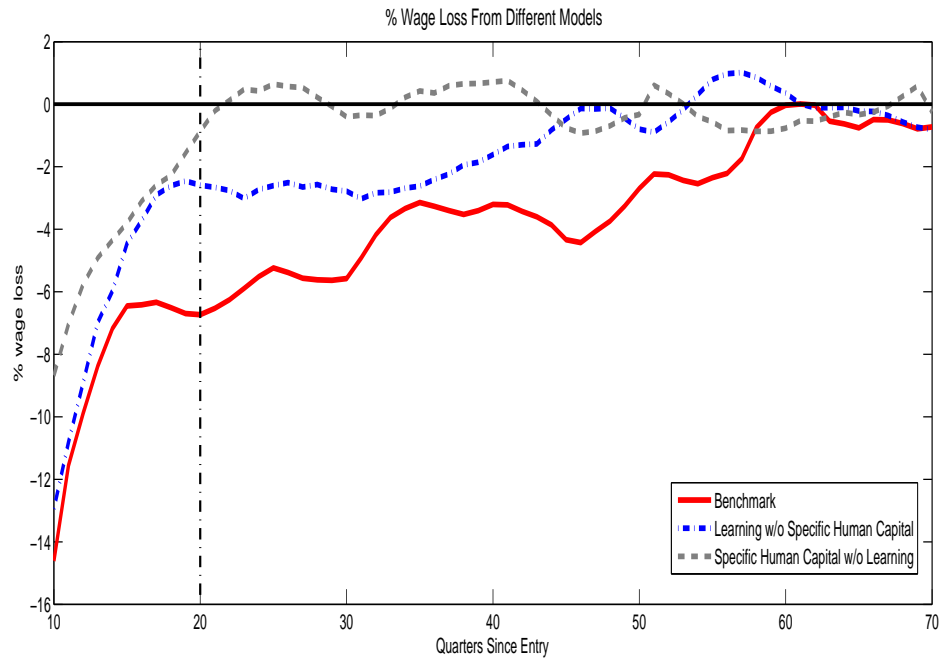


Fig. A.20: Percentage Wage Losses in Different Model Specifications

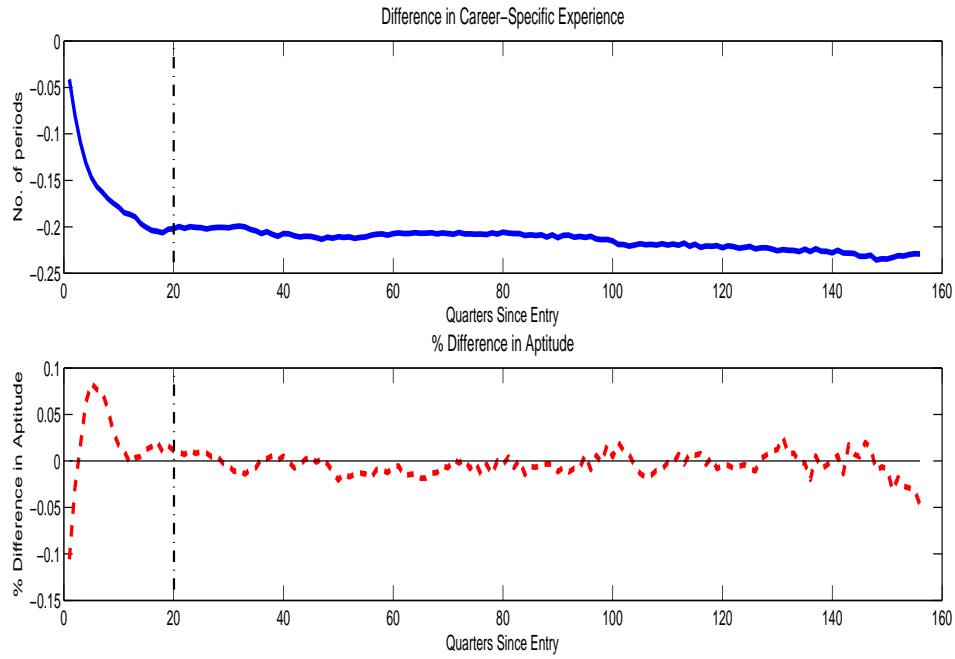


Fig. A.21: Differences in Levels of Experience and Aptitude at Current Job (No Learning)

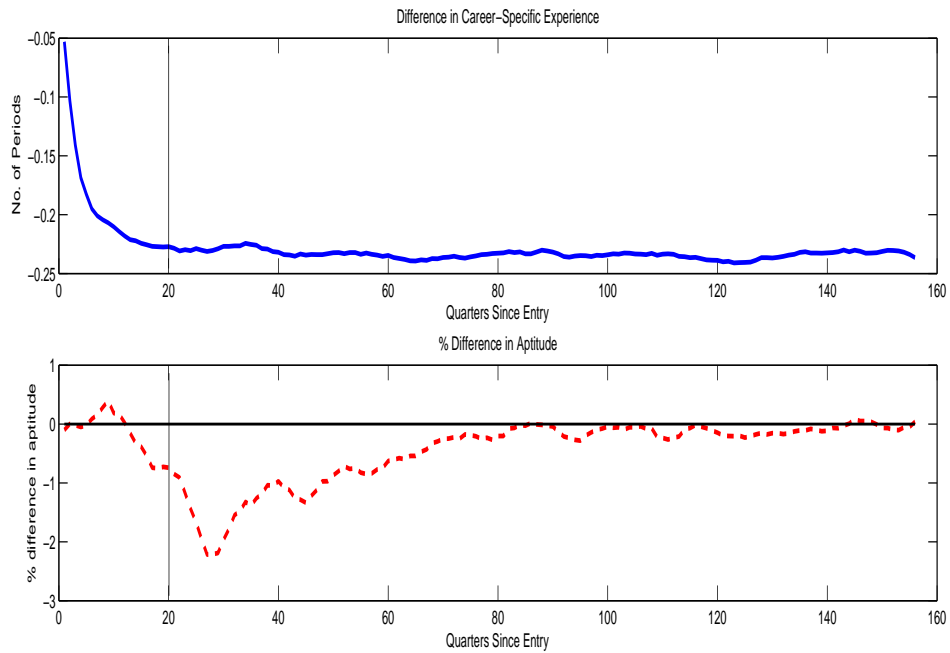


Fig. A.22: Differences in Levels of Experience and Aptitude at Current Job (No Specific Human Capital)

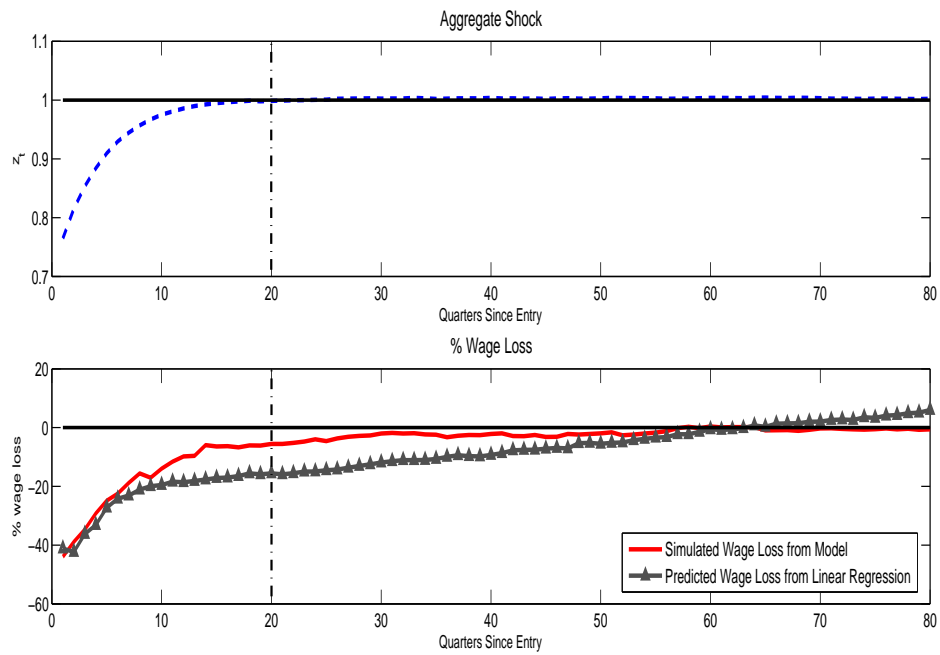


Fig. A.23: Percentage Wage Losses in Simulated Data and Linear Regression Model

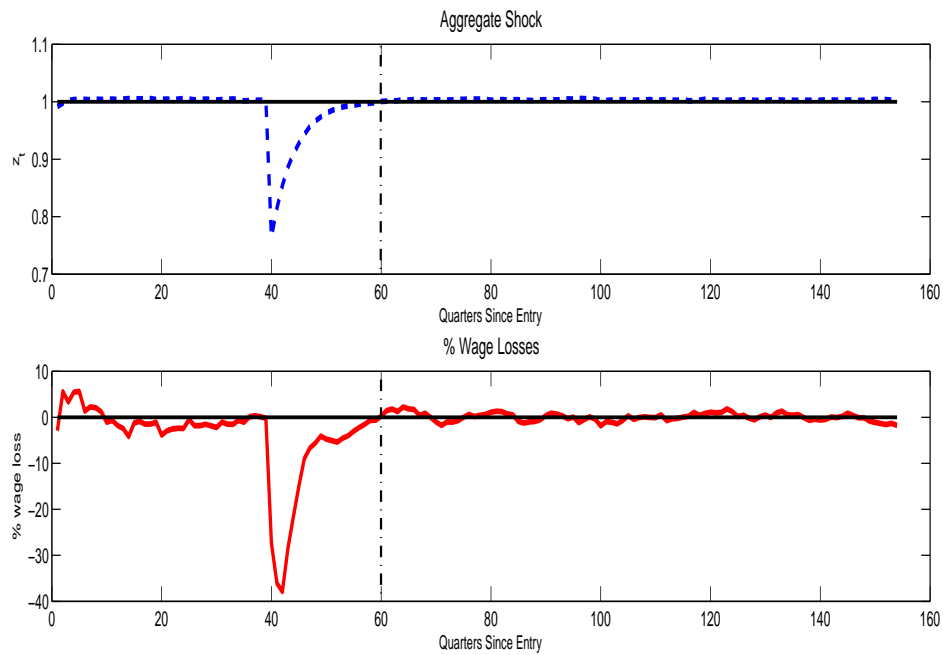


Fig. A.24: Wage Loss for Mature Workers in Booms vs. Recessions



## Chapter 2: Consumer Pricing and Product Durability: Implications for Firm Pricing Strategies

### *2.1 Introduction*

A delayed response in prices has been deemed key for monetary shocks to generate real effects in output. Yet, despite a plethora of research on sticky prices, a lack of consensus on a conclusive mechanism to explain the existence of nominal rigidities remains. This paper seeks to contribute to the existing literature by exploring how differential consumer search costs in durables and non-durable goods can result in price rigidity as seen in the data. Understanding how consumers' search behavior affects firms' pricing strategies is important; survey evidence from Blinder et al. (1998) reveals that consumer aversion and competitive pressures are the two most cited reasons for the lack of price adjustment by firms. In contrast, menu costs and costly information are less cited by firms as reasons for their reluctance to change prices. Given these findings, this paper attempts to rationalize how search frictions in the product market affect firms' pricing behavior for durable and non-durable goods under different cost environments, and examines the implications of firm pricing for overall aggregate price stickiness.

The distinction between durable and non-durable goods is not arbitrary. Durable goods play a key role in business cycle fluctuations and tend to be one of the more volatile components in GDP. Barsky et al. (2007) show that monetary policy is neutral so long as durable goods are flexibly priced; this is true even if non-durable goods exhibit price stickiness. The role of durable goods in consumption smoothing suggests that monetary shocks can only have significant real effects on output if durable goods are price sticky.

In addition, the considerable heterogeneity in average price durations observed across different categories of goods suggests that the propagation effects of monetary policy need not be uniform across all goods. However, it is not immediately clear whether and/or why durable goods would have more flexible prices. Apart from Transportation goods, it is not evident that all durable goods are more flexibly priced than non-durable goods. Table B.1 demonstrates that the majority of goods with price duration less than 4.3 months, the mean price duration, are non-durable goods. To this end, this paper builds a model of consumer search behavior and explores various assumptions about firms' expectations of their costs to reconcile how goods of different degrees of durability may exhibit differing levels of price stickiness.

A priori, durable goods may actually be more price sticky than non-durable goods because they involve higher consumer search costs. Intuitively, searching and attaining multiple price quotes for a non-durable product such as shampoo is signif-

ificantly easier than searching and attaining multiple price quotes for a durable good such as a motorcycle. This variability in search costs impacts the consumer's ability to sample different price quotes and consequently affects the mass of loyal customers a firm can expect to retain. This, in turn, affects the firm's pricing strategy. For example, when consumer search costs are negligible - i.e. consumers face little to no costs in attaining alternative price quotes - the firm lacks a loyal customer base and its revenues largely derive from its sales to shoppers. In such a scenario, the firm would engage in more competitive pricing to attract shoppers and maximize his profits. Work by Caglayan et al. (2008) show that more frequent price changes are observed in market environments with low search costs. Using a Turkish dataset, Caglayan et al find that the greatest turnover in prices occurs in bazaars compared to small convenience stores and supermarkets.

Accounting for consumer search behavior can explain to some degree why various goods have differing levels of price stickiness. Higher informational costs involved in shopping for durable goods can explain why durable goods such as household furnishings tend to have more sticky prices than non-durable goods. Nonetheless, the data shows that there exist durable goods that are more price-flexible than non-durables. This is particularly true for goods such as new vehicles. To account for these features, this paper argues that the longevity or durability of the good also matters in determining its degree of price stickiness. Because durable goods are stock variables, consumers can choose to postpone new purchases and consume out of their current stock when prices are too high. The longevity of the durable good

therefore gives the consumer added bargaining power and limits the pricing power of the firm. The existence of extremely long-lived goods with depreciation rates close to zero and the ability of the consumer to postpone purchases suggests that firms selling such goods must price more competitively to ensure sales. This paper presents a model which accounts for how consumer search behavior and the durability of the product interact to affect firms' pricing strategies. Markets with high consumer search costs are expected to be more price sticky and to observe higher mark-ups as consumers are locked in and cannot switch easily to other sellers. Goods that are longer-lived are expected to observe more competitive pricing regimes and enjoy less of a mark-up premium since consumers can choose to delay purchases whenever prices are deemed to be too high.

This paper is related to the consumer search models considered by Head, Liu, Menzio and Wright (2012) and Kleshchelski and Vincent (2009). In their paper, Head et al. (2012) (henceforth known as HLMW) embed the Burdett and Judd (1983) nonsequential search structure into the Lagos and Wright (2005) monetary framework to examine the interaction between monetary shocks and price rigidity. They find that the incorporation of consumer search costs in a decentralized market enables them to match many of the facts concerning prices in the micro-data such as the average price duration and the existence of many small individual price changes amid large changes in the average price level. HLMW observe money to be neutral in their model; a monetary shock in their model causes the whole price distribution to respond immediately and shift. This finding contradicts empirical results from

Christiano et al. (1999) and that of Boivin et al. (2009). Notably, the latter observes that even disaggregated prices are sticky in response to macroeconomic disturbances such as monetary policy shocks although they are flexible in response to sector specific shocks. Crucially, HLMW assume that there are no customer base dynamics in the firm's problem and that all customers are shoppers each period. This removes an element of price rigidity that can result from firms' fear of antagonizing current customers by raising prices.

Unlike HLMW, the model in this paper does not require consumers to search decentralized markets every period but allows consumers at the start of each period a choice of staying with the firm they were previously attached to last period. This additional feature gives rise to the existence of a loyal customer base and a tradeoff problem similar to that faced by firms in Kleshchelski and Vincent (2009). Incorporating elements of Kleshchelski and Vincent (henceforth known as KV) leads to a clustering of firms around one price; this is different from the pricing dynamics in HLMW, where firms are completely indifferent between charging any price in the distribution.

