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Essays in labor and information economics

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ESSAYS IN LABOR AND INFORMATION ECONOMICS

by

Sun Hyung Kim

A thesis submitted in partial fulfillment of the
requirements for the Doctor of Philosophy
degree in Economics
in the Graduate College of
The University of Iowa

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Thesis Supervisor: Associate Professor David Frisvold

To my parents,

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ABSTRACT

This dissertation contributes to theoretical and empirical studies in microeconomics, with a focus on evaluating policy relevant problems to provide new insights into questions. Within labor economics, I strive to understand the labor market returns to skills, taking into consideration the business cycle. In the first chapter, I investigate how the labor market returns to cognitive skills and social skills vary during recessions. In the second chapter, I examine the short-, medium and long-term career outcomes of college graduates as a function of economic conditions at graduation and both cognitive and social skills. In the third chapter, within information economics, I study how asymmetric information and demand uncertainty influence pricing strategies through learning.

In Chapter 1, I examine how labor market returns to cognitive skills and social skills vary with the business cycle over the past 20 years, using data from the NLSY79 and the NLSY97. Exploiting a comparable set of cognitive and social skill measures across survey waves, I show that an increase in the unemployment rate led to higher demand for cognitive skills in the 2000s. High unemployment also sorted more workers into information use intensive occupations that require computer skills in the 2000s, but it sorted more workers into routine occupations in the 1980s and 1990s. This evidence suggests that recessions accelerate the restructuring of production toward routine-biased technologies. I also find that the returns to social skills increase during periods of high unemployment, though only in terms of the likelihood of full-time employment for experienced workers. Furthermore, an increase in unemployment increases the social skill task intensity of a worker's occupation

in the 2000s, while it shows the contrary in the 1980s and 1990s. Based on these results, I argue that routine-biased technological change may not readily substitute for workers in tasks requiring interpersonal interaction, and therefore such technologies demand experienced laborers who have high social skills during recessions.

In Chapter 2, I study the impacts of entry conditions on labor market outcomes to cognitive and social skills for the US college graduating classes of 19791989. Using the National Longitudinal Survey of Youth 1979, I find that Workers with higher cognitive skills are more likely to be employed, find job more quickly and have higher-quality employment, while those with higher social skills voluntarily switch jobs more often. I also show that graduating in a worse economy intensifies the roles of social skills, allowing workers with higher social skills to catch up more quickly from poor initial conditions by switching jobs more often. This could partly explain why wage returns to cognitive skills declines but wage returns to social skills increases from graduating in recessions.

In Chapter 3, We consider a dynamic pricing problem facing a seller who has private information about the quality of her good, but is uncertain about the arrival rate of buyers. Restricting attention to the equilibria in which the high-quality seller insists on a constant price, we show that the low-quality seller's expected payoff and equilibrium pricing strategy crucially depend on buyers' knowledge about the demand state. If they are also uncertain about the demand state, then demand uncertainty increases the low-quality seller's expected payoff, and her optimal pricing strategy is to offer a high price initially and drop it to a low price later. If buyers know the demand state, then demand uncertainty does not affect the low-quality seller's expected payoff, and a simple cutoff pricing strategy cannot be a part of equilibrium. In the latter case, we show that there exists an equilibrium in which the low-quality seller begins with a low price, switches up to a high price, and eventually reverts back to the low price.

PUBLIC ABSTRACT

This dissertation contributes to theoretical and empirical studies in microeconomics, with a focus on evaluating policy relevant problems to provide new insights into questions. Within labor economics, I strive to understand the labor market returns to skills, taking into consideration the business cycle. In the first chapter, I investigate how the labor market returns to cognitive skills and social skills vary during recessions. In the second chapter, I examine the short-, medium and long-term career outcomes of college graduates as a function of economic conditions at graduation and both cognitive and social skills. In the third chapter, within information economics, I study how asymmetric information and demand uncertainty influence pricing strategies through learning.

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CHAPTER 1
RECESSIONS AND LABOR MARKET RETURNS TO COGNITIVE AND SOCIAL SKILLS

1.1 Introduction

A long literature in economics demonstrates that recessions spur changes in labor inputs, in a manner consistent with technological change. Beginning with the Schumpeter cleansing model, in which older, less productive firms are replaced by newer, more productive firms (Schumpeter 1939), several classes of theoretical models with adjustment costs have attempted to explain this result. For instance, during recessions, firms may experience a negative product demand shock, which lowers the opportunity cost to adjust production (Hall 2005), changes the costs and benefits of firing employees (Berger 2012, Jaimovich and Siu 2012) or managerial attention from growth to efficiency (Koenders and Rogerson 2005). This negative demand shock induces firms in the face of technological change to reallocate or restructure optimally.

