Title
Essays on Decision Making in the Labor and Housing Market

Author
Xia, Xiaoyu

Publication Date
2014

Peer reviewed|Thesis/dissertation

Essays on Decision Making in the Labor and Housing Market

by

Xiaoyu Xia

A dissertation submitted in partial satisfaction of the
requirements for the degree of
Doctor of Philosophy

in

Economics

in the

Graduate Division

of the

University of California, Berkeley

Committee in charge:

Professor David Card, Chair
Professor Patrick Kline
Professor Steven Raphael

Spring 2014

Essays on Decision Making in the Labor and Housing Market

Abstract

Essays on Decision Making in the Labor and Housing Market

by

Xiaoyu Xia

Doctor of Philosophy in Economics

University of California, Berkeley

Professor David Card, Chair

My dissertation consists of three studies that incorporate behavioral economics element in analyzing decisions of individuals in the labor and housing market.

The first chapter studies how college students learn about the earning opportunities associated with different majors. I use data from two major longitudinal surveys to develop and estimate a learning model in which students update their expectations based on the contemporaneous earning realizations of older siblings and parents. Reduced-form models show that the probability of choosing a major that corresponds to the occupation of an older sibling or parent is strongly affected by whether the family member is experiencing a positive or negative earnings shock at the time the major choice is made. Building on this finding, I estimate a model of major choice that incorporates learning from family-based information sources. The results imply that students overestimate the predictive power of family members' earnings: the decision weight placed on family wage realizations is much larger than can be justified by the empirical correlation between their own earnings and their family members' earnings.

My second chapter focuses on how workers' time preference affect their job searching under unemployment insurance (UI) policies. Previous studies find that higher UI benefit, extended UI eligibility duration, bonus payment or severance pay affects unemployed workers job-finding hazard rate but not the subsequent job match quality. I construct and estimate a dynamic job search model endogenizing both the search intensity and reservation wage with hyperbolic discounting. Using data from several state job bonus experiments from the 1980s (the Illinois UI Incentive Experiments), I find the model with hyperbolic discounting fits the effect of the job-bonus treatment better, and an unemployed workers reservation wage decreases slower during search duration under the hyperbolic discounting framework, implying that bonus payments induce higher search effort but do not significantly decrease workers' reservation wages.

The third chapter is a joint work with Tristan Gagnon-Bartsch and Antonio Rosato. In this study, we propose and empirically test a theoretical model of loss aversion in the housing market. Compared to the empirical findings of Genesove and Meyer (2001), our model makes

a new prediction: sellers who suffer a relatively small loss (when the current market value is lower than the previous purchasing price) will set prices equal to their original purchase price. Hence the model predicts an asymmetric distribution of gains to sellers which assigns less mass to small negative values than to equally size positive values and has a spike at zero. We first use the same data-set used by Genesove and Meyer to test our new prediction and find that between 4% and 10% sellers incurring a loss "bunch" by asking a price within $5,000 of the original purchasing price. We also collect new real-estate data from the San Francisco Bay Area in 2011 and find that the pricing behavior of individual sellers is still consistent with loss aversion.

Contents

Contents **i**

List of Figures **iii**

List of Tables **iv**

1 Forming Wage Expectations through Learning: Evidence from College Major Choice **1**

1.1 Introduction 1
1.2 Motivating Evidence 4
1.3 A Model of Learning from Family Members 9
1.4 Evidence on Learning about Match-Quality 15
1.5 Over-learning from Family Experience 17
1.6 Conclusion 21

2 The Impact of Time Preference on Job Search with Unemployment Insurance **31**

2.1 Introduction 31
2.2 Theoretical Framework 33
2.3 Estimation Strategy 37
2.4 Estimation and Policy Simulation 40
2.5 Conclusion 44

3 Bunching at the Original Purchase Price: New Evidence of Loss Aversion in the Housing Market **53**

3.1 Introduction 53
3.2 The Model 54
3.3 Empirical Analysis 56
3.4 Conclusions and Extensions 59

A Chapter 1 **68**

A.1 Summary Statistics 68
A.2 Mapping occupations to college major 69

A.3 Structural Estimation 71
A.4 Robustness Check 71
A.5 Discussion for $\bar{w}_1 > \bar{w}_2$ in Section 5.2 73

B Chapter 2 **76**
B.1 A Search Model with Initial Asset 76

Bibliography **80**

List of Figures

2.1 Empirical Survival Rate of Unemployment Spell 49
2.2 Empirical Hazard Rate of Exit Week 50
2.3 Empirical Hazard Rate of Exit Week by Treatment 51
2.4 Simulated Hazard Rate of Exit Week by Treatment (Exponential) 51
2.5 Simulated Hazard Rate of Exit Week by Treatment (Hyperbolic) 52

3.1 How Loss-averse Seller Sets Listing Price Case 1 61
3.2 How Loss-averse Seller Sets Listing Price Case 2 61
3.3 How Loss-averse Seller Sets Listing Price Case 3 62
3.4 Sellers in Loss: Price Difference in Asking and Previous Transaction Price . . . 62
3.5 Sellers in Gain: Price Difference in Asking and Previous Transaction Price . . . 63
3.6 Price Difference in Asking and Previous Transaction Price in Redfin Data 63

List of Tables

1.1 Summary Statistics 23
1.2 The Impact of a Sibling's Wages on a Student's Major Choice 24
1.3 The Impact of a Parent's Wage on Major Choice 25
1.4 The Impact of a Sibling's Wage on a Student's Ideal Job 25
1.5 Structural Parameter 26
1.6 Heterogenous Learning 27
1.7 Correlation between a Sibling's Wages and a Student's Wages 28
1.8 Students' Labor Market Outcomes and Siblings' Wage Shocks 29
1.9 Students' Starting Wages and Family Income Changes 30

2.1 Summary Statistics 45
2.2 Treatment Effect on Average Worker's Labor market ofttimes 46
2.3 Treatment Effect by Pre-Unemployment Wage Distribution 46
2.4 Parameter Estimation 47
2.5 Policy Simulation 48

3.1 Relative Bunching Rates of Asking Price in Boston Data 64
3.2 Relative Bunching Rates of Asking Price in Redfin Data 64
3.3 Relative Bunching Rates of Market Price in Boston Data 64
3.4 Relative Bunching Rates of Asking Price Across Classes of Ownership 65
3.5 Regression of Asking Price on Loss and Market Value 66
3.6 Placebo Tests in Bunching Price using Boston Data 66
3.7 Round vs Non-Round Prices in Selling Price using Boston Data 67

A.1 Distribution of Major and Occupation in NLSY79 68
A.2 Family Income Distribution in NELS88 69
A.3 Mapping Occupations to College Majors 70
A.4 Rank of Population Preferences for College Major 71
A.5 The Impact of a Sibling's Wage on a Student's Major Choice 72
A.6 Unconditional Correlation between Siblings' Wages 72

Acknowledgments

I thank my committee chair David Card and committee members for invaluable advice and support. I also thank Stefano DellaVigna, Enrico Moretti, Matthew Rabin, as well as Jesse Rothstein and Christopher Walters. I also thank various classmates and friends at University of California, Berkeley for their help.

Chapter 1

Forming Wage Expectations through Learning: Evidence from College Major Choice

1.1 Introduction

Young people often have to make important decisions — such as which college to attend or which job to take — in the presence of substantial uncertainty about the future consequences of their choices. How do they form expectations about the payoffs to different options? A long line of social science research, dating at least from Hyman 1942, has argued that people learn from the choices and outcomes of "reference groups."[1] Perhaps the most important reference group for many decisions is the family.[2] There are strong family correlations in many socioeconomic outcomes (see Black and Devereux, 2011 for a recent survey), including occupational status. However, whether this correlation arises though learning opportunities or through other potential channels, such as correlated abilities or tastes, remains unclear.

In this chapter I use data from two major longitudinal surveys to directly examine the role of learning from the labor market experiences of close family members (older siblings and parents) in the choice of college major. Choice of major is an important first step in the careers of many college students and is a significant determinant of their subsequent earnings and occupational status (Arcidiacono, 2004; Hamermesh and Donald, 2008; Altonji *et al.*, 2012). I develop and estimate a model in which students incorporate information from the wage realizations of close family members in deciding whether to pursue a major that corresponds to the occupation of the family member. Specifically, I assume that the wage

[1] A recent example in economics field is the survey in Dominican Republic conducted by Jensen 2010. His data shows that students' main source of information about earnings were the people they knew in their community.

[2] Studies across social science fields have documented the influence of family members on youth behavior in a broad range, such as Weast 1956, Bank, Slavings, and Biddle 1990, Brody 1998 and Duncan, Boisjoly, and Harris 2001.

information a student receives can be captured by the wage shock of her family member — the difference between the family member's realized wage and the predictable wage.[3] By examining the impact of family members' wage shocks on students' subsequent earnings, I can also test whether students use this family-based information optimally.

Simple reduced-form models show that college students are more likely to choose a major associated with the occupation of a family member who is experiencing a positive wage shock, and less likely to make such a choice if the family member is experiencing a negative wage shock. Estimates from a multinomial logit model confirm that family wage shocks exert a significant effect on a student's major choice. Moreover, adding information on individual wage realizations of close family members leads to an improvement in model fit relative to a benchmark "rational expectations" model used in previous studies.[4]

The effect of family member wages on students major choice is surprisingly large, leading me to investigate whether students "overreact" to family-based information. Using the correlation of students' post-college earnings with the family wage outcomes observed at the time of their initial major decision, I show that on average students place too much weight on family-based earnings information. Students who choose a major corresponding to positive family wage shocks perform worse later in the labor market than others whose family members received negative wage shocks, implying students overestimate the predictive power of family wage shocks.

My main data source is the National Longitudinal Survey of Youth 1979 (NLSY79). It includes a relatively large number of sibling pairs, allowing me to link the college major choice of the younger sibling to the earnings of the older sibling. I use an additional data set, the National Education Longitudinal Study of 1988 (NELS88), to link major choice to changes in parental income.

I begin by establishing the importance of family based labor market information flows using a reduced-form model of the probability that a student adopts a major choice corresponding to the occupation of their older sibling or parent. I find that a student is more likely to pursue a major that is related to the occupation of their family member when the family member experiences a wage increase during a student's time in high school or college. There is no such correlation between a student's major choice and the wage changes experienced by her siblings or parents in later years. The marginal elasticity of a student's major choice with respect to a family member's wage change is 0.77, which is about seven times larger than the elasticity with respect to average earnings in the occupation estimated by previous literature (e.g., Blom, 2012, Zafar and Wiswall, 2012, Beffy *et al.*, 2012). The comparison suggests that earlier studies may have substantially under-estimated the sensitivity of student major choice to perceived earnings opportunities.

[3]The predictable component of a worker's wage in one occupation is the average wage of all workers in that occupation conditional on observable characteristics, such as gender, race, region and birth cohort.

[4]Imposing the assumption that students have rational expectations that equal to the realized occupation average wage conditional on observables is a common approach taken by previous major-choice studies, for example, Siow 1984, Berger 1988, Keane and Wolpin (1997), Rosen and Ryoo (2004).

To understand the role of family information in a student's career planning, I go on to develop a more complete multinomial choice model of major choice in which students update their expected earnings in response to their family members' wage shocks. This choice model also generates an empirical prediction that can test whether students are learning as Bayesians. I assume a student believes that the future wages associated with a given major can be decomposed into two components: a predictable wage component that is known to her before she starts working and an unknown component measuring the match quality between her skills and the occupations associated with that major. Because the occupation-specific skills may be shared across family members, to form her belief about the match quality, the student relies on the wage shocks of her family member, who works in an occupation related to the major under consideration. I then compare whether different subgroups of students process family-based earnings information differently, and verify that students respond more to family wage shocks if those wage shocks contain more information about their own match quality.

The effect of family wage shocks on students' major choices therefore identifies to what extent students learn from family-based information. My point estimate for the weight students place on family wage shocks when they update their expectations of future earnings is 0.57. However, by examining the empirical wage correlation between siblings in the NLSY79, I find the upper bound of the empirical correlation is between 0 to 0.1, much lower than my point estimate of students' perceived correlation. This comparison suggests that students overestimate the correlation of wage outcomes between close family members. Consistent with this result, I also find that students who choose a major corresponding to the occupation of a family member who was experiencing a positive wage shock at the time of the choice suffer a greater incidence of changing college majors and have lower earnings in later years, indicative of the lower match quality that would be expected if students are overestimating the informativeness of the wage shocks.

Taken together, the main contribution of this chapter is to provide a testable learning mechanism that sheds new light on how young people form their expectations. Motivated by earlier thinking on how students forecast their potential earnings (Freeman, 1975, 1975, 1976; Willis and Rosen, 1979; Manski and Wise, 1983), my model incorporates both the conventional rational expectation and the new within-family "cob-web" expectation. This generalized model predicts students' major choices more accurately, and it can provide a direct test on whether students' expectations are consistent with Bayesian learning. While there is a perennial debate on expectations assumptions in economic thinking, the findings in this paper favor models of individual-specific adaptive expectations in decision-making.

This study calls attention to an information channel for how family background affects students' educational decisions. If students rely on parental earnings to learn about the returns to education or training, this channel can provide one causal mechanism that explains intergenerational persistence in education attainment and occupational choice.[5] This infor-

[5]For example, studies by Hellerstein and Morrill(2011), Corak and Piraino (2011), show that a large portion of children in recent cohorts work in the same occupation as their parents.

mation channel also helps to explain the result found by Cameron and Heckman (2001) that parental income has its greatest influence on their children's college attendance by enhancing the abilities and attitudes required for entering college rather than through actual financing.

More broadly, within a growing body of work on people's misuse of information, this study supplements the findings that decision makers might overreact to information that comes from local sources.[6] Even without specifying the exact psychological reason for why students overreact, the policy implication of the results in this paper appears far reaching. Considering the availability of precise wage information from school career centers or public agencies, students can potentially improve their predictions of future earnings by utilizing these sources of outside information.

The rest of the chapter is laid out as follows. Section 2 provides the motivating evidence that family members' wage changes affect students' career planning. Section 3 develops and estimates a multinomial logit model in which students update beliefs about future earnings based on family member's wage changes. Section 4 explores learning heterogeneity across students to collect more evidence on learning about match quality. Section 5 shows the correlation between a student's labor market performance and her family member's wage shocks. Section 6 concludes.

1.2 Motivating Evidence

This section establishes the importance of family-based information using a reduced-form model of the probability that a student adopts a major choice corresponding to the occupation of their older sibling or parent. It provides motivating evidence that family members' wage changes affect students' career planning. Section 2.1 introduces the data sources. Section 2.2 presents the evidence that a student is more likely to choose a college major related to her older sibling's or parent's occupation if the family member has received a recent wage increase. Moreover, a student reports that her "ideal" occupation is the occupation that her older sibling works in more often when the latter has experienced a recent wage increase.

Data: Linking Students with Family Members

My main data source is the National Longitudinal Survey of Youth 1979 (NLSY79), which connects students' educational choices with their older siblings' wages. The Bureau of Labor Statistics has collected the NLSY79 since 1979 using a sample of 12,686 men and women born between 1957 and 1964. This survey first interviewed all individuals aged between 15 and 22 in a household in 1979, and then follows them with annual interviews until 1994, and continues on a bi-annual basis.

[6] Shabani (2010) discovers local stale news affects stock prices; Gallagher 2013 reports the insurance take-up increases because of the flood news about other communities, without any changes in actual flood probabilities.

The NLSY79 surveys the baby-boom cohort, and therefore a large faction of families in the survey has records for multiple siblings. There are 3,448 sibling pairs in the NLSY79. Older siblings are defined as siblings entering the labor market first. After dropping sibling pairs in which younger siblings have not attended a college or declared a college major, 1,639 siblings pairs remain for use in this study. The survey includes the 1970 census 3-digit occupation code to record the occupation of all respondents. I group all the professional occupations (1970 Census occupation codes 001-245) into 23 categories that can be directly mapped into college majors listed in the NLSY79.[7] In my analysis, the occupation variable for an older sibling is thus defined as the first full-time professional occupation during 1979-1992.[8] By excluding the students with older siblings who do not have records of working in a professional occupation, I construct a Student-Sibling sample (S1) with 1,004 sibling pairs. Table 1.1 Panel A summarizes the mean and standard deviations of key variables in the NLSY79 and my S1 sample.

The definition of the time period of interest is crucial for my analysis. Students in the NLSY79 declare their first college major in a certain year between 1979 and 1992. As the focus is on the effect of family wage outcomes on a student's major choice, the time window of interest is a few years before and after a student declares her major. In the S1 sample, around 25% of the older siblings' earnings records are missing in any given year. The issue of missing data in combination with the concern that the NLSY79 switched to a bi-annual survey after 1994 explains why I use a 4-year time window as the relevant time period. For example, if a student declares her first major in year 1985, the pre-choice time window is 1982-1985 and the post-choice one is 1986-1989. In this way, I can construct a balanced average wage variable in the pre-choice time window and the post-choice window for most students in my sample.[9] In particular, the average wage in pre-choice window is referred to as the "contemporaneous wage" of a family member.[10]

The key variables for my reduced-form models are a student's first declared major and her older sibling's wage at the time the student was making her decision.[11] A student's first major choice is the main dependent variable. A sibling's wage is measured in log hourly rate that is normalized to 2010 dollars. I use the hourly wage rate because it tells a student

[7]Table A1 lists the 23 majors in the NLSY79, and Table A3 maps each professional occupations to an associated college major. Which major an occupation matches to is determined by the college major held by the majority of college educated workers in that occupation. I also examine the major-occupation match-matrix from American Community Survey (ACS) 2009. It has very similar pattern to the NLSY79.

[8]All students in the NLSY79 have declared their first college major during 1979-1992.

[9]The regression results are robust to changing time window length to 3-year span or 5-year span. Yet, the number of observations would decrease significantly if the length of the time window changes to 2-year span.

[10]There are three reasons why I focus on the wage in pre-choice window. First, this time period is likely to be the critical learning time for students to form wage expectations. Second, the wage records in this time period are available for most students, while earlier wage records are incomplete. Third, around 90% siblings in S1 have a age difference smaller than 4-year, therefore the contemporaneous wage captures most wage information students received from their older siblings.

[11]Approximately 30% of students have changed their majors during college years, but family backgrounds may affect their initial college major most.

more about the net payoff for a certain occupation compared to the annual earnings.[12] By calculating a sibling's average log wage in the pre-choice time window and the post-choice one, I construct the main explanatory variables as "Pre-Choice Sibling's Wage" and "Post-Choice Sibling's Wage".

I use the National Education Longitudinal Study of 1988 (NELS88) as an additional data set. It includes a nationally representative sample of eighth graders first surveyed in 1988 then re-surveyed through four follow-ups in 1990, 1992, 1994, and 2000. There are around 20,000 students who have completed all follow-up surveys. Among those, 7,299 students had declared a college major by 1992 and have records of their parents' occupations. The NELS88 provides an opportunity to link students' education choices with their parents' labor market experiences. However, it codes a parent's occupation in an aggregated way that there were only 16 different occupations for all parents.[13] Among the 16 occupations, the only professional occupations that can be directly mapped to a college major are those of a manager and a school teacher. Thus I use 1,093 students whose parent works as a manager to form the first Student-Parent sample (S2-Manager), and 705 students with a parent who works as a school teacher to form the second Student-Parent sample (S2-Teacher). The time of period of interest in the NELS88 is the time between 1988 and 1992, when students were attending high school. I construct the change of family income between 1988 and 1992 as the proxy for the change in parental income. Table 1.1 Panel B lists the summary statistics for the NELS88 and my S2 sample.

According to Table 1.1, students in sample S1 and S2 are similar to the population of college students in the NLSY79 and the NELS88. There is slightly positive selection based on AFQT scores or after-college wages in my sample, which is likely because all students in sample S1 and S2 have at least an older sibling or a parent working in a professional occupation. Panel A of Table 1 also shows that older siblings have lower AFQT scores and earn lower wages compared to their younger siblings. This is because in my sample the older siblings might not have attended any college, while all younger siblings have received at least some college education.

Major Choice and Contemporaneous Family Wages

I begin my analysis by examining the determinants of major choices in a descriptive way. Specifically, I estimate the correlation between a student's major choice and her older sibling's wages. The outcome variable is a binary indicator for whether a student's college major matches her sibling's occupation. One important control variable is an older sibling's permanent wage, which is the average log wage from 1979 to 1992. By taking the difference between a sibling's pre-choice wage and a siblings's permanent wage, I construct a wage shock

[12] In robustness checks, I show the regression results in the same specification but with a worker's wage measured by annual income.

[13] The 16 categories are: Clerical, Craftsperson, Farmer, Homemaker, Laborer, Manager, Military, Operative, Account/Artist/Nurse, Dentist/Lawyer, Proprietor, Protective Service, Sales, School Teacher, Service, Technical.

variable “Sibling’s Wage Pre-Choice - Permanent”. Similarly, I construct a post-choice wage shock variable “Sibling’s Wage Post-Choice - Permanent”. Other control variables include occupation average wage in pre-choice and post-choice window, a student’s AFQT score, demographic characteristics, and a student’s pre-determined taste for certain occupations, captured by a variable that records a student’s ideal occupation in 1979.

Table 1.2 shows that the wage shock an older sibling received in the pre-choice window strongly correlates with a student’s major choice, while there is no such correlation between a sibling’s wage shock received in the post-choice window and a student’s choice. The difference between Column 1 and Column 3 provides a first identification of which channel is more likely to explain the influence on students’ major choices. If a sibling’s wage in both time windows is associated with a student’s major choice similarly, family-correlated preferences may explain the observed correlation. Instead, if only the pre-choice sibling’s wage affects a student’s choice, learning from family-based information is more likely to be the underlying mechanism.

Based on Column 1, a 10% increase in a sibling’s pre-choice wage results in a 1.23% increase in a student’s likelihood to choose the same major as the older sibling’s occupation. Given the average match-ratio of 16%, the marginal elasticity of a student’s major choice with respect to a change in her sibling’s wage is 0.77. The value is much larger than previous estimates of the elasticity with respect to the change in occupation wage. For example, Blom (2012) finds that a 10% increase in median hourly wages results in a 0.17% increase in the probability that a student chooses a related major; Wiswall and Zafar (2012), Beffy *et al.* (2012) find the elasticity with respect to the changes in occupation wage is around 0.1. The difference between my estimate and their estimates imply that though students respond little to changes in occupation average wage, they strongly respond to perceived earning opportunities based on their family wage outcomes.

Columns 2 and 4 add controls for the average wage of the occupation that a sibling works in. The coefficient on the “Permanent Occupational Average Wage” suggests that a 10% increase in occupation long-term average wage results in a 1.5% increase in the student’s likelihood to choose the major associated with her older sibling’s occupation. The effect of “Pre-Choice Sibling’s Wage” is still in similar magnitude after controlling for any change in the occupation average wage. This pattern indicates that students are responding to wage changes of their older siblings in addition to any change in the occupation average wage. Appendix Table A5 lists similar results in a specification with wages measured by log annual income.

The coefficient on a sibling’s permanent wage is around 0.09 without controlling for occupation average wage, and it becomes smaller once adding the control of occupation average wage. The coefficients in Columns 1 and 2 show that the influence of an older sibling’s long-term average wage is smaller than the effect of wage difference in “Pre-Choice” window, thus students seem to respond more to recent wage fluctuations than permanent level of earnings. The sign of coefficients for other control variables is as predicted: a student’s ideal occupation before going to college strongly predicts her major choice, and she is more likely to choose a major that matches the occupation of a sibling of the same gender.