KV adopt a different strategy from HLMW and assume heterogeneous customer switching costs amongst consumers. In their model, consumers draw taste shocks each period and have a choice to continue purchasing from the same firm or to expend a search cost and switch to another firm. As such, firms have two kinds of customer bases (loyals and shoppers) to attend to when deciding how to

set their posted prices. In the presence of cost shocks, the firm tends to post more stable prices in an effort to maintain a "loyal" customer base. KV observe that the amount of cost pass-through shares a non-monotonic relationship with the level of switching costs but note that the addition of some menu cost is still necessary to generate price stickiness in their model in response to cost shocks. In a similar vein, Nakamura and Steinsson (2011) look at habit formation by consumers in particular products, and find that consumers, knowing that they are partially locked-in, form forward looking expectations and select firms that can credibly commit to not raising their price. As a consequence of consumers' shopping behavior, price stickiness results as an equilibrium response. This paper imposes no physical costs of price adjustment on the part of the firm or habit formation on the consumer but instead shows how consumer search costs and firms' expectations of future cost states can cause clustering around one price and hence lead to overall price stickiness.

Finally, this paper is also related to the literature on consumer markets and customer loyalty as discussed in Gourio and Rudanko (2011) (henceforth known as GR). GR acknowledge that the presence of search frictions generates long-term customer relationships and argue that the customer base of a firm is sluggish to adjust. Customers are valued by firms as a form of 'capital' or asset. In their model, firms face a trade-off in maximizing profits and must balance the profits gained from expanding their customer base against the costs of attracting a new customer. In their model, firms advertise to increase their customer base. Under a representative household setting, GR assume that all firms charge their long-term customers

the same price, i.e. the buyer's maximum willingness to pay. Firms, however, do compete for new customers by offering discounts. As GR are primarily concerned with firms' investment behavior in response to the changes in their customer base and the firms' individual idiosyncratic cost shocks, they abstract from endogenous separation of buyer-seller matches. All new customers or shoppers in a market result from exogenous separations and no customer voluntarily leaves a firm once he has been matched. I argue that endogenous terminations of buyer-seller relationships are important for understanding firms' pricing strategies and resultant overall price stickiness. In particular, this paper models how loyal customers can act as a disciplining device on the firm's amount of cost pass-through.

In the baseline version of the model, there exist both search costs and search frictions in the market. There exists a single large household made up of a unit measure of family members who act as buyers in the market for durable goods<sup>1</sup>. Starting from a stationary equilibrium, each buyer is initially attached to the firm that they were matched to in the last period. The household issues instructions to its buyers at the start of every period on how many units of the durable good to buy so long as the price observed is less than the household's maximum willingness to pay. In addition, the household also chooses a threshold switching price rule and instructs its buyers to switch firms and search the market whenever prices are above the threshold level. The buyers (and consequently the household) face a fixed cost

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<sup>1</sup> Note the model can be easily adjusted for non-durable goods by assuming that the depreciation rate is equal to 1

of search. In addition to paying this fixed cost, search in the market for durable goods is noisy. Buyers who search have some positive probability of meeting only one seller and some probability of meeting two sellers.<sup>2</sup>

Before markets open, firms selling the durable goods post prices to maximize profits. High search costs imply that for some range of prices, firms are able to lock in consumers who have previously purchased from them as it is costly for consumers to re-search the market. At any point in time, there is an exogenous positive probability of separation. This ensures that a set of shoppers always exist in the market. Shoppers also include consumers who upon observing the price posted by the firm they were matched to last period, have found it optimal to break ties with that firm and search the market. Thus, in choosing an optimal price schedule, firms face a trade off between extracting the maximum surplus from its existing loyal customer base, and lowering prices so as to build its customer base by attracting and retaining shoppers.

The rest of the paper is organized as follows: Section 2 describes the empirical evidence motivating this study and illustrates how an aggregate shock leads to differential pricing dynamics for durables vs non-durable goods. Section 3 outlines the model of this paper while Section 4 highlights how different cost assumptions drive differing levels of price stickiness in the model . Section 5 then looks at some

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<sup>2</sup> One can generalize the model such that there is a positive probability of meeting more than one seller. However, the possibility of the buyer encountering two sellers is enough to induce strategic competitive pricing behavior.



quantitative results and Section 6 concludes.

## 2.2 *Empirical Evidence*

Figures B.1 and B.2 demonstrate that both the Consumer Price Index and Personal Consumption Expenditure Price Index inflation rates for non-durable goods tend to be more volatile than those of durable goods, suggesting more frequent price fluctuations in non-durable goods. Even after stripping out food and energy prices from non-durable goods, Figures B.3 and B.4 reveal that the log changes in the CPI and PCE price indices for non-durable goods less food and energy continues to be more volatile relative to durable goods<sup>3</sup>. The standard deviation of the CPI inflation rate for non-durables less food and energy (0.0043) is about twice the standard deviation of the inflation rate for durable goods (0.0023). Figure B.5 shows similar results for the PCE price indices weighted by shares of household expenditure<sup>4</sup>. Figures B.6 and B.7 examine the distribution of log changes in the item-level prices underlying the CPI and PCE price indices for durable goods and non-durable goods less food and energy. Notably, the modal inflation rate for non-durable goods less food and energy prices is small but positive, consistent with previous studies using scanner data that record frequent and small positive price changes.<sup>5</sup> In contrast, Figures B.6 and B.7 shows that price changes for durable goods tend to be

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<sup>3</sup> The price index for non-durable goods less food and energy was constructed using 1998-2005 ELI weights for individual product categories. Data on the ELI weights was taken from Bils and Klenow (2004) Data Appendix

<sup>4</sup> The shares of household expenditure were calculated using monthly PCE nominal expenditure data. The advantage of using the ‘share-weighted’ index is that the weights are time-varying and better able to account for potential substitution bias between product categories.

<sup>5</sup> Using data from Dominicks, Midrigan (2011) documents many small but positive changes in a firm’s posted price

clustered around zero. This suggests that durable goods tend to be more price sticky.

As a quick verification, I run a simple regression estimating the amount of pass-through of cost shocks for price indices for both durable and non-durable goods less food and energy. Using the corresponding PPI inflation rate data as a proxy for changes in marginal costs of final consumer goods, I run the following regression of the log change in consumer good retail prices against current and lagged log changes in corresponding wholesale prices:<sup>6</sup>

$$\Delta P_t^R = \sum_{k=0}^4 \beta_k \Delta P_{t-k}^w + \epsilon \quad (2.2.1)$$

where  $\Delta$  represents the log change operator,  $P^R$  refers to the retail price as measured by either the CPI or PCE price index, and  $P^w$  refers to the wholesale price as proxied by the PPI.  $k$  refers to the number of lags<sup>7</sup>.

Table B.2 shows the main results from the regression. Notably, a 1 percent increase in wholesale prices of durables goods today, as proxied by the PPI, leads to a 0.18 percent rise in the consumer price of durable goods. Lagged wholesale inflation of durable goods have a persistent impact on the consumer price of durable goods; a 1 percent increase in the wholesale price of durable four periods ago increases durable goods prices today by 0.16 percent. In contrast, a 1 percent rise in

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<sup>6</sup> Correspondence codes from the Supplement of Nakamura and Steinsson (2008) were used to match CPI indices to their corresponding PPI categories. The same exercise cannot be conducted for Services as there is insufficient PPI data on services.

<sup>7</sup> While not shown here, I experiment with using 4, 5, 8 and 12 lags and find an optimal lag length of 4 per Akaike's Information Criterion (AIC).

the PPI for nondurables less food and energy today is associated with a contemporaneous increase of 0.30 percent in consumer prices, roughly two-thirds larger than the contemporaneous impact for durable goods. Notably, the effect of nondurable wholesale prices is not as persistent as for durable goods; an increase in non-durable goods wholesale prices two quarters ago has no significant impact on today's consumer prices. This reinforces the hypothesis that non-durable goods undergo more frequent fluctuations in price and are on average, more volatile. Table B.3 shows the same regression results for PCE price indices. Here, the initial response of consumer prices for non-durable goods less food and energy to an increase in wholesale prices is only marginally stronger than that of durables. Nonetheless, the impact of wholesale costs on consumer prices continues to be more persistent for durable goods.

Parsing this down to finer categories, however, it is not always the case that prices are more flexible for non-durable goods. Table B.4 shows the median, mean, standard deviation and persistence in the CPI inflation rates for some product types.<sup>8</sup> It is not evident from the reported standard deviations that non-durable goods are necessarily more price flexible than durable goods. Inflation rates for non-durable goods do tend to be more persistent than those of durable goods, suggesting that once prices start to increase in non-durable good categories, they continue to move upward in later months. In fact, it seems that the high persistence in broad

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<sup>8</sup> The full range of major product categories for both durable and non-durable goods are not reported here. In particular, other miscellaneous non-durable goods that do not fall into a clear broad category have been left out. In addition, the PPI data lacks sufficient coverage on services. As such, summary statistics and pass-through coefficients have not been calculated for service categories.

durable goods inflation is largely driven by Transportation goods and Appliances. Finally, Table B.4 also reports the contemporaneous pass-through in CPI inflation rates from a 1% increase in the underlying wholesale prices. With the exception of Transportation goods and Appliances, products with longer expected lifetimes (as measured by a lower depreciation rate  $\delta$ ) tend to demonstrate less pass-through and exhibit no contemporaneous statistical relationship between retail and wholesale inflation.<sup>910</sup> Table B.5 presents the same summary statistics for PCE inflation rates. Again, there is no discernible difference in the volatility of durable versus non-durable inflation rates at the less aggregated level. Similar to the CPI results, non-durable goods expected to perish within a year tend to have higher persistence in their inflation rates. Unlike the CPI results, however, the degree of pass-through does not seem to be related to the longevity of the good.

Finally, I conduct some vector autoregression (VAR) analyses to check whether there is a differential response in durable goods and non-durable goods to shocks in monetary policy. I use monthly US national accounts data on real personal consumption expenditure and monthly CPI data for the period spanning 1959m1 through 2007m10.<sup>11</sup> To estimate the responses to monetary policy shocks, I split consumption expenditure into durable goods expenditure, non-durable goods expen-

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<sup>9</sup> One could argue that processed food should have a longer life-time than raw food and that the results in Table B.4 are not inconsistent.

<sup>10</sup> Data on  $\delta$  in Tables B.4 and B.5 is taken from Bils and Klenow (1998) which documents the expected lifetime of a product. Note that depreciation,  $\delta$ , is calculated as 1 over the expected lifetime of the product.

<sup>11</sup> Monthly consumption expenditure data from the BEA was used whenever available. Investment data is only available on a quarterly basis. In this case, I apply cubic splines to get estimates of monthly investment data. Monthly CPI data is publicly available from the BLS.

diture and services expenditure, and run separate parsimonious five-variable VAR for these three consumption series. For durables, my five-variable VAR includes current and four lags of real personal consumption expenditure on durables (LDUR), the consumer price index for durables (LCPIDUR), the CRB BLS spot price index for 22 sensitive material prices (LCRB), the federal funds rate (FF), and the logarithm of M1 money holdings (LM1).<sup>1213</sup> Specifications for non-durables and services are similar.

I identify impulse responses by applying a Cholesky decomposition to the VAR. The main policy variable in the regression is the Federal Funds Rate (FF). I assume that the monetary authority observes durable goods expenditure (LDUR), the aggregate price of durable goods (LCPID), and the spot price index for sensitive commodities (LCRB) before setting the Federal Funds Rate.<sup>14</sup> Under this assumption, real expenditure on durable goods and price indices do not change on initial impact of the monetary shock. This assumption allows me to identify the impact of a monetary policy disturbance on the output and price variables. In contrast, money holdings (LM1) are assumed to respond immediately to shocks to FF. The regressions were conducted over the period 1959M1:2007M10. Bootstrap

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<sup>12</sup> LCRB is similar to the PCOMM price index that Christiano, Eichenbaum and Evans use in their paper. The CRB BLS spot price index was obtained from a dataset publicly made available on [www.economagic.com](http://www.economagic.com). The VAR regression for non-durables and services follows the same configuration as that of durable goods expenditure; where appropriate, real personal consumption expenditure numbers on nondurables (LNONDUR) and services (LSER), and the consumer price indices for non-durables (LCPINONDUR) and services (LCPISER) replaced the values for LDUR and LCPIDUR.

<sup>13</sup> Lag length was chosen using the AIC.

<sup>14</sup> Christiano, Eichenbaum and Evans (1999) make a similar assumption in their paper where they argue that real GDP expenditure and the GDP deflator is known but with delay.

simulations were conducted for 100 re-samplings of the data and used to construct the confidence bands for the impulse response functions . Similar exercises were conducted using the Personal Consumption Expenditure (PCE) Price Indices for durables, non-durable goods and services.

Figures B.8 and B.9 present the impulse responses of real consumption expenditure and CPI prices following a positive interest rate shock from the three separate five-variable VAR regressions. Notably, durable goods expenditure observes a sharp drop-off relative relative to non-durable goods and services expenditure. By the end of the first year, durable goods expenditure drops by 1.3% and only bottoms out by 40 months after the initial monetary shock. In contrast, real consumption expenditures on non-durable goods and services decline by only 0.1% one year after the shock and do not decline by more than 0.3% in the subsequent periods. Note that Figure B.9 displays a price puzzle similar to that noted by Sims (1992). Because of this apparent price puzzle, I focus on what happens to the response in prices from months 30 and beyond. Figure B.9 demonstrates that the CPI for non-durables goods falls below its initial value 32 months after the shock while the CPI for durables continues to increase. Put simply, the price puzzle is resolved much faster for non-durable goods than for durable goods. Figures B.10 and B.11 present the impulse responses when PCE price indices were used in place of the CPI. Similar to the CPI results, durable goods expenditure shows a sharp drop-off in response to the shock while there exists negligible change in non-durable and services expenditures. In addition, the PCE price index for non-durables observes a faster correction

than for durable goods.

The above VAR analyses assume that the only consumer good in the economy is either a durable good, non-durable good or a service ‘good’. A more realistic description of the economy should encompass these three different categories of consumption expenditure and allow for interaction or substitution effects. To this end, I formulate a ten-variable VAR using the logarithms of real personal consumption expenditure on durables (LDUR), real personal consumption expenditure on non-durables (LNONDUR), real personal consumption expenditure on services (LSER), real private investment expenditure (LINV), the consumer price index for durables (LCPIDUR), the consumer price index for non-durables (LCPINONDUR), the consumer price index for services (LCPISER), an investment expenditure deflator (LINVDEF), the CRB BLS spot price index of 22 sensitive material prices (LCRB), and the federal funds rate (FF). The VAR is conducted with a lag order of 4 over the same time period of 1959M1 - 2007M10. The identification strategy assumes that the federal funds rate is the main policy instrument and that the monetary authority sets the federal funds rate only after observing all expenditures and their relevant prices.

Figure B.12 shows the results from the ten-variable VAR analysis. There are a few features that stand out from this analysis. The typical hump-shaped responses in both consumption and investment spending to monetary shocks are captured in these results. The decline in non-durables and services consumption expenditure is,

however, negligible compared to the drop in durables and investment spending. Figure B.13 is a magnified view of the impulse responses in consumption expenditures from the same VAR analyses. The trends in the different categories of consumption expenditure are similar to the results seen earlier in the parsimonious five-VAR regression. Noticeably, durable goods expenditure declines by 1.7% 12 months after the shock, while non-durable goods and services expenditure decline only 0.2% after 12 months. More interestingly, inclusion of the different categories of consumption expenditure in the full 10-variable VAR specification gives us different effects on prices. Figure B.14 is a magnified view of the impulse responses in CPI for the different consumption expenditure groups. Unlike the result from the earlier five-variable regressions, Figure B.14 shows that in the full VAR specification, durable goods prices demonstrate very little change relative to the prices for non-durable goods and services. The CPI for non-durable goods and services return to their initial level 14 and 29 months after the interest rate shock while the CPI for durable goods only corrects itself 35 months after the shock.