Clearly, changes in technology alter the types of jobs available and what those jobs pay. In the last few decades, one noticeable change has been job polarization, in which employment disproportionately shifts from occupations in the middle of the skill distribution to those at the top and bottom of the skill distribution. The compelling explanation for this phenomenon is that the technological change is biased towards replacing middle-skill labor in routine tasks (routine-biased technological change, RBTC), and in turn complementary to high-skill cognitive jobs (Autor et al. 2003; Autor et al. 2008; Goos and Manning 2007; Autor and Dorn 2013). If this is the case, we might expect to see the rising importance of cognitive skills in recessions driven by such technological changes.

Although information technology has proven advantageous in high-skilled labor, technology cannot fully replace person-to-person interaction for tasks such as communication and persuasion (Autor 2015). Therefore, recent technological change may amplify the comparative advantage of workers in supplying social skills. If this is the case, the demand for social skills would rise during recessions and thus the returns to social skills would increase.

In this paper, I show that recessions spurred changes in labor demand in a way consistent with routine biased technological change, by focusing on returns to both cognitive and social skills and occupation task intensity associated with these skills. In particular, I find that the RBTC literature has only partially captured the recent phenomenon; RBTC leads to higher demand for experienced workers who have high social skills as well as high cognitive skills.

This result draws on a number of important literature. First, I provide evidence that recessions lead firms to restructure their production toward greater use of routine-biased technologies. Whether technological changes are episodic - concentrated around recessions - or smooth is an important policy issue to understand how to reallocate workers following a recession. Second, my measure of sociability provides a unique opportunity to study social skills across cohorts. I modified a measure of social skills constructed by Deming (2017) in a way to maximize comparability across survey waves and support robust findings. Third, I contribute to a growing literature documenting the labor market returns to both cognitive skills and social skills. My findings help to clarify work by Deming (2017) in addition to consideration of business cycle.

In this paper, I begin by investigating the relative importance of cognitive and social skills during recessions. Using data from the 1979 and 1997 National Longitudinal Surveys of Youth (NLSY79 and NLSY97, respectively), I compare how the labor market returns (wage and employment) to both cognitive and social skills vary with the business cycle. Cognitive skills, social skills and other covariates are defined to maximize the comparability across NLSY waves; cognitive skills are captured by performance on the Armed Services Vocational Aptitude Battery (ASVAB) test, and social skills are measured via two questions that capture the extroversion factor from the Big 5 personality inventory (e.g. Goldberg 1993; Judge et al. 1999; Barrick and Mount 1991). For the baseline model, I restrict the sample to ages 23-33 to exploit the overlap in ages across cohorts, while I remove this age restriction to capture how sufficiently experienced workers alters the results in later sections.

Exploiting variation in economic conditions of cohorts between the ages of 23 and 33 who entered the labor market in the mid-1980s and the mid-2000s, I establish a new fact: during recessions, there has been a growing emphasis on cognitive skills, but not social skills. My estimates suggest that a one standard deviation increase in the unemployment rate lowers the wage return to cognitive skills from 17.5 percent to 15.9 percent in the 1980s. In contrast, in the 2000s, a one standard deviation increase in the unemployment rate yields a wage gain from 7.3 percent to 9.2 percent. However, the returns to social skills are not significantly affected by the unemployment rate across survey waves.

These results raise the possibility that a structural shift in demand for skill occurred in line with RBTC. Particularly, cognitive skills are known to complement routine-biased technologies (Autor et al. 2003; Brynjolfsson and McAfee 2011). In this case, we would expect changes in returns to cognitive skills to be accelerated by an adoption of such technologies. While I cannot directly measure the IT capital investments, I use the empirical analogs, the content of workplace tasks; routine, social skills, information use and math task intensities. These are created by Deming (2017) who uses data sets from the 1998 Occupational Information Network (O*NET) to measure task content of occupations.

Indeed, in the 2000s, I find that an increase in the unemployment rate sorts more workers into information use-intensive occupations that require computer skills, while it reduce the information use task intensity in the 1980s and 1990s. Cognitive skills can be partially captured by other task measures, such as nonroutine analytical or deductive and inductive reasoning. I thus additionally explore different task content of occupations. I find that an increase in the unemployment rate increases both nonroutine analytical (math) and deductive and inductive reasoning task intensities of occupations[1]. Taken together, increased demand for cognitive skills during recession appears closely linked to the routine-biased technological change in recent decades. This is consistent with Hershbein and Kahn (2016), who show that firms located in areas more severely affected by the Great Recession were induced to restructure their production toward greater use of technology and higher-skilled workers.