I find similar results in the NELS88. Table 1.3 displays the positive correlation between a student's family income and the probability that she chooses the major associated with her parent's occupation. The dependent variable is a binary indicator for whether a student's major matches her parent's occupation. The key explanatory variable is a dummy variable recording whether a household income increases between 1988 and 1992.[14] Other control variables include a student's ideal occupation, parental years of education, student test scores, as well as other demographic characteristics. Column 1 of Table 3 shows the impact of changes in family income in the S2-Manager sample, and Column 2 shows the effect in the S2-Teacher sample.

Older siblings' wage outcomes not only affect students' choices of major, but also influence their earlier career planning. In 1979 and 1982, the NLSY79 surveyed students who plan to work at age 35 with a question "what kind of work (1970 Census 3-digit occupation code) would you like to be doing when you are 35 years old?". A student's "ideal job" is a proxy for her career plans, and it can be used as an outcome variable to test how an older sibling's wages affect a student's career planning. The dependent variable records whether a student's ideal job is the same as her sibling's occupation (3 digit occupation code level), and the central explanatory variable is a sibling's average wage during 1979-1982. Control variables are a sibling's permanent wage, whether a sibling's occupation is the same as her parent's occupation and other background characteristics.[15]

In Table 1.4, I find that a student is more likely to plan to work in the same occupation as a sibling if the latter earned a higher wage during 1979-1982. The coefficient on the "Sibling's Wage during Survey Years" indicates that a 10% increase of hourly wage of a sibling increases the probability of a student wishing to work in sibling's occupation by 0.2%. Among 2,396 respondents, 1.59% of the students wished to work in the exact occupation of their siblings. Thus the corresponding elasticity of a student's ideal occupation with respect to the change in her sibling's hourly wage is around 1.[16] The effect of a sibling's wage on "ideal occupation" is robust to controlling the match between the sibling's occupation with a parent's occupation, and a student is more likely to follow an older sibling's footstep if the sibling chooses the same occupation as their parents'. Again, only a sibling's wage received during the survey years but not the permanent wage is associated with a student's ideal occupation, which is consistent with the learning mechanism hypothesis.

[14]The household income distribution is listed in Appendix Table A2. Instead of using the dummy variable to record whether a student's household incomes increases, I can use an indicator to record whether the income increases above a given cutoff (e.g. $10,000). The regression results are the same.

[15]Define a parent's occupation as the father's longest occupation when available. When a father's occupation information is missing, I use a mother's longest occupation as parent's occupation.

[16]Sample size in Table 1.4 is larger than that in Table 2 because the sample used in Table 4 is not restricted by college attendance.

1.3 A Model of Learning from Family Members

Previous section demonstrates the correlation between students' major choices and the recent wage fluctuations of their family members. Though the results provide suggestive evidence that students are learning from family-based wage information, it is difficult to infer the exact learning process or test whether students are using the information optimally based only on the reduced form models. To completely explain how recent wages of family members affect a student's choice of major, I propose a multinomial logit model that embeds how students adjust beliefs of future earnings after observing a family member's wage realizations. Section 1.3.1 introduces the setting. Sections 1.3.2 - 1.3.4 describe how a student updates her belief in detail. Sections 1.3.5 - 1.3.7 develop an estimation strategy and show the structural estimations.[17]

Setting

Preferences

A student s decides whether to declare major $j \in J = \{1, 2, ..., 22\}$ in college, and she has a family member f already working in the occupation associated with one specific major k (equivalent to occupation k in this section). To simplify the notation, the theoretic model treats the return to major j as the average wage in occupation j.[18]

The value function of student s when she considers choosing major j includes three components: flow utility while attending college, u_s^j; utility from expected future earnings as a linear function of log wage, W_s^j; and an idiosyncratic preference, ξ_s^j. Specifically,

$$V_s^j = u_s^j + \theta W_s^j + \xi_s^j \tag{1.1}$$

where θ is the utility weight on future earnings, and ξ_s^j is drawn from a Type I Extreme Value (Gumbel) distribution.

Flow utility. A student's flow utility from studying major j can be divided into two components. The first component is a population taste shared by every student, c_0^j. The second is a proxy for individual-specific taste T_s^j.

The flow utility from studying major j is

$$u_s^j = c_0^j + c_1 T_s^j. \tag{1.2}$$

Utility from Future Wage. A student does not know her future earnings W_s^j, so she updates her belief through a learning process. By imposing the assumption that students

[17]The structural estimation is only based on the S1 sample from the NLSY79, because only the NLSY79 has the detailed annual wage information for a student's family member.

[18]In the estimation section (Section 3.6), I will introduce the details about how to map average occupation wage to average return to each major.

are risk-neutral, only the expected value of future wages enters her utility function. A more general model may add risk aversion in students' preferences, then a student can update her belief about the mean, the variance and other moments of the future wages.

Wage Determination Process

Suppose a representative worker's realized earning in a given occupation j, w^j, can be decomposed as

$$w^j = A^j + \eta^j$$

A^j stands for the ex-ante predictable component for a worker's wage in occupation j (which I will refer to as predictable wage), and each worker knows it before they start working. η^j represents the unknown match quality of personal skills to occupation j for that worker (which I will refer to as match quality), unknown to the worker till he starts working.[19] A worker knows her η^j is a random drawn from $N(0, \sigma_j^2)$, and certain workers' match-quality components can be correlated.

A Student's Expected Return to College Majors

For any $j \in J$, student s believes her expected future earnings will be in the form of

$$W_s^j = A_s^j + \eta_s^j. \tag{1.3}$$

She does not know the exact value of η_s^j, but she knows it is drawn from $N(0, \sigma_j^2)$.

Student s observes her family member's wage realization, w_f^k, and she understands that it follows the wage determination process:

$$w_f^k = A_f^k + \eta_f^k \tag{1.4}$$

where η_f^k is drawn from $N(0, \sigma_k^2)$.

Importantly, when student considers major k, she believes own match quality component η_s^k is correlated with her family member f's η_f^k.

Assumption 1. *Assume that the perceived correlation coefficient between η_s^j and η_f^k is such that*

$$corr(\eta_s^j, \eta_f^k) = \begin{cases} \lambda & \text{if } j = k \\ 0 & \text{if } j \neq k \end{cases} \tag{1.5}$$

[19] η^j represents the generic ex-ante unknown wage determinant to each worker, but an intuitive interpretation of η^j is the match quality component (Jovanovic, 1979).

Student s observes w_f^k and A_f^k, but not η_f^k. According to Equation (4), $w_f^k - A_f^k$ represents family member f's match quality, η_f^k.

I assume a student updates her belief about η_s^k in the way:

$$E(M_s^k | w_f^k, A_f^k) = \lambda(w_f^k - A_f^k). \tag{1.6}$$

If student s is Bayesian, she updates her belief about own match quality in major k in the following manner:

$$E(M_s^k | w_f^k, A_f^k) = \frac{Cov(\eta_s^k, \eta_f^k)}{Var(w_f^k)}(w_f^k - A_f^k) = \rho(w_f^k - A_f^k) \tag{1.7}$$

where ρ represents the actual correlation between η_s^k and η_f^k

Combining the above two scenarios, I define λ as:

Definition 1.3.1. λ is the weight students place on family match quality signals when they update their beliefs about own future earnings, $\lambda \in [0, 1]$. If students are Bayesian, $\lambda = \rho$.

Student s also observes own predictable wage, therefore she updates her expected wage in occupation j to

$$E(W_s^j | w_f^k, A_s^j, A_f^k) = \begin{cases} A_s^k + \lambda(w_f^k - A_f^k) & \text{if } j = k \\ A_s^j & \text{if } j \neq k \end{cases} \tag{1.8}$$

An Econometrician's Knowledge of Wage Determinants

Though an econometrician does not observe A_s^j or A_f^k, it is possible to estimate these parameters. Student s' predictable wage, A_s^j, for each major can be decomposed as

$$A_s^j = X_s' \Pi_j + \epsilon_s^j \tag{1.9}$$

where $X_s' \Pi_j$ represents the average wage in occupation j conditioned on pre-determined observable characteristics, and ϵ_s^j is an econometrician's measurement error in A_s^j, which is assumed to be normal with distribution $N(0, \sigma_s^2)$.[20]

To estimate A_f^k, an econometrician can use the family member's predictable wage $\tilde{X}_f' \tilde{\Pi}_k$. As a family member already starts works in occupation k, the econometrician may utilities extra information (Z_f) to estimate the predictable wage in occupation k for f, which is denoted as $\tilde{X}_f = (X_f, Z_f)$.[21]

$$A_f^k = \tilde{X}_f' \tilde{\Pi}_k + \tilde{\epsilon}_f^k \tag{1.10}$$

[20] In previous studies on educational decisions, $X_s' \Pi_j$ usually represents a student's rational expectation for future returns, such as in Rosen and Willis (1979), Siow 1984, Berger (1988), Keane and Wolpin (1997), Rosen and Ryoo (2004). In these studies, students have common knowledge of the actual process generating life-cycle incomes conditional on personal variables, and they apply such knowledge to forecast future personal income should he or she choose a major.

[21] Section 3.6 describes the empirical specification of $\tilde{X}_f^k$.

where $\tilde{X}_f'\tilde{\Pi}_k$ is the estimate for the predictable wage of family member f, and $\tilde{\epsilon}_f^k$ represents an econometrician's measurement error in A_f^k, which is assumed to be normal with distribution $N(0, \sigma_f^2)$

Definition 1.3.2. To simplify notation, define family wage shock S_f^k by $S_f^k = w_f^k - \tilde{X}_f'\tilde{\Pi}_k = w_f^k - A_f^k + \tilde{\epsilon}_f^k$. Family wage shock S_f^k equals the difference between f's realized wage, w_f^k, and the estimate of her predictable wage, $\tilde{X}_f'\tilde{\Pi}_k$. S_f^k is an estimate for the match quality signal a student receives from her family member, which by construction contains the true match quality component, $w_f^k - A_f^k$ and a measurement error term, $\tilde{\epsilon}_f^k$.

By substituting Equations (9), (10), and Definition 2 into Equation (8), a student's expected wage in occupation j is given by

$$E(W_s^j|w_f^k, A_s^j, A_f^k) = \begin{cases} X_s'\Pi_k + \epsilon_s^k + \lambda(S_f^k - \tilde{\epsilon}_f^k) & \text{if } j = k \\ X_s'\Pi_j + \epsilon_s^j & \text{if } j \neq k \end{cases} \tag{1.11}$$

A Student's Updated Value Function

Based on the previous discussion, the student's updated value function can be rewritten as:

$$V_s^j = \begin{cases} u_s^k + \theta[X_s'\Pi_k + \epsilon_s^k + \lambda S_f^k - \lambda\tilde{\epsilon}_f^k] + \xi_s^k & \text{if } j = k \\ u_s^j + \theta[X_s'\Pi_j + \epsilon_s^j] + \xi_s^j & \text{if } j \neq k \end{cases} \tag{1.12}$$

where ξ_i^j is drawn from a Type I Extreme Value distribution.

With the measurement error terms ϵ_s^j and $\tilde{\epsilon}_f^k$, the econometrician can only estimate the following model

$$V_s^j = \begin{cases} u_s^k + \theta X_s'\Pi_k + \theta\lambda S_f^k + \zeta_s^k & \text{if } j = k \\ u_s^j + \theta X_s'\Pi_j + \zeta_s^j & \text{if } j \neq k \end{cases} \tag{1.13}$$

where $\zeta_s^k = \theta(\epsilon_s^k - \lambda\tilde{\epsilon}_f^k) + \xi_s^k$ and $\zeta_s^j = \theta\epsilon_s^j + \xi_s^j$.

I can estimate the above model using quasi-maximum-likelihood method by assuming ζ_s^j still follows a Type I Extreme Value distribution. Previous studies, such as Lee 1982, find that estimating a multinomial logit model with independent omitted variables does not generate biased estimators, and the direction of potential bias can be analyzed based on the covariances between the the omitted variables and explanatory variables.[22] Importantly, $\tilde{\epsilon}_f^k$ is known to the students and they do not incorporate it when they calibrate the match quality component. However, as an econometrician cannot observe $\tilde{\epsilon}_f^k$, the estimate for the match quality signal S_f^k inevitably includes the measurement error term $\tilde{\epsilon}_f^k$, which could cause biases in the estimations.

[22]If the estimate for A_f^k is quite accurate, i.e. $\tilde{\epsilon}_f^k$ is small, the heteroscedasticity problem in the estimation is not severe. An alternative estimation strategy is to use Heteroscedastic Extreme-Value (HEV) model, though estimating a HEV model with independent omitted variables might generate biased estimators that are hard to analyze.

Potential Bias in Estimation

The econometrician estimates a multinomial logit model with omitted variables. The estimators of θ and λ can be biased if the omitted variables are correlated with explanatory variables $X_s'\Pi_k$ and S_f^k, thus I discuss the following covariances.

- $Cov(X_s'\Pi_k, \tilde{\epsilon}_f^k)$: the measurement error of the family member's predictable wage is unlikely to correlate with a student's average wage based on pre-determined observables.
- $Cov(S_f^k, \tilde{\epsilon}_f^k)$: $\tilde{\epsilon}_f^k$ is the measurement error in family member's predictable wage A_f^k. According to Definition 2, there exists a positive correlation between S_f^k and $\tilde{\epsilon}_f^k$. However, this positive correlation only means that student s responds to an actual match-quality signal that is smaller than the estimate by the econometrician, thus the estimator based on Equation (13) is a downward biased estimator of λ, i.e. $\hat{\lambda} < \lambda$.
- $Cov(X_s'\Pi_k, \epsilon_s^k)$: these two terms are orthogonal by construction (Equation 9).
- $Cov(S_f^k, \epsilon_s^k)$: if ϵ_s^k is not correlated with $\tilde{\epsilon}_f^k$, then ϵ_s^k is unlikely to correlate with S_f^k. However, if ϵ_s^k and $\tilde{\epsilon}_f^k$ are positively correlated, then ϵ_s^k can be positively correlated with S_f^k. As longs as the positive correlation between S_f^k and ϵ_s^k is smaller than the correlation between S_f^k and $\tilde{\epsilon}_f^k$ multiplied by λ (the equivalent condition is $corr(\epsilon_s^k, \tilde{\epsilon}_f^k) < corr(\eta_s^k, \eta_f^k)$), my estimate of λ based on Equation (13) is still downward biased, and part of the original bias caused by $Cov(S_f^k, \tilde{\epsilon}_f^k)$ can be canceled out because of positive correlation between ϵ_s^k and $\tilde{\epsilon}_f^k$.

Therefore, I claim $\hat{\lambda}$ estimated by model in Equation (13) is a lower-bound estimator of λ.

Estimation Strategy

Estimating θ and λ requires the specification of T_s^j, $X_s'\Pi_j$ and S_f^k. A student's individual taste proxy, T_s^j, is the number of classes she has taken in high school related to major j, adjusted by the population average and standard deviation. I also add a dummy variable recording if a student's family member works in occupation j as the robustness check specification for the individual taste proxy.

I estimate $X_s'\Pi_j$ using a Mincerian wage regression with 1990 census micro data.[23] In the 1990 census sample, a representative worker n's wage in occupation j can be characterized

[23] I use the census data to estimate Π_j, because it gives very small standard error for the estimate of Π_j. There are 1,272,594 individuals born between 1957 and 1964 with a professional occupation that can be categorized into 22 college majors. The observable variables X shared by NLSY79 and 1990 Census 5% Micro Sample include gender, race, years of education, and birth year dummies.

as

$$w_n^j = X_n' \Pi_j + \varepsilon_n^j \tag{1.14}$$

where X_n include gender, race, birth cohorts, years of education, a quadratic function of working experience, and ε_n^j is a normal noise term.

This regression gives occupation-specific wage coefficients $\hat{\Pi}_j$. Thus, the predictable wage to major j for student s is $X_s'\hat{\Pi}_j$ — the average starting wage of a student conditional on pre-determined observables.[24] However, since students enrolled in major j can potentially work in occupations other than j, the value of $X_s'\hat{\Pi}_j$ is the weighted average of an occupational starting wage multiplied the match-probability between any occupation and major j. The match-probability between professional occupation j_1 and major j is calculated by the fraction of workers who graduated with major j working in occupation j_1, coded as Pr^{jj_1}. The predicted return to major j is $X_s'\hat{\Pi}_j = \sum_{j_1=1}^{22} Pr^{jj_1} X_s'\hat{\Pi}_{j_1}$.

To estimate S_f^k, recall Definition 1.2

$$S_f^k = w_f^k - \tilde{X}_f'\tilde{\Pi}_k.$$

I regress a family member's contemporaneous wage w_f^k (the average wage in the pre-choice window) on the observable characteristics of family member f, $\tilde{X}_f$. $\tilde{X}_f$ include the pre-determined observables that shared with the student, X_f, f's AFQT score, and year fixed-effect dummies DY_{time} — capturing the population average wage of all workers at the time when student s declares her major.[25] The wage shock S_f^k therefore is the residual of the following regression, which measures the additional wage a student's family member earns than the average wage of all workers working in occupation k.

$$\begin{aligned} w_f^k &= \tilde{X}_f'\tilde{\Pi}_k + S_f^k \qquad (1.15)\\ \tilde{X}_f'\tilde{\Pi}_k &= X_f\hat{\Pi}_k + b_1 AFQT_f + b_2 DY_{time} \end{aligned}$$

where X_f include a family member's gender, race, birth cohort, region, and years of education.

Structural Parameter Estimation

The parameters of interest include the weight on predictable wage, θ; the weight on match quality based on family-based information, $\theta \cdot \lambda$; and flow-utility function parameters c_0^j and c_1. Table 1.5 lists the estimation for these parameters.

[24] I use the starting wage as a proxy of life earnings. Flyer 1997 finds that the correlation coefficient between projected occupational starting wage and projected occupational life-cycle earnings (with mobility) is over 0.5 in all six occupations. In five of the six occupations the simple correlation coefficient is greater than 0.65.

[25] w_f^k equals 4-year-average log hourly wage before the student declares her major, defined in Section 2.1.

$\hat{\theta} \cdot \hat{\lambda}$ is 0.62, which is positive and significant, confirming that students update beliefs about their future earnings based on family wage shocks. Adding learning from a sibling's wage shock passes the likelihood ratio test, therefore adding information on contemporaneous wage realizations of siblings leads to an improvement in model fit relative to a benchmark major choice model that assumes students' expectations are based on average wages in the occupation.[26]

$\hat{\theta}$ is 1.10, positive and significant. Predictable wage is an important factor in determining student's major choice. The value of $\hat{\theta}$ is close to the comparable parameter in a previous study by Arcidiacono, Hotz, and Kang 2012. They estimate the same value function, but they use the directly elicited students' expectations of future wages by a survey. Their $\hat{\theta}$ ranges from 1.46 to 1.69, which result provides a cross-validation for my estimates. The estimates of other parameters in flow utility functions are all in the sign as predicted. Appendix Table A4 lists the population taste estimates $\hat{c_0}^j$.

Dividing $\hat{\theta} \cdot \hat{\lambda}$ by $\hat{\theta}$ gives the estimator $\hat{\lambda}$, and its standard error can be calculated by the Delta method. My point estimate of λ is 0.57, which means students perceive the correlation between η_s^k and η_f^k at least at the level of 0.57. Yet, the standard error of $\hat{\lambda}$ is quite big, it is hard to generate a precise range for λ, but it is different from 0 at 10% significance level.

1.4 Evidence on Learning about Match-Quality

To further prove students are learning about match quality when they observe the wage outcomes of their family members, I take the approach by separating students into subgroups and compare the estimates of $\hat{\theta}$ and $\hat{\theta} \cdot \hat{\lambda}$ across the subgroups. If the shocks appear to be more informative signals to one subgroup, students in that group should put more weight on family wage shocks when they are deciding which major to choose. Specifically, I compare the responses of students with different backgrounds in gender, age, AFQT score, high school quality, family member's occupation, and family's education level.

The estimates show that students consider the correlation of match quality more across the siblings of the same gender and siblings who have attended college; they weigh siblings wage shocks more heavily in forming wage expectations if their siblings work in occupations with larger cross-sectional wage variance (business, arts, and health professions); they put more weight on the wage shocks when there is a larger age difference between them and their siblings; and students from higher socio-economic status families (those whose parents have college or higher education or those students attending better high schools) use more information from their older siblings' wage outcomes to form their own wage expectations.

Table 1.6 shows the detailed analysis by subgroups. Row 1 separates the sample by gender. The value of $\hat{\theta} \cdot \hat{\lambda}$ shows that male students strongly respond to family wage shocks. However, female students put negative weight on predicted wages, $\hat{\theta} < 0$. This may be because female workers care more about nonpecuniary characteristics of an occupation, a result consistent with the findings of Fortin 2008.

[26]For example, see Siow 1984, Berger 1988, Keane and Wolpin 1997, and Ryoo and Rosen 2004.

Row 2 of Table 6 separates students by their older sibling's gender. Students who have older brothers weigh family wage shocks more heavily than students with older sisters. This could be because that students perceive the wage shocks from older brothers as better predictors of match quality or because it is easier for students to observe their older brothers' wage shocks. Separating these two hypotheses requires detailed measurement of the information exchanged between siblings, such as records of older sibling's consumption behavior.

Row 3 partitions the sample by the gender-match indicator. The value of $\hat{\theta}$ is approximately the same across the two groups, suggesting that students have similar knowledge about predicted wages of their siblings' occupations. However, the difference in the value of $\hat{\theta} \cdot \hat{\lambda}$ between the two groups is huge and statistically significant. The point estimate of $\hat{\lambda}$ for gender-match group is 1.04, while the estimate for the gender-not-match groups is only 0.06. This difference indicates that students put much more weight on the wage shocks experienced by the siblings of the same gender. An intuitive explanation would be that the wage shocks experienced by a sibling of the same gender contain more information about the match quality between the student and the occupation in which her older sibling works.

Row 4 shows that students respond more to wage shocks if their siblings work in occupations with higher cross-sectional wage variance (business, arts, and health professions). The value of $\hat{\theta}$ is higher for siblings who work in occupations with lower wage variance (such as education and engineering), possibly because the predictable wage component determines the majority of a student's wage expectation for those occupations. In occupations with higher wage variance, the unknown match quality component could be relatively more important in determining future wages, thus students respond more to family wage signals when considering those occupations.

Row 5 compares cases where the older sibling went to college and cases where she did not. The result suggests that students mostly respond to wage shocks only if their siblings have attended college. The point estimate of $\hat{\lambda}$ for siblings with college education group is 0.73, while the estimate for the siblings with high school only groups is only -0.08. This difference indicates that the information in wages for "college grad" siblings is more useful to students.

Row 6 demonstrates that students with larger age differences with their siblings weigh siblings' wage shocks more. Both the values of $\hat{\theta}$ and $\hat{\theta} \cdot \hat{\lambda}$ are higher for students who have at least a two-year age difference between them and their siblings. This pattern indicates that students have better knowledge of the predictable wage and learn more about match quality when there is a bigger age difference. One explanation could be that the wage outcomes of older siblings are more informative about future earnings to students than are the wage outcomes of the siblings at a similar age.

Rows 7 and 8 show behavior is similar among students with different siblings and different AFQT scores. Students with more older siblings use slightly more of the predictable wage in forming wage expectations (the value of $\hat{\theta}$ is higher in Row 7 for the first subgroup). Row 8 demonstrates that students with low or high AFQT scores respond similarly to both predictable wages and the match quality component.