Figure B.15 shows the results from same 10-variable VAR analysis using PCE price indices instead. Figures B.16 and B.17 provide magnified views of the impulse responses in consumption and PCE price indices respectively. The trends in consumption expenditure and their corresponding price indices are similar to those in the CPI specification. Again, consumption expenditure on durables observes a steeper hump-shaped decline following the monetary shock while durable goods prices exhibit very little adjustment. These findings highlight that there is



significant variation between the price responses in durables vs. non-durable goods towards shocks in monetary policy. I proceed to explain these differences with the model suggested in the next section.

## 2.3 *The Model*

### 2.3.1 *Household's Problem*

There is a single, infinitely-lived large household in this model. In every period, the household consumes both a consumer good,  $C_t$ , and a durable good,  $D_t$ . The consumer good is sold in a Walrasian market at a competitive price of  $q_t$ . The household has a measure one of family members that act as buyers in the decentralized market for the durable good. At the start of each period, each buyer is attached to the durable goods firm that he was matched with in the last period, and observes the price posted by that firm without cost. The buyer then has a choice of whether to stay with that durable goods seller or to separate and search the market. Each buyer is only allowed to search the market once every period, and buyers incur a fixed cost of  $\kappa$  whenever they separate from their current firm and search the market for an alternative seller. There is no perfect recall and buyers cannot return to the seller they were previously attached to once the choice has been made to search the market. In addition, there is an exogenous separation shock that occurs with probability  $\lambda$ , indicating that at any point in time, there are at least  $\lambda$  buyers in the market who are constrained to be shoppers. These shoppers also face the same fixed cost of  $\kappa$  when they search for a new firm. Once buyers choose to search the market,

there is a probability of  $\alpha$  that the buyer only meets one seller and a probability of  $(1 - \alpha)$  that the buyer meets two sellers<sup>15</sup>.

The household knows the distribution of prices,  $F(p)$ , but does not know the exact price posted by each seller prior to sending out its buyers into the decentralized market. Therefore, in purchasing the durable good, the household takes the price distribution as given and gives the following set of instructions:

1. Observe the posted price of the firm  $j$  that the buyer was matched with from the previous period.
- 2a If the posted price  $p_j > p^r$ , leave the matched firm from the previous period, pay  $\kappa$  and search the decentralized market for an alternative seller.
- 2b If the posted price  $p_j \leq p^r$ , stay with the seller from last period and do not search the market.
3. If search results in meeting two sellers, match with the seller who has the lower price. If search results in meeting with one seller, match with that seller.
4. Upon matching with a seller  $k$ , buy one unit of the durable good if  $p_k \leq \bar{p}$ .

Otherwise, buy zero units of the good.

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<sup>15</sup> While it is possible to extend the model to allow the buyer to have some positive probability of meeting more than one seller, it is useful to note that the possibility of meeting two sellers is sufficient enough to induce strategic price competitive behaviour amongst firms. This is shown formally in Burdett and Judd (1983)

Here,  $p_j$  is the price posted by firm  $j$ ,  $\bar{p}$  is the household's maximum willingness to pay for one unit of the durable good and  $p^r$  represents the threshold price above which the buyer leaves the seller it was previously attached to and searches the market. Since the buyer only purchases one unit of the durable good each period whenever  $p_j \leq \bar{p}$ , this implies that the household's total expenditure on the durable good is equivalent to  $\int_{\underline{p}}^{\bar{p}} \hat{\eta}(p)p dF(p)$  where  $\underline{p}$  is the lowest price durable goods firms would choose to offer.  $\hat{\eta}(p)$  corresponds to the mass of buyers that purchase one unit of the durable good at price  $p$ . Since there is a possibility that more than one firm charges the same price, equation 2.3.1 provides the link between the mass of customers that each firm charging  $p$  has at the end of the period with the total mass of buyers purchasing the good at price  $p$ .

$$\hat{\eta}(p) = \int \eta_{j,t}(p) dj \quad (2.3.1)$$

where  $\eta_{j,t}(p)$  is the mass of customers matched at the end of period  $t$  with firm  $j$  charging price  $p$ . At the end of each period, after buyers have completed their transactions, they return to the household to pool their purchases of the durable good. Assuming a single large household and pooling of durable goods purchases implies that there is perfect risk sharing and hence only a single household durable good history, aggregate  $D_t$ , to track. Accordingly, the household's stock of durables evolves according to the following equations:

$$D_t = (1 - \delta)D_{t-1} + X_t \quad (2.3.2)$$

where

$$X_t = \int_{\underline{p}}^{\bar{p}} \hat{\eta}(p) dF(p) \quad (2.3.3)$$

and given a unit measure of buyers, it must be the case that:

$$0 \leq X_t \leq 1 \quad (2.3.4)$$

where  $\delta$  is the rate of depreciation. In choosing the optimal amount of durable good,  $X_t$ , to purchase each period, the household is effectively optimizing with respect to  $\bar{p}$ , the maximum price he is willing to pay in the market. Given that buyers always buy one unit of the good as long as the price encountered  $p$  is less than or equals to  $\bar{p}$ , and because the household takes the price distribution as given, optimizing with respect to  $\bar{p}$  is equivalent to choosing the total amount of  $X_t$  the household would like to purchase that period. Moreover, the household seeks to maximize his utility from the consumption of both the consumer good and the durable good given his budget constraint; this is analogous to the household solving an expenditure minimization problem where it chooses the threshold price rule for which buyers must switch sellers whenever they observe price  $p$  above  $p^r$ . Thus, in setting up the household's problem, the optimal level of  $X_t$  can be obtained by solving for the optimal pricing rules of  $\bar{p}$  and  $p^r$ .

Hence, while the price distribution,  $F(p)$ , is stationary in equilibrium, the dispersion of prices and mass of firms offering a particular price  $p$  are affected by the household's optimal choice of  $\bar{p}$  and  $p^r$ . This implies that  $\hat{\eta}(p)$  is an equilibrium object that is a function of both  $\bar{p}$  and  $p^r$ . Deriving formal expressions for  $\hat{\eta}(p)$  and  $\eta_{j,t}$  requires an examination of the firm's problem, which is discussed in the subsequent section. For the time-being, it important to stress that the mass of customers purchasing the good at price  $p$ , i.e.  $\eta(p)$ , crucially depends on the household's choice of  $p^r$ , the threshold switching price.

In order to examine how prices respond to monetary policy in an environment where search is costly, I consider a money in the utility (MIU) model.<sup>16</sup> Households receive utility both from the consumption of consumer and durable goods and from holding money, and suffer disutility from supplying their labor. The household is also the single shareholder of all consumer and durable goods firms in the market. Formally, the household problem can be written as:

$$V(M_{t-1}, B_{t-1}, D_{t-1}) = \max u(C_t) + \nu(D_t) + \mu(M_t) - L_t + \beta EV(M_t, B_t, D_t) \quad (2.3.5)$$

s.t.

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<sup>16</sup> An earlier version of this paper built heavily on the Lagos-Wright framework used in HLMW, this has since been modified as the insurance derived from the rebalancing of money holdings under the Lagos-Wright structure is equivalently accomplished in the assumption of a single large household, i.e. money holdings collapse to a degenerate distribution in both models.

$$M_t + B_t + q_t C_t + \int_{\underline{p}}^{\bar{p}} \hat{\eta}(p) p dF(p) = w_t L_t + M_{t-1} + R_{t-1} B_{t-1} + \Pi_t^C + \Pi_t^D + T_t - \kappa N_t^s \quad (2.3.6)$$

and equations (2.3.2),(2.3.3), (2.3.4).

where the  $M_t$  and  $B_t$  refer to the household's holdings of money and bonds in period  $t$ , and  $w_t L_t$  is the nominal wage income the household receives from supplying labor  $L_t$  to the market. Accordingly, the real wage is defined as  $\omega_t = w_t/P$  where  $P$  is the aggregate price level.  $\Pi_t^c$  and  $\Pi_t^d$  are the aggregate dividend profits the household receives from the consumer good and durable good firms respectively, while  $T_t$  is a lump-sum transfer payment the household receives from the government. Finally,  $((1 - \lambda)\{\int_{p^r}^{\bar{p}} \{\int \eta_{j,t-1}(p) \mathbb{I}(p_{j,t} = p) dj\} dF(p)\})$  of buyers choose to switch firms every period, where  $\eta_{j,t-1}(p)$  is the mass of customers that were attached to firm  $j$  at the end of last period. This implies a mass of shoppers,  $N_t^s$ , in the decentralized market for durable goods in each period  $t$ . Formally,  $N_t^s$  is given as

$$N_t^s = (1 - \lambda) \left( \int_{p^r}^{\bar{p}} \left\{ \int \eta_{j,t-1}(p) \mathbb{I}(p_{j,t} = p) dj \right\} dF(p) \right) + \lambda \quad (2.3.7)$$

The first component in  $N_t^s$  describes the mass of “buyers” who are not exogenously separated from the firm they were matched to last period but who voluntarily choose to leave the firm because the price charged by the firm is above the household's threshold switching price. The second component of  $N_t^s$  consists of the buyers who

are constrained to become shoppers every period because of some exogenous shock of separation. Accordingly, the total nominal cost of search incurred by the household is  $\kappa N_t^s$ .

We can re-write the budget constraint as follows:

$$L_t = \frac{1}{w_t} \left( M_t + B_t + q_t C_t + \int_{\underline{p}}^{\bar{p}} \hat{\eta}(p) p dF(p) - M_{t-1} - R_{t-1} B_{t-1} - \Pi_t^c - \Pi_t^d - T_t + \kappa N_t^s \right) \quad (2.3.8)$$

Using equation (2.3.8), we can re-write the household's problem as:

$$\begin{aligned} V(M_{t-1}, B_{t-1}, D_{t-1}) &= \max u(C_t) + \nu(D_t) + \mu(M_t) & (2.3.9) \\ &- \frac{1}{w_t} \left( M_t + B_t + q_t C_t + \int_{\underline{p}}^{\bar{p}} \hat{\eta}(p) p dF(p) \right. \\ &- \left. M_{t-1} - R_{t-1} B_{t-1} - \Pi_t^c - \Pi_t^d - T_t + \kappa N_t^s \right) \\ &+ \beta EV(M_t, B_t, D_t) \end{aligned}$$

The household chooses  $\{C_t, M_t, B_t, \bar{p}, p^r\}$  to maximize (2.3.9). Before solving for the household's optimality conditions, it is useful to describe the firm's problem so that we can derive an expression for  $\hat{\eta}(p)$  and hence solve for the household's optimal pricing rules.

### 2.3.2 Firms' Problem

#### Consumer Goods Firms

The problem of the consumer good firm is standard. The consumer goods firm faces a linear production function  $f(L_t) = A_t L_t$ , and hires labor at nominal wage  $w_t$ . Consumer goods are purchased by both the household and durable goods firms. The latter buys the consumer good as an input and converts it into a durable good at some cost  $q_t z$ , where  $q_t$  is the price of the consumer good. There are no search frictions in the consumer goods market. This gives us the following set-up for consumer goods firm's profit function:

$$\pi_t^c = q_t A_t L_t - w_t L_t \tag{2.3.10}$$

Solving the consumer goods firm's problem, we get:

$$q_t A_t = w_t \tag{2.3.11}$$

As the consumer good is an input in the production of the durable good, equation (2.3.11) provides us the link as to how aggregate shocks can affect the pricing of durable goods. Notably, any negative TFP shock (a smaller  $A_t$ ) directly affects the ratio  $\frac{w_t}{q_t}$  which in turn affects the household's budget constraint and the household's choice of  $\bar{p}$ .



## *Durable Goods Firms*

There is a mass  $n$  of durable goods firm in the decentralized market. At the start of each period, durable goods firms purchase consumer goods from the consumer good firm. The durable goods firm possesses a linear production technology that allows him to convert one unit of the consumer good into one unit of the durable good. For simplicity, I assume that all firms face the same constant marginal cost. The cost for firm  $j$  of converting a consumer good into a durable good every period is thus given by  $q_t z$ . Durable goods firms observe  $q_t$  as well as the exogenous probability of separation  $\lambda$  before posting prices to maximize expected profits.

As aforementioned, buyers that choose to search the market have some positive probability  $\alpha$  of meeting only one firm and probability  $(1 - \alpha)$  of meeting two firms. The presence of search frictions implies that a firm cannot capture the whole market even if he cuts prices to marginal cost, while the positive probability of a buyer meeting two firms implies that charging the monopoly price is not necessarily always optimal. In addition, each firm starts off the period with a mass of “base” customers who purchased from him last period. In choosing the optimal price to post, the firm encounters a trade-off in setting prices between extracting the maximum surplus from the customer base or setting prices such that he attracts the maximum number of customers.

Formally, the firm’s problem can be formulated as:

$$J(\eta_{j,t-1}) = \max_{p_{j,t}} \{ \pi_{j,t}^D(\eta_{j,t-1}) + \beta EJ(\eta_{j,t}) \} \quad (2.3.12)$$

s.t.

$$\eta_{j,t} = (1 - \lambda)\eta_{j,t-1}\mathbb{I}\{p_{j,t} \leq p^r\} + \frac{N_t^s}{n}[\alpha + 2(1 - \alpha)(1 - F(p))] \quad (2.3.13)$$

and

$$\pi_{j,t}^D(\eta_{j,t-1}) = \eta_{j,t}(p_{j,t} - qtz) \quad (2.3.14)$$

where the first term of equation 2.3.12 represents the current profits of the durable goods firm and the second term denotes its continuation value.  $\eta_{j,t}$  refers to the mass of customers a firm  $j$  attracts at the end of each period and equation (2.3.13) represents its law of motion. The mass of customers a firm can attract is made up of two components. Firstly,  $\eta_{j,t-1}(1 - \lambda)$  is the mass of base customers a firm  $j$  has after the separation shock occurs. Because buyers only stay with the firm if prices are below  $p^r$ , the total number of base customers that stay with a firm is  $(1 - \lambda)\eta_{j,t-1}\mathbb{I}\{p_j \leq p^r\}$ . The second term on the RHS of equation (2.3.13) represents the mass of shoppers a firm  $j$  is able to attract and sell to in period  $t$ .  $N_t^s$  is the total mass of shoppers in the market. Since there is a positive mass of  $n$  durable goods firms in the market, the largest possible number of shoppers a firm can receive is  $\frac{N_t^s}{n}$ . The existence of search frictions, however, implies that  $\frac{N_t^s}{n}\alpha$  of shoppers meet only

with firm  $j$ . Correspondingly,  $\frac{N_t^s}{n}2(1-\alpha)(1-F(p))$  represents the mass of shoppers firm  $j$  is able to attract if buyers meet two sellers in the market when they search. Note that while  $(1-\alpha)$  is the probability that that the shopper meets two firms,  $(1-F(p))$  is the probability that the other firm charges a higher price. Finally, the current profit per customer enjoyed by firm  $j$  is given by  $p_{j,t} - q_t z$  while  $\beta EJ(\eta_{j,t})$  represents the firm's continuation value.

The evolution of the customer base as described by equation (2.3.13) and the role of  $p^r$  point toward the importance of the consumer search method for firms' pricing decisions. There is a discontinuity in the mass of buyers when prices increase from  $p^r$  to  $p^r + \varepsilon$  where  $\varepsilon \rightarrow 0^+$ ; no firm can retain a base customer if he charges above  $p^r$ . Thus, the household's threshold switching price rule plays an important role in dictating firms' strategic pricing decisions.

Given the price distribution  $F(p)$  and the household's pricing rule, the firm's decision of whether or not to set prices so as to retain base customers is inherently dependent on the cost parameters assumed in the model. Under different assumptions on the persistence and probability of being in a high cost state, a firm may choose to sacrifice his customer base in order to maximize lifetime profits.