[1]In a previous version of this paper, I additionally looked at the deductive and inductive reasoning, which is the average of three ability variables, 1) written comprehension, 2) deductive reasoning and 3) inductive reasoning. The results are not introduced here, because the occupation-level correlation between the information use intensity and deductive and inductive reasoning task intensity is so high that both task intensities of worker's occupation show very similar results.

Furthermore, if occupational sorting is indeed linked with routine-biased technology, I would expect the strongest change to routine occupations that are most susceptible to such technologies. For routine occupations, I see evidence consistent with the traditional view exhibited in the job polarization literature and the technological change model with adjustment costs. That is, as unemployment increased, more workers sorted into routine occupations in the 1980s and 1990s but they were less likely to sort into routine occupations in the 2000s. Overall, these evidences support that recessions hasten technical changes in a way that the computers substitute for workers in performing routine tasks.

However, in contrast to this conventional view of RBTC, an increase in unemployment also increases the social skill task intensity of occupations in the 2000s, and this sorting leads to within-worker wage gains that are increasing in the unemployment rate. This indicates that changes in labor demand include social skills as well as cognitive skills. This is something of puzzle, especially given the estimation results of the baseline model that labor market outcomes to social skills do not vary with the unemployment. I hypothesize part of the solution to this puzzle is that social skills are actually required at a relatively later age, as workers' experience grow. Specifically, social skills gain importance in professional, technical, and managerial occupations which require high education and long experience. I demonstrate that the social skill task intensity becomes highest among all other tasks when workers have about 15 years of experience.

These patterns increase the likelihood that an adoption of new technologies requires "experienced" workers in tasks requiring social skills. In the baseline model, I limit my analysis to the 23-33 age group in order to exploit the overlap between the NLSY79 and

NLSY97. This may be the reason why my estimations do not capture the importance of social skills during recessions. I thus focus on sufficiently experienced workers and additionally explore the labor market returns to skills with the unemployment rate. I find that, with an indicator for being employed, an interaction between social skills and the unemployment rate is positive and statistically significant; an increase in the unemployment rate increases the returns to social skills from 1.2 percent to the 1.7 percent in terms of the probability of full-time employment. Although it does not show a significant effect with wage, I show the link between social skills and routine-biased technological changes in recessions.

To better understand the impacts of social skills on labor market outcomes and different results between wages and full-time employment probability, I next examine the decisions of workers on labor supply and job change. It turns out that workers with higher social skills are likely to change jobs more often, but social skills have no bearing on retaining the current jobs. These results suggest various interpretation. It is unclear if workers with higher social skills are able to increase the probability of employment or changing jobs based on their network or connection, or if employers prefer workers with higher social skills as a way to overcome the economic crisis because social networks benefit firms during recessions. What is clear is that social skills become valuable in a bad economy.

To sum up, my results suggest that firms affected by recessions have been induced to restructure their production toward greater use of technology and higher cognitive skills. I also argue that recently, the social skills are likely to gain importance because such technological changes demand experienced labors having high social skills.

To the best of my knowledge, this is the first study to provide evidence that recessions spur changes in labor demand in terms of both cognitive and social skills. A growing body of work studies the labor market return to noncognitive skills or soft skills, including social skills and leadership skills, with little thought of business cycle (Kuhn and Weinberger 2005; Heckman et al. 2006; Lindqvist and Vestman 2011; Heckman and Kautz 2012; Borghans et al. 2014; Deming 2017). In particular, this paper builds on the observation of Deming (2017), which investigates the growing importance of social skills. The polarization literature mainly focuses on RBTC complementary to only high-skill cognitive jobs. This paper can be viewed as an attempt to extend and formalize two particular dimensions of tasks that cannot be readily substituted by technological changes – the cognitive skill and the ability to work and communicate with others.

Furthermore, RBTC cannot explain why employment and wages recently have not grown in high-skill occupations, in spite of its success in explaining many decades of data. Growing importance of social skills in conjunction with cognitive skills during recessions can be an alternative hypothesis to explain this phenomenon.

1.2 Data

The main data source is from the 1979 and 1997 waves of the National Longitudinal Survey of Youth (NLSY). The NLSY79 is a nationally representative sample of 12,686 youth ages 14 to 22 in 1979, and the NLSY97 samples 8,984 youth ages 12 to 16 in 1997. The data contains detailed measures of pre-market ability, education, parental and personal characteristics, employment and wages. Most variables across the NLSY79 and NLSY97 are compatible, but some variables which are not comparable are adjusted to facilitate comparison. Specifically, Altonji et al. (2012) suggest methods to achieve compatibility, and I mainly follow their methodologies where applicable.