Rows 9 and 10 reveal that students from higher socio-economic status families use more information from their older siblings' wage outcomes to form their own wage expectations. Students with highly educated parents (Row 9) and those who attend better high schools (Row 10) respond more to siblings' wage shocks. One reason for students from those families to weigh match-quality signals more heavily could be that the match-quality component is a more important determinant of wages for these students, as they are more likely to work in professional occupations.

1.5 Over-learning from Family Experience

Can the estimations in Section 3 and 4 tell whether students are using family-based wage information optimally?

This section takes two different approaches to answer this question. I first compare my estimate of perceived correlation by students, $\hat{\lambda}$, with the actual correlation between siblings' wages reflected in the data. The comparison shows that the lower bound of the decision weight students placed on family wage shocks is much larger than the empirical correlation between their own earnings and their siblings' earnings. Another approach is to compare the labor market performance w_s^k between students who received positive match-quality signals to those who received negative signals. I find that students who received positive match-quality signals perform worse later in the labor market than those who received negative match-quality signals, a result inconsistent with Bayesian learning about match quality.

Perceived v.s. Empirical Correlation of Match Quality

Recall the wage determination process defined in Section 1.3.1, a student and her family member's potential wage realization in occupation k can be written as:

$$w_s^k = A_s^k + \eta_s^k$$
$$w_f^k = A_f^k + \eta_f^k$$

Recall Equation (7), $\lambda = corr(\eta_s^k, \eta_f^k) \leq corr(w_s^k, w_f^k)$. I run the following two regressions conditional on the match between students' majors and their siblings' occupations:

$$w_s^k = \overline{\lambda} w_f^k + q_0 X_s + \varepsilon_s^1 \tag{1.16}$$
$$w_s^k = \underline{\lambda} S_f^k + q_1 \hat{A}_f^k + q_0 X_s + \varepsilon_s^2 \tag{1.17}$$

where $\hat{A}_f^k = \tilde{X}'_f \tilde{\Pi}_k$, ε_s^1 and ε_s^2 are noise terms.

The ideal dependent variable for above regressions is the potential wage w_s^k for every student. However, as the econometrician can only observe the realized wage of students who actually declared major k, I need to correct the selection for above regressions. The instrument variables for a student's realized wage is the indicator variable recording whether a student's pre-determined ideal occupation match with her sibling's ideal occupation.

Table 1.7 presents the results for above regressions both with and without selection correction. Columns 1 and 2 estimate the correlation coefficient without selection correction. The correlation coefficient estimates, $\overline{\lambda}$ and $\underline{\lambda}$, are both negative. Columns 3 and 4 demonstrate the same regression adding selection correction. The point estimates are very similar but the standard error becomes very large. According to my model, if students interpret the information contained in the match-quality signals correctly, the correlation between older and younger siblings' realized earnings should be larger conditional on major match than the not conditional on major match (Table A6).

Table A.6 in appendix reveals the unconditional correlation between students realized wage and their siblings' wages is larger. Columns 1 shows that the correlation coefficient between a student's starting wage with her older sibling's wage is around 0.09. Column 2 shows the direct correlation between w_s^k and the match-quality signal proxy S_f^k is around 0.08. Columns 3 and 4 focus on the subgroups of students whose siblings are of the same gender. The point estimate of $\overline{\lambda}$ is 0.17, and $\underline{\lambda}$ is around 0.13.

Recall my point estimates of λ for the whole sample in Section 3.7 is 0.57. In any case, students' perceived correlation is larger than the correlation coefficient for w_f^k or S_f^k in Table 7 or Table A6, implying that students overestimate the predictive power of family members earnings — they are learning about match quality in a non-Bayesian way. Additionally, the students whose siblings are of the same gender may overreact to family wage information even more. The point estimate of λ for gender-match sample in Row 3 of Table 5 is 1.04, suggesting that students believe the wage shocks experienced by siblings of same gender are 100% transferrable to their own potential earnings.

My estimate for $\hat{\lambda}$ has large standard error. In order to further test whether students actually place too much weight on family wage shocks, I take an alternative approach by comparing the labor market performance between students who received positive match-quality signals to those who received negative signals.

Students' Labor Market Outcomes

The learning model predicts that students sort into or out of a major in response to family wage shocks. Because a positive wage shock tells students about the match quality, students with a slightly lower predictable wage choose the major associated with family's occupation. Yet, positive signals should be good news on average, so when students interpret the match quality signals correctly, students who received positive match-quality signals should have higher *overall* realized wage compared to those who received negative match-quality signals.

To investigate whether this intuition is true based on my model, suppose a student is considering whether to choose major k when her family member works in occupation k. Recall Equation (1) and (3), a student's decision is based on the expected value of her wages in occupation k, W_s^k and the best alternative option she has $\bar{O}_s$.[27] A student's expected

[27] Excluding the difference in flow utility function in the decision function can be interpreted as students choosing majors by using the expected wages after controlling for the compensating differentials.

wage becomes,

$$W_s^k = A_s^k + \hat{\eta}_s^k$$

where $\hat{\eta}_s^k = \lambda \eta_f^k$. Student s chooses major k if and only if $W_s^k > \bar{O}_s$.

The student's potential realized earnings in occupation k, w_s^k, is give by[28]

$$w_s^k = A_s^k + \eta_s^k$$

If student s is Bayesian, she uses her information optimally, $\lambda = \rho$. Thus $\hat{\eta}_s^k = \eta_s^k$, and $w_s^k = W_s^k$.

The following discussion focuses on occupation k specifically. To simplify the notation, drop the and subscript and superscript of η_s^k and A_s^k. The goal of the discussion is to prove: given the distributions of predictable wage component A, the distribution of family wage shocks η_f, the estimation of λ in Section 1.3.8, and students are responding to family wage shocks as Bayesians, the average realized wage of all students whose family members received positive wage shocks is larger than the average realized wage of students whose family members only experienced negative wage shocks.

Among students whose family members are working in occupation k, divide them to two groups **1** and **2**. The family member of each student in group **1** has experienced a positive wage shock $\eta_f > 0$, and this wage shock is directly translated as the match-quality signal to a student, $M_1 = \lambda \eta_f > 0$; while students in group **2** receive negative match-quality signal from their family members $M_2 = \lambda \eta_f < 0$. M_1 is drawn from the positive half of the normal distribution $N(0, \sigma_k^2)$, M_2 is drawn from the negative half of that distribution, and $\lambda = 0.57$.

The selection rule for each student to chooses major k in group **1** is $w_1^k > \bar{O}_1$. Similarly, group **2** students choose major k if and only if $w_2^k > \bar{O}_2$. According to Equation (1), $\bar{O}_1$ and $\bar{O}_2$ are the extreme values of students' expected wages for all majors except major k, which still follows Type I Extreme Value distribution because of the I.I.A. feature of the multinomial logit model.

The wage determination process in Section 1.3.1 indicates that a student's predictable wage component A is independent from the match quality component M as well. Hence the distribution of A is the same across the two groups. Assume A across students in each group is from a normal distribution $N(\mu, \sigma_\alpha^2)$. According to Assumption 1, any student's best alternative option is independent from the student's family wage shocks, thus the distribution of $\bar{O}_1$ and $\bar{O}_2$ is the same across the two groups and its c.d.f. is denoted as $H(o)$.

The average realized wage in group **1** is $\bar{w}_1$

$$\begin{aligned}
\bar{w}_1 =& \frac{\iiint (A+M)\mathbf{1}(A+M>o)\mathbf{1}(M>0)f(M)h(o)g(A)dodAdM}{\iiint \mathbf{1}(A+M>o)\mathbf{1}(M>0)f(M)h(o)g(A)dodAdM} \\
=& \frac{\iint (A+M)H(A+M)\mathbf{1}(M>0)f(M)g(A)dAdM}{\iint H(A+M)\mathbf{1}(M>0)f(M)g(A)dAdM}
\end{aligned}$$

[28] w_s^k is not observable for students who do not choose major k.

The average realized wage in group **2** is $\bar{w}_2$

$$\begin{aligned}\bar{w}_2 =& \frac{\iiint (A+M)\mathbf{1}(A+M>o)\mathbf{1}(M<0)f(M)h(o)g(A)dodAdM}{\iiint \mathbf{1}(A+M>o)\mathbf{1}(M<0)f(M)h(o)g(A)dodAdM}\\ =& \frac{\iint (A+M)H(A+M)\mathbf{1}(M<0)f(M)g(A)dAdM}{\iint H(A+M)\mathbf{1}(M<0)f(M)g(A)dAdM}\end{aligned}$$

Appendix Section A.5 shows that $\bar{w}_1 > \bar{w}_2$ for students in my sample.

In summary, when students are Baysians, the students whose family members receive positive wage shocks should do better than others who receive negative family wage shocks. However, my regressions on a student's labor market outcome and her family wage shocks show that students who received positive match-quality signals are actually doing *worse* than those who did receive negative match-quality signals, consistent with the hypothesis that students overreact to family wage shocks.

In the following specification, I use LM_s as a representation of the labor market outcome for student s, $Y_s = 1$ as an indicator for that a student works in the same occupation as her close family member, and ν_s as a random noise term. The labor market outcome measurements include: a student's starting wages after college graduation, whether a student changes major during college years, and whether a student becomes unemployed or remains in a low-skilled occupation within five years after graduation.

r_4 measures the effect on LM_s when a student who chooses a major matched with her family member's occupation and her family member received a negative shock in wage ($S_f^k < 0$). $r_5 = (\bar{w}_1 - \bar{w}_2)$, which is the differential effect between a student who chooses a matched major after her family member experienced an increase in wages ($S_f^k > 0$) and other students who choose a matched major when their family members experienced negative wage shocks ($S_f^k < 0$).

$$LM_s = r_0 + r_1 X_s + r_2 S_f^k + r_3 \mathbf{1}(S_f^k > 0) + r_4 Y_s + r_5 Y_s \cdot \mathbf{1}(S_f^k > 0) + \nu_s \tag{1.18}$$

Table 1.8 presents the regression results from the above specification in the NLSY79. Compared to students who choose a major that is not related to an older sibling's occupation, a student who chooses a major matched with her sibling's occupation while the sibling only experiences negative wage shocks earns a higher wage, is less likely to change college major and more likely to find a professional job. However, when a student chooses a matched major when her older sibling received a positive wage shock, compare to others whose siblings experience a negative wage shock, this student is 21% more likely to switch majors in college, 10% less likely to find a professional job in her field, and earns a 27% lower hourly wage.

Table 1.9 shows the similar results for students in S2 of the NELS88. Columns 1 and 2 demonstrate that a student earns a 6-10% lower wage when she chooses a matched major after her parent received a positive income shock, relative to others whose parents only received a negative income shock, though this wage difference is not significantly different from 0 for S2-Teacher sample.

All these results indicate that worse-matched students sort into a major associated with family's occupation after observing positive wage shocks of their family members. If the wage shocks are informative and students place the appropriate weight on the wage shocks when they update their beliefs, there will not be such a huge difference in overall labor market performances between students whose siblings received positive wage shocks and other students whose siblings received negative wage shocks. All the results in this section point in direction that students overreact to wage shocks experienced by their family members.

1.6 Conclusion

This paper examines how students form expectations about future earnings based on the wage changes of their family members. Students interpret the family wage shocks as extra information about their own match-quality for a certain occupation. However, they are likely to overestimate the predictive power of family members earnings. The decision weight students place on family wage shocks is much larger than the empirical correlation between their own earnings and their family members' earnings, and there is strong evidence that students who receive positive match-quality signals perform worse later in the labor market than those who receive negative match-quality signals.

Previous studies have found large wage premiums for business, engineering and science majors, suggesting many students could earn higher wages if they choose alternative majors.[29] And yet, enrollment for many high-wage college majors stays low while the enrollment for low-wage majors remains high.[30] For this reason, the President's Council of Advisors on Science and Technology thus calls for a big increase in college graduates in science, technology, engineering and mathematics (STEM majors).

How can we inform students that there is an increasing market demand for STEM majors relative to some currently popular majors, such as business, social sciences, history or education? Previous survey studies have shown students have very limited information about occupation wage differentials.[31] However, estimations in this paper reveal that young people strongly respond to perceived earnings opportunities. If their choices are restricted by their limited information about labor market conditions, they could not respond to the increasing market demand even though they prefer higher earnings. The fact that students have limited information may also be the reason that they overly rely on the wage information coming from close family members. Considering the availability of precise wage information from school career centers or public agencies like the Bureau of Labor Statistics, students can

[29] Hamermesh and Donald 2008 estimate that there is a 40% gap in annual earnings between college graduates who majored in business and those who majored in humanities after controlling for hours of work, academic performance, and other background characteristics. Similar findings are shown in Arcidiacono 2004 and Altonji, Blom, and Meghir 2012.

[30] The potential supply of students in STEM majors are usually not restricted by program size, though the early-decision deadline and college preparatory requirements may limit the size of the applicant pool.

[31] Betts 1996 first documents that college students have limited knowledge of salaries by fields of major. Arcidiacono, Hotz, and Kang 2012 and Wiswall and Zafar 2012 find similar results.

potentially improve their predictions of future earnings by utilizing these sources of outside information.

The heterogeneity in learning by family backgrounds found in this paper also has direct policy implications for promoting intergenerational mobility. If family socio-economic status strongly influences students' expectations on future earnings, students from disadvantaged families may never have the opportunity to know the actual return to higher education or the wages in certain professions, their career planning is constrained by the insufficient information. For example, a recent study by Hoxby and Avery (2012) finds that students with high-achievement but from low-income families misunderstand the actual cost of prestigious private universities. The empirical results in this paper suggest that providing information on career prospects to students from disadvantaged families may help them expand their choice sets of education and occupation options.

Table 1.1: Summary Statistics

Panel A: NLSY79	College Sample	Student-Sibling (S1)	
		Student	Siblings
Male	45.9%	48.3%	48.8%
Female	54.1%	51.7%	51.2%
Non-Hispanic White	62.8%	62.9%	62.8%
African American	23.5%	21.2%	21.2%
Hispanic	13.7%	15.9%	16.0%
AFQT Score	58.0	60.9	55.0
Average Hourly Wage during Age 30-35 (2010 $)	22.2	23.5	21.5
Average Annual Labor Income during Age 30-35 (2010 $)	43k	48k	42k
Total Weeks Unemployed during Age 30-35	12.5	13.3	10.1
Years of Completed Education	15.0	15.6	13.9
N	5585	1004	1004
Student's Major = Sibling's Occupation		16.2%	
Panel B: NELS88	Whole Sample	Student-Parent (S2)	
		Manager	Teacher
Male	45.5%	45.9%	49.5%
Female	54.5%	54.1%	50.5%
Non-Hispanic White	70.7%	76.0%	80.1%
African American	9.6%	6.0%	7.9%
Hispanic	8.3%	7.5%	6.1%
Other Race	11.4%	10.5%	5.8%
1999 Annual Labor Income (1999 $)	23k	27k	26k
N	7335	1094	705
Student's Major = Parent's Occupation		16.5%	13.5%

Table 1.2: The Impact of a Sibling's Wages on a Student's Major Choice

Dependent Variable: **Student's Major = Sibling's Occupation**	(1)	(2)	(3)	(4)
Sibling's Wage Pre-Choice - Permanent	0.123***	0.110***		
	[0.0364]	[0.0365]		
Occupation Average Wage Pre-Choice - Permanent		−0.373***		
		[0.125]		
Sibling's Wage Post-Choice - Permanent			0.0424	0.0359
			[0.0406]	[0.0398]
Occupation Average Wage Post-Choice - Permanent				−0.191
				[0.180]
Sibling's Permanent Wage	0.0872**	0.0644*	0.0419	0.0191
	[0.0347]	[0.0358]	[0.0299]	[0.0311]
Occupation Permanent Wage		0.150**		0.232***
		[0.0659]		[0.0608]
Ideal Occupation = Sibling's Occupation	0.437***	0.445***	0.418***	0.420***
	[0.0549]	[0.0537]	[0.0544]	[0.0536]
Same Gender with Sibling	0.0638***	0.060**	0.0645***	0.0668***
	[0.0243]	[0.0241]	[0.0231]	[0.02311]
Education & Demographics	X	X	X	X
Observations	853	852	908	908
R-squared	0.167	0.181	0.153	0.164
Point Elasticity	0.765	0.735	0.265	0.224

Note:
1. Clustered standard errors by household in brackets, *** p<0.01, ** p<0.05, * p<0.1
2. Siblings' wages are measured in logged hourly wage in 2010 Dollars
3. Pre-choice window: 0-3 years before the major choice; Post-choice window: 1-4 years after the choice.
4. Control variables include gender, race, region, birth year dummies, own and sibling's education, own and sibling's AFQT score, highest education of parents, and the age when declaring the major.

Table 1.3: The Impact of a Parent's Wage on Major Choice

Dependent Variable:	S2-Manager	S2-Teacher
Student's Major = Parent's Occupation	(1)	(2)
Increase in Family Income in Pre-Choice Window	0.0196**	0.0283***
	[0.0097]	[0.0101]
Ideal Occupation = Parent's Occupation	0.243***	0.237***
	[0.0613]	[0.0683]
Average Math Test Score	0.114	−0.150*
	[0.0702]	[0.0826]
Average Reading Test Score	-0.119	0.0815
	[0.0735]	[0.0805]
Base Year Family Income	X	X
Education & Demographics	X	X
Observations	1,093	705
R-squared	0.057	0.107

Note:
1. Clustered standard errors by household in brackets, *** p<0.01, ** p<0.05, * p<0.1
2. Income in 1999 dollars. Base Year Family Income is a category variable.
3. Control variables include gender, race, region, birth year dummies, and parental education.

Table 1.4: The Impact of a Sibling's Wage on a Student's Ideal Job

Dependent Variable:	Hourly Rate Wage		Annual Income	
Student's Ideal Occupation = Sibling's Occupation	(1)	(2)	(3)	(4)
Sibling's Wage during Survey Years	0.0212*	0.0236*	0.0114**	0.0094*
	[0.0125]	[0.0129]	[0.0051]	[0.0056]
Sibling's Permanent Wage	-0.0073	−0.0109*	-0.0075	-0.0095
	[0.0058]	[0.0058]	[0.0066]	[0.0065]
Sibling's Occupation = Parental Occupation		0.146**		0.154**
		[0.0587]		[0.0617]
Sibling in Same Gender	0.023***	0.024***	0.023***	0.024***
	[0.0073]	[0.0074]	[0.0073]	[0.0074]
Education & Demographics	X	X	X	X
Observations	1,192	1,051	1,194	1,054
R-squared	0.020	0.059	0.021	0.061
Point Elasticity	1.33	1.48	0.717	0.591

Note:
1. Clustered standard errors by household in brackets, *** p<0.01, ** p<0.05, * p<0.1
2. All wages are measured in logged term and normalized by 2010 Dollars
3. Control variables include gender, race, region, birth year dummies, sibling's education, and AFQT score.

Table 1.5: Structural Parameter

Major Choice	(1)	(2)	(3)	(4)
Log-likelihood (N=1004)	-2413.45	-2410.83	-2407.99	-2405.71
$\hat{\theta}$ - Predictable Wage	1.087**	1.095**	1.103**	1.111**
	[0.439]	[0.439]	[0.439]	[0.439]
$\hat{\theta}\hat{\lambda}$ - Match Quality		0.624**		0.543**
		[0.271]		[0.254]
$\hat{c_1}$ - Personal Taste T_s	0.285***	0.287***	0.285***	0.287***
	[0.027]	[0.027]	[0.027]	[0.027]
$\hat{c_1'}$ - Family-correlated Taste T_s'			0.328***	0.319***
			[0.097]	[0.097]
$\hat{c_0}^j$ - Population Taste	X	X	X	X
# Parameter	23	24	24	25
Perceived Correlation of Match Quality	$\hat{\lambda} = 0.569^*$ [0.335]		$\hat{\lambda} = 0.488$ [0.409]	

Table 1.6: Heterogenous Learning

	$\hat{\theta}$	$\hat{\theta}\cdot\hat{\lambda}$	$\hat{\lambda}$	$\hat{\theta}$	$\hat{\theta}\cdot\hat{\lambda}$	$\hat{\lambda}$
(1) Gender	Male (N=420)			Female (N=449)		
	2.381***	0.945**	0.397**	−0.839*	0.338	-0.403
	[0.481]	[0.399]	[0.185]	[0.509]	[0.378]	[0.514]
(2) Sibling's Gender	Older Brother (N=423)			Older Sister (N=446)		
	1.228**	0.871**	0.709*	0.962**	0.301	0.313
	[0.493]	[0.362]	[0.410]	[0.490]	[0.408]	[0.452]
(3) Sibling-Student Gender	Match (N=468)			Not Match (N=401)		
	1.081**	1.130***	1.045*	1.103**	0.065	0.059
	[0.484]	[0.373]	[0.581]	[0.500]	[0.395]	[0.359]
(4) Sibling's Occupation	High Var(Wage)(N=454)			Low Var(Wage) (N=415)		
	0.902*	0.744**	0.825	1.284***	0.216	0.168
	[0.490]	[0.311]	[0.563]	[0.493]	[0.570]	[0.448]
(5) Sibling's Education	College or Above (N=613)			High School Only (N=256)		
	1.181**	0.861***	0.729*	0.962*	-0.076	-0.078
	[0.475]	[0.312]	[0.393]	[0.524]	[0.533]	[0.555]
(6) Age Difference	$>$ 2 years (N=346)			$\leq$ 2 years (N=523)		
	1.581***	1.136***	0.718**	0.917**	0.206	0.225
	[0.558]	[0.395]	[0.355]	[0.457]	[0.360]	[0.407]
(7) Number of Older Siblings	$>$ 2(N=306)			$\leq$ 2 (N=563)		
	1.057**	0.523	0.495	1.120**	0.673**	0.601
	[0.528]	[0.477]	[0.518]	[0.471]	[0.331]	[0.386]
(8) AFQT	Top Half (N=451)			Bottom Half (N=418)		
	1.531***	0.762*	0.498	0.840*	0.538	0.641
	[0.525]	[0.422]	[0.323]	[0.469]	[0.355]	[0.553]
(9) Parent Education	College or Above (N=417)			High School Only (N=452)		
	1.162**	1.054***	0.907*	1.045**	0.193	0.184
	[0.521]	[0.384]	[0.524]	[0.470]	[0.386]	[0.377]
(10) High School Quality	Top Half HS (N=354)			Bottom Half HS (N=275)		
	1.261***	0.787**	0.624*	0.886*	0.239	0.270
	[0.483]	[0.323]	[0.349]	[0.507]	[0.495]	[0.579]

Table 1.7: Correlation between a Sibling's Wages and a Student's Wages

Dependent Variable:	Not Selection Corrected		Selection Corrected	
Student's Starting Wage	(1)	(2)	(3)	(4)
Sibling's Total Wage w_f	-0.106		-0.172	
	[0.103]		[0.488]	
Sibling's Wage Shock S_f		-0.226^{*}		-0.252
		[0.119]		[0.547]
Education & Demographics	X	X	X	X
Observations	151	145	148	144
R-squared	0.146	0.158	0.147	0.162

Note:
1. Clustered standard errors by household in brackets, *** p<0.01, ** p<0.05, * p<0.1.
2. All wages are measured in logged hourly rate 2010 Dollars
3. Control variables include gender, race, region, and birth year dummies.