### 2.3.3 Government

To account for money holdings, there is also a government in this economy. The role of the government in this economy is to print money and issue non-state

contingent bonds. Accordingly, the government's budget constraint takes the following form:

$$M_t + B_t = T_t + M_{t-1} + R_{t-1}B_{t-1} \quad (2.3.15)$$

where

$$M_t = (1 + \xi_t)M_{t-1} \quad (2.3.16)$$

### 2.3.4 Equilibrium Conditions

Given the equilibrium price distribution, I return now to the household's problem and solve for the optimality conditions. Recall that the mass of buyers purchasing one unit of the durable good at price  $p$  is :

$$\hat{\eta}(p) = \int \eta_{j,t}(p) d_j \quad (2.3.17)$$

where  $\eta_{j,t}(p)$  is given by equation (2.3.13). For ease of exposition we can rewrite the total amount of durable goods purchased this period, i.e.  $X_t = \int_{\underline{p}}^{\bar{p}} \hat{\eta}(p) dF(p)$  in the following manner and apply Leibniz's rule when taking first order conditions with respect to  $\bar{p}$  and  $p^r$ :

$$\begin{aligned}
\int_{\underline{p}}^{\bar{p}} \hat{\eta}(p) dF(p) &= \int_{\underline{p}}^{p^r} \left\{ \int \left( (1-\lambda)\eta_{j,t-1} \right. \right. & (2.3.18) \\
&+ \left. \left. \frac{N_t^s}{n} [\alpha + 2(1-\alpha)(1-F(p))] \right) \mathbb{I}(p_{j,t} = p) dj \right\} dF(p) \\
&+ \int_{p^r}^{\bar{p}} \left\{ \int \frac{N_t^s}{n} [\alpha + 2(1-\alpha)(1-F(p))] \mathbb{I}(p_{j,t} = p) dj \right\} dF(p)
\end{aligned}$$

Denote  $\tilde{X}_t = \int_{\underline{p}}^{\bar{p}} p \hat{\eta}(p) dF(p)$ .  $\tilde{X}_t$  is the household's investment expenditure on new durable goods this period. Returning to the household's problem in equation (2.3.9) and taking first order conditions with respect to  $\{C_t, M_t, B_t, \bar{p}, p^r\}$ , the following optimality conditions are derived:

$$L_t = \frac{1}{w_t} [M_t + B_t + q_t C_t + \int_{\underline{p}}^{\bar{p}} \hat{\eta}(p) p dF(p) - M_{t-1} - R_{t-1} B_{t-1} - \Pi_t^c - \Pi_t^d - T_t + \kappa N^s] \quad (2.3.19)$$

$$u'(C_t) = \frac{q_t}{w_t} \quad (2.3.20)$$

$$\mu'(M_t) \frac{q_t}{u'(C_t)} = \frac{R_t - 1}{R_t} \quad (2.3.21)$$

$$\frac{1}{R_t} = \beta E \frac{w_t}{w_{t+1}} \quad (2.3.22)$$

$$\nu'(D_t) + \beta(1-\delta) E \frac{1}{w_{t+1}} \left[ \frac{\left( \frac{d\tilde{X}_{t+1}}{d\bar{p}_{t+1}} + \kappa \frac{dN_{t+1}^s}{d\bar{p}_{t+1}} \right)}{\frac{dX_{t+1}}{d\bar{p}_{t+1}}} \right] = \frac{1}{w_t} \left[ \frac{\left( \frac{d\tilde{X}_t}{d\bar{p}_t} + \kappa \frac{dN_t^s}{d\bar{p}_t} \right)}{\frac{dX_t}{d\bar{p}_t}} \right] \quad (2.3.23)$$

$$\nu'(D_t) + \beta(1-\delta) E \frac{1}{w_{t+1}} \left[ \frac{\left( \frac{d\tilde{X}_{t+1}}{d\bar{p}_{t+1}} + \kappa \frac{dN_{t+1}^s}{d\bar{p}_{t+1}} \right)}{\frac{dX_{t+1}}{d\bar{p}_{t+1}}} \right] = \left[ \frac{\left( \frac{d\tilde{X}_t}{d\bar{p}_t} + \kappa \frac{dN_t^s}{d\bar{p}_t} \right)}{\frac{dX_t}{d\bar{p}_t}} \right] \quad (2.3.24)$$

Equation (2.3.19) gives us the household's optimality condition for labor and

equation (2.3.20) is the household's optimal consumption of consumer goods. Equations (2.3.21) and (2.3.22) give us the household's optimal holdings of money and bonds respectively. Equation (2.3.23) is the household's first order condition with respect to  $\bar{p}$ , where  $\bar{p}$  affects the total amount of  $X_t$  the household buys in equilibrium. Equation (2.3.24) implicitly gives us the household's threshold switching price rule  $p^r$ . In the appendix, I show that  $\frac{dX_t}{d\bar{p}_t} > 0$ ,  $\frac{dN_t^s}{d\bar{p}_t} \geq 0$  and  $\frac{d\tilde{X}_t}{d\bar{p}_t} > 0$ . Equation (2.3.23) highlights that the marginal benefit of increasing the maximum price the household is willing to pay for durable goods is higher than the marginal benefit of increasing his maximum willingness to pay for non-durable goods (in which case  $\delta = 1$ ). Intuitively, this arises because raising the maximum willingness to pay for durable goods today increases the stock of durable goods the household has available to eat from tomorrow. This in turn reduces the amount of resources the household expends on search in the future. In contrast, there is no stock of non-durable goods that the household may consume from tomorrow. All else equal, this implies that the maximum willingness to pay and the dispersion of prices observed for durable goods may be larger relative to that of non-durables.

Recall from the consumer firm's problem, the following equilibrium conditions results:

$$q_t A_t = w_t \tag{2.3.25}$$

Equation (2.3.25) implies that the consumer goods firm earns zero profits in

equilibrium, so that  $\Pi_t^c = 0$  in every period. The durable goods firms' optimal choice of  $p_{j,t}$  characterizes the equilibrium price distributions given specific cost parameterizations. In aggregate, the profits from durable goods firms are:

$$\Pi_t^D = \int_{\underline{p}}^{\bar{p}} \left\{ \int \pi_{j,t}^D(p) dj \right\} dF(p) \quad (2.3.26)$$

where  $\pi_{j,t}(p)$  refers to the firm's current profit at the end of period  $t$ . The household, being the single shareholder of all firms, receives this lump-sum transfer of profits from the durable goods firms at the end of every period.

Combining these equations together with the government's budget constraint as given in equation 2.3.15, we get the following feasibility constraint:

$$q_t AL_t + \Pi_t^D = q_t C_t + \tilde{X}_t + \kappa N_t^s \quad (2.3.27)$$

Equation (2.3.27) says that all nominal expenditure must equal nominal GDP.

## 2.4 Steady State Equilibrium Conditions

A stationary monetary equilibrium is defined by a sequence of quantities  $\{M^*, D^*, C^*, B^*, L^*\}$  and prices  $\{q_t^*, w_t^*, F_t(p)^*\}$  such that:

1  $M^*, C^*, B^*, H^*$  solve the household's problem and satisfy equations (2.3.20), (2.3.21), (2.3.22) and (2.3.8).

2  $D^*, X^*, \bar{p}^*, p^{r*}$  solve the household's problem in the decentralized market for

durable goods and satisfy equations (2.3.2), (2.3.3), (2.3.4), (2.3.23) and (2.3.24).

3 The consumer good firm pays labor input its marginal product:

$$q^*A = w^* \quad (2.4.1)$$

As such, total profits from the consumer good firm are equal to zero,  $\Pi^{*c} = 0$ .

4 From the consumer good firm's problem, the feasibility constraint holds:

$$q^*AL^* + \Pi^{*D} = q^*C^* + \tilde{X}^* + \kappa N^{*s}$$

5 The price distribution,  $F(p)$  is consistent with the solution to the durable goods firm's problem.

6 The household receive aggregate profits from the individual durable good firms:

$$\Pi^{*d} = \int_{\underline{p}}^{\bar{p}} \left\{ \int \pi_j^{*D}(p) dj \right\} dF(p)$$

7 Household money holdings are equivalent to the total money supplied by the government. The government budget constraint holds.

$$M'^* + B'^* = (1 + \xi)M^* + R^*B^* + T^*$$

8 In steady state, nominal variables increase at the rate of money growth,  $\xi$ ,



while real variables are constant, i.e.

$$M'^* = ((1 + \xi)M^*, F_{t+1}^*(\xi p) = F_t^*(p))$$

$$w'^* = (1 + \xi)w^*, q'^* = (1 + \xi)q^*$$

and

$$D'^* = D^* = D^{ss}, C^* = C^{ss}$$

$$X^* = X^{ss} = \delta D^{ss}, L^* = L^{ss}$$

## 2.5 Distribution assumptions

### 2.5.1 No Loyal Customer Base

The model with non-durable goods, constant marginal cost and no loyal customer base among all firms collapses to the price dispersion observed in Burdett-Judd (1983). In this case, all buyers are shoppers,  $N^s = 1$  and all firms are indifferent between charging any price in the distribution  $F(p)$  with support over  $[\underline{p}, \bar{p}]$ . The price distribution in this case collapses to the following:

$$F(p) = \begin{cases} 0 & \text{if } p \leq \underline{p} \\ 1 - \frac{\alpha}{2(1-\alpha)} \frac{\bar{p}-p}{p-\underline{p}} & \text{if } \underline{p} \leq p \leq \bar{p} \\ 1 & \text{else} \end{cases}$$

HLMW establish that prices can be sticky at the micro-level but flexible in the aggregate in response to monetary policy shocks when there exist search frictions in a “Burdett-Judd” product market with no loyal customer base. That is, the aggregate price distribution shifts rightward with a positive monetary policy shock (an increase in the interest rate), and hence monetary policy is neutral. In the results section, I replicate this exercise and show that the same results arise in my model when we assume no loyal customer base.

### 2.5.2 With Loyal Customers

In contrast, the model with the retention of a customer base presents interesting dynamics. Consider the case where marginal costs are again constant but firms are allowed to retain a loyal customer base so long as they do not raise their price above the threshold switching price  $p^r$ . Note that when all firms have the same marginal cost, no firm would have an incentive to set price  $p > p^r$  if  $z < p^r$ .

**Claim 1.** *Given constant marginal cost, no firm has an incentive to charge above the reservation threshold switching price  $p_t^r$ .*

To see this, suppose there are two firms, both of which have customer base  $\eta_{j,t-1}$  at the start of time  $t$  and constant marginal cost  $z$ . Suppose also that one firm chooses to charge  $p' = p^r + \varepsilon$ . Then accordingly the value function for the firm that charges price  $p'$  is:

$$J(p', \eta_{j,t-1}) = \frac{N_t^s}{n} [\alpha + 2(1 - \alpha)(1 - F(p'))](p' - q_t z) + \beta E J(\eta_{j,t})$$

In contrast, a firm that charges  $p_t^r$  gets to retain his customer base, which implies the following value function:

$$J(p^r, \eta_{j,t-1}) = \left\{ (1 - \lambda)\eta_{j,t-1} + \frac{N_t^s}{n} [\alpha + 2(1 - \alpha)(1 - F(p^r))] \right\} (p^r - q_t z) + \beta E J(\eta_{j,t}^R)$$

As  $\varepsilon \rightarrow 0$  and given continuous  $F(p)$ ,  $F(p') \approx F(p^r)$  for small enough  $\varepsilon$ . It is clear that for small enough  $\varepsilon$ ,  $J(p^r, \eta_{j,t-1}) > J(p', \eta_{j,t-1})$  as the firm charging  $p^r$  gets to enjoy additional profits from catering to current base customers as well as well as attracting new customers to enhance future profits. Thus, firms are indifferent between charging any price within the distribution of  $F(p)$  which is bounded between  $[\underline{p}, p^r]$ . In the model with no cost heterogeneity, the upper bound  $\bar{p}$  is the same as the threshold switching price,  $p^r$ . This implies that the mass of shoppers consists those who were exogenously separated from their current firm, i.e.  $N_t^s = \lambda$  for all  $t$ .

Importantly, firms with the same customer base are indifferent between charg-

ing any price from the following conditional price distribution for all  $p \in [\underline{p}, p^r]$ :

$$\begin{aligned}
 F(p|\eta_{j,t-1}) &= 1 - \frac{\alpha}{2(1-\alpha)} \frac{p^r - p}{p - \underline{p}} & (2.5.1) \\
 &- \frac{n}{N^s} \frac{1-\lambda}{2(1-\alpha)} \frac{p^r - p}{p - \underline{p}} \eta_{j,t-1} - \frac{n}{N^s} \frac{1}{p - \underline{p}} \frac{1}{2(1-\alpha)} \beta E[J(\eta_{j,t}^R) - J(\eta_{j,t})]
 \end{aligned}$$

where  $\eta_{j,t}^R$  represents the customer base the firm carries into the next period when he charges the maximum price the customer is willing to pay, here  $\bar{p} = p^r$ . Notably, the first line of Equation (2.5.1) resembles the price distribution in a product market with no customer base. The second line of Equation (2.5.1), however, shows that the assumption of a customer base modifies the price distribution. In allowing for the retention of a customer base, the firm's problem is no longer static and the size of the customer base from the last period becomes an important state variable. Note that only firms with the same initial customer base are indifferent between charging any price from the conditional price distribution  $F(p|\eta_{j,t-1})$ . To recover the unconditional price distribution, one must aggregate across the distribution of firms over its initial customer base.

## 2.6 Computation

### 2.6.1 Computational Method

The following algorithm is applied to compute the equilibrium price distribution of the economy.

- 1 Guess an equilibrium price distribution,  $F_0(p)$ .

- 2 Start from the steady state and solve the household's equilibrium conditions given the price distribution. Find the threshold pricing rule from the household's optimality condition.
- 3 Guess a value function,  $J_0$ , given the firm's profit function
- 4 Solve the durable good firm's problem: find the range of prices that maximizes profits given  $p^R$ , the price distribution and the initial guess of the firm's value function,  $J_0$ .
- 5 Calculate an updated guess of the firm's value function  $J_1$ . Repeat steps 4-5 until  $J_1 - J_0 \rightarrow \varepsilon$  where  $\varepsilon \rightarrow 0$ .
- 6 Given the optimal range of prices firms are willing to charge, update guess of  $F_0(p)$ .
- 7 Repeat process until convergence.

## 2.7 Preliminary Results

### 2.7.1 No Cost Heterogeneity

Table A.11 summarizes the parameter values used for the quantitative exercise. I assume the following utility functions for the consumption of  $\{C_t, D_t, M_t\}$  respectively:  $u(C_t) = \frac{(C_t)^{1-\gamma_c}}{1-\gamma_c}$ ,  $\nu(D_t) = \frac{(D_t)^{1-\gamma_d}}{1-\gamma_d}$  and  $\mu(M_t) = \log(M_t)$ . To examine how a monetary price shock affects the price distribution of sellers, I first look at what happens in a "Burdett-Judd" market, i.e. a product market with search frictions, no

cost heterogeneity, and no customer base. Figure ?? replicates the result of HLMW and shows that the price distribution shifts rightward with a one-time permanent positive monetary policy shock, i.e. with an increase in the growth rate of money. Thus, while some sellers are able to maintain the same prices and exhibit price rigidity, the aggregate price distribution on average is flexible. Only sellers who no longer remain within the support of the new price distribution  $F_{t+1}(p)$  are forced to reprice.

Figure B.19 shows the difference in price distributions between durables versus non-durables goods, i.e. when  $\delta < 1$  and  $\delta = 1$  respectively. Notably, the price distribution for durable goods has a much larger support. This is consistent with equation (2.3.23) which demonstrates that the marginal cost of increasing the household's maximum willing to pay must be equal to its marginal benefit. Since raising the maximum willingness to pay enables the household to add to its stock of durable goods available tomorrow, the maximum willingness to pay for a durable good is higher than that observed for a non-durable good.