Respondents under the age of 23 and over the age of 33 are excluded from the analysis, since the oldest individual in the NLSY97 turned 33 in the 2013. By restricting the sample to ages 23-33, I can exploit the overlap in ages across surveys. This suggests that I can compare workers during the 1980-1998 period to youth during the recent 2003-2013 period. Individuals who are enrolled in school and in military service and who are missing information on key variables are excluded from the analysis. My main outcome is the real log hourly wage (indexed to 2013 dollars) conditional on full-time employment and an indicator for full-time employment. I consider individuals who earn real hourly wages within the range of \$3 to \$200, following Altonji et al. (2012). Note that the results are robust to alternative outcome variables such as using log annual earnings or conditioning on 20 or more weeks of full-time work.

Armed Forces Qualifying Test (AFQT) has been widely used as the proxy for cognitive skills. Many other studies (e.g., Neal & Johnson 1996; Altonji et al. 2012) use AFQT scores in the literature as a measure of the cognitive achievement. AFQT scores are adjusted following a procedure described in Altonji et al. (2012); they achieve comparability between NLSY79 and NLSY97 by considering differences in in test format, age-at-test and other idiosyncrasies. I use normalized test scores to have mean zero and standard deviation one.

Deming (2017) constructs a pre-market measure of social skills, which is used as proxy for social skills. Since none of the panel surveys includes psychometrically valid and field-tested measures of social skills, Deming (2017) constructs a measure of social skills that measures behavioral extroversion and prosocial orientation as an alternative. For instance, a measure of social skills in the NLSY79 uses the following two variables: (i) self-reported sociability in 1981 (extremely shy, somewhat shy, somewhat outgoing, extremely outgoing) (ii) self-reported sociability in 1981 at age 6 (retrospective). A measure of social skills in the NLSY97 is constructed using the following two variables: (i) self-reported personality scale: extroverted or enthusiastic (disagree strongly, disagree moderately, disagree a little, neither agree nor disagree, agree a little, agree moderately, agree strongly) (ii) self-reported personality scale: reserved or quiet. These questions capture the extroversion factor from Big 5 personality traits[2] (e.g. Goldberg 1993; Judge et al. 1999; Barrick and Mount 1991) which is a taxonomy for personality traits.

Regarding this measure in Deming (2017), I address the important compatibility issue that arises due to difference in questions between the NLSY79 and NLSY97. The fact that social skill measures are designed to use different variables across waves to capture the identical personal trait, the extroversion, could make them less comparable. Furthermore, many studies argue that during the early years of life, mean-level changes in traits are obvious and dramatic, while mean-level changes in traits are less extreme later in life (e.g. Borghans et al. 2008). This means that self-reported sociability at age 6 is likely to change

[2]The five factors are openness to experience, conscientiousness, extroversion, agreeableness and neuroticism. This theory suggests five broad dimensions commonly used to describe the human personality and psyche.

after childhood. I find that the correlation between the two variables which measure social skills in the NLSY79 is about 0.39 in the analysis sample. It indicates that the two variables in the NLSY79 show somewhat weak association, and therefore constructing a composite variable should be done with caution.

Another concern is that family background characteristics may play an important role in determining children's social and emotional development (e.g., Blau 1999). In that case, the measure of social skills that captures sociability at age 6 may reflect measurement error. If labor market outcomes are determined by the measure of social skills that is measured with error, controlling for the family background significantly changes the coefficient on the return to social skills.

To account for the possible bias mentioned above, I reconstruct a new measure of social skills in the NLSY79, while I use a measure of social skills that is constructed by Deming (2017) in the NLSY97. In the recent survey year, 2014, the NLSY79 contains exactly the same questions in the NLSY97; self-reported personality scale: (i) extroverted and (ii) reserved. I modify the construction of the social skill measures from the NLSY79 in a way that the measure of social skills uses these same questions with the NLSY97. This maximizes the comparability of the two measures of social skills across the 1979 and 1997 waves of the NLSY. Furthermore, this survey was conducted in adulthood, and therefore the measure of social skills does not vary much with family background. Note that following Deming (2014), each variable is normalized to have a mean of zero and a standard deviation of one. Then, I take the average and then re-normalize it to have the same distribution with cognitive skills.

Some studies argue that workers with higher AFQT scores are likely to be more educated and this pattern could change over time. To address this issue, I check the correlation between the AFQT scores and years of schooling. It turns out that the correlation is considerably stable, 0.57 in NLSY79 and 0.53 in NLSY97[3]. Another