Table 1.8: Students' Labor Market Outcomes and Siblings' Wage Shocks

Dependent Variable:	**Changing Major**	**Low-Skill Job**	**Unemployment**	**Starting Wage**
	(1)	(2)	(3)	(4)
Major Match & $S_f^k > 0$ ($\bar{w}^1 - \bar{w}^2$)	0.211^{**}	0.104^{*}	0.0729	-0.276^{***}
	[0.0872]	[0.0621]	[0.0669]	[0.102]
Student's Major = Sibling's Occupation	-0.136^{**}	-0.0703^{*}	-0.0111	0.246^{***}
	[0.0579]	[0.0419]	[0.0466]	[0.0808]
Match Quality Signal $S_f^k > 0$	-0.0357	0.0104	-0.0226	0.0868^{*}
	[0.0522]	[0.0386]	[0.0388]	[0.0447]
Pre-college Ideal Major = Initial Major	-0.0705^{*}	-0.0118	0.0442	0.001
	[0.0373]	[0.0297]	[0.0301]	[0.0348]
Education & Demographics	X	X	X	X
Occupation Fixed Effect	-	-	X	X
Observations	694	694	694	689
R-squared	0.117	0.055	0.073	0.181

Note:

1. Clustered standard errors by household in brackets, *** p<0.01, ** p<0.05, * p<0.1
2. Wages are measured in logged hourly rate and normalized by 2010 Dollars
3. Control variables include gender, race, region, birth year dummies, years of education and AFQT score.

Table 1.9: Students' Starting Wages and Family Income Changes

Dependent Variable: **Student's Annual Income in 1999**	S2-Manager (1)	S2-Teacher (2)
Major Match & Positive Family Income Change ($\bar{w}^1 - \bar{w}^2$)	-0.103^{**}	-0.0639
	[0.0478]	[0.0988]
Student's Major = Parents's Occupation	0.269^{***}	-0.112
	[0.0536]	[0.0801]
Positive Family Income Change	0.0195	0.0235
	[0.0217]	[0.0283]
Average Math Score	0.352^{**}	0.403^{**}
	[0.140]	[0.193]
Average Reading Score	-0.347^{**}	-0.294^{*}
	[0.139]	[0.173]
Female	-0.102^{**}	-0.150^{***}
	[0.0471]	[0.0541]
Base Year Family Income	X	X
Occupation FE	X	X
Education & Demographics	X	X
Observations	1,002	643
R-squared	0.085	0.109

Note:
1. Robust standard errors, *** p<0.01, ** p<0.05, * p<0.1
2. Income in 1999 dollars. Base Year Family Income is a category variable.
3. Control variables include gender, race, region, birth year dummies, years of education.

Chapter 2

The Impact of Time Preference on Job Search with Unemployment Insurance

2.1 Introduction

The design of Unemployment Insurance (UI) policy is an important research area in public finance and labor economics. Policy evaluation literature on UI programs finds significant effect on job search intensity but modest effect in workers' subsequent job match quality. For example, Classen 1977 uses data of UI recipients from Pennsylvania and Arizona in the late 1960s and finds that an increase in benefits leads to an increase in the duration of unemployment, but the increase in benefits does not lead to the generation and acceptance of more lucrative job offers. Studies of UI policy outside of US also find similar results. For example, Card and Hyslop 2005 find that a wage subsidy program in Canada has a substantial short-term impact on the reduction in welfare participation but only a small and insignificant influence on worker's re-employment wage.[1]

As the changes in UI policy alter the utility of staying unemployed, search theory predicts that workers re-optimize their searching effort and reservation wages according to the new policy. The structural job search models starts with McCall's model (1970). It derives an optimal job-searching strategy by setting a cut-off reservation wage under a partial-

[1]Other studies include Card *et al.* (2007) exploit the discontinuities in eligibility for severance pay and extended UI benefits at the 36th working month in Austria. Their study finds higher lump-sum severance payment and extension of the potential duration of UI benefits would reduce the job-finding rate, but have no effect on subsequent job match quality. Schmieder *et al.* (2010) apply similar method to examine the administrative data of extended UI benefits in Germany, and he finds extension of UI has modest effects on non-employment durations but not job matching quality. One exception is that Centeno and Novo (2006) finds match quality measured by job tenure costively correlated with and the level of UI generosity using NLSY data. Compared to other panel-data studies, this paper relies cross-sectional survey data, which result might suffer the bias from institutional difference of labor market cross states and over time.

equilibrium framework. Many papers (Kiefer and Neumann, 1979; Chesher and Lancaster, 1983; van den Berg, 1990) have extended the basic McCall model by augmenting it with features such as the dynamic sequential search model and variable search intensity. Another line of search theory derive optimal searching strategy under a general equilibrium framework that links employers and workers together. For the purpose of UI policy evaluation, the search model focusing on labor supply is more tractable, thus this chapter follows the convention of using partial equilibrium search framework.

This chapter investigates the impact of UI policy on workers' unemployment duration and subsequent job quality. In particular, to explain the widely-documented fact that changing benefit amount or eligibility duration has close-to-zero effect on worker's re-employment wage, I extend the sequential search model with workers choosing optimal search intensity and cut-off reservation wage by adding hyperbolic discounting time preferences. Job searching choices involve making the effort today and receiving the benefit in the future. If an unemployed worker has hyperbolic discounting preference, he invests little effort today, thinks of searching hard tomorrow, thus has a similar reservation wage but much lower searching effort at each period compared to an exponential discounting worker. The time inconsistency in searching effort drives the difference in relative effect of UI policy on employment duration and the re-employment wage between the exponential discounting search model and the hyperbolic discounting model.

In this chapter, I focus on one type of cash incentive in UI policy intervention. The UI program aims to provide short-term income support to involuntarily unemployed individuals while they seek work. To promote rapid reemployment, the program currently uses work-search requirements and employment-service referrals. However, policy interest has recently been expressed in providing additional job-search assistance and other employment oriented services to UI claimants, including additional monetary incentives for claimants to seek work on their own. These monetary incentives could be provided in the form of a reemployment bonus — a lump-sum benefit paid to those who become reemployed or self-employed quickly. A reemployment bonus would compensate for the reemployment disincentives inherent in the regular UI system, which pays benefits to claimants for the weeks in which they remain unemployed.

The reemployment bonus treatment serves a potential identification for hyperbolic discounting from exponential discounting in time preference because the two assumptions generate different predictions about workers' job-search outcomes. For workers who procrastinate in job search, reemployment bonus accelerates their job acceptance and possibly improves their subsequent job-match quality. Exponential discounting workers substitute future wages for a current reemployment bonus, and thus workers received a reemployment bonus can end up with a less well-matched job. Using data from Illinois Unemployment Insurance Experiments, I compare the explanatory power of a model of job search with hyperbolic discounting to a model with exponential discounting preference. I find that a model with hyperbolic discounting preference fits the treatment effect better.

In the Illinois Unemployment Insurance Experiments, eligible claimants were randomly assigned to the claimant experiment or control groups. Reemployment bonuses were available to the claimant if specified employment conditions were met. I find that the average UI benefit receipt was lower in the treatment group than in the control group, but there is no evidence of post unemployment match-quality deterioration. This result indicates that a job-search incentive program does not decrease the intensity of job search, consistent with the prediction of hyperbolic discounting search model. In the structural estimation, in order for exponential discounting model to fit the data, workers have wage offer distributions with very low variation, thus a worker's reservation wage does not vary much after the change of unemployment insurance policy. The estimates based on a hyperbolic discounting model suggest workers are less patient about the future and their wage offer distribution have larger variation, which is more consistent with the empirical wage variation found in the data.

This chapter proposes a new theory on how time preferences determine the effect of UI policies. Previous studies focusing on the time-discounting effect on job search include DellaVigna and Paserman (2005) and Paserman (2008). They predict short-term impatience in hyperbolic discounting model negatively correlates with search effort and the unemployment exit rate and is orthogonal to reservation wages. I extend their framework to directly analyze the effect of UI policy intervention under two distinctive assumptions of timing preferences. Spinnewijn (2010) uses a survey conducted in Michigan and Maryland from 1996 to 1998 to show that unemployed workers overestimate how quickly they will find work, but underestimate the return to their search efforts. This evidence on beliefs of unemployed workers further supports the assumption of hyperbolic discounting in workers' job search behavior.

The rest of the paper is laid out as follows. Section 2.2 presents a job search model with a variation of exponential and hyperbolic discounting time preference. Section 2.3 describes the estimation strategy and simulation of the policy impact based on structural estimation. The results show that hyperbolic discounting model fits empirical job match-quality change better than traditional exponential discounting model. Section 2.4 concludes.

2.2 Theoretical Framework

This section starts with a sequential job search model with a limited duration UI benefit as a benchmark. In this model, a worker's reservation wage declines and search intensity increases as the UI benefit expiration approaches. I later extend this model by introducing hyperbolic discounting when workers evaluate future outcomes. An unemployed worker with hyperbolic discounting preference procrastinates in job search today but believing he would search hard tomorrow. Compared to other workers with exponential discounting preference, his reservation wage is as high as others' but he exerts less searching effort during each period. If the reservation wage profile is a downward sloping curve, a hyperbolic discounting worker is more likely to exit unemployment spell later, which put him at the low-end of the reservation wage curve. Therefore, the worker experiences smaller effect on reemployment wage after the change of UI policy.

Job Search with Unemployment Insurance Benefit

In the model, unemployed workers aim to choose optimal searching intensity and reservation wage at each period. I assume workers' time preference, marginal searching cost and workers' potential wage offers are predetermined that do not depend on the design of UI policy. The general design of UI policy is that workers have limited time eligibility to receive UI benefit, and the benefit amount is correlated with their pre-unemployment wage but capped by a threshold. In the US, the standard maximum eligibility duration is 26 weeks since a worker filed his unemployment.

There are three key assumptions for this model. An unemployed worker is aware of the wage offer distribution he is facing, and he knows the exact amount of UI benefit he can receive at each period. The time horizon is the time after a worker loses his job. A worker lives forever but he only has opportunity to look for a job in a finite periods. This time line assumption characterizes that a workers lives a long time but he has to find a job in a limited time.

Since being unemployed till the final period, a workers exerts search effort which can be translated into the probability a wage offer arrives. To decide whether to accept a wage offer, the worker compares the wage with his reservation wage given the wage offer distribution. If an unemployed worker finds a job, he keeps the job forever. If he does not find a job at the end of searching period, he takes the normalized utility of staying unemployed for the rest of his life.

In each period, the worker exerts search effort that incurs a utility cost. The worker decides whether to accept the offer after comparing the consumption value of the given the wage offer and the option value of searching next period. In particular, I assume that workers live hand-to-mouth, and there is no on-the-job search. I discuss how the optimal searching intensity and reservation wage depends on a worker's time preference in the following section.

Search Model — Benchmark Case

A worker with exponential discounter factor δ faces a job search problem: he has the opportunity to look for a job from week 1 to week T; his UI benefit eligible for T_1 weeks ($T_1 < T$) with the benefit amount b_t; the wage offer distribution is given $log(w) \sim N(\mu, \sigma^2)$, and the probability density function (p.d.f.) is denoted as $f(\cdot)$.

A worker's consumption utility of receiving wage w at time t (as there is no saving) is

$$u_t(w) = \frac{w^{1-\eta}}{1-\eta}$$

The searching effort s_t equals the probability of that wage offer arrives, and a worker bears a cost $c(s_t)$

$$c(s_t) = \frac{1}{2}\gamma s_t^2$$

A wage offer arrives during the current searching period but the wage will be paid only in the period after the offer's arrival. The net present value for accepting job with wage w at week t becomes

$$V_t^E(w) = \frac{w^{1-\eta}}{(1-\delta)(1-\eta)}$$

The value function if the worker is unemployed at week t is

$$V_t^U = \frac{b_t^{1-\eta}}{1-\eta} - c(s_t) + \delta(1 - s_t Pr(w_t > w_t^*))V_{t+1}^U + \delta s_t Pr(w_t > w_t^*)E[V_{t+1}^E(w)|w > w^*]$$

To decide whether to accept a wage offer, this worker sets a reservation wage w_t^* which makes him indifferent between working or staying unemployed. The reservation wage is solved by equalizing V_{t+1}^E and V_{t+1}^U.

$$w_t^* = ((1-\delta)(1-\eta)V_{t+1}^U)^{1/(1-\eta)}$$

A worker's consumption is his current wage or the UI benefit. After the final week T, there is no more chance to search for a job. Assume the value of being unemployed for the rest of his life V_{T+1}^U is

$$V_{T+1}^U = 0$$

A worker accepts any job offer at week T, so his reservation wage $w_T^* = 0$. His value function of being unemployed at T is

$$V_T^U = -c(s_T) + \frac{\delta s_T}{(1-\delta)(1-\eta)}E[w^{1-\eta}]$$

Solving the model with backward induction for $t < T$ yields

$$V_t^U = \frac{b_t^{1-\eta}}{1-\eta} - c(s_t) + \delta(1 - s_t Pr(w_t > w_t^*))V_{t+1}^U + \delta s_t Pr(w_t > w_t^*)E[V_{t+1}^E(w)|w > w^*]$$

Using the first order condition gives the optimal searching intensity

$$\frac{\partial V_t^U}{\partial s_t} = 0 \Longrightarrow s_t = \frac{1}{\gamma}\delta Pr(w_t > w_t^*)(E[V_{t+1}^E(w)|w > w^*] - V_{t+1}^U)$$

Combining with the reservation profile, the model can be solved by following equations:

$$w_t^* = ((1-\delta)(1-\eta)V_{t+1}^U)^{1/(1-\eta)} \quad (2.1)$$

$$s_t^* = \frac{1}{\gamma}\delta Pr(w_t > w_t^*)(E[V_{t+1}^E(w)|w > w^*] - V_{t+1}^U) \quad (2.2)$$

$$s_t = \begin{cases} s_t^* & \text{if } s_t^* \in [0,1] \\ 0 & \text{if } s_t^* < 0 \\ 1 & \text{if } s_t^* > 1 \end{cases} \tag{2.3}$$

$$b_t = \begin{cases} b & \text{if } t \leq T_1 \\ 0 & \text{if } t > T_1 \end{cases} \tag{2.4}$$

A Search Model with Hyperbolic Discounting

A worker with a hyperbolic discounting preference, parameterized by a long-term discounter factor δ and short-term discounter factor β, faces a similar decision to the benchmark case.

The flow utility function, assumptions about time horizon and the general UI policy setting are the same for a worker with hyperbolic discounting preference. The difference is that the net present value for accepting job with wage w at time t becomes

$$V_t^E(w) = \beta \frac{w^{1-\eta}}{(1-\delta)(1-\eta)}$$

The value function if the worker is unemployed at week t becomes

$$V_t^U = \frac{b_t^{1-\eta}}{1-\eta} - c(s_t) + \delta\beta(1 - s_t Pr(w_t > w_t^*))V_{t+1}^U + \delta\beta s_t Pr(w_t > w_t^*)E[V_{t+1}^E(w)|w > w^*]$$

The optimal reservation wage is determined by the option value of staying unemployed verse the value of taking a job. As the reservation wage is only based on comparison of future value functions, a hyperbolic discounting worker has the same reservation wage profile to the exponential discounting workers'. The reservation wage w_t^* equalizes V_{t+1}^E and V_{t+1}^U so the worker is indifferent between working or staying unemployed.

$$w_t^* = ((1-\delta)(1-\eta)V_{t+1}^U)^{1/(1-\eta)}$$

However, a worker's optimal searching effort is different in the hyperbolic discounting setting. The intrinsic dynamic inconsistency embeds in a hyperbolic discounting job search model so that a worker's actual searching effort is lower than his anticipated searching effort. In other words, the hyperbolic discounting model predicts that a worker procrastinates in the job search in current period. Specifically, in week $t-1$, the worker's anticipated search effort $\tilde{s}_t$ is different from his actual searching effort s_t.

The actual searching effort can be derived from the first order condition of value functions

$$\frac{\partial V_t^U}{\partial s_t} = 0 \Longrightarrow s_t = \frac{1}{\gamma}\beta\delta Pr(w_t > w_t^*)(E[V_{t+1}^E(w)|w > w^*] - V_{t+1}^U)$$

The anticipated future searching effort can be derived by assuming the worker has exponential discounting preference.

$$\tilde{s}_t = \frac{1}{\gamma}\delta Pr(w_t > w_t^*)(E[V_{t+1}^E(w)|w > w^*] - V_{t+1}^U)$$

Therefore, a worker with hyperbolic discounting preference has the same reservation wage but lower searching effort compared to workers with exponential discounting preferences. With the same bounding conditions (3) and (4), the solution for a model with hyperbolic discounting preference can be characterized as

$$w_t^* = ((1-\delta)(1-\eta)V_{t+1}^U)^{1/(1-\eta)} \tag{2.5}$$

$$s_t^* = \frac{1}{\gamma}\beta\delta Pr(w_t > w_t^*)(E[V_{t+1}^E(w)|w > w^*] - V_{t+1}^U) \tag{2.6}$$

$$\tilde{s}_{t+1}^* = \frac{1}{\gamma}\delta Pr(w_t > w_t^*)(E[V_{t+2}^E(w)|w > w^*] - V_{t+2}^U) \tag{2.7}$$

2.3 Estimation Strategy

This section applies the above model in a reemployment bonus experiment setting. In the experiment, eligible claimants were randomly assigned to the claimant experiment or control group. Reemployment bonuses were available to the claimant if the worker found a job before week T_0. Suppose $T_0 = 11$, and the worker receives bonus amount X dollars after working m weeks ($m = 12$). A worker's value functions depend on time preference parameters, therefore I separately derive the likelihood function of worker's search outcome under the assumptions of exponential discounting and hyperbolic discounting.

Exponential Discounting Model for Bonus Experiment

Divide a worker's decision process into two phases: the bonus phase and the UI benefit collection phase.

Phase I: $t < T_0$, bonus phase

When the reemployment bonus is available, a worker's value for accepting job with wage w is

$$V_t^E(w) = \frac{w^{1-\eta}}{(1-\delta)(1-\eta)} + \delta^m \frac{X^{1-\eta}}{1-\eta}$$

His value function of staying unemployed is

$$V_t^U = \frac{b_t^{1-\eta}}{1-\eta} - c(s_t) + \delta(1 - s_t Pr(w_t > w_t^*))V_{t+1}^U + \delta s_t Pr(w_t > w_t^*)E[V_{t+1}^E(w)|w > w^*]$$

His reservation wage w_t^* is

$$w_t^* = ((1-\delta)(1-\eta)(V_{t+1}^U - \delta^m \frac{X^{1-\eta}}{1-\eta}))^{1/(1-\eta)}$$

The searching effort s_t is

$$s_t = \frac{1}{\gamma}\delta Pr(w_t > w_t^*)(E[V_{t+1}^E(w)|w > w^*] - V_{t+1}^U)$$

Phase II: $t > T_0$ and $t < T_1$, UI benefit collecting phase

Reemployment bonus is not eligible for a worker, but he still can claim unemployment insurance benefit $b_t = b$. The value for accepting job with wage w becomes

$$V_t^E(w) = \frac{w^{1-\eta}}{(1-\delta)(1-\eta)}$$

The value of him staying unemployed is

$$V_t^U = \frac{b_t^{1-\eta}}{1-\eta} - c(s_t) + \delta(1 - s_t Pr(w_t > w_t^*))V_{t+1}^U + \delta s_t Pr(w_t > w_t^*)E[V_{t+1}^E(w)|w > w^*]$$

His reservation wage w_t^* becomes

$$w_t^* = ((1-\delta)(1-\eta)V_{t+1}^U)^{1/(1-\eta)}$$

The searching effort s_t is

$$s_t = \frac{1}{\gamma}\delta Pr(w_t > w_t^*)(E[V_{t+1}^E(w)|w > w^*] - V_{t+1}^U)$$

Hyperbolic Discounting Model for Bonus Experiment

Similarly to previous section, a worker's decision process can be divided into two phases.

Phase I: $t < T_0$, bonus phase

When reemployment bonus is eligible, a worker's value for accepting job with wage w is

$$V_t^E(w) = \beta[\frac{w^{1-\eta}}{(1-\delta)(1-\eta)} + \delta^m \frac{X^{1-\eta}}{1-\eta}]$$

His value function of staying unemployed is

$$V_t^U = \frac{b_t^{1-\eta}}{1-\eta} - c(s_t) + \delta\beta(1 - s_t Pr(w_t > w_t^*))V_{t+1}^U + \delta\beta s_t Pr(w_t > w_t^*)E[V_{t+1}^E(w)|w > w^*]$$

His reservation wage w_t^* is the same as in the exponential discounting case

$$w_t^* = ((1-\delta)(1-\eta)(V_{t+1}^U - \delta^m \frac{X^{1-\eta}}{1-\eta}))^{1/(1-\eta)}$$

His searching effort s_t is now lower

$$s_t = \frac{1}{\gamma}\delta\beta Pr(w_t > w_t^*)(E[V_{t+1}^E(w)|w > w^*] - V_{t+1}^U)$$

Phase II: $t > T_0$ and $t < T_1$, UI benefit collecting phase

The worker cannot collect the reemployment bonus in this phase, but he still can claim unemployment insurance benefit $b_t = b$. The value for accepting job with wage w becomes

$$V_t^E(w) = \beta\frac{w^{1-\eta}}{(1-\delta)(1-\eta)}$$

The value function of him staying unemployed is

$$V_t^U = \frac{b_t^{1-\eta}}{1-\eta} - c(s_t) + \delta\beta(1 - s_t Pr(w_t > w_t^*))V_{t+1}^U + \delta\beta s_t Pr(w_t > w_t^*)E[V_{t+1}^E(w)|w > w^*]$$

His reservation wage w_t^* is

$$w_t^* = ((1-\delta)(1-\eta)V_{t+1}^U)^{1/(1-\eta)}$$

The searching effort is s_t is

$$s_t = \frac{1}{\gamma}\beta\delta Pr(w_t > w_t^*)(E[V_{t+1}^E(w)|w > w^*] - V_{t+1}^U)$$

Building likelihood function:

The key parameters include the discounting factor and the wage offer distribution. Denote μ and σ as the mean and standard deviation of the wage offer distribution, where $log(w) \sim N(\mu, \sigma^2)$ and the corresponding p.d.f is $f(w)$. γ represents the marginal search effort utility loss. The discounter factors include a short-term discounter factor β and a long-term exponential discounter factor (weekly) δ. I also assume there is a wage measurement error ϵ – the discrepancy between true accepted wage and observed wage – is drawn from a normal distribution $N(0, \theta^2)$. w_1 represents the realized re-employment wage and it satisfies the condition that $ln(w_1) = ln(w) + \epsilon$. To control the heterogeneity across workers, I use a worker's wage before the unemployment spell (w_0) as the base line of the mean of wage offer distribution. Therefore, the parameter of interest μ is transformed to α, where $\mu = \alpha w_0$.

The log likelihood function for individual i exits unemployment at week k:

$$\begin{aligned} LL &= \prod_i Pr_i(k) = \prod_i \{\prod_{t=1}^{k-1}(1 - s_t(1 - \Phi(\tfrac{log(w_t^*)-\mu}{\sigma})))\} \\ &\cdot s_t(1 - \Phi(\tfrac{log(w_k^*)-\mu-\rho(log(w_1)-\mu)}{\sigma\sqrt{1-\rho^2}})) \cdot \phi(\tfrac{w_1-\mu}{\sqrt{\sigma^2+\theta^2}}) \end{aligned}$$

where $\rho = \frac{\sigma}{\sqrt{\sigma^2+\theta^2}}$. The products inside the bracket is the joint probability that a worker does not receive a wage offer or reject any wage offer till $t = k-1$, so that the worker stays unemployed till week $k-1$. $s_t(1 - \Phi(\frac{log(w_k^*)-\mu-\rho(log(w_1)-\mu)}{\sigma\sqrt{1-\rho^2}}))$ represents the joint probability that a worker receives a wage offer and accepts it, and the last term is the p.d.f. of a worker's reemployed wage.