Figure B.20 shows the same experiment in a model where firms are now allowed to retain a loyal customer base so long as they do not charge above the threshold switching price  $p_t^r$ . When firms are allowed to retain loyal customers, increasing  $M$  is no longer neutral. Importantly, while the lower support of the price distribution shifts rightward with the increase in nominal marginal costs, Figure B.20 shows that the whole price distribution does not shift rightward. The potential loss of a customer base causes prices to remain sticky at the upper end of the price distribution. Firms who used to charge between  $[\underline{p}, \underline{p}']$  are forced to reprice as before. However,

firms also know that so long as they charge below  $p^r$ , they can retain their loyal customer base. Since firms earn substantially lower profits from charging  $p > p^r$ , prices are sticky at the upper end of the price distribution. Because the household acts like a monopsonist and has price-setting power over  $p^r$ , the household is able to exert bargaining power and control the rise in  $p^r$ . When marginal costs rise due to the interest rate shock, the household does re-price  $p^r$ , however, the increase in  $p^r$  is much smaller than observed in the model with no customer base. Here,  $p^r$  increases marginally from 8.6 to 8.65 while in the model with no customer base,  $p^r$  rises from 8.6 to about 8.9.

## 2.8 Conclusion

The model considered thus far has many testable implications. In particular, the model derives a clean rule for how firms are affected by consumers' search methods as firms internalize the threshold switching price of households and can engage in price sticky regimes to retain customers. This paper has also highlighted a tractable way of explaining how the longevity of a product may affect the pricing decision of firms as well as the size of mark-ups. By examining the durability of the product and how it affects customers' maximum willingness to pay, this paper also shows how firms' mark-ups are constrained by the expected lifetime of a good. While the numerical examples above highlight the importance of the customer base in terms of generating non-neutral responses to money, future work will focus on using micro-level data on the frequency of household purchases as well as the transacted prices

paid for durable vs. non-durable goods to discipline the model.



## Chapter B: Appendix for Chapter 2

### B.1 Household Equilibrium Conditions

Taking first order conditions with respect to  $\{C_t, M_t, B_t, \bar{p}, p^r\}$ , we get:

$$u'(C_t) = \frac{q_t}{w_t} \quad (\text{B.1.1})$$

$$\mu'(M_t) + \beta EV_m(M_t, B_t, D_t) = \frac{1}{w_t} \quad (\text{B.1.2})$$

$$\beta EV_b(M_t, B_t, D_t) = \frac{1}{w_t} \quad (\text{B.1.3})$$

$$[\nu'(D_t) + \beta EV_d(M_t, B_t, D_t)] \frac{dX_t}{d\bar{p}_t} = \frac{1}{w_t} \left[ \frac{d\tilde{X}_t}{d\bar{p}_t} + \kappa \frac{dN_t^s}{d\bar{p}_t} \right] \quad (\text{B.1.4})$$

$$[\nu'(D_t) + \beta EV_d(M_t, B_t, D_t)] \frac{dX_t}{dp_t^r} = \frac{1}{w_t} \left[ \frac{d\tilde{X}_t}{dp_t^r} + \kappa \frac{dN_t^s}{dp_t^r} \right] \quad (\text{B.1.5})$$

The envelope conditions are given by:

$$V_m(M_{t-1}, B_{t-1}, D_{t-1}) = \frac{1}{w_t} \quad (\text{B.1.6})$$

$$V_b(M_{t-1}, B_{t-1}, D_{t-1}) = \frac{R_{t-1}}{w_t} \quad (\text{B.1.7})$$

$$\begin{aligned}
V_d(M_{t-1}, B_{t-1}, D_{t-1}) &= (\nu'(D_t) + \beta EV_d(M_t, B_t, D_t))(1 - \delta) \quad (\text{B.1.8}) \\
&= \frac{1}{w_t} \left[ \frac{\left( \frac{d\bar{X}_t}{d\bar{p}_t} + \kappa \frac{dN_t^s}{d\bar{p}_t} \right)}{\frac{dX_t}{d\bar{p}_t}} \right] (1 - \delta)
\end{aligned}$$

Updating equations (B.1.6) and (B.1.7), we get :

$$\mu'(M_t) + \beta E \frac{1}{w_{t+1}} = \frac{1}{w_t} \quad (\text{B.1.9})$$

$$\beta E \frac{R_t}{w_{t+1}} = \frac{1}{w_t} \quad (\text{B.1.10})$$

Updating equation (B.1.8) and plugging it into equation B.1.4, we get back equation 2.3.23.

Finally, one must solve for the following functional forms:

$$\frac{dN_t^s}{d\bar{p}_t} = (1 - \lambda) \int \eta_{j,t-1}(\bar{p}) dj f(\bar{p}) \quad (\text{B.1.11})$$

$$\begin{aligned}
\frac{dX_t}{d\bar{p}_t} &= \int_{\underline{p}}^{\bar{p}} \left\{ \int \frac{dN_t^s}{d\bar{p}_t} \frac{1}{n} [\alpha + 2(1 - \alpha)(1 - F(p))] \mathbb{I}(p_{j,t} = p) dj \right\} dF(p) \quad (\text{B.1.12}) \\
&+ \int \frac{N_t^s}{n} \alpha \mathbb{I}(p_{j,t} = \bar{p}) dj f(\bar{p})
\end{aligned}$$

$$\begin{aligned} \frac{d\tilde{X}_t}{d\bar{p}_t} &= \int_{\underline{p}}^{\bar{p}} p \left\{ \int \frac{dN_t^s}{d\bar{p}_t} \frac{1}{n} [\alpha + 2(1 - \alpha)(1 - F(p))] \mathbb{I}(p_{j,t} = p) dj \right\} dF(p) \\ &+ \bar{p} \int \frac{N_t^s}{n} \alpha \mathbb{I}(p_{j,t} = \bar{p}) dj f(\bar{p}) \end{aligned} \quad (\text{B.1.13})$$

$$\frac{dN_t^s}{dp_t^r} = -(1 - \lambda) \int \eta_{j,t-1}(p^r) dj f(p^r) \quad (\text{B.1.14})$$

$$\begin{aligned} \frac{dX_t}{dp_t^r} &= \int_{\underline{p}}^{\bar{p}} \left\{ \int \frac{dN_t^s}{dp_t^r} \frac{1}{n} [\alpha + 2(1 - \alpha)(1 - F(p))] \mathbb{I}(p_{j,t} = p) dj \right\} dF(p) \\ &+ \int (1 - \lambda) \eta_{j,t-1} \mathbb{I}(p_{j,t} = p^r) dj f(p^r) \end{aligned} \quad (\text{B.1.15})$$

$$\begin{aligned} \frac{d\tilde{X}_t}{dp_t^r} &= \int_{\underline{p}}^{\bar{p}} p \left\{ \int \frac{dN_t^s}{dp_t^r} \frac{1}{n} [\alpha + 2(1 - \alpha)(1 - F(p))] \mathbb{I}(p_{j,t} = p) dj \right\} dF(p) \\ &+ p_t^r \int (1 - \lambda) \eta_{j,t-1} \mathbb{I}(p_{j,t} = p^r) dj f(p^r) \end{aligned} \quad (\text{B.1.16})$$

## B.2 Tables and Figures

Tab. B.1: Flexible and Sticky Prices in the CPI Market

Basket

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Item	Frequency	Rel. Importance	Type
Motor fuel	0.7	3.2	Non-durable
Car and truck rental	1.2	0.1	Service
Fresh fruits and vegetables	1.3	0.9	Non-durable
Fuel oil and other fuels	1.5	0.3	Non-durable
Gas and electricity	1.6	4.2	Service
Meats, poultry, fish, and eggs	1.9	1.9	Non-durable
Used cars and trucks	2.0	1.6	Durable
Leased cars and trucks	2.0	0.6	Service

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Table B.1 – Continued

Item	Frequency	Rel. Importance	Type
New vehicles	2.0	4.5	Durable
Women's and girls' apparel	2.3	1.5	Non-durable
Dairy and related products	2.6	0.9	Non-durable
Nonalcoholic beverages, beverage materials	2.7	1.0	Non-durable
Lodging away from home	3.1	2.5	Service
Processed fruits and vegetables	3.2	0.3	Non-durable
Men's and boys' apparel	3.2	0.9	Non-durable
Cereals and bakery products	3.3	1.2	Non-durable
Footwear	3.4	0.7	Non-durable
Other food at home	3.6	2.0	Non-durable
Continued on Next Page...			

Table B.1 – Continued

<b>Item</b>	<b>Frequency</b>	<b>Rel. Importance</b>	<b>Type</b>
Jewelry and watches	3.9	0.4	Durable
Motor vehicle parts and equipment	4.1	0.4	Durable
Tobacco and smoking products	4.2	0.8	Non-durable
Infants' and toddlers' apparel	5.3	0.2	Non-durable
Household furnishings and operations	5.3	4.8	Durable
Motor vehicle maintenance and repair	5.8	1.2	Service
Motor vehicle insurance	5.9	2.0	Service
Medical care commodities	6.2	1.6	Non-durable
Personal care products	6.7	0.7	Non-durable
Alcoholic beverages	7.3	1.1	Non-durable

Continued on Next Page...

Table B.1 – Continued

Item	Frequency	Rel. Importance	Type
Recreation	7.9	5.7	Durable
Miscellaneous personal goods	8.1	0.2	-
Communication	8.4	3.2	Service
Public transportation	9.4	1.1	Service
Tenants' and household insurance	10.1	0.3	Service
Food away from home	10.7	6.5	Service
Rent of primary residence	11.0	6.0	Service
Education	11.1	3.1	Service
Medical care services	14.0	4.8	Service
Water, sewer, trash collection services	14.3	1.0	Service

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Table B.1 – Continued

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<b>Item</b>	<b>Frequency</b>	<b>Rel. Importance</b>	<b>Type</b>
Motor vehicle fees	16.4	0.5	Service
Personal care services	23.7	0.6	Service
Miscellaneous personal services	25.9	1.1	Service

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<sup>0</sup> Sources: Bureau of Labor Statistics; Bils and Klenow (2004)  
Table from Cleveland Fed Research Note: <http://www.clevelandfed.org/Research/commentary/2010/2010-2.cfm>



Tab. B.2: Pass-Through Results: CPI

Variable	Coefficient (Std. Err.)
Non-durables Less Food & Energy	
$\Delta P_t^w$	0.304** (0.060)
$\Delta P_{t-1}^w$	0.238** (0.060)
$\Delta P_{t-2}^w$	0.006 (0.060)
$\Delta P_{t-3}^w$	-0.019 (0.060)
$\Delta P_{t-4}^w$	0.233** (0.060)
Durables	
$\Delta P_t^w$	0.180** (0.028)
$\Delta P_{t-1}^w$	0.184** (0.028)
$\Delta P_{t-2}^w$	0.168** (0.027)
$\Delta P_{t-3}^w$	0.134** (0.028)
$\Delta P_{t-4}^w$	0.159** (0.028)

Standard errors reported in parenthesis. †, \*, \*\* refer to 10%, 5% and 1% significance levels respectively.  $P^r$  refers to the retail price (CPI) while  $P^w$  refers to the corresponding wholesale price as proxied by the PPI

Tab. B.3: Pass-through Results: PCE

Variable	Coefficient (Std. Err.)
Non-durables Less Food & Energy	
$\Delta P_t^w$	0.228** (0.045)
$\Delta P_{t-1}^w$	0.256** (0.045)
$\Delta P_{t-2}^w$	0.037 (0.045)
$\Delta P_{t-3}^w$	-0.034 (0.044)
$\Delta P_{t-4}^w$	0.197 (0.044)
Durables	
$\Delta P_t^w$	0.201** (0.024)
$\Delta P_{t-1}^w$	0.206** (0.024)
$\Delta P_{t-2}^w$	0.149** (0.024)
$\Delta P_{t-3}^w$	0.131** (0.024)
$\Delta P_{t-4}^w$	0.100** (0.025)

Standard errors reported in parenthesis. †, \*, \*\* refer to 10%, 5% and 1% significance levels respectively.  $P^r$  refers to the retail price (PCE price index) while  $P^w$  refers to the corresponding wholesale price as proxied by the PPI

Tab. B.4: Summary Statistics of CPI Inflation (1986m1-2007m12)

Variable	Median	Mean	Std. Dev	AR(1)	Pass-thru	$\delta$
Durables	0	0.0002	0.0023	0.415** (0.0403)	0.180** (0.024)	0.1
Non-Durables	0.0019	0.0020	0.0043	-0.066 (0.043)	0.304** (0.060)	1
Raw Food	0.0026	0.0038	0.013	0.130** (0.024)	0.169** (0.023)	1
Processed Food	0.0018	0.0021	0.0027	0.207** (0.037)	0.068 (0.053)	1
Gas	0.0026	0.0048	0.0342	0.463** (0.027)	0.380** (0.016)	1
Apparel	0.0019	0.0016	0.0043	0.231** (0.0254)	0.095 (0.033)	0.34
Medical Commodities	0.0043	0.0045	0.0034	0.286** (0.034)	0.102** (0.017)	1
Personal Care	0.0025	0.0029	0.0047	0.159** (0.042)	-	
Household Furnishing	0.0024	0.0020	0.0062	0.028 (0.043)	0.046 (0.075)	0.11
Recreation	0.0010	0.0012	0.0018	0.009 (0.076)	0.078 (0.068)	0.11
Video & Audio	0	0.0004	0.0033	0.080 (0.072)	-0.008 (0.040)	0.08
Appliances	-0.0010	-0.00090	0.0044	0.416** (0.084)	0.259 <sup>†</sup> (0.132)	0.08
Transportation	0.0032	0.0033	0.0079	0.332** (0.018)	0.234** (0.044)	0.11

Summary statistics reported for major product categories. Standard errors reported in parenthesis. †, \*, \*\* refer to 10%, 5% and 1% significance levels respectively. Data on  $\delta$  taken from Bils and Klenow (1998).  $\delta$  is calculated as 1 over the expected lifetime of the product. Information on the expected lifetime of personal care products is unavailable. Pass-through for personal care products is also not calculated as there lacks direct 1 to 1 correspondence with the PPI indices. Non-durables are less food and energy

Tab. B.5: Summary Statistics of PCE Inflation (1959m1-2007m12)

Variable	Median	Mean	Std. Dev	AR(1)	Pass-thru	$\delta$
Durables	0.0010	0.0011	0.0034	0.256** (0.032)	0.201** (0.024)	0.1
Non-durables	0.0023	0.0023	0.0036	0.055* (0.028)	0.228** (0.045)	1
Raw Food	0.0019	0.0029	0.0113	0.208** (0.022)	0.298** (0.024)	1
Processed Food	0.0023	0.0030	0.0045	0.424** (0.027)	0.155** (0.021)	1
Gas	0.0019	0.0042	0.0314	0.427** (0.023)	0.368** (0.016)	1
Apparel	0.0014	0.0011	0.0045	0.140** (0.030)	-0.511 (0.995)	0.34
Medical Commodities	0.0029	0.0030	0.0033	0.325** (0.038)	0.136** (0.018)	1
Personal Care	0.0020	0.0022	0.0045	0.041 (0.035)	-	-
Household Furnishing	0.0011	0.0013	0.0038	0.152** (0.036)	0.254** (0.056)	0.11
Recreation	-0.0008	-0.0012	0.0047	0.189** (0.026)	0.115** (0.042)	0.11
Video & Audio	-0.0014	-0.0024	0.0051	0.218** (0.027)	0.012 (0.033)	0.08
Appliances	0.0001	0.0007	0.0046	0.237** (0.033)	0.215** (0.040)	0.08
Transportation	0.0019	0.0020	0.0049	0.222** (0.027)	0.217** (0.030)	0.11

Summary statistics reported for major product categories. Standard errors reported in parenthesis. †, \*, \*\* refer to 10%, 5% and 1% significance levels respectively. Data on  $\delta$  taken from Bils and Klenow (1998).  $\delta$  is calculated as 1 over the expected lifetime of the product. Information on the expected lifetime of personal care products is unavailable. Pass-through for personal care products is also not calculated as there lacks direct 1 to 1 correspondence with the PPI indices. Non-durables are less food and energy