2.4 Estimation and Policy Simulation

This section uses data from Illinois Unemployment Insurance Experiments to compare the explanatory power of a model with hyperbolic discounting to a model with exponential discounting preference, and I find that a model with hyperbolic discounting fits the treatment effect better. Section Data introduces the data and the background of these experiments. The next section verifies the effect of bonus treatment and compares the results to previous studies of UI policy changes. The last two sections show the structural estimation and demonstrate the policy implication of hyperbolic discounting job search model.

Data

In late 1980s, The Department of Employment Security in Illinois and later U.S. Department of Labor conducted a series re-employment bonus experiments in three states: Illinois Unemployment Insurance Experiment (1984-85), Pennsylvania Reemployment Bonus Demonstration (1988-89), and the Washington Reemployment Bonus Experiment (1985-89). These experiments tested the effect of alternative reemployment bonuses on the reemployment and UI receipt of UI claimants. The results showed that reemployment bonuses can reduce the amount of time spent on UI, thereby reducing benefit payments, but there was little evidence that the bonus offers increased the employment and earnings of claimants. The data from these experiments used in this chapter include administrative data of employment characteristics, wage history, unemployment benefits received, selection date, treatment group assignment, and demographic information. The estimations in this chapter focuses on Illinois Unemployment Insurance Experiments, because only Illinois experiment has the exact date when unemployed workers find the next job, while Pennsylvania and Washington experiment only have the duration of benefit drawing of an individual worker.

Between mid-1984 and mid-1985, the Illinois Department of Employment Security conducted trial experiments at its Job Search Offices. The results of the trial are contained in the Illinois Unemployment Insurance Experiments public use data (1984-85). In order to assess whether it is possible to reduce the cost to the Department and the duration of unemployment, those who qualified for benefits received random assignment into either the claimant experiment, employer experiment, or the control group. Some experiments offered bonuses to employers while offered them to claimants, the later being relevant for this project. In terms of claimants, a baseline survey, a myriad of available administrative data (from the Illinois Department of Employment Security Benefits Information System and the Illinois Department of Employment Security Wage Records databases, as well as Job Service office logs), as well as base period earnings, demographic characteristics and other information together provided elements of the data set analyzed here.

Job Search Incentive Experiment, the treatment's official name, offered new UI claimants a cash bonus. Claimants received $500 once they met the following three conditions. First, claimants needed to file a claim for UI and to be eligible for receiving these benefits. Second, claimants needed to find a position within no more than eleven weeks of receiving the UI benefit. Third, they had to be employed for no less four months and, fourth, to work on a job no less than 30 hours per week.

There are a total of 8138 records, but 3322 of claimants failed to find a position during the required period and another 27 have a hiring data defined as incorrect. The remainder are divided between the treatment group (with 2555 observations) and the control group (with 2234 observations).

Summary statistics on the duration of unemployment spells, reemployment wages, and demographic characteristics are presented in Table 2.1. Figures 2.1 and 2.2 present the survival rate of the unemployment spell and the exit-week hazard rate distribution. The final report for the Illinois Unemployment Insurance Incentive Experiments (I refer it as the final report) confirmed that the treatment was assigned randomly. Figure 1 and 2 shows the pattern of the unemployment spell. The majority of workers manage to find a job within the 30 weeks, and there is non-trivial heterogeneity across workers. 30% of workers find their next job within 8 weeks after first filing of unemployment insurance, but other workers are evenly distributed from the 9th week till the 26th week (which is the maximum UI benefit eligibility duration for most workers). There is also a drop in exit-rate in unemployment after week 26, suggesting that workers try to avoid staying unemployed after losing UI benefit.

The Impact of Reemployment Bonus

This section discusses how the reemployment bonus affects workers' job finding time and future wage. In the final report, average benefit receipt was lower in the treatment group than in the control group by $158 to $194 over the whole benefit year, and there is the 1.15-week reduction in the duration of unemployment, suggesting that a bonus program could be effective in reducing UI program costs.

Table 2.2 confirms this result. Columns 1 and 2 show that participants in the treatment group receive 1.5 fewer weeks UI benefit and find the next job 1 week faster. However, the theory of job-search suggests that the shorter search time might result in a less favorable match between worker and job, which would manifest itself in lower earnings in the subsequent job. If a participant who submitted a Notice of Hire (or received a bonus) simply accepted the first job that presented itself, the claimant's earnings after reemployment and the efficiency of the labor market would both be reduced. Columns 3 and 4 address the concern that participants may have sacrificed earnings in their post-program job in order to obtain the bonus.[2] Column 3 shows average base period earnings of claimants in the treatment group is not significantly lower than the earnings of control group. In Column 4, I find that claimants in the treatment group are not more likely to refile unemployment claims. The failure to find any evidence of post unemployment match-quality deterioration tends to reinforce the conjecture that that a job-search incentive program can increase the intensity of job search if workers have hyperbolic discounting preferences.

Table 2.3 explores the heterogeneous treatment effect for two groups classified by their previous earnings. The low earnings group includes workers in the bottom half of the sample distribution of previous weekly wages; the top earnings group includes individuals in the top half. Columns 1 and 2 show that participants with low-earning and high-earning both reduce the duration of drawing UI benefit for about 1-2 weeks. However, bonus effects on workers' after unemployment earnings are different across the two groups. Columns 3 and 4 indicate that high-earning workers end up with 6.8% lower weekly earnings after bonus treatment but there is no reduction in post-UI earnings for low-earning workers. The result shows that low-earning workers are more likely to be helped by bonus treatment, a finding consistent with Paserman (2008) who finds that low and medium wage workers have a substantial degree of hyperbolic discounting.

Structural Parameter Estimates

This section applies the estimation strategy in the data based on the Illinois Re-employment Bonus Experiment. The key parameters of interest are workers' discounting factor, their wage offer distribution and searching effort. To reduce the burden of computation, hold risk aversion parameter constant $\eta = 0$ so workers are risk-neutral. All the parameters can be estimated using maximum likelihood method.

Table 2.4 presents the estimates of the structural parameters in exponential discounting model (with long-term discount factor δ) and hyperbolic discounting model (with discount factor β and δ) in the first specification. In the exponential discounting model, long-time discount factor $\delta = 0.9999$, which means workers are quite patient in the long-term and would like to invest a lot for future returns. The ratio parameter for the mean wage offer distribution $\alpha = 1.079$, which means the average wage offer they receive is similar to his previous wage. The standard deviation of logged wage is $\sigma = 0.0025$, implying that workers'

[2] The table displays data on the pre- and post-program earnings of claimants. All results are based on the sub-sample of claimants who terminated benefits (at some point following the initial claim that brought them into the experiment), and had positive earnings in the first full quarter following benefit termination. That is, claimants who exhausted benefits and failed to find new employment, as well as claimants who dropped out of the labor force, are excluded from consideration here. Since our concern focuses on the earnings of those who found new employment, and whether these earnings are lower for treatment group.

wage offer distribution has very small variation. The searching effort cost parameter is $\gamma = 22711$, which measures the net present value cost of increasing wage offer arrival rate by search harder. In hyperbolic discounting model, short-time impatience $\beta = 0.7619$, which is significantly smaller than 1. The long-term discount factor $\delta = 0.9896$, close to the long-term discount factor in a exponential discount model. This result indicates that workers would like to invest more for the future but they also dramatically discount future compared to today. The mean of wage offer distribution $\alpha = 1.3271$, thus the potential wage offer a worker receives has a higher average value relative to his previous wage. The standard deviation of the wage offer distribution $\sigma = 0.074$, which is larger than the estimate in exponential discounting model. The searching effort parameter $\gamma = 17494$.Estimates of γ reflects that searching cost is higher in exponential discounting model.

The estimate of the exponential discounting factor δ degree is close to the boundary 1, suggesting workers care about future earning. The point estimates for β is around 0.7. Fang and Silverman (2004) estimate a similar model of job search for women receiving welfare, and they estimate β equals to 0.61. Laibson, Repetto and Tobacmans (2007) structural estimates of β, based on life-cycle consumption choices, range between 0.51 and 0.82, and Paserman (2008) has the range of 0.40 - 0.89. Altogether, my point estimates are roughly comparable to those found elsewhere.

Compared to the estimates based on exponential discounting model, the estimates based on hyperbolic discounting model suggest workers are less patient about future and their wage offer distribution have a higher mean and standard deviation. In order for exponential discounting model to fit the data, the estimations require that workers have constant wage offers, which is inconsistent with the empirical variation in workers earnings over time. I compare a worker's after unemployment wage with his wage before unemployment. The approximated wage offer mean parameter $\hat{\alpha} = \frac{w_0}{w_1} = 1.356$. This estimate supports that the hyperbolic discounting model fits empirical wage trend better. The standard deviation of the wage offer distribution is harder to estimate because the individual heterogeneity can be huge. One way to estimate σ is to regress the re-employment wage on observable variables, then use the variation of the residuals as the standard deviation for wage off distribution $\hat{\sigma} = 0.878$. Yet, the estimated standard deviation of the wage distribution in both models lies substantially below the standard deviation of observed wages, which deserves attention in future studies.

Policy Simulation

One of the main advantages of structural estimation is that it allows one to simulate the effects of different policy interventions in a behaviorally consistent manner. According to the model, this sections analyzes the predicted effect on UI duration and job-match quality after introduction of the bonus experiment. Workers in the control group can take unemployment insurance for 26 weeks. Workers in treatment groups can take unemployment insurance for 26 weeks as well, but they can also choose to take a \$500 lump sum bonus if they find a job within 11 weeks after filling unemployment. The simulation is based on a representative worker with an average weekly benefit at \$120 and his wage offer distribution with a mean of logged wage at $\mu = \ln(240)$.

Figures 2.3 - 2.5 compare the hazard rate of exiting unemployment and wage distribution across groups. In the realized hazard rate graph (Figure 2.3), the workers in the treatment group have a higher hazard rate in exiting unemployment in the first 10 weeks, with the marginal probability at around 5%. Figure 2.4 shows that the exponential discounting search model predicts a similar pattern in the treatment effect but with higher marginal probably at the level of 10%. Figure 2.5 draw the treatment effect in a hyperbolic discounting for a representative worker. After adjusting the scale difference, it shows similar pattern compared to realized hazard rate trend and it predicts a lower level of marginal probability than exponential discounting model.

I present the calibrated averaged treatment effect of the reemployment bonus treatment in Table 2.5. The first three columns present the policy impact using parameter estimates from a exponential discounting model based on Table 2.4. The last three columns of the Table 2.5 presents the effects of the policies using parameter estimates from the hyperbolic model, holding the variance of the wage offer distribution constant. Given estimated $\sigma = 0.1$, Column 1 and Column 4 show the average treatment effect on UI duration is 14 weeks in exponential discounting model and 10 weeks in hyperbolic discounting model, while the treatment effect on match quality, defined by the difference between pre-unemployment and re-employment wage, is 3.9% in exponential discounting model but only 0.03% in hyperbolic discounting model. This difference in match-quality prediction persists for other values of σ, therefore the hyperbolic discounting model generate more consistent predictions of the small treatment effect on job match quality. Figures 2.4 and 2.5 illustrate that the hyperbolic discounting workers have lower hazard rate on average but the treatment effect is similar across the two models, consistent with Table 2.5.

2.5 Conclusion

The common empirical finding in previous literature is that higher UI benefit, extended UI eligibility duration, bonus payment or severance pay affects the job-finding hazard rate but not subsequent job match quality. Previous studies on Illinois UI Incentive experiments (e.g. Meyer 1995) conclude that bonus payment increase the speed with which people leave the unemployment insurance rolls, but the shortened unemployed spell does not decrease the subsequent reemployment wage and duration. The final report of Pennsylvania and Washington experiment shows there is no significant impact on other measurements of job match quality either, including earning, job turnover, union membership and self-employment. The Washington report also suggest that the bonus payment increases worker's job search intensity.

This chapter use Illinois UI Incentive Experiments data to re-examines how hyperbolic discounting time preference explains why UI policy changes such as bonus payment can affect the job-finding hazard rate but not subsequent job match quality. Under the classic sequential job search model with exponential discounting preference, the empirical fact can be explained by the small variation of wage offers distribution, but this explanation is hard to reconcile the realized wage variation of each working during his life time. Because job searching choices involve making the effort today and receiving the benefit in the future, a hyperbolic discounting unemployed worker invests little effort today but thinks of searching hard tomorrow. As they exit unemployment later, their reserve wage profile are flatter. Therefore, the effect of UI policy change on re-employment wage is smaller in a hyperbolic discounting job search model.

The results found in this chapter have broad policy implications. Understanding dynamic-inconsistent search behavior of unemployed workers helps policy makers to reduce workers' procrastination in job search. The design of specific policy such as job counseling is important in speeding up job-finding process. Thought there is no direct measurement of searching effort in this study, but a future study can take advantage of time-use data to explore the direct evidence of job search intensity.

Table 2.1: Summary Statistics

Demographic Characteristics	
Male	57.8%
Female	42.2%
White	71.6%
Black	19.4%
Hispanic	7.0%
Other Race	1.5%
Age	32.5
Labor Market Outcomes	
Unemployment Spell (day)	86.0
Weekly Benefit	120.2
Earning Before Unemployed	255.8
Earning After Re-employed	229.4
Treatment Ratio	*Received Bonus*
53%	13%
N	3812

Table 2.2: Treatment Effect on Average Worker's Labor market ofttimes

Dep Var:	UI Benefit	Job-Finding	Post-UI Wage	Refiling UI
Bonus Treatment	-1.429***	-1.007***	-0.0188	0.0029
	(0.374)	(0.256)	(0.0285)	(0.0158)
Weekly UI Benefit	0.0126	0.0147*	0.0053***	0.0013***
	(0.0108)	(0.0077)	(0.0009)	(0.0004)
Pre-UI Wage	-0.776	-0.500	-0.743***	-0.167***
	(0.606)	(0.422)	(0.0494)	(0.0250)
Age	-0.0115	0.0238	0.0031*	0.0038***
	(0.0209)	(0.0152)	(0.0017)	(0.0009)
Black	1.853***	0.657*	-0.0298	0.102***
	(0.524)	(0.342)	(0.0393)	(0.0206)
Male	1.245***	0.606**	0.143***	0.108***
	(0.377)	(0.264)	(0.0293)	(0.0162)
Ethnicity	X	X	X	X
Observations	3,811	3,811	3,811	3,811
R-squared	0.012	0.011	0.138	0.045

Robust standard errors in parentheses

Table 2.3: Treatment Effect by Pre-Unemployment Wage Distribution

Dep Var:	UI Benefit Week		Wage Diff Post-Pre UI	
	Bottom Half	Top Half	Bottom Half	Top Half
Bonus Treatment	-1.169**	-1.673***	0.0005	-0.0681*
	(0.560)	(0.494)	(0.0451)	(0.0373)
Weekly UI Benefit	0.0043	0.0246	-0.0053***	-0.0011
	(0.0092)	(0.0212)	(0.0008)	(0.0015)
Age	-0.0043	-0.0177	0.0055**	-0.0044*
	(0.0301)	(0.0287)	(0.0028)	(0.0023)
Black	2.165***	1.659**	0.0858	-0.0586
	(0.711)	(0.779)	(0.0572)	(0.0569)
Male	2.094***	0.210	0.226***	0.0513
	(0.553)	(0.521)	(0.0463)	(0.0402)
Ethnicity	X	X	X	X
Observations	1,908	1,904	1,907	1,904
R-squared	0.016	0.012	0.036	0.007

Robust standard errors in parentheses

Table 2.4: Parameter Estimation

Parameter	Exponential	Hyperbolic
δ	0.9999	0.9896
β	-	0.7619
α	1.0789	1.3271
σ	0.0025	0.0743
γ	22711	17494
LL	766.7779	762.6871

Table 2.5: Policy Simulation

Average Effect	Exponential ($\delta = 0.999$)			Hyperbolic ($\delta = 0.989$, $\beta = 0.76$)		
	$\sigma = 0.1$	$\sigma = 0.2$	$\sigma = 0.07$	$\sigma = 0.1$	$\sigma = 0.1$	$\sigma = 0.07$
UI Week (Control)	40.17	36.58	36.58	25.16	29.65	24.42
UI Week (Treatment)	25.87	31.35	22.28	14.49	17.98	13.83
Post-UI Wage (Control)	275.6	326.7	263.3	249.06	272.1	246.0
Post-UI Wage (Treatment)	271.7	315.1	261.2	249.03	268.3	245.8
Difference in Week	14.3	4.8	13.7	10.7	11.8	10.6
Difference in Wage %	3.9	10.6	1.9	0.03	3.8	0.2

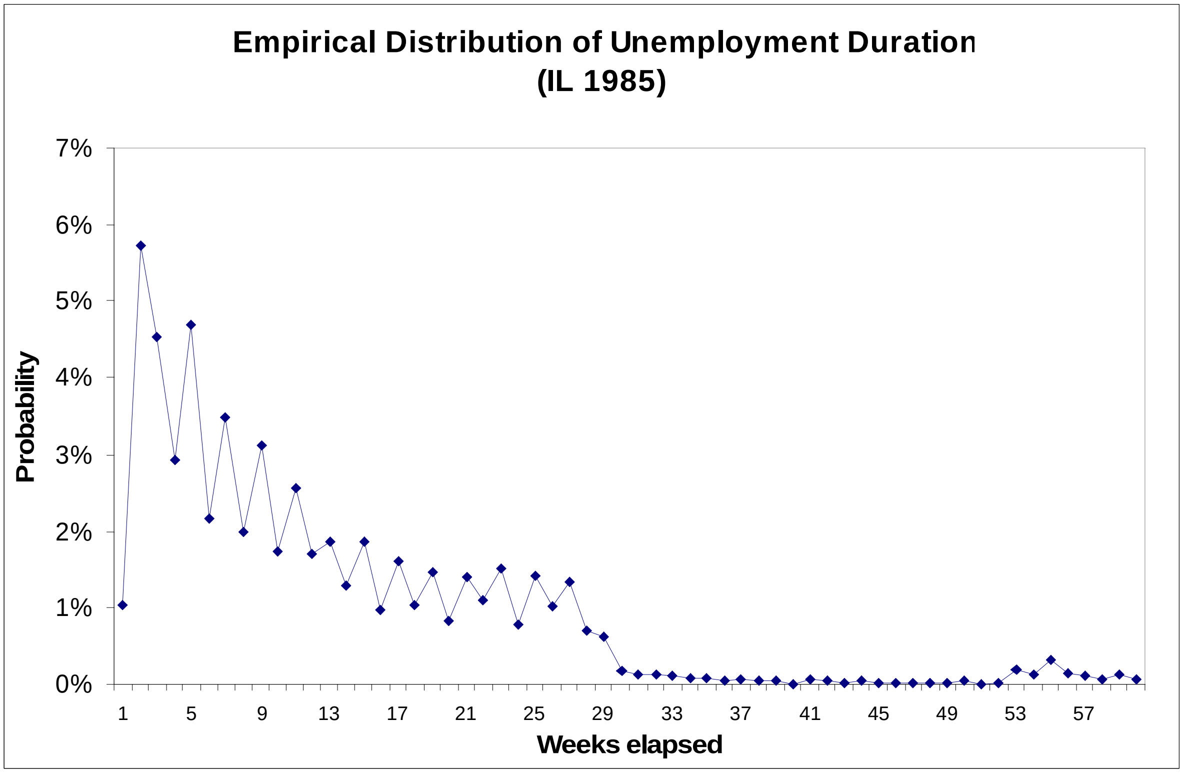

Figure 2.1: Empirical Survival Rate of Unemployment Spell

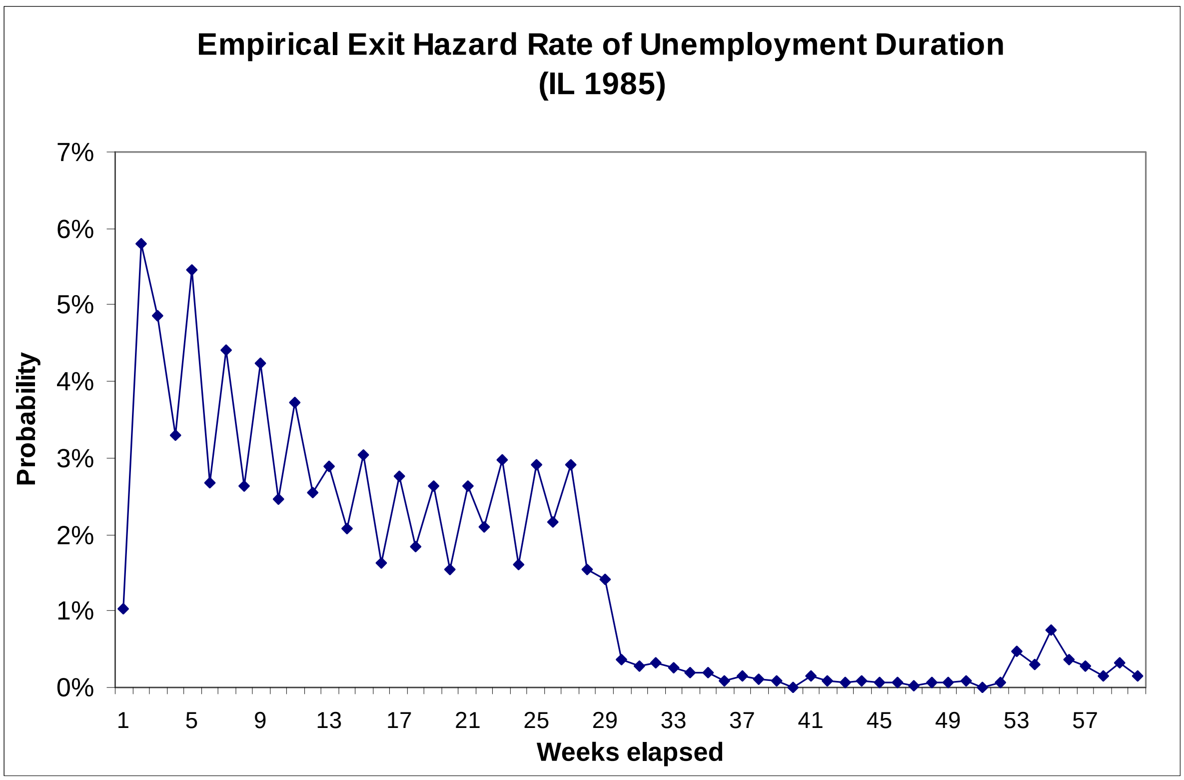

Figure 2.2: Empirical Hazard Rate of Exit Week

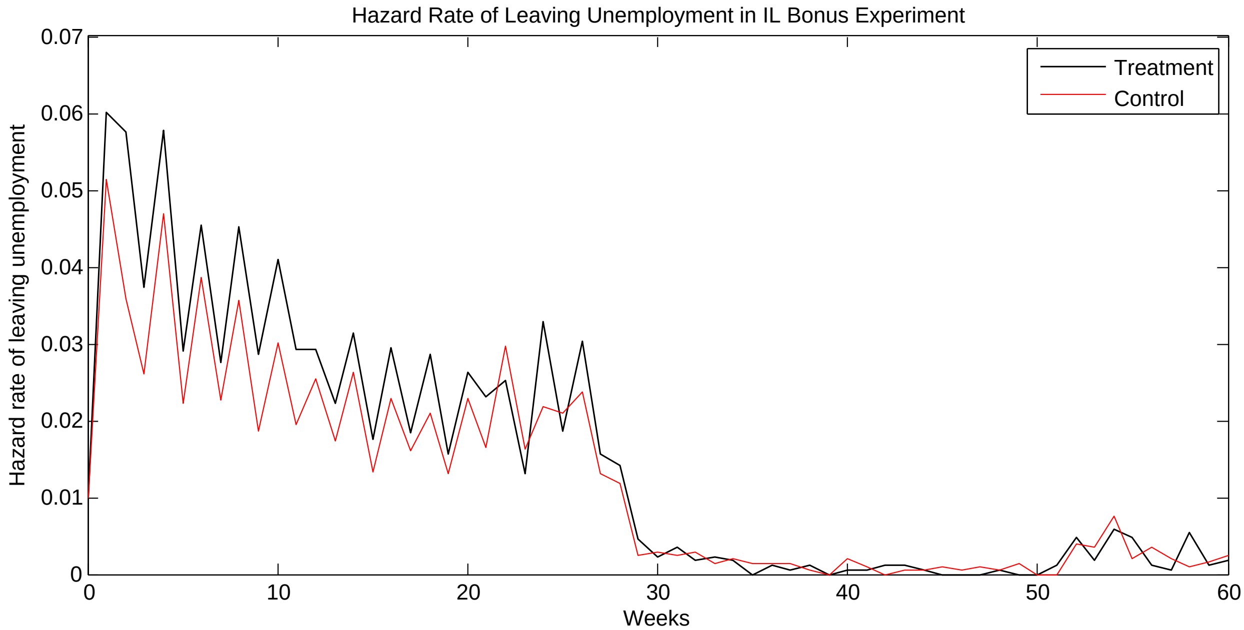

Figure 2.3: Empirical Hazard Rate of Exit Week by Treatment

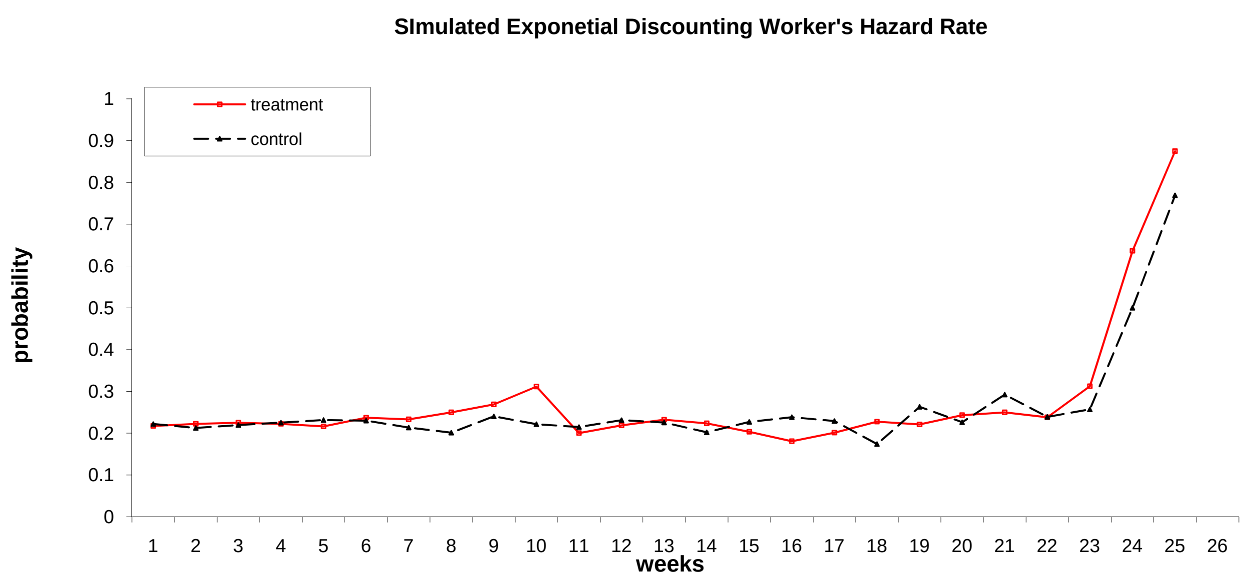

Figure 2.4: Simulated Hazard Rate of Exit Week by Treatment (Exponential)

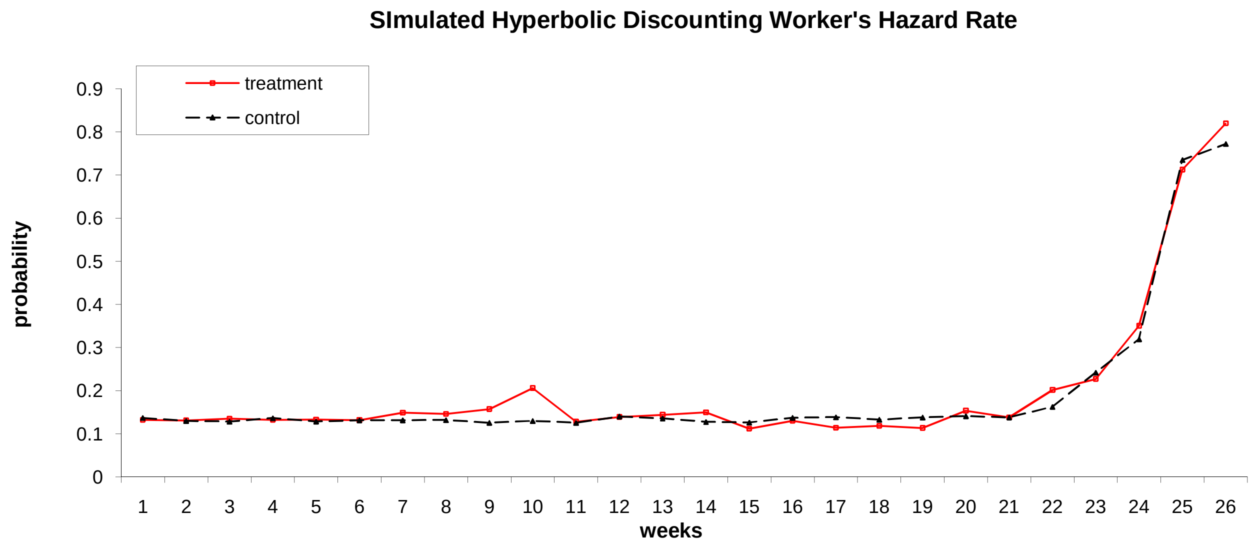

Figure 2.5: Simulated Hazard Rate of Exit Week by Treatment (Hyperbolic)

Chapter 3

Bunching at the Original Purchase Price: New Evidence of Loss Aversion in the Housing Market

3.1 Introduction

The notion that individuals weight losses more than equal-size gains is generally accepted. Accordingly, the phenomenon has generated a rich literature incorporating this aspect of human behavior into formal economic theory, beginning with the seminal work of Kahneman and Tversky 1979. The theory of loss aversion (or similarly reference dependent preferences) has touched on numerous applications, providing insight toward behavior that may otherwise be considered anomalous if interpreted using the standard framework, for example the disposition effect and small scale risk aversion.

Despite the theory's intuitiveness and the substantial evidence supporting it, applying the theory to observational field data has been quite difficult so far. The subjective nature of one's reference point adds another unobserved dimension to an individual's preferences, and how one's reference point adapts over time is for the most part not well understood. Although these difficulties exist, given the proper environment, a simple model of reference dependent preferences can potentially be useful in explaining observed data and can provide additional, more subtle insights that can be empirically tested.

The aim of our paper is to explicitly apply a simple model of reference dependent preferences to the problem studied in Genesove and Mayer 2001, and test a hypothesis of the model that has yet to be considered in this context: the bunching of asking prices in the neighborhood of the reference point. In their paper, Genesove and Mayer analyze seller pricing behavior in the Boston condominium market. Using data on original purchase prices and asking prices, they demonstrate that those sellers who have experienced a loss (that is, the market value of their home had fallen below the original purchase price at the time of sale), tend to list asking prices significantly above the market value. In our paper, we test our new prediction and find that between 4% and 10% of sellers incurring a loss bunch by asking a price within \$5,000 of the original purchasing price in Genesove and Mayer's data. The bunching result is less strong in a online real-estate agency data from the San Francisco Bay Area from 2011, but the pricing behavior of individual sellers is still consistent with loss aversion.

While there is a growing body of literature on the general trend of housing market price (Case and Shiller 1989; Cutler, Poterba, and Summers. 1991; Capozza, Hendershott, and Mack 2004; and Glaeser et al. 2013; Guren 2014), there still exists limited micro empirical evidence on how sellers decide the listing price. Some other recent evidence on the effect of previous purchasing price on transaction price is provided by Anenberg 2011 who uses a long panel data of the San Francisco Bay Area real estate market. The contribution of our paper is to give a structural explanation of seller's behavior and it verifies the empirical prediction based on our model. Our results on sellers' pricing strategy can also link to research on goals and decision making. For example, Markle et al. 2013 test reference dependence using goals in marathon running.

In Section 3.2 we outline a simple model of reference-dependent preferences where the utility of an agent has two components: the first is the standard intrinsic consumption utility and the other is a gain-loss function capturing whether the agent perceives a given outcome as a gain (if she is above her reference point) or as a loss (if she is below her reference point). Although simple, this model is capable of rationalizing the empirical findings in Genesove and Mayer (2001) and of generating an additional prediction: the bunching of asking prices around the previous purchasing price. In Section 3 we describe the data and the empirical strategy and we discuss the empirical evidence in support of our theoretical model. We use both the data from the original study of Genesove and Mayer (2001) and the new real-estate data collected from the San Francisco Bay Area housing market during the Great Recession. Finally, in Section 3.4 we conclude and point to some extensions left for future research.

3.2 The Model

Consider a risk-neutral seller choosing the price P, with $P \in \mathbb{R}_+$, at which she is willing to sell her house. The seller's utility from realizing the sale takes the following form:

$$V(P|P_0) = m(P) + \mu(P - P_0)$$

where $m(\cdot)$ is standard consumption utility, $\mu(\cdot)$ is "gain-loss" utility in the sense of Koszegi and Rabin 2006 and P_0 is the seller's reference price that we assume to be equal to the price at which the seller previously purchased the house she is now trying to sell. In what follows we assume both components of the seller's utility have a linear form as: $m(P) = P$, $\mu(P - P_0) = \eta(P - P_0)$ if $P \geq P_0$ and $\mu(P - P_0) = \eta\lambda(P - P_0)$ if $P < P_0$, with $\eta > 0$ and $\lambda > 1$.The parameters η and λ represent the weight the seller puts on the gain-loss component of her overall utility and the degree of loss aversion, respectively.

In the original formulation of gain-loss utility of Koszegi and Rabin the reference point coincides with the rational expectations held by the agent. Here, we depart from this formulation of the reference point and assume instead that the latter is given by the price P_0 at which the seller previously purchased the house she is now trying to sell.

A sale occurs if there is a buyer who is willing to pay the price asked by the seller. We do not model the demand side of the housing market but instead assume that the probability of realizing the sale is a differentiable and non-increasing function of the selling price[1]: $\pi(P)$, with $\pi'(P) \leq 0$ and $\pi''(P) \geq 0$.

Finally, let $\overline{U}$ denote the seller's reservation utility in the event that no sale is realized. The seller then will choose the price P^* that solves the following maximization program

$$\max_P \pi(P) V(P|P_0) + (1 - \pi(P)) \overline{U}.$$

Taking the FOC and re-arranging yields[2]:

$$\pi(P)(1+\eta) = -\pi'(P)\left[P + \eta(P - P_0) - \overline{U}\right] \quad \text{if} \quad P \geq P_0$$

and

$$\pi(P)(1+\eta\lambda) = -\pi'(P)\left[P + \eta\lambda(P - P_0) - \overline{U}\right] \quad \text{if} \quad P < P_0.$$

First, consider the usual case of reference-free preferences with $\eta = 0$ and $P_0 = 0$: in this case the two conditions simply reduce to

$$\pi(P) = -\pi'(P)\left[P - \overline{U}\right]$$

where the left hand side and right hand side of the above condition represent the marginal gain and the marginal cost of choosing a higher price respectively; as usual, at the optimum the two need to be equal.

This intuition carries over to the case when the seller is loss averse, but now the marginal benefit and marginal cost schedules display a kink at $P = P_0$. Let $P^*_{\lambda=1}$ be the optimal asking price for a seller with no loss averse preferences and P^* be the optimal asking price for a loss averse seller; then, we can distinguish three cases.

[1] That is, we assume each seller acts as a monopolist facing a unit-demand function that is nothing but a survival function: $\Sigma(p) = 1 - F(p)$.

[2] The second order condition for an interior maximum is satisfied if

$$2\pi'(P)(1+\eta) + \pi''(P)\left[P + \eta(P - P_0) - \overline{U}\right] < 0$$

and

$$2\pi'(P)(1+\eta\lambda) + \pi''(P)\left[P + \eta\lambda(P - P_0) - \overline{U}\right] < 0$$

respectively.

CASE I ($P^*_{\lambda=1} < P_0$ and $P^* < P_0$)

A loss averse seller chooses a price higher than the one chosen by a non loss averse seller, but she is still unable to fully recover the loss: $P^*_{\lambda=1} < P^* < P_0$. The empirical prediction in this case is that houses owned by a loss averse seller sit longer on the market than houses of similar market value but owned by a non loss averse seller. This case is depicted in Figure 3.1.

CASE II ($P^*_{\lambda=1} < P_0$ and $P^* = P_0$)

Here loss aversion induces bunching at (or around of) the seller's original purchasing price. In this case the seller is able to fully recoup her loss, but again her house will sit longer on the market because her asking price is above the one chosen by non loss averse sellers. This case is depicted in Figure 3.2

CASE III ($P^*_{\lambda=1} \geq P_0$ and $P^*_{\lambda=1} = P^*$)

Loss aversion does not play any role because the seller is in the gain domain. Hence, she will choose the same price as a seller with reference-free preferences. This is the case in Figure 3.3.

3.3 Empirical Analysis

In this section we present evidence on the bunching of asking prices around original purchase prices. We use two source of housing market data for this study. The first one is the same data set used in Genesove and Mayer (2001), which covered the majority transactions in the Boston condominium market from 1997 to 2001. The second data set is from a national online real estate brokerage company (Redfin) that provides detailed information about housing transaction in the core of San Francisco in 2011. In both data sets, we observe the asking price at which houses were listed on the market, the price at which the seller subsequently purchased the property, and basic characteristics for every house sold such as square footage, lot size, year built, latitude and longitude, and a unique property id.

As addressed in Genesove and Mayer, we do not directly observe the market value of a house, which adds some difficulty to the analysis at hand. How do we thus define a loss when we cannot observe the true value of the home? We use the same strategy as in Genesove and Mayer (2001) to deal with this problem. We construct the expected selling price via a linear function of observable attributes, the quarter of listing (entry on the market), and an unobservable component (equation (2) in the original paper). We assume that this is a legitimate estimate of the market price and use this value to define the loss (or gain) a seller incurs in what follows. We call this constructed market value P_M.[3] For instance, if $P_M < P_0$

[3]Though we do not directly have Genesove and Mayer's constructed market price in our data set, we can back out the expected selling price by adding the residual of their regression (which is recorded in the data) and the previous selling price.

we say the seller experiences a loss and we quantify this loss (or in some cases, gain) simply by the measure $P_M - P_0$. Finally, let P_A be the price listed by the seller.

First we examine the empirical distributions of $P_M - P_0$ and $P_A - P_0$. The histograms and kernel densities are presented below in Figures 3.4 and 3.5 for Genesove and Mayer's data. Looking at the distribution of market price, we do not see any irregularities around the original purchase price. On the other hand, there is a slight abnormality in the distribution of the asking price. Right around P_0 there is a slight spike in the density. This spike, however, fails to be large enough to provide compelling evidence. Figure 6 and 7 draw the distribution of asking price using the Redfin's transaction data from June 2011 to December 2011. If we measure the housing price in bins with the scale \$2000, there is suggestive evidence of the spike of asking price at the original purchasing price, though this pattern disappeared if measuring housing price with a larger size bin.

Due to perhaps limited memory and rounding of asking prices, we believe it is highly unlikely that a seller would price *exactly* at the price which he or she originally paid. Thus we examine the rates at which sellers price within a given interval around the original purchase price. We compare these bunching rates between sellers who experienced a loss and those who have not (recall, the measure of loss is defined by our estimate of the market price). Our model, above, predicts that bunching should be relatively more frequent for those who experienced a loss (CASE II in the model of the previous section).

Table 3.1 presents the bunching rates in the asking prices of sellers in the loss and gain domains, where bunching is defined in four ways. The first column shows the percent of the sample who are exactly bunching. The second column is our preferred definition of bunching, which is defined by pricing within \$5,000 of the original purchase price (the average selling price of the houses in our sample is \$500,000). The next two columns are presented as robustness checks, as they define bunching in a more confined and broad sense, respectively.

Column 2 in Table 1 is consistent with our hypothesis: those sellers who experienced a loss are twice as likely to bunch around the original asking price as those who experienced a gain (and the difference is significant at the 1% level). We realize these results could be more compelling if the interval used to define bunching was formed via a percent of the original asking price rather than defined in absolute terms. However, in this case, we feel that the absolute definition is appropriate here due to the homogeneity in prices in our sample. Table 3.2 replicates the bunching result using Redfin data. We still observe that sellers who experienced a loss are more likely to bunch around the original asking price as those who experienced a gain, though the differences in Column 2-4 is not statistically significant due to smaller sample size.

Table 3.3 adds further evidence to the loss aversion explanation for the observed bunching in our sample. Table 3.1 shows that bunching is relatively more likely in the loss domain. But what if, for some reason, the true market value for many houses was bunched slightly below the original purchase price? In this case we would observe a high rate of bunching in asking prices for those sellers who experienced a loss even if the sellers were pricing rationally (that is, listing an asking price that equals the market value). We check for such bunching of the market value and the results are presented in Table 3.2. The market price is evenly distributed across gains and losses, hence we can rule out that the bunching of asking prices is driven by an associated bunching in market values.

Table 3.4 compares the bunching patterns between sellers who live in their houses (that is, the home they are putting on the market is their primary residence) and investors who do not live in the house they are selling. The top panel provides bunching rates for the owner occupants (separated into loss and gain domains), while the bottom panel reports the results for investors. We find that the effect of loss aversion on bunching behavior is stronger in the sample of owner occupants than in the sample of investors. Perhaps, as argued in other studies, the effect of experience in the market acts to reduce the endowment effect and the significance of loss aversion (see List 2003).

We then examine one last prediction of our model. The bunching case explored above in Section 3.2 shows that sellers who experienced a relatively small loss will bunch, and hence inflate their asking price upward so that it matches the previous purchase price. On the other hand, sellers who experience a large loss (CASE 1 in our model) will inflate their asking price above the market value, but not to the extent that it equals the original purchase price. This implies that the effect of one's loss should approach unity in a regression of asking price on market value and loss as the size of the loss gets small. We divide our sample of those who experienced a loss into quartiles and run this regression in each quartile. The results are presented in Table 3.5 below. As in Genesove and Mayer, we provide a lower and upper bound for the effect of loss, and do so for each quartile.

The results are not quite as we predicted, but interesting in their own right. We see that within the quartile that experienced the lowest loss, the effect of loss on the mark-up of the asking price over the market value is indeed the strongest. Clearly we do not find that this value converges to unity; however, this may be due to the rough aggregation of quartiles. Perhaps if we divided the data more finely, we would observe this phenomenon. Finally, the "U-shaped" pattern of the effect merits attention. The effect of loss is strong in the two extreme quartiles, but fails to be significant for losses in the median range. What, exactly, caused this feature of the data is not entirely obvious. Perhaps those with extreme losses are so bewildered that they list unreasonable asking prices that end up being revised downward prior to sale. We should thus check if the same pattern emerges when analyzing the mark-up in *sales* prices over the market value, rather than asking prices, as done here. Our model is silent with regards to such behavior, but we believe this phenomenon, and its cause, are worth considering in our future work on this topic.

3.4 Conclusions and Extensions

This paper provides three contribution to the literature on loss aversion in the housing market.

First, it provides a formal model of reference-dependent preferences that can organize in a systematic way results that previously appeared in the literature.

Second, the model generates an additional prediction that has been ignored in the literature so far and that might allow researchers to directly test different competing theories about the sellers' behavior in the housing market. The main advantage of our model, we believe, is to make clear when loss aversion has a significant impact on the seller' behavior. Loss aversion does not play a role when the seller is in the gain domain and it also plays different roles in the loss domain depending on the size of the loss itself (overpricing vs. overpricing + bunching). This distinction should not be under-looked by the literature as the case of bunching is a distinctive feature of the reference-dependent model.

There may in fact be different competing explanations for why sellers tend to ask prices higher than the true market value of their house. One of them is overconfidence. In our model we assume the seller exactly knows how the price she chooses will affect her probability of selling. But some sellers might have wrong or excessively optimistic beliefs about the likelihood of selling their house at the price they want. Another plausible explanation would be projection bias. If a seller does not know what is the true market value of her house, her best guess about how much a buyer would be willing to pay is likely to be the same price at which she previously bought the house (excluding the possibility of big shocks in the market or of events that unambiguously modify the market value of the house).

We do not exclude *a priori* the possibility that these other theories could play a role in rationalizing the original findings of Genesove and Mayer. However, among the proposed explanations only loss aversion predicts that when the loss is positive but relatively small we should observe bunching.

Last, we provide evidence that the additional prediction of our model is not rejected in the data.

Indeed, we find that sellers that are at a small loss tend to ask a price in a small neighborhood (within \$2,000-\$10,000) of the original purchasing price. This finding constitutes suggestive evidence for bunching (CASE II in our theoretical model) and is robust to different specifications of the bunching range. As in Genesove and Mayer, we compare the behavior of homeowners and investors and find that the latter do not bunch around the original purchasing price of the house (neither they are subject to other effects of loss aversion).

There are several directions for future research based on the three findings:

(i) Expectations: our model does not have a clear theory of what the seller's expectations are when choosing the price to ask for her house. We implicitly assume the seller chooses a price that she thinks will be also the final transaction price. However, it is very likely that sellers in practice know they are going to face some sort of bargaining game and so they might start with asking a price above their desired or expected selling price.

(ii) The role of real estate agents: we could interview a sample of real estate agents to gather more information about the interaction with their clients. In fact, there likely is an agency problem between the agent who wants to sell as soon as possible to move to another contract and the homeowner who wants to sell at a price as high as possible. Our model predicts that loss-averse seller in the loss domain will ask a price above the market value for her house and thus will spend more time on the market waiting for a buyer. If this is the case, real estate agents might be less willing to work for homeowners who are in the loss domain because they would have to spend more time to conclude a sale.