Figures

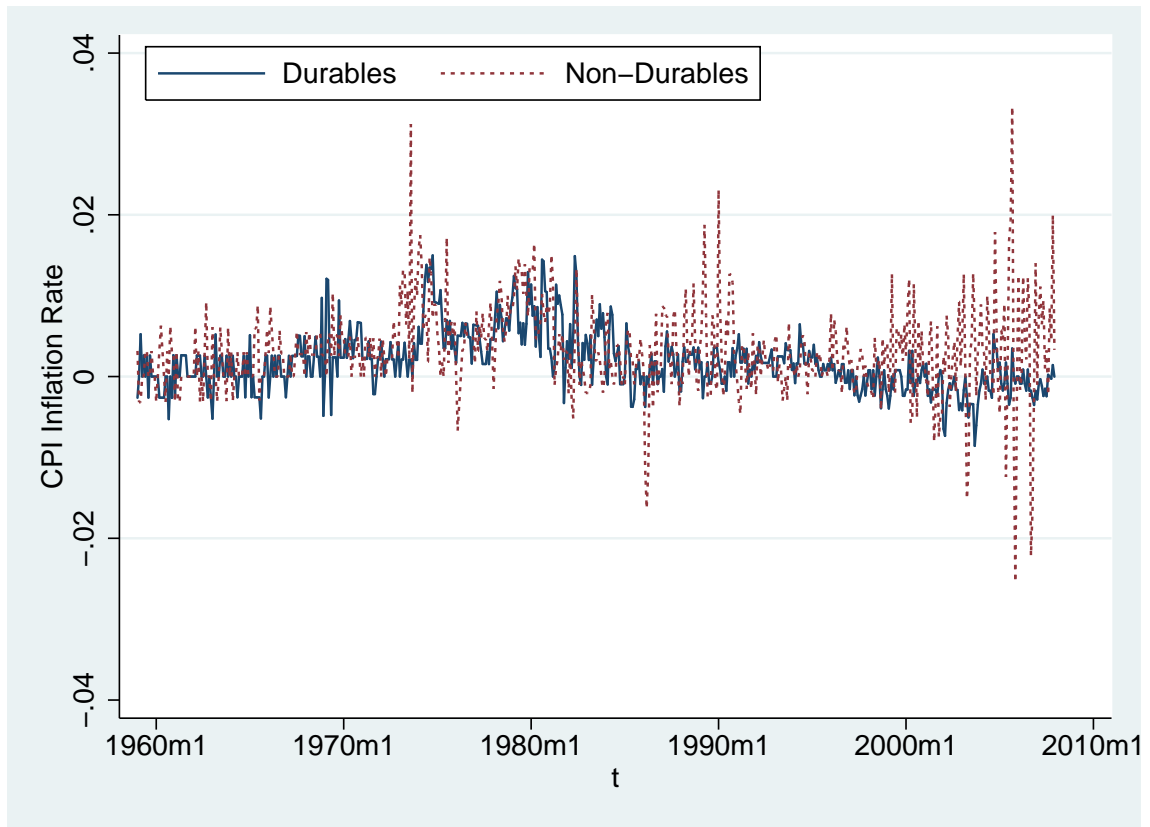


Fig. B.1: CPI Inflation Rates: Durables vs. Non-Durables

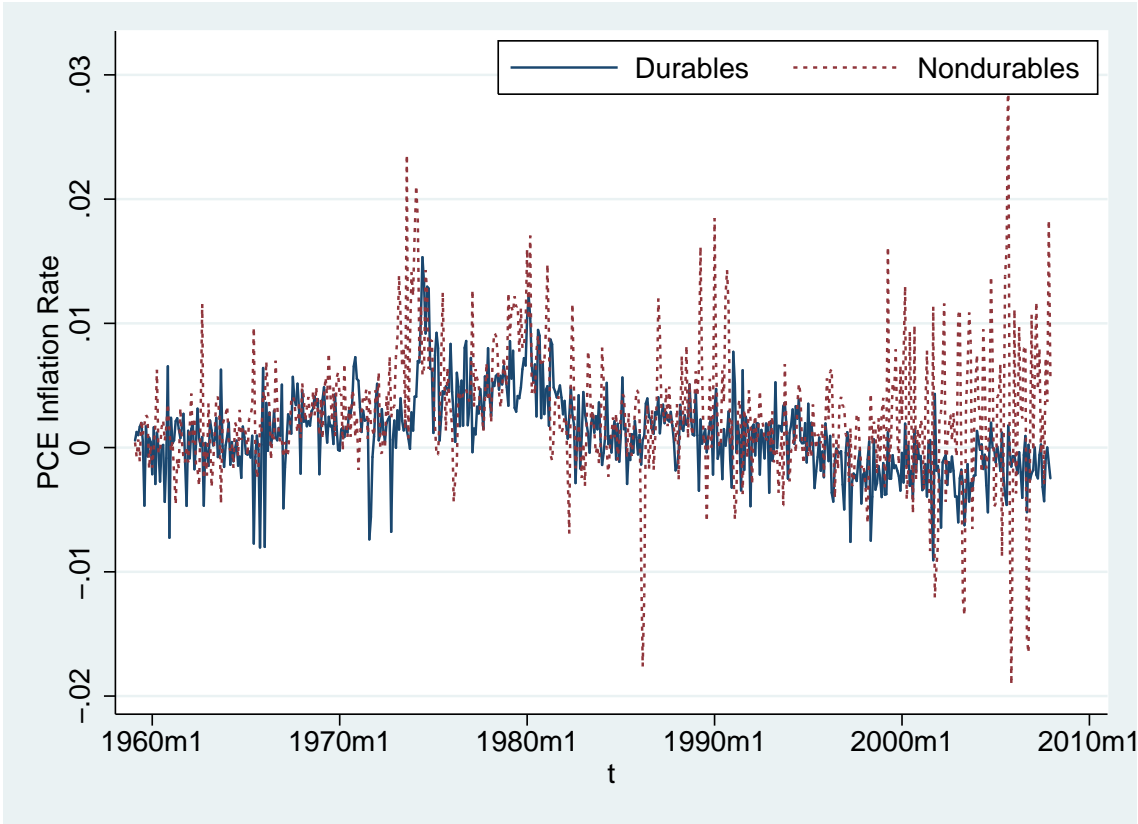


Fig. B.2: PCE Inflation Rates: Durables vs. Non-Durables

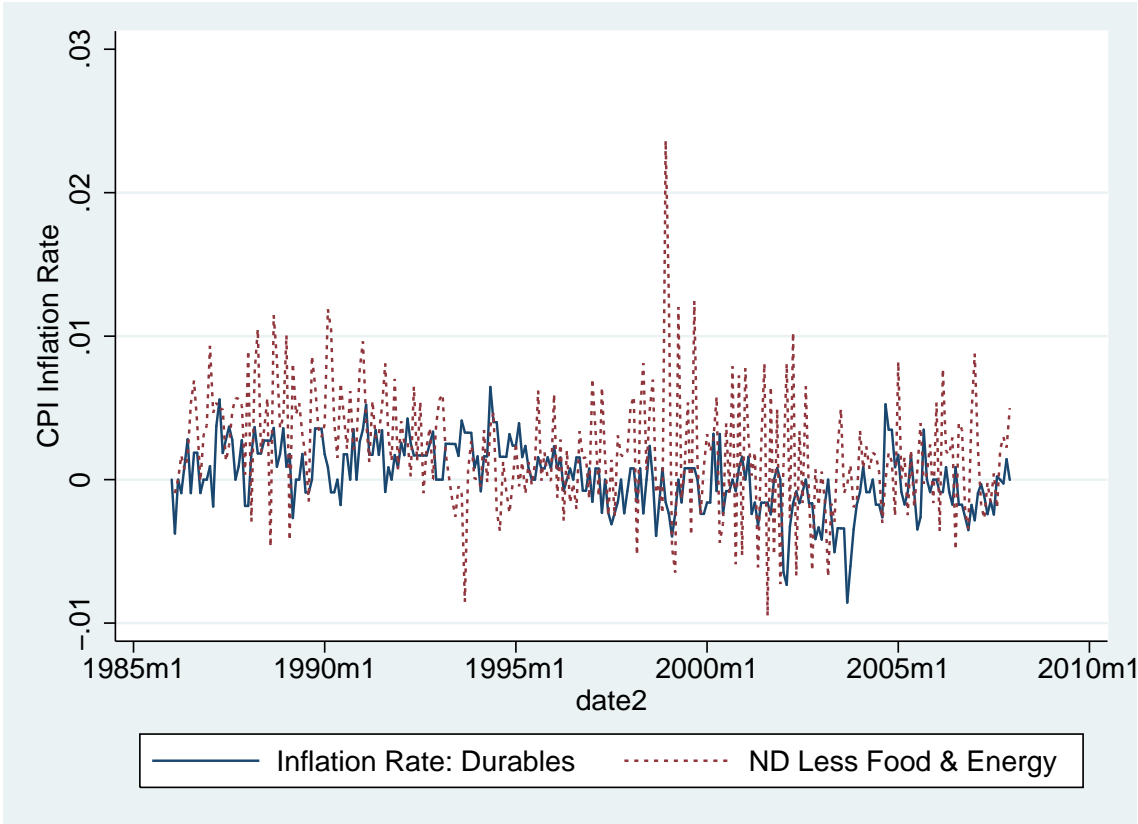


Fig. B.3: CPI Inflation Rates: Durables vs. ND Less Food & Energy, weighted by ELI weights

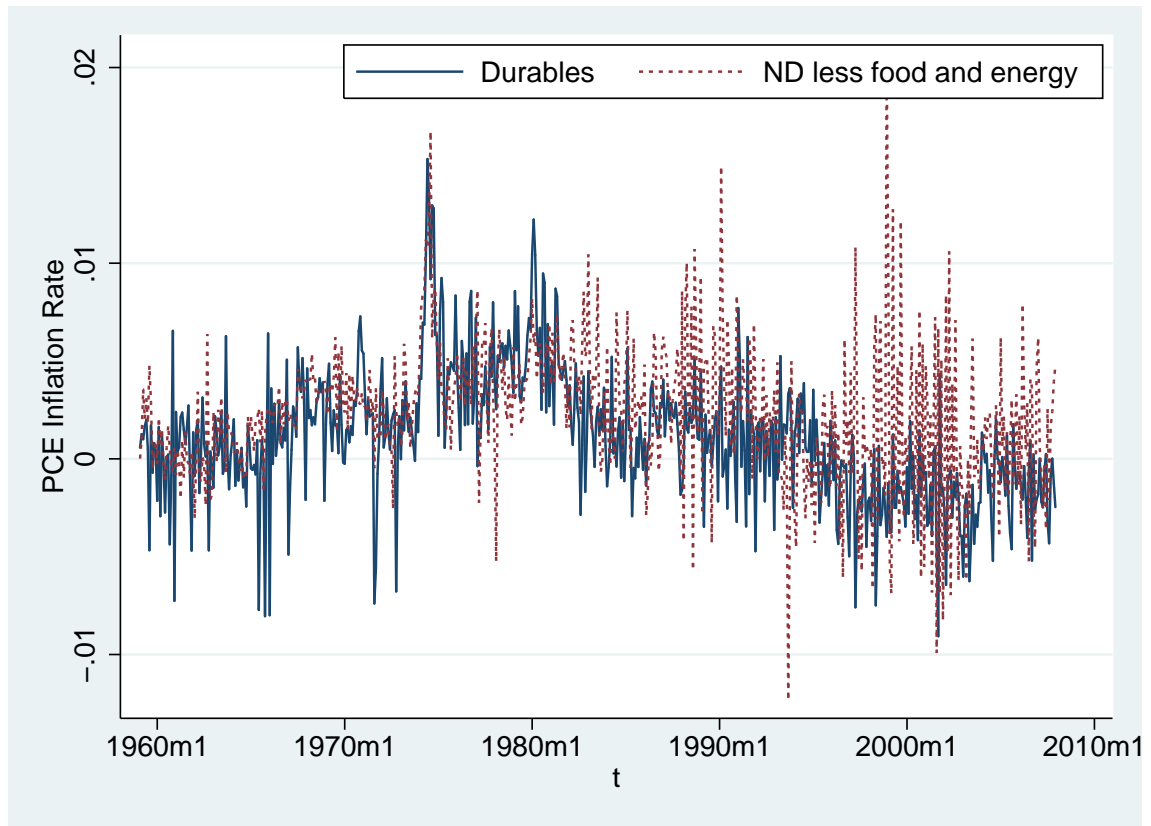


Fig. B.4: PCE Inflation Rates: Durables vs. ND Less Food & Energy, weighted by ELI weights



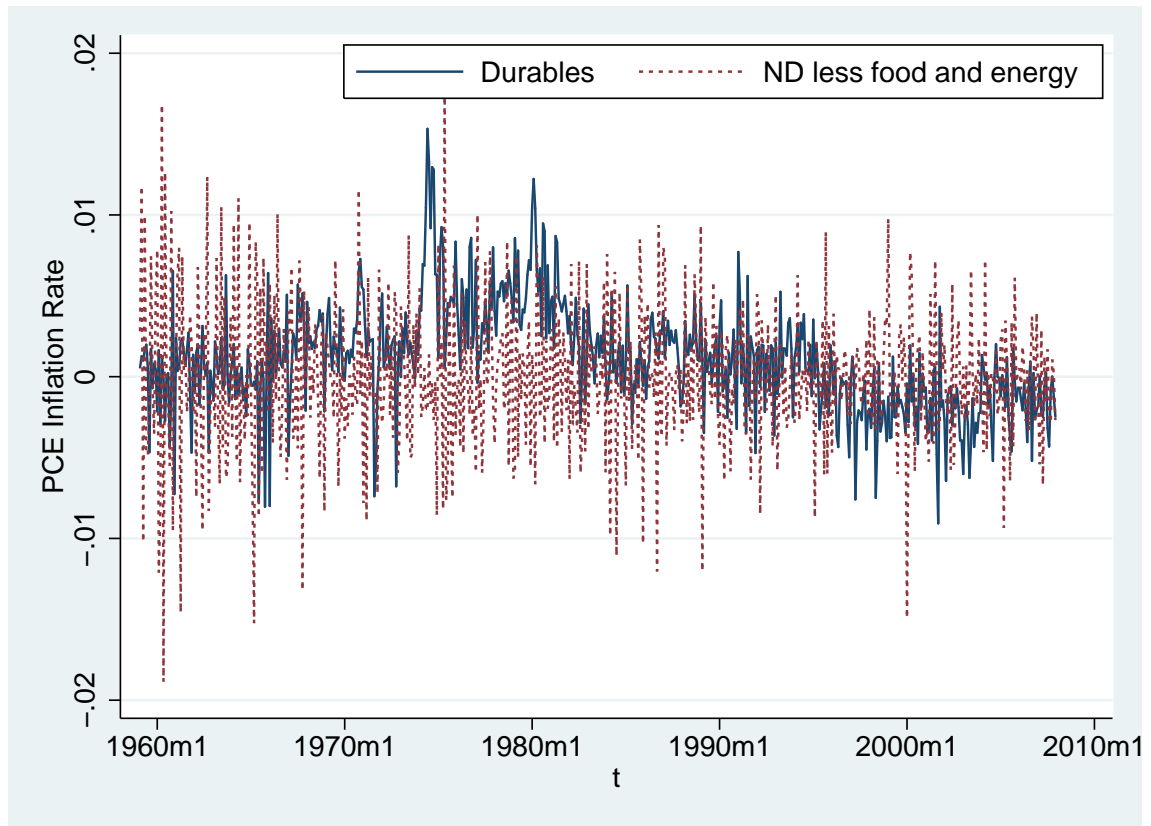


Fig. B.5: PCE Inflation Rates: Durables vs. ND Less Food & Energy, weighted by share in Consumption expenditure

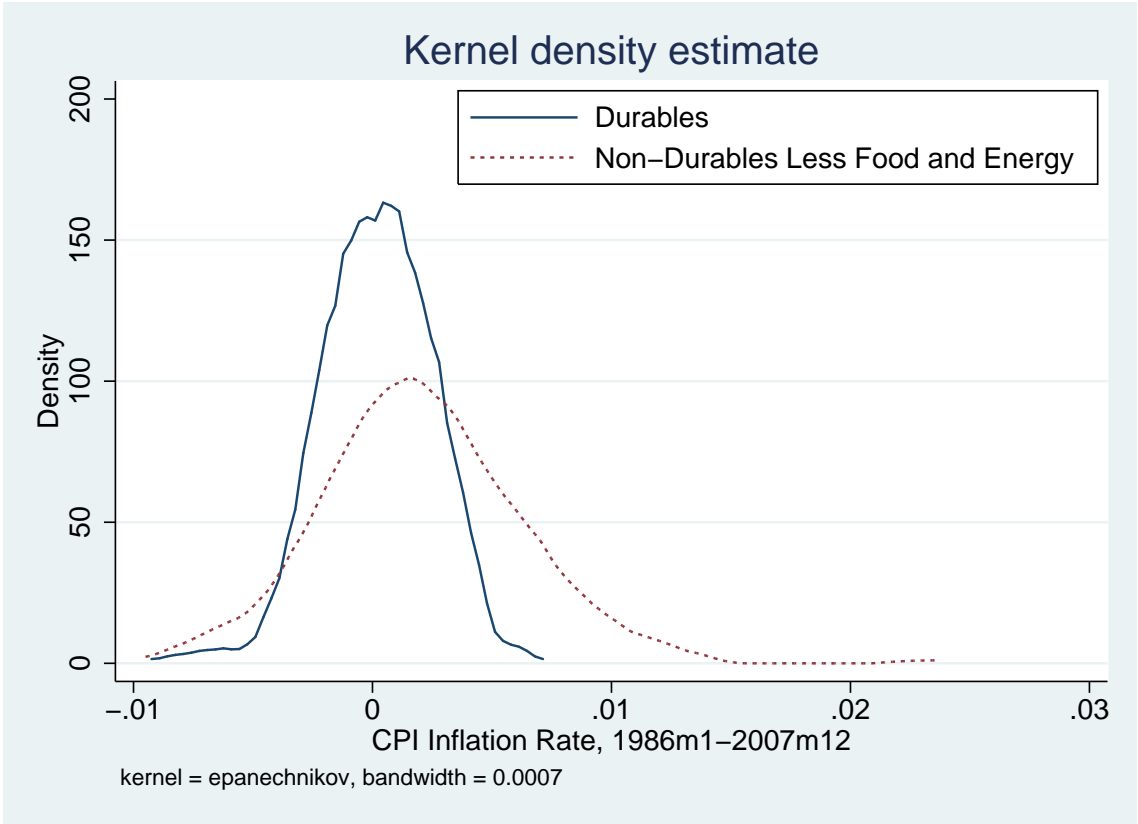


Fig. B.6: Distribution of Monthly Log Change in Prices, CPI

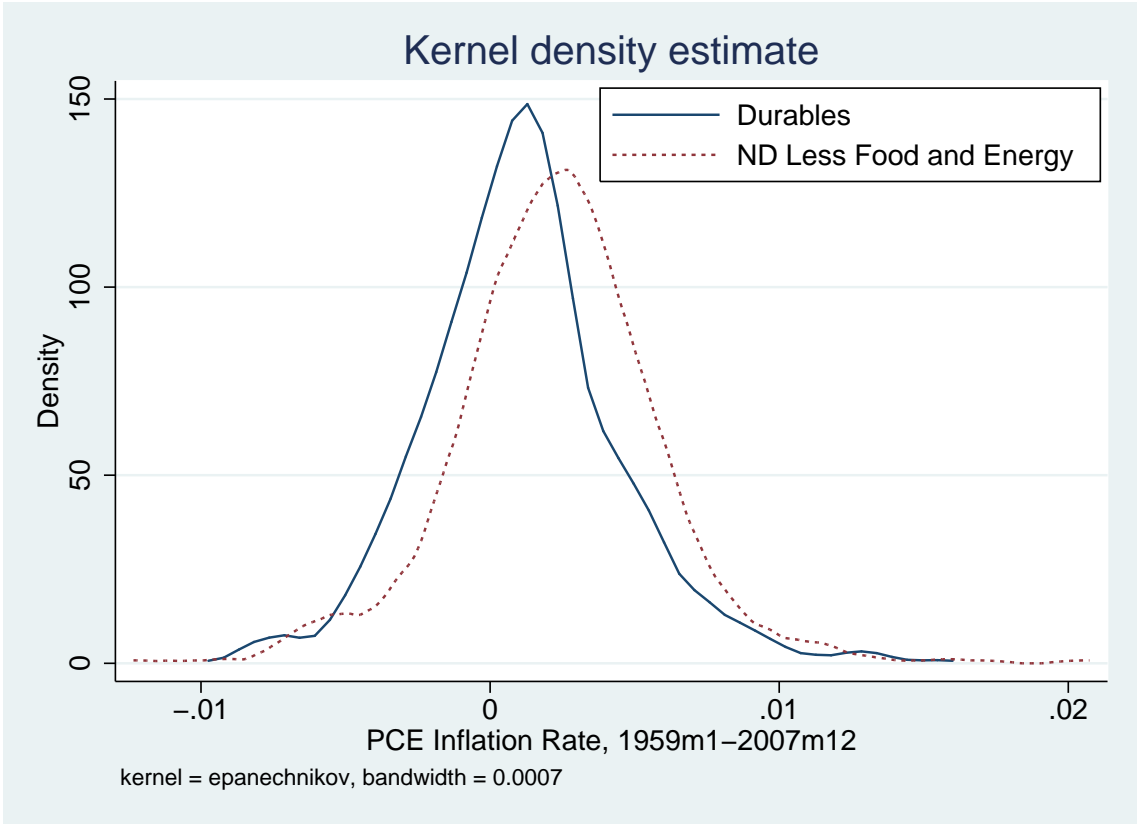


Fig. B.7: Distribution of Monthly Log Change in Prices, PCE

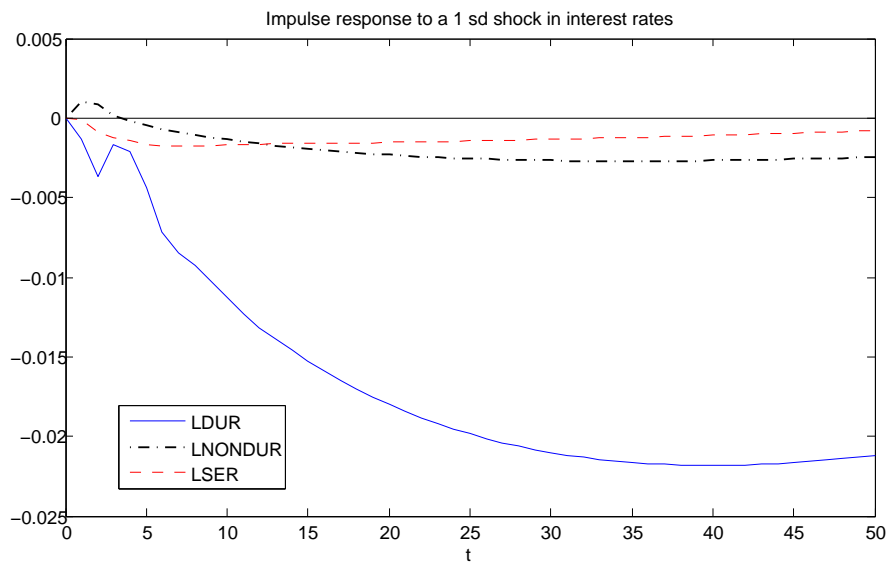


Fig. B.8: Impulse Response in Real Consumption Expenditures, 5-VAR CPI specification

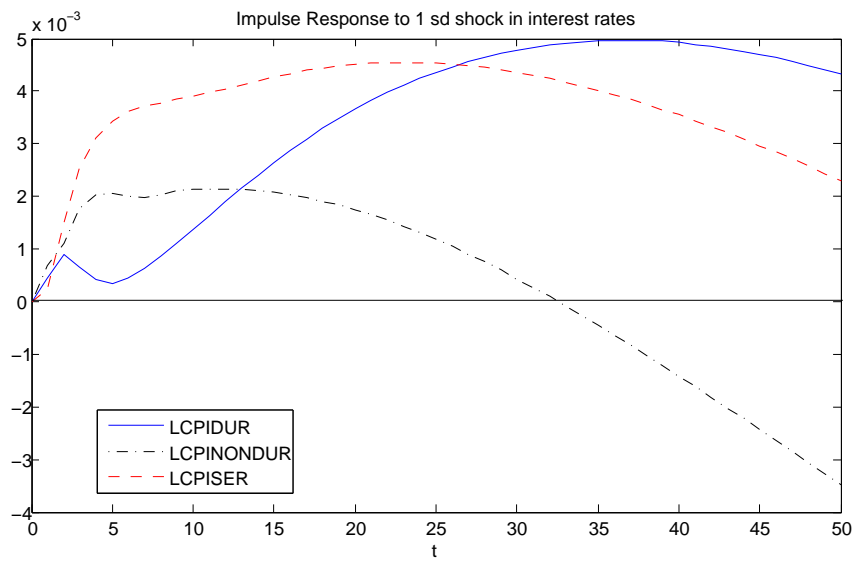


Fig. B.9: Impulse Response in Prices, 5-VAR CPI specification

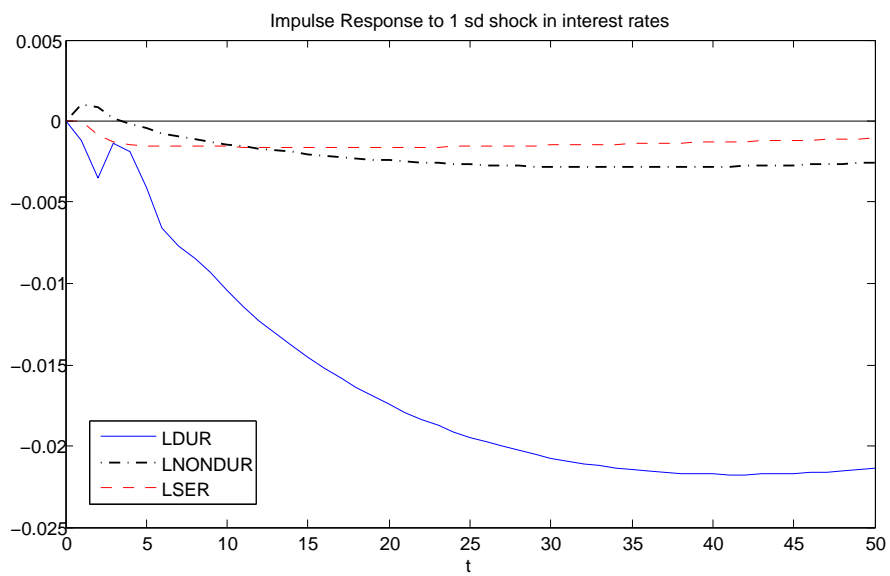


Fig. B.10: Impulse Response in Real Consumption Expenditures, 5-VAR PCE specification

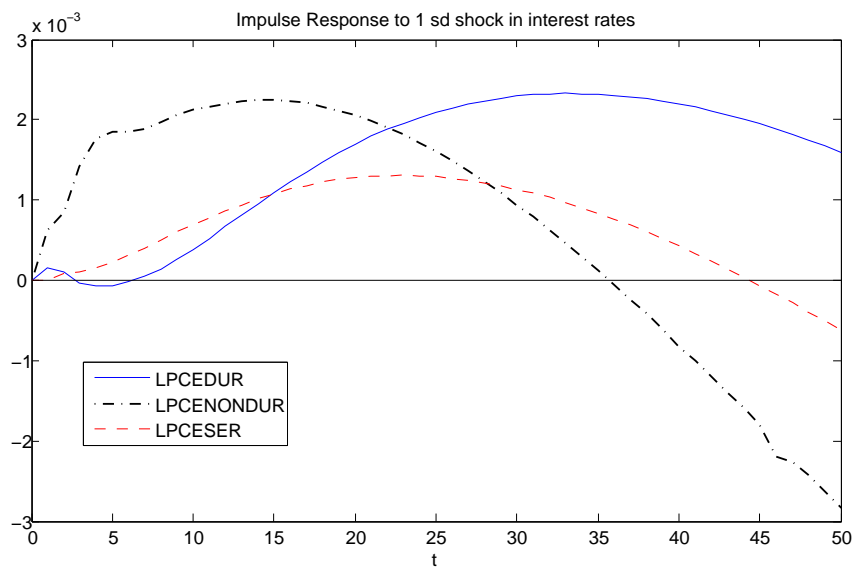


Fig. B.11: Impulse Response in Price, 5-VAR PCE specification

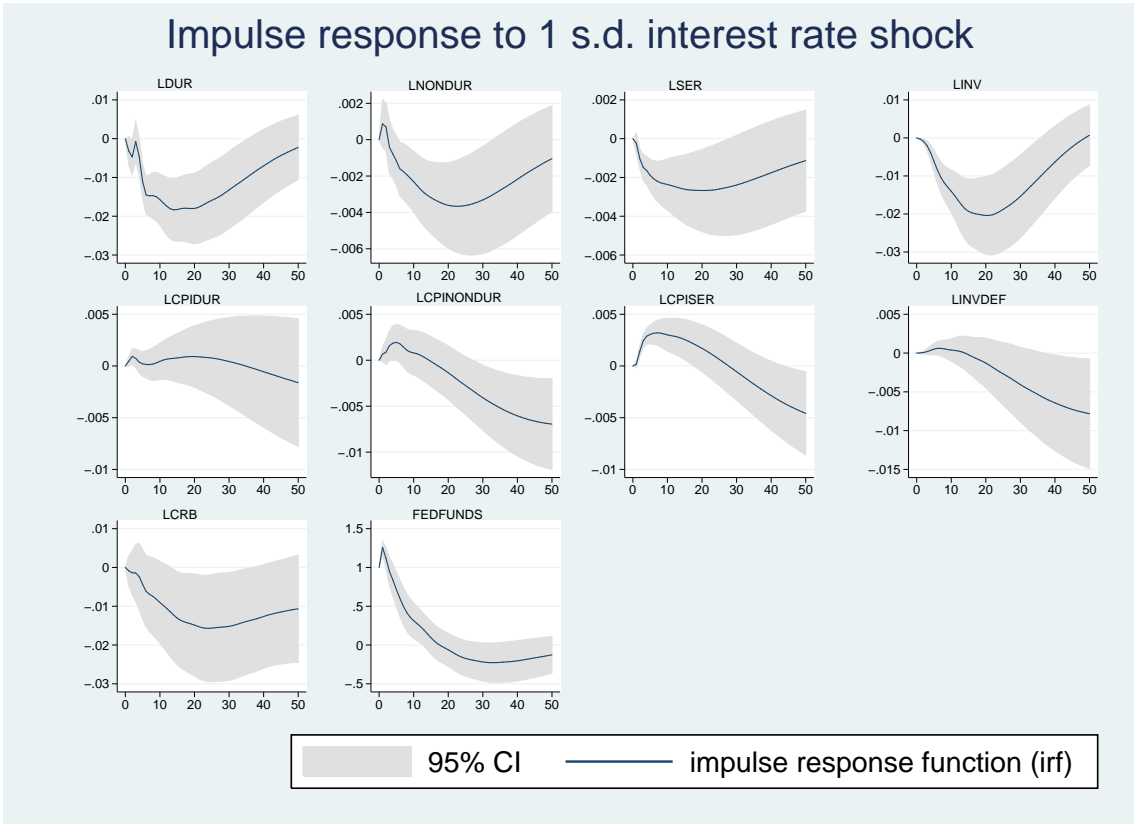


Fig. B.12: Impulse Response to 1 sd shock in the Federal Funds Rate, 10-VAR CPI specification