Figure 3.1: How Loss-averse Seller Sets Listing Price Case 1

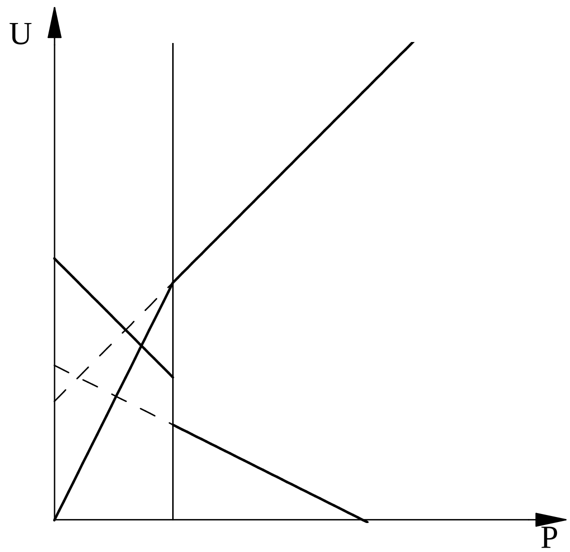

Figure 3.2: How Loss-averse Seller Sets Listing Price Case 2

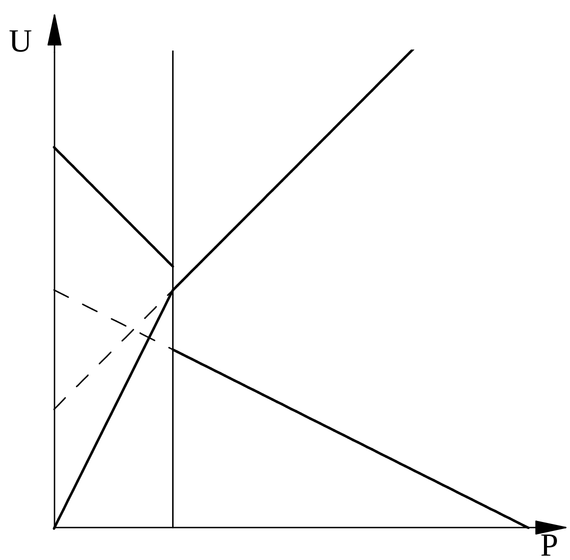

Figure 3.3: How Loss-averse Seller Sets Listing Price Case 3

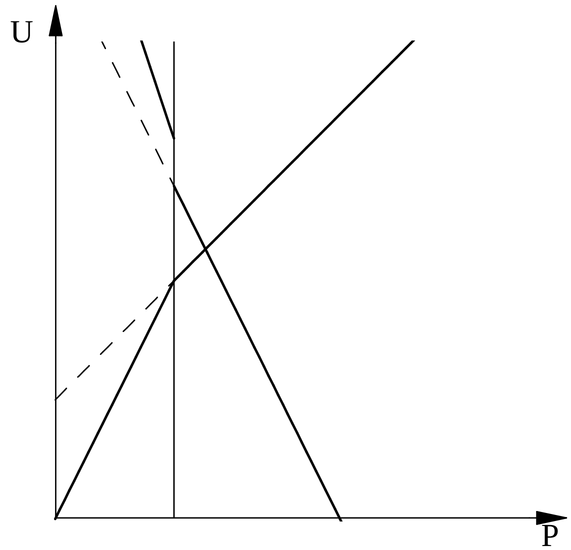

Figure 3.4: Sellers in Loss: Price Difference in Asking and Previous Transaction Price

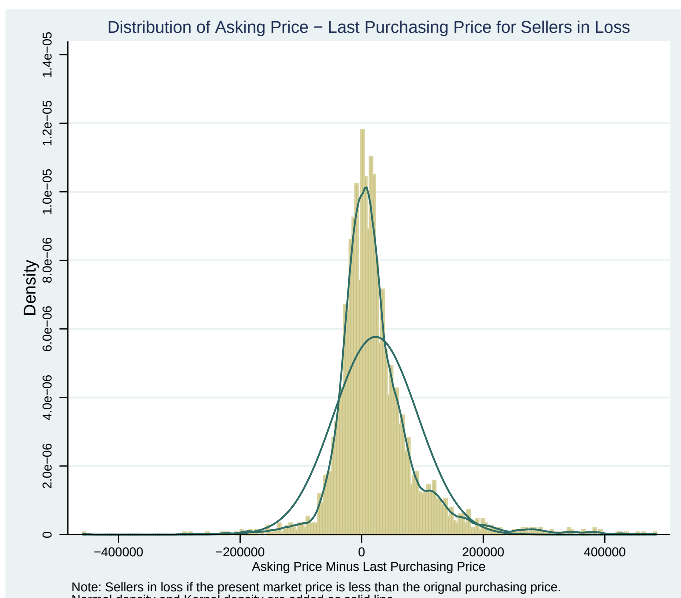

Figure 3.5: Sellers in Gain: Price Difference in Asking and Previous Transaction Price

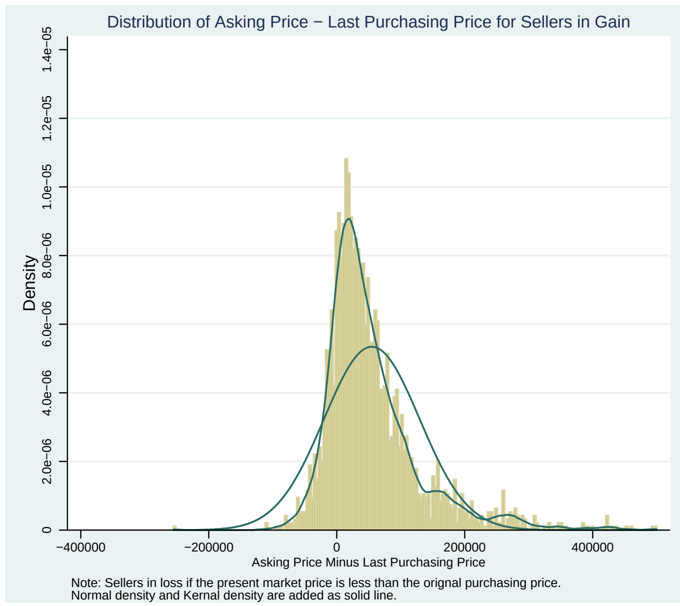

Figure 3.6: Price Difference in Asking and Previous Transaction Price in Redfin Data

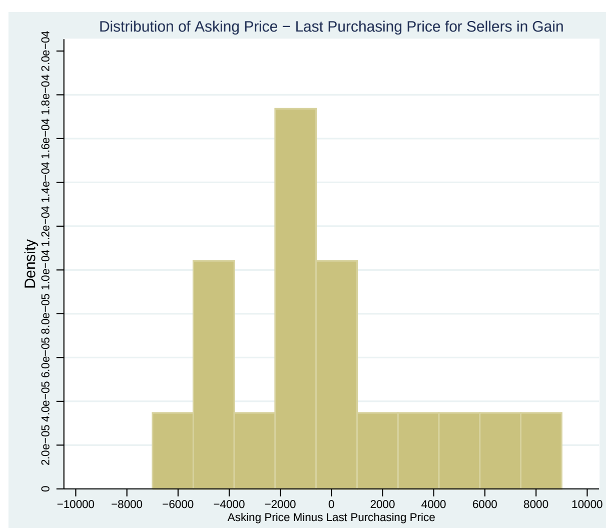

Table 3.1: Relative Bunching Rates of Asking Price in Boston Data

	Observations	$P_A = P_0$	$\lvert P_A - P_0 \rvert \leq 5,000$	$\lvert P_A - P_0 \rvert \leq 2,000$	$\lvert P_A - P_0 \rvert \leq 10,000$
Loss	3233	1.613	9.308	4.282	19.578
No Loss	2569	0.817	6.773	3.0751	14.130
Difference		0.796**	2.535***	1.206**	5.448***
		(0.284)	(0.712)	(0.493)	(0.979)

Note: Rates are presented as the percent of the given sample satisfying the given criteria regarding asking price.

Table 3.2: Relative Bunching Rates of Asking Price in Redfin Data

	Observations	$P_A = P_0$	$\lvert P_A - P_0 \rvert \leq 5,000$	$\lvert P_A - P_0 \rvert \leq 2,000$	$\lvert P_A - P_0 \rvert \leq 10,000$
Loss	1164	1.031	2.921	2.148	4.897
No Loss	546	0.366	2.198	1.282	3.297
Difference		0.665*	0.711	0.866	1.600
		(0.393)	(0.798)	(0.642)	(0.992)

Note: Rates are presented as the percent of the given sample satisfying the given criteria regarding asking price.

Table 3.3: Relative Bunching Rates of Market Price in Boston Data

	Observations	$P_M = P_0$	$\lvert P_M - P_0 \rvert \leq 5,000$	$\lvert P_M - P_0 \rvert \leq 2,000$	$\lvert P_M - P_0 \rvert \leq 10,000$
Loss	3233	0.000	11.356	4.406	24.666
No Loss	2569	0.000	12.729	5.099	26.041
Difference		0.000	−1.373	−0.693	−1.375
		(−−)	(0.862)	(0.565)	(1.151)

Note: Rates are presented as the percent of the given sample satisfying the given criteria regarding asking price.

Table 3.4: Relative Bunching Rates of Asking Price Across Classes of Ownership

Class		Observations	$P_A = P_0$	$\lvert P_A - P_0\rvert \leq 5,000$	$\lvert P_A - P_0\rvert \leq 2,000$	$\lvert P_A - P_0\rvert \leq 10,000$
Owner Occupants	Loss	1149	1.1314	11.488	4.5257	23.325
	No Loss	889	0.8999	6.6367	2.8121	13.161
	Difference		0.2315	4.8516***	1.7135**	10.1638***
			(0.4446)	(1.2578)	(0.8267)	(1.6858)
Investors	Loss	936	2.3504	10.577	5.7692	23.611
	No Loss	683	0.2928	8.9312	3.8067	19.327
	Difference		2.0576***	1.6457	1.9625*	4.2846**
			(0.5361)	(1.4830)	(1.0563)	(2.0508)
Double Difference			−1.8261**	3.2058*	−0.2490	5.8792**
			(0.6965)	(1.9445)	(1.3413)	(2.6548)

Note: Rates are presented as the percent of the given sample satisfying the given criteria regarding asking price. Standard errors for the differences are in parentheses. "Difference" denotes the difference within the given class of ownership between loss and non-loss cases. "*Double Difference*" is the difference in differences between the two classes of ownership. *** indicates $p < 0.01$, ** indicates $p < 0.05$, and * indicates $p < 0.1$.

Table 3.5: Regression of Asking Price on Loss and Market Value

	First		Second		Third		Fourth	
Loss	0.2197***	0.1891***	0.2543***	0.2519***	0.0900	0.0860	0.3003***	0.2974***
	(0.0671)	(0.0630)	(0.0545)	(0.0548)	(0.0641)	(0.0642)	(0.0647)	(0.0653)
LTV	0.0225	0.0270	0.0070	0.0073	0.0232	0.0230	0.0029	0.0031
	(0.0225)	(0.0228)	(0.0139)	(0.0141)	(0.0186)	(0.0186)	(0.0167)	(0.0166)
Est. Value in 1990	1.0828***	1.0826***	1.1107***	1.1111***	1.0747***	1.0747***	1.0752***	1.0753***
	(0.0337)	(0.0336)	(0.0222)	(0.0222)	(0.0270)	(0.0270)	(0.0195)	(0.0195)
Est. Current Price Index	0.9739***	0.9531***	0.8363***	0.8348***	0.6566***	0.6512***	0.7245***	0.7221***
	(0.0797)	(0.0735)	(0.0564)	(0.0564)	(0.0580)	(0.0590)	(0.0612)	(0.0611)
Months Since Last Sale	−0.0010***	−0.0010***	−0.0007***	−0.0007***	−0.0007***	−0.0007***	−0.0004**	−0.0004**
	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Residual		0.0621		0.1191		0.2686		0.1185
		(0.1127)		(0.2610)		(0.4049)		(0.3279)
Constant	−0.6090	−0.6053	−0.8780***	−0.9013***	−0.3520	−0.3748	−0.4917 ∗∗	−0.4952 ∗∗
	(0.4193)	(0.4170)	(0.2756)	(0.2793)	(0.3217)	(0.3150)	(0.2407)	(0.2411)
N	752	752	778	778	779	779	768	768
R^2	0.79	0.79	0.85	0.85	0.83	0.83	0.85	0.85

Note: Robust standard errors are in parentheses. *** indicates $p < 0.01$, ** indicates $p < 0.05$, and * indicates $p < 0.1$.

Table 3.6: Placebo Tests in Bunching Price using Boston Data

	$\widetilde{P_1}$	$\widetilde{P_2}$	$\widetilde{P_3}$	$\widetilde{P_4}$
$P_A = \widetilde{P}$	6	7	25	29
$\lvert P_A - \widetilde{P} \rvert \leq \$2,000$	159	156	141	-
$\lvert P_A - \widetilde{P} \rvert \leq \$5,000$	400	342	365	-
$\lvert P_A - \widetilde{P} \rvert \leq \$10,000$	780	818	864	-

Notes: $\widetilde{P_1} = .9P_0$, $\widetilde{P_2} = 1.2P_0$, $\widetilde{P_3} = 1,000 \times \text{round}\left(\frac{.9P_0}{1,000}\right)$, and $\widetilde{P_4} = 1,000 \times \text{round}\left(\frac{1.2P_0}{1,000}\right)$.

Table 3.7: Round vs Non-Round Prices in Selling Price using Boston Data

	Total	Round	Not Round
$P_A = P_0$	73 (52 at a loss)	72 (52 at a loss)	1 (0 at a loss)
$\lvert P_A - P_0 \rvert \leq \$2,000$	217 (138 at a loss)	173 (116 at a loss)	44 (22 at a loss)
$\lvert P_A - P_0 \rvert \leq \$5,000$	474 (301 at a loss)	350 (227 at a loss)	124 (73 at a loss)
$\lvert P_A - P_0 \rvert \leq \$10,000$	994 (634 at a loss)	743 (479 at a loss)	251 (152 at a loss)

Appendix A

Chapter 1

A.1 Summary Statistics

Table A.1: Distribution of Major and Occupation in NLSY79

	College Major		Occupation	
FIELD OF STUDIES/PROFESSION	Whole	S1	Whole	S1
0100 Agriculture and Natural Resources	1.5%	1.7%	10.4%	5.3%
0200 Architecture and Environmental Design	1.5%	1.3%	0.3%	0.6%
0300 Area Studies	0.2%	0.1%	0.0%	0.0%
0400 Biological Sciences	3.7%	4.7%	1.3%	1.5%
0500 Business and Management	26.5%	27.2%	27.8%	28.4%
0600 Communications	3.1%	2.2%	0.5%	0.9%
0700 Computer and Information Sciences	7.3%	8.5%	8.2%	9.0%
0800 Education	9.5%	9.8%	6.5%	10.4%
0900 Engineering	9.2%	10.0%	6.9%	6.3%
1000 Fine and Applied Arts	5.2%	4.7%	4.7%	4.8%
1100 Foreign Languages	0.7%	0.6%	0.1%	0.2%
1200 Health Professions	10.8%	10.8%	19.1%	18.9%
1300 Home Economics	0.9%	1.3%	1.9%	1.4%
1400 Law	1.4%	1.1%	0.4%	1.0%
1500 Letters	2.1%	1.3%	0.4%	0.6%
1600 Library Science	0.0%	0.0%	0.3%	0.3%
1700 Mathematics	1.4%	1.3%	0.1%	0.2%
1800 Military Sciences	0.2%	0.2%	0.5%	0.2%
1900 Physical Sciences	2.0%	1.8%	0.7%	0.6%
2000 Psychology	4.1%	3.2%	0.1%	0.2%
2100 Public Affairs and Services	3.8%	3.8%	9.6%	8.2%
2200 Social Sciences	4.9%	4.5%	0.2%	0.9%
2300 Theology	0.0%	0.0%	0.3%	0.5%

Table A.2: Family Income Distribution in NELS88

NELS88 Parent-Child Sample	Manager-Business	Teacher-Education
1988 Family Income		
$1,000 - $2,999	0.09%	0.14%
$3,000 - $4,999	0.09%	
$5,000 - $7,499	0.37%	0.57%
$7,500 - $9,999	0.82%	0.14%
$10,000 - $14,999	2.65%	1.28%
$15,000 - $19,999	3.38%	1.42%
$20,000 - $24,999	4.30%	6.10%
$25,000 - $34,999	14.72%	15.04%
$35,000 - $49,999	25.05%	29.79%
$50,000 - $74,999	28.88%	31.35%
$75,000 - $99,999	9.23%	7.94%
$100,000 - $199,999	8.32%	4.54%
$200,000 OR MORE	2.01%	1.28%
1992 Family Income		
$1,000-$2,999	0.09%	
$3,000-$4,999	0.18%	
$5,000-$7,499	0.37%	
$7,500-$9,999	0.82%	0.85%
$10,000-$14,999	2.10%	1.13%
$15,000-$19,999	3.38%	1.42%
$20,000-$24,999	4.11%	4.11%
$25,000-$34,999	8.96%	8.94%
$35,000-$49,999	17.55%	20.43%
$50,000-$74,999	31.54%	36.74%
$75,000-$99,999	13.25%	13.76%
$100,000-199,999	14.81%	10.50%
$200,000 OR MORE	2.83%	2.13%

A.2 Mapping occupations to college major

The NLSY79 code students' college majors in twenty-three categories. Each individual's occupation is recorded in 1970 Census Occupational Code. To link a sibling's occupation with a student's college major, I map all professional occupations in 1970 Census to a certain major by the college major held by the majority of college educated workers of that occupation. The mapping between major and occupations are in Table A3.

Table A.3: Mapping Occupations to College Majors

College Major	1970 Census Occupation Code							
0100 Agriculture and Natural Resources	25	801	802	821	822	*24*	*102*	*42*
0200 Architecture and Environmental Design	2	*213*	*95*					
0300 Area Studies	*135*							
0400 Biological Sciences	44	74	105	140	150	195	104	
0500 Business and Management	1	56	91	*116*	202	205	216 - 225	230 - 235
0600 Communications	184	192	193					
0700 Computer and Information Sciences	3	4	5	482	343	*156*	*172*	*342*
0800 Education	115-145	240	382	*952*				
0900 Engineering	006-023	*53*	55	112	151-162	*111*		
1000 Fine and Applied Arts	175	182-191	194	260	*181*			
1100 Foreign Languages	130							
1200 Health Professions	61-85	113	212	921-926	426			
1300 Home Economics	131	402	*26*	425	613			
1400 Law	*30*	31	*132*					
1500 Letters	130	*120*	126	362				
1600 Library Science	32	33						
1700 Mathematics	34	*35*	*36*	112	*156*			
1800 Military Sciences	471							
1900 Physical Sciences	43	45	51-54	151	*103*	*110*		
2000 Psychology	93	*114*						
2100 Public Affairs and Services	100	101	961-965					
2200 Social Sciences	94-96	91	*92*	*116*	*121*	*122*		
2300 Theology	86	90	*133*					

Note: Italic Occupation Code are not observed in NLSY79 data.

A.3 Structural Estimation

Table A.4: Rank of Population Preferences for College Major

1	Business and Management
2	Education
3	Engineering
4	Computer and Information Sciences
5	Biological Sciences
6	Health Professions
7	Social Sciences
8	Psychology
9	Public Affairs and Services
10	Fine and Applied Arts
11	Communications
12	Physical Sciences
13	Mathematics
14	Letters
15	Agriculture and Natural Resources
16	Home Economics
17	Architecture and Environmental Design
18	Law
19	Foreign Languages
20	Military Sciences
21	Library Science
22	Theology

A.4 Robustness Check

Table A.5: The Impact of a Sibling's Wage on a Student's Major Choice

Dependent Variable: **Student's Major = Sibling's Occupation**	(1)	(2)
Pre-Choice Sibling's Wage	0.0648***	0.0570***
	[0.0132]	[0.0131]
Pre-Choice Occupation Average Wage		0.202***
		[0.0363]
Sibling's Permanent Wage	-0.0126	-0.0223
	[0.0279]	[0.0272]
Ideal Occupation = Sibling's Occupation	0.411***	0.418***
	[0.0547]	[0.0538]
Same Gender with Sibling	0.0731***	0.0732***
	[0.0232]	[0.0229]
Education & Demographics	X	X
Observations	875	874
R-squared	0.181	0.202

Note:
1. Clustered standard errors by household in brackets.
2. Sibling's wage is measured by annual incomes in 2010 Dollars
3. Controls: gender, race, region, birth year, years of education, AFQT score, parents' education, and a student's the age when declaring the major.

Table A.6: Unconditional Correlation between Siblings' Wages

Dependent Variable:	Whole Siblings Sample		Siblings of Same Gender	
Student's Starting Wage	(1)	(2)	(3)	(4)
Sibling's Total Wage w_f	0.0950***		0.167***	
	[0.0347]		[0.0483]	
Sibling's Match Quality $\hat{M}_f$		0.077**		0.131***
		[0.0364]		[0.0478]
Sibling's Predictable Wage $\hat{\alpha}_f$		0.257**		0.310*
		[0.121]		[0.180]
Education & Demographics	X	X	X	X
Observations	866	843	474	462
R-squared	0.110	0.109	0.109	0.107

Note:
1. Clustered standard errors by household in brackets, *** p<0.01, ** p<0.05, * p<0.1
2. All wages are measured in logged hourly rate 2010 Dollars
3. Control variables include gender, race, region, and birth year dummies.

A.5 Discussion for $\bar{w}_1 > \bar{w}_2$ in Section 5.2

The average realized wage in group **1** is $\bar{w}_1$

$$
\begin{aligned}
\bar{w}_1 =& \frac{\iiint (A+M)\mathbf{1}(A+M>o)\mathbf{1}(M>0)f(M)h(o)g(A)dodAdM}{\iiint \mathbf{1}(A+M>o)\mathbf{1}(M>0)f(M)h(o)g(A)dodAdM} \\
=& \frac{\iint (A+M)H(A+M)\mathbf{1}(M>0)f(M)g(A)dAdM}{\iint H(A+M)\mathbf{1}(M>0)f(M)g(A)dAdM} \\
\doteq& \frac{X}{Y}
\end{aligned}
$$

The average realized wage in group **2** is $\bar{w}_2$

$$
\begin{aligned}
\bar{w}_2 =& \frac{\iiint (A+M)\mathbf{1}(A+M>o)\mathbf{1}(M<0)f(M)h(o)g(A)dodAdM}{\iiint \mathbf{1}(A+M>o)\mathbf{1}(M<0)f(M)h(o)g(A)dodAdM} \\
=& \frac{\iint (A+M)H(A+M)\mathbf{1}(M<0)f(M)g(A)dAdM}{\iint H(A+M)\mathbf{1}(M<0)f(M)g(A)dAdM} \\
\doteq& \frac{U}{V}
\end{aligned}
$$

$M = \lambda\eta_f$ and its p.d.f. is $f(M)$. η_f is the family wage shock with a normal distribution $N(0, \sigma_k^2)$. A is from another normal distribution $N(\mu, \sigma_\alpha^2)$, independently from M, its p.d.f. is $g(A)$. $H(\cdot)$ is the c.d.f. for Type I extreme value function with the scale parameter τ and location parameter 0.