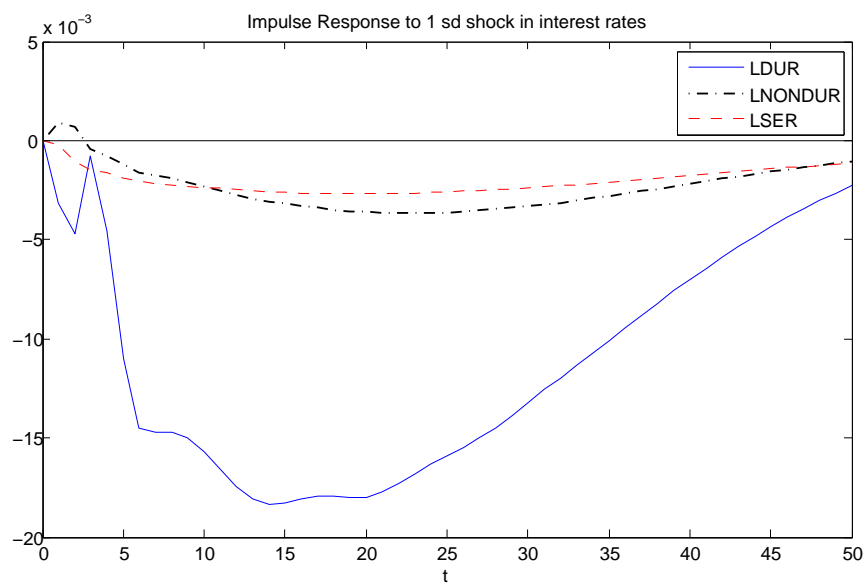


Fig. B.13: Impulse Response in Real Consumption Expenditures, 10-VAR CPI specification

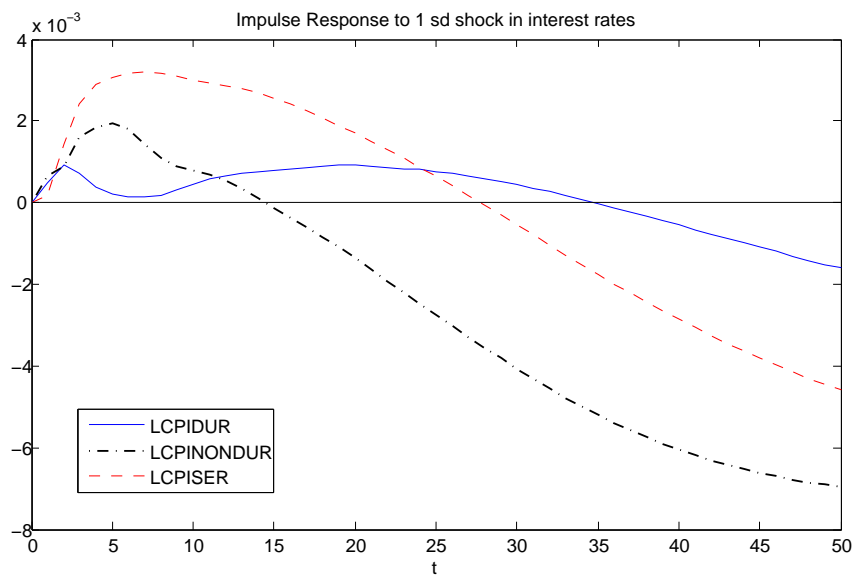


Fig. B.14: Impulse Response in Prices, 10-VAR CPI specification

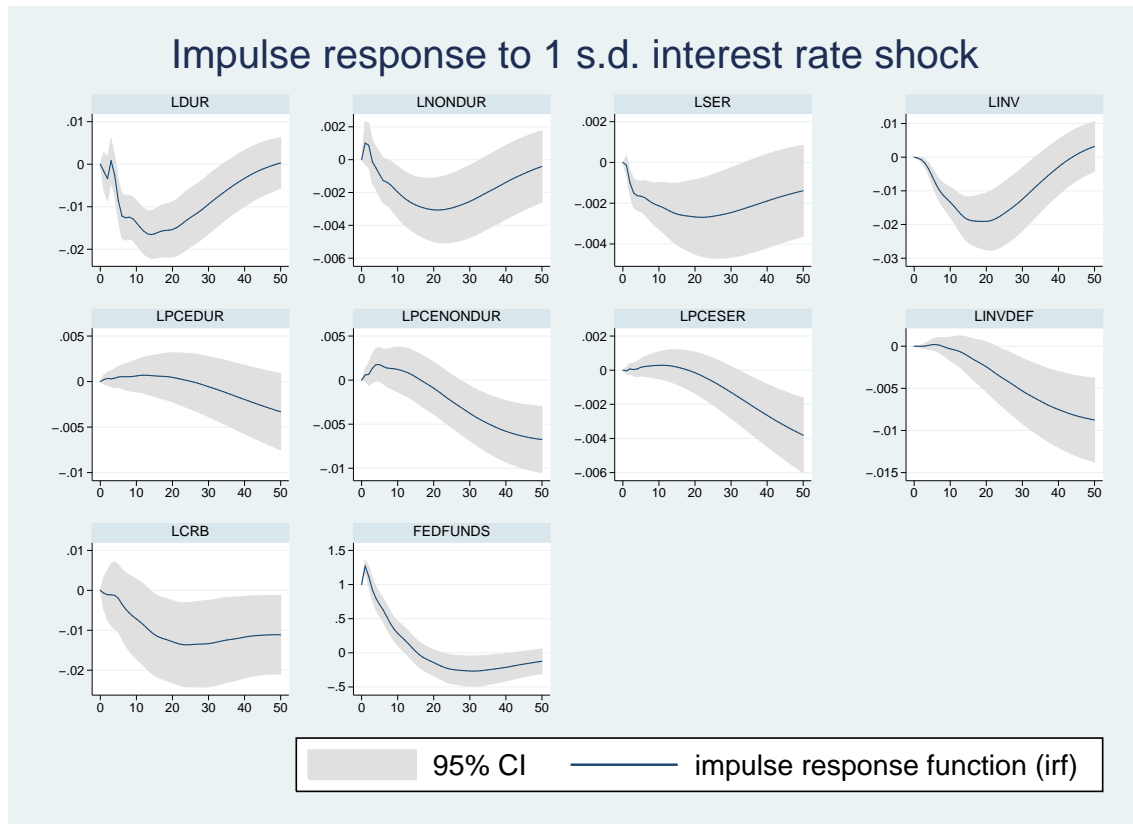


Fig. B.15: Impulse Response to 1 sd shock in the Federal Funds Rate, 10-VAR PCE specification

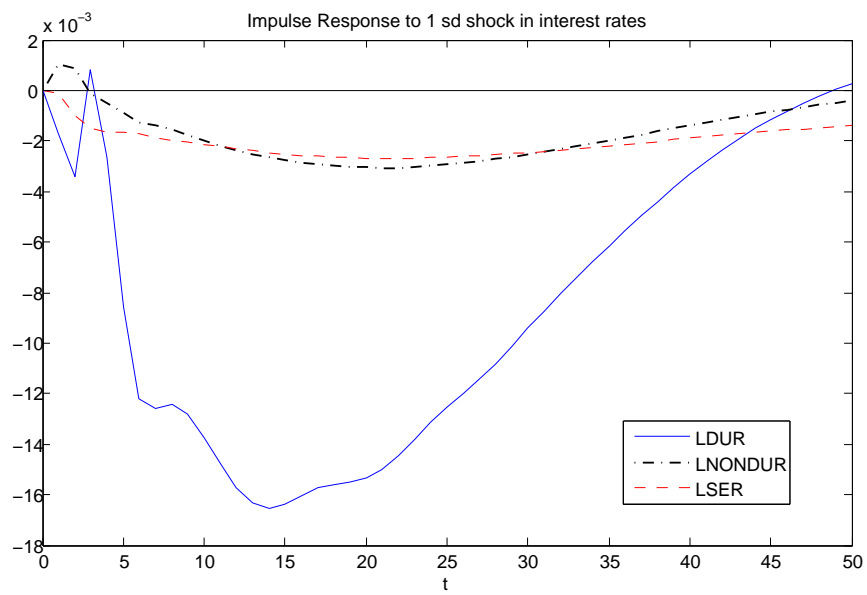


Fig. B.16: Impulse Response in Real Consumption Expenditures, 10-VAR PCE specification

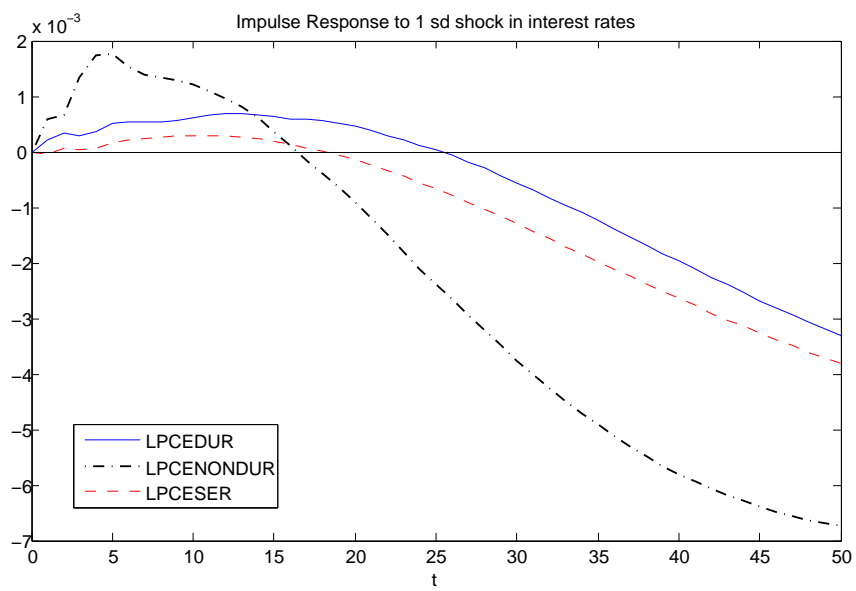


Fig. B.17: Impulse Response in Prices, 10-VAR PCE specification

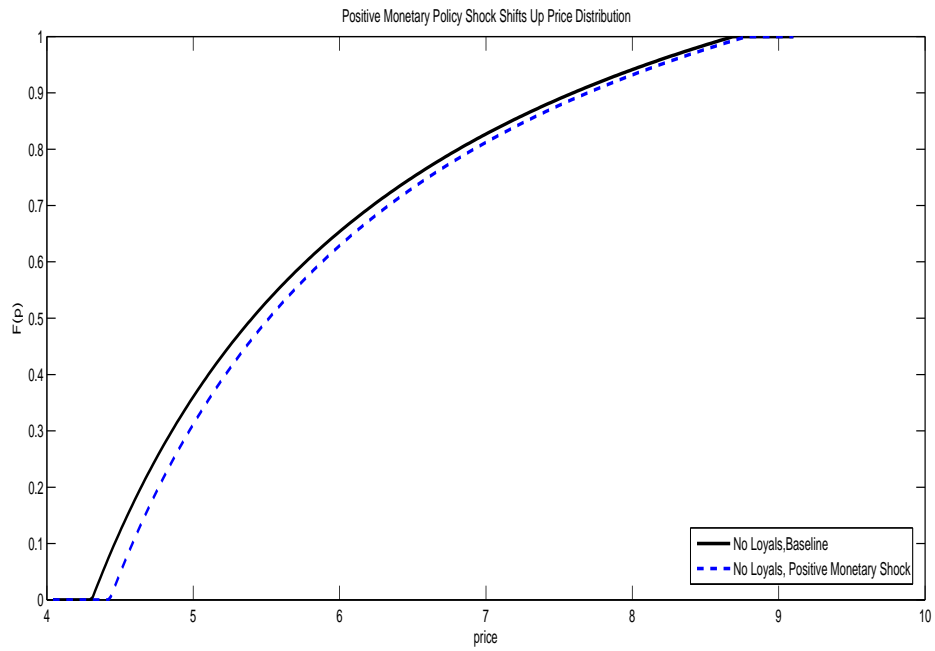


Fig. B.18: Change in Price Distribution With No Loyal Customer Base

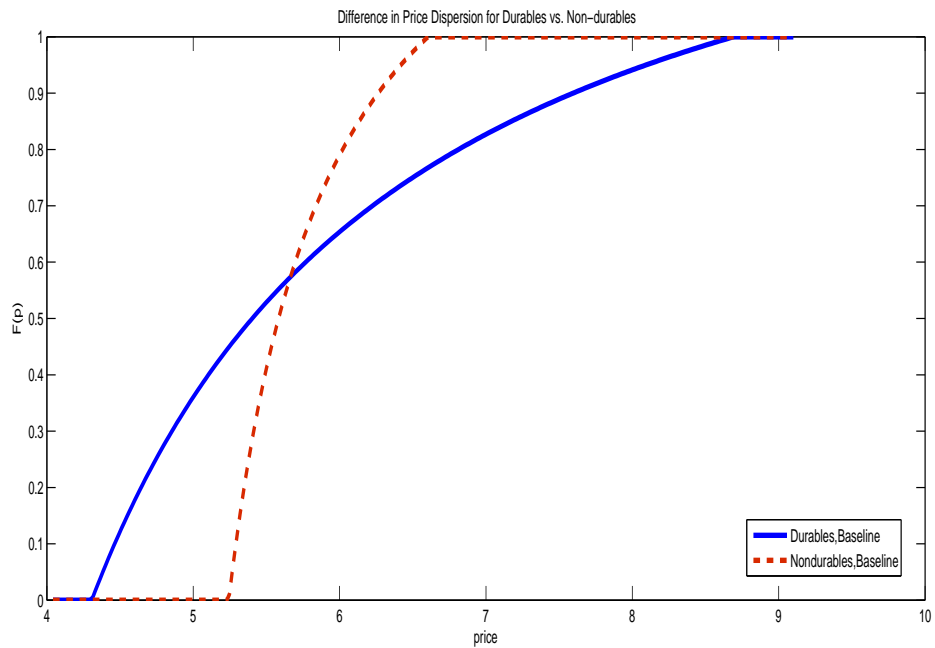


Fig. B.19: Durables Price dispersion vs. Non-durables, No Loyal Customer Base

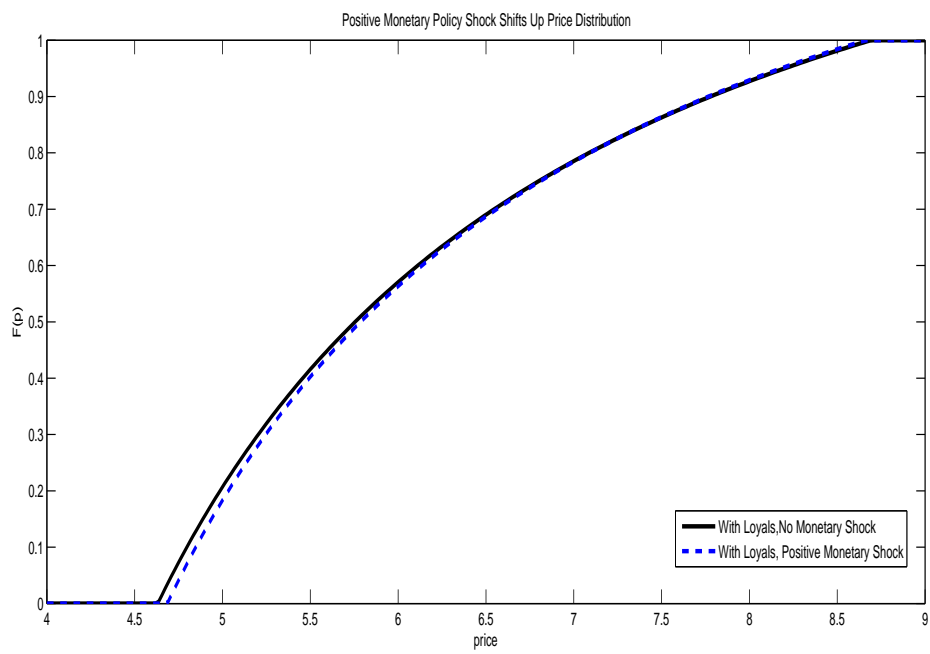


Fig. B.20: Change in Price Distribution with Loyal Customer Base

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