To get some intuition for the above integral, recall that:

- A represents the predictable wage in log hourly rate, which is in the range of $[1.7, 2.7]$ for most students. Its mean $\mu = 2.2$
- $M = \lambda\eta_f$ is the correlated match quality component. $M = 0.1$ means a student's sibling receives a $\frac{10\%}{\lambda}$ increase in hourly wages. Students in my sample observe a $M \in [-0.5\lambda, 0.5\lambda]$.
- $f(M)$ is p.d.f. of a normal distribution $N(0, (\lambda\sigma_k)^2)$.
- According to the estimation in Section 3.8, $\lambda = 0.57$. σ_k in the data is 0.3335.
- $\int M \cdot \mathbf{1}(M > 0)f(M)dM = EM^+$ is the expectation of M at the right half of the distribution, $EM^+ = \frac{\sqrt{2}}{\sqrt{\pi}}\lambda\sigma_k = 0.15$
- $H(\cdot)$ is the c.d.f. of a Type I extreme value distribution, it is in the range of $[0, 1]$ and monotonically increasing.
- $A \pm M \in [1.4, 3.0]$ for most students in my data.

To prove $\frac{X}{Y} > \frac{U}{V}$, given that $X, Y, U, V > 0$, it is equivalent to prove $XV > YU$

Rewrite X as

$$\begin{aligned}
X &= \iint (A+M)H(A+M)\mathbf{1}(M>0)f(M)g(A)dAdM \\
&> \iint (A+M)H(A)\mathbf{1}(M>0)f(M)g(A)dAdM \\
&= \int AH(A)g(A)dA \int \mathbf{1}(M>0)f(M)dM + \int [\int M\mathbf{1}(M>0)f(M)dM]H(A)g(A)dA \\
&= 0.5 \int AH(A)g(A)dA + 0.15 \int H(A)g(A)dA \doteq X'
\end{aligned}$$

Rewrite V as

$$\begin{aligned}
V &= \iint H(A+M)\mathbf{1}(M<0)f(M)g(A)dAdM \\
&> \iint H(1.4)\mathbf{1}(M<0)f(M)g(A)dAdM \\
&= H(1.4)\int [\int \mathbf{1}(M<0)f(M)dM]g(A)dA = H(1.4)\cdot\frac{1}{2} \doteq V'
\end{aligned}$$

Rewrite U as

$$\begin{aligned}
U &= \iint (A+M)H(A+M)\mathbf{1}(M<0)f(M)g(A)dAdM \\
&< \iint (A+M)H(A)\mathbf{1}(M<0)f(M)g(A)dAdM \\
&= \int AH(A)g(A)dA \int \mathbf{1}(M<0)f(M)dM + \int [\int M\mathbf{1}(M<0)f(M)dM]H(A)g(A)dA \\
&= 0.5 \int AH(A)g(A)dA - 0.15 \int H(A)g(A)dA \doteq U'
\end{aligned}$$

Rewrite Y as

$$\begin{aligned}
Y &= \iint H(A+M)\mathbf{1}(M>0)f(M)g(A)dAdM \\
&< \iint H(3.0)\mathbf{1}(M>0)f(M)g(A)dAdM \\
&= H(3.0)\int [\int \mathbf{1}(M>0)f(M)dM]g(A)dA = H(3.0)\cdot\frac{1}{2} \doteq Y'
\end{aligned}$$

Notice that:

$$
\begin{aligned}
X > X' > 0 \\
V > V' > 0 \\
0 < Y < Y' \\
0 < U < U'
\end{aligned}
$$

Therefore, $X'V' - Y'U' > 0 \Rightarrow XV - YU > 0$. $X'V' - Y'U' > 0$ can be proved by following induction:

$$
\begin{aligned}
X'V' - Y'U' =& H(1.4)[0.5\int AH(A)g(A)dA + 0.15\int H(A)g(A)dA] \\
& - H(3)[0.5\int AH(A)g(A)dA - 0.15\int H(A)g(A)dA] \\
=& 0.5[H(1.4) - H(3)]\int AH(A)g(A)dA + 0.15[H(1.4) + H(3)]\int H(A)g(A)dA
\end{aligned}
$$

Remember that $H(1.4) - H(3) < 0$, $H(1.4) + H(3) > 0$, $A \in [1.7, 2.7]$, so

$$
\begin{aligned}
0.5[H(1.4) - H(3)]\int AH(A)g(A)dA > 0.5[H(1.4) - H(3)]\int AH(2.7)g(A)dA \\
0.15[H(1.4) + H(3)]\int H(A)g(A)dA > 0.15[H(1.4) + H(3)]\int H(1.7)g(A)dA
\end{aligned}
$$

Therefore

$$
\begin{aligned}
X'V' - Y'U' &> 0.5[H(1.4) - H(3)]H(2.7)\int Ag(A)dA + 0.15[H(1.4) + H(3)]H(1.7) \\
&= 0.5[H(1.4) - H(3)]H(2.7)\mu + 0.15[H(1.4) + H(3)]H(1.7) \doteq \Delta
\end{aligned}
$$

where $\mu = 2.2$ according to my data, and $H(\cdot)$ is the c.d.f. of Type I extreme value function with location parameter 0 and scale parameter τ.

For any τ, I find

$$
\Delta = 0.5[H(1.4) - H(3)]H(2.7) \cdot 2.2 + 0.15[H(1.4) + H(3)]H(1.7) > 0
$$

Thus $\frac{X}{Y} > \frac{U}{V}$, $\bar{w}_1 > \bar{w}_2$.

Appendix B

Chapter 2

B.1 A Search Model with Initial Asset

Reservation wage not only depends on the relative utility of staying on unemployed, also depends on cash-on-hand. In particular, if the unemployed workers has very low cash on hand, he will take any job offer. While if he has a good buffer when he lost his job, he might focus on non-monetary characteristics of the job, given the wage is above the highest reservation wage. Search intensity is determined by the utility difference between working and staying unemployed. A good representative example of current state of job search model with saving and variable searching effort and constant reservation wage is Chetty 2008.

Reservation Wage

The value function for an individual at the beginning of period t with assets A_t, is

$$V_t(A_t) = \frac{c_t^{1-\eta}}{1-\eta} + \delta V_{t+1}(A_{t+1})$$

Saving equals

$$i_t = \frac{A_{t+1}}{1+r} - A_t$$

If he finds a job at period t, consumption is

$$c_t = w_t - i_t - e_t = A_t - \frac{A_{t+1}}{1+r} + w_t$$

If he remains unemployed, his consumption is

$$c_t = b_t - i_t = A_t - \frac{A_{t+1}}{1+r} + b_t$$

For workers with a job:

The value function for an individual with a job at period t with wage w_t.

$$\begin{aligned}
W_t(A_t) &= \frac{c_t^{1-\eta}}{1-\eta} + \delta W_{t+1}(A_{t+1}) \\
c_t &= -i_t + w_t \\
i_t &= \frac{A_{t+1}}{1+r} - A_t \\
\sum_{i=t}^{\infty} \frac{c_i}{(1+r)^{i-t}} &= \sum_{i=t+1}^{\infty} \frac{w_i}{(1+r)^{i-t}} + A_t
\end{aligned}$$

Once the worker find the job, he knows w_t and e_t and his optimizing problem becomes

$$\begin{aligned}
\frac{\partial W_t(A_t)}{\partial c_t} &= c_t^{-\eta} + \delta \frac{\partial W_{t+1}(A_{t+1})}{\partial A_{t+1}} \cdot \frac{\partial A_{t+1}}{\partial c_t} \\
w_t - c_t &= \frac{A_{t+1}}{1+r} - A_t \\
\frac{\partial W_t}{\partial A_t} &= \delta \frac{\partial W_{t+1}}{\partial A_{t+1}}(1+r)
\end{aligned}$$

Euler equation:

$$c_t^{-\eta} = (1+r)\delta c_{t+1}^{-\eta}$$

Assume $(1+r)\delta = 1$, then optimal consumption path is $c_{t+1} = c_t$

Budget constraint takes the simple form:

$$\frac{c_t}{1-\delta} = \frac{w}{1-\delta} + A_t$$

Final solution is

$$\begin{aligned}
c_t^W &= w + (1-\delta)A_t \\
W_t(A_t) &= \frac{(w + (1-\delta)A_t)^{1-\eta}}{(1-\delta)(1-\eta)}
\end{aligned}$$

Unemployed workers face a decision with following value function, budget constraint at each period, and life-time budget constraint.

$$\begin{aligned}
J_t(A_t) &= \frac{c_t^{1-\eta}}{1-\eta} + \delta s Pr(w_t > w_t^*) E[W_t(A_t, w) | w > w_t^*] + \delta(1 - sPr(w_t > w_t^*)) J_{t+1}(A_{t+1}) \\
c_t &= -i_t + b_t = -\frac{A_{t+1}}{1+r} - A_t + b_t
\end{aligned}$$

with reservation wage w_t^*, a worker is indifferent between accepting the job with wage w_t^* and staying unemployed.

$$\begin{aligned} J_{t+1}(A_{t+1}) &= W_{t+1}(A_{t+1}, w_t^*) = \frac{(w_t^* + (1-\delta)A_t)^{1-\eta}}{(1-\delta)(1-\eta)} \\ w_t^* &= ((1-\delta)(1-\eta)J_{t+1}(A_{t+1}))^{1/(1-\eta)} - (1-\delta)A_t \end{aligned}$$

More restrictions on reservation wage include

$$\begin{aligned} w_t^* = 0,\ A_t < \underline{A} \\ w_t^* = w_0,\ A_t > \bar{A} \end{aligned}$$

UI benefit eligibility requires

$$\begin{aligned} b_t = b,\ t \le T_1 \\ b_t = 0,\ otherwise \end{aligned}$$

Maximizing $J_t(A_t)$ generates following F.O.C.

$$\begin{aligned} \frac{\partial J_t}{\partial c_t} &= c_t^{-\eta} - (1 - sPr(w_t > w_t^*))\delta(1+r)\frac{\partial J_{t+1}}{\partial A_{t+1}} = 0 \\ \frac{\partial J_t}{\partial A_t} &= s\delta Pr(w_t > w_t^*)E[(w + (1-\delta)A_t)^{-\eta} | w > w_t*] \\ &\quad +(1 - sPr(w_t > w_t^*))\delta(1+r)\frac{\partial J_{t+1}}{\partial A_{t+1}} \end{aligned}$$

Euler equation:

$$\begin{aligned} c_t^{-\eta} &= s\delta Pr(w_{t+1} > w_{t+1}^*)(1 - sPr(w_{t+1} > w_{t+1}^*))E[(w + (1-\delta)A_{t+1})^{-\eta} | w > w_{t+1}^*] \\ &\quad +c_{t+1}^{-\eta}(1 - sPr(w_t > w_t^*)) \end{aligned}$$

Summarized solution of the model is

$$\begin{aligned} w_t^* &= ((1-\delta)(1-\eta)J_{t+1}(A_{t+1}))^{1/(1-\eta)} - (1-\delta)A_t \\ w_t^* &= 0,\ A_t < \underline{A} \\ w_t^* &= w_0,\ A_t > \bar{A} \\ A_{t+1} &= (A_t - c_t + b_t)(1+r) \end{aligned}$$

Comparative Statics

$$
\begin{aligned}
\frac{\partial w_t^*}{\partial A_t} &= (1-\delta)(J_{t+1}^{\eta/(1-\eta)}\frac{\partial J_{t+1}}{\partial A_{t+1}}\frac{dA_{t+1}}{dA_t} - 1) > 0 \\
\frac{\partial w_t^*}{\partial b_t} &= (1-\delta)J_{t+1}^{\eta/(1-\eta)}\frac{\partial J_{t+1}}{\partial b_t} > 0
\end{aligned}
$$

$\frac{\partial w_t^*}{\partial A_t}$ shows the effect of increase severance pay on reservation wage and $\frac{\partial w_t^*}{\partial b_t}$ indicates the effect of increase unemployment benefit. Both derivatives' magnitude decreases as initial asst (cash-on-hand) increases. With the same amount of total money paid between lump-sum severance pay and UI benefit, increasing benefit has larger the impact on reservation wage.

Similarly

$$
T_1 = (1-\delta)J_{t+1}^{\eta/(1-\eta)}\frac{\partial J_{t+1}}{\partial T_1} > 0, \ if\, t < T_1.
$$

As the extension of UI benefit increases the value of staying unemployed, reservation wage increases as the duration of eligibility is extended, while the influence of extension smaller with higher initial asset. Come back to the bounding condition of reservation wage. All previous comparative statics are conditional on $\underline{A} < A_t < \bar{A}$. If $A < \underline{A}$ or $A_t > \bar{A}$, reservation wage will be 0 or at a constant reasonable high level. Policy impact on reservation wage is smaller compared to no-saving case as unemployed workers also adjust searching intensity to accommodate the change of utility difference between working and unemployed. Searching effort and reservation wage jointly determine the duration of unemployment. Assume workers can optimize searching effort, the impact of UI policy change on search intensity is larger for workers with lower initial asset.

Bibliography

[1] Joseph G. Altonji, Erica Blom, and Costas Meghir. "Heterogeneity in Human Capital Investments: High School Curriculum, College Major, and Careers". In: *NBER Working Paper No. 17985* (2012).

[2] E. Anenberg. "Loss Aversion, Equity Constraints and Seller Behavior in the Real Estate Market". In: *Regional Science and Urban Economics* 41.1 (2011), pp. 67–76.

[3] Peter Arcidiacono. "Ability Sorting and the Returns to College Major". In: *Journal of Econometrics* 121.1-2 (2004), pp. 343–375.

[4] Peter Arcidiacono, Joseph Hotz, and Songman Kang. "Modeling College Major Choices Using Elicited Measures of Expectations and Counterfactuals". In: *Journal of Econometrics* 166.1 (2012), pp. 3–16.

[5] Barbara J. Bank, Ricky L. Slavings, and Bruce J. Biddle. "Effects of Peer, Faculty, and Parental Influences on Students' Persistence". In: *Sociology of Education* 63.3 (1990), pp. 208–225.

[6] Magali Beffy, Denis Fougere, and Arnaud Maurel. "Choosing the Field of Study in Post-Secondary Education: Do Expected Earnings Matter?" In: *The Review of Economics and Statistics* 94.1 (2012), pp. 334–347.

[7] Gerard J. van den Berg. "Nonstationarity in Job Search Theory". In: *Review of Economic Studies* 57.2 (1990), pp. 255–277.

[8] Mark C. Berger. "Predicted Future Earnings and Choice of College Major". In: *Industrial and Labor Relations Review* 41.3 (1988), pp. 418–429.

[9] Julian R. Betts. "What Do Students Know about Wages? Evidence from a Survey of Undergraduates". In: *Journal of Human Resources* 31.1 (1996), pp. 27–56.

[10] Sandra Black and Paul J. Devereux. "Recent Developments in Intergenerational Mobility". In: *Handbook of Labor Economics* 4.5 (2011), pp. 1489–1541.

[11] Erica Blom. "Labor Market Determinants of College Major". In: *Manuscript* (2012).

[12] Gene H. Brody. "Sibling Relationship Quality: Its Causes and Consequences". In: *Annual Review of Psychology* 49 (1998), pp. 1–24.

[13] Stephen V. Cameron and James J. Heckman. "The dynamics of educational attainment for black, hispanic, and white males". In: *Journal of Political Economy* 109.3 (2001), pp. 455–499.

[14] D. R. Capozza, P. H. Hendershott, and C. Mack. "An Anatomy of Price Dynamics in Illiquid Markets: Analysis and Evidence from Local". In: *Real Estate Economics* 32.1 (2004), pp. 1–32.

[15] David Card, Raj Chetty, and Andrea Weber. "Cash-On-Hand and Competing Models of Intertemporal Behavior New Evidence from the Labor Market". In: *The Quarterly Journal of Economics* 122.4 (2007), pp. 1511–1560.

[16] David Card and Dean R. Hyslop. "Estimating the Effects of a Time-Limited Earnings Subsidy for Welfare-Leavers". In: *Econometrica* 73.6 (2005), pp. 1723–1770.

[17] K. E. Case and Robert. J. Shiller. "The Efficiency of the Market for Single-Family Homes". In: *American Economic Reivew* 79.1 (1989), pp. 125–137.

[18] Mario Centeno and Alvaro A. Novo. "The Impact of Unemployment Insurance Generosity on Match Quality Distribution". In: *Economics Letters* 93.2 (2006), pp. 235–241.

[19] Raj Chetty. "Moral Hazard versus Liquidity and Optimal Unemployment Insurance". In: *Journal of Political Economy* 116.2 (2008), pp. 173–234.

[20] Kathleen P. Classen. "The Effect of Unemployment Insurance on the Duration of Unemployment and Subsequent Earnings". In: *Industrial and Labor Relations Review* 30.4 (1977), pp. 438–444.

[21] Miles Corak and Patrizio Piraino. "The Intergenerational Transmission of Employers". In: *Journal of Labor Economics* 29.1 (2011), pp. 37–68.

[22] David M. Cutler, James M. Poterba, and Lawrence H. Summers. "Speculative dynamics". In: *The Review of Economic Studies* 58.3 (1991), pp. 529–546.

[23] Stefano DellaVigna and M. Daniele Paserman. "Job Search and Impatience". In: *Journal of Labor Economics* 23.3 (2005), pp. 527–588.

[24] Greg J. Duncan, Johanne Boisjoly, and Kathleen M. Harris. "Sibling, Peer, Neighbor, and Schoolmate Correlations as Indicators of the Importance of Context for Adolescent Development". In: *Demography* 38.3 (2001), pp. 437–447.

[25] Hanming Fang and Dan Silverman. "On the compassion of time-limited welfare programs". In: *Journal of Public Economics* 88.7 (2004), pp. 1445–1470.

[26] Fredrick A. Flyer. "The Influence of Higher Moments of Earnings Distributions on Career Decisions". In: *Journal of Labor Economics* 15.4 (1997), pp. 689–713.

[27] Nicole M. Fortin. "The Gender Wage Gap among Young Adults in the United States: The Importance of Money versus People". In: *Journal of Human Resources* 43.4 (2008), pp. 884–918.

[28] Richard B. Freeman. "A Cobweb Model of the Supply and Starting Salary of New Engineers". In: *Industrial and Labor Relations Review* 29.2 (1976), pp. 236–248.

[29] Richard B. Freeman. "Legal Cobwebs: a Recursive Model of the Labor Market for New Lawyers". In: *The Review of Economics and Statistics* 57.2 (1975), pp. 171–179.

[30] Richard B. Freeman. "Supply and Salary Adjustments to the Changing Science Manpower Market: Physics, 1948-1973". In: *The American Economic Review* 65.1 (1975), pp. 27–39.

[31] Justin Gallagher. "Learning about an Infrequent Event: Evidence from Flood Insurance Take-up in the US". In: *Manuscript* (2013).

[32] David Genesove and Christopher Mayer. "Loss Aversion and Seller Behavior: Evidence from the Housing Market". In: *Quarterly Journal of Economics* 116.4 (2001), pp. 1233–1260.

[33] E. L. Glaeser et al. "Housing Dynamics". In: *Working Paper* (2013).

[34] Adam M. Guren. "The Causes and Consequences of House Price Momentum". In: *Working Paper* (2014).

[35] Daniel S. Hamermesh and Stephen G. Donald. "The Effect of College Curriculum on Earnings: An Affinity Identifier for Non-ignorable Non-response Bias". In: *Journal of Econometrics* 144.2 (2008), pp. 479–491.

[36] Judith K. Hellerstein and Melinda S. Morrill. "Dads and Daughters The Changing Impact of Fathers on Women's Occupational Choices". In: *Journal of Human Resources* 46.2 (2011), pp. 333–372.

[37] Caroline M. Hoxby and Christopher Avery. "The Missing One-Offs: The Hidden Supply of High-Achieving, Low Income Students". In: *NBER Working Paper* 18586 (2012).

[38] Herbert H. Hyman. "The Psychology of Status". In: *Archives of Psychology (Columbia University)* 269 (1942), p. 94.

[39] Robert Jensen. "The (Perceived) Returns to Education and the Demand for Schooling". In: *The Quarterly Journal of Economics* 125.2 (2010), pp. 515–548.

[40] Boyan Jovanovic. "Job Matching and the Theory of Turnover". In: *Journal of Political Economy* 87.5 (1979), pp. 972–990.

[41] Daniel Kahneman and Amos Tversky. "Prospect Theory: An Analysis of Decision under Risk". In: *Econometrica* 47.2 (1979), pp. 263–291.

[42] Michael P. Keane and Kenneth I. Wolpin. "The Career Decisions of Young Men". In: *Journal of Political Economy* 105.3 (1997), pp. 473–522.

[43] Nicholas M. Kiefer and George R. Neumann. "An Empirical Job-Search Model, with a Test of the Constant Reservation-Wage Hypothesis". In: *Journal of Political Economy* 87.1 (1979), pp. 89–107.

[44] Botond Koszegi and Matthew Rabin. "A Model of Reference-Dependent Preferences". In: *Quarterly Journal of Economics* 121.4 (2006), pp. 1133–1165.

[45] David Laibson, Andrea Repetto, and Jeremy Tobacman. "Estimating Discount Functions with Consumption Choices over the Lifecycle". In: *NBER Working Paper* 13314 (2007).

[46] Tony Lancaster and Andrew Chesher. "An Econometric Analysis of Reservation Wages". In: *Econometrica* 51.6 (1983), pp. 1661–1676.

[47] Lung-Fei Lee. "Specification Error in Multinomial Logit Models: Analysis of the Omitted Variable Bias". In: *Journal of Econometrics* 20.2 (1982), pp. 197–209.

[48] John List. "Does Market Experience Eliminate Market Anomalies?" In: *Quarterly Journal of Economics* 118.1 (2003), pp. 41–71.

[49] Charles F. Manski and David A. Wise. *College Choice in America*. Cambridge, Mass.: Harvard University Press, 1983.

[50] A. Markle et al. "Goals as reference points in marathon running: A novel test of reference dependence". In: *Working Paper* (2013).

[51] John J. McCall. "Economics of Information and Job Search". In: *The Quarterly Journal of Economics* 84.1 (1970), pp. 113–126.

[52] Bruce D. Meyer. "Lessons from the U.S. Unemployment Insurance Experiments". In: *Journal of Economic Literature* 33.1 (1995), pp. 91–131.

[53] M. Daniele Paserman. "Job Search and Hyperbolic Discounting: Structural Estimation and Policy Evaluation". In: *The Economic Journal* 118.531 (2008), pp. 1418–1452.

[54] Jaewoo Ryoo and Sherwin Rosen. "The Engineering Labor Market". In: *Journal of Political Economy* 112.S1 (2004), S110–S140.

[55] Johannes F. Schmieder, Till von Wachter, and Stefan Bender. "The Effects of Extended Unemployment Insurance Over the Business Cycle: Evidence from Regression Discontinuity Estimates over Twenty Years". In: *Working Paper* (2010).

[56] Reza Shabani. "Corporate News, Asset Prices, and the Media". In: *Manuscript* (2010).

[57] Aloysius Siow. "Occupational Choice under Uncertainty". In: *Econometrica* 52.3 (1984), pp. 631–645.

[58] Johannes Spinnewijn. "Unemployed but optimistic: Optimal insurance design with biased beliefs". In: *London School of Economics* Mimeo (2010).

[59] Harry P. Weast. "The Influence of Older Siblings". In: *The High School Journal* 39.6 (1956), pp. 340–343.

[60] Robert J. Willis and Sherwin Rosen. "Education and Self-Selection". In: *Journal of Political Economy* 87.5 (1979), S7–S36.

[61] Matthew Wiswall and Basit Zafar. "Determinants of College Major Choice: Identification Using an Information Experiment". In: *Working Paper* (2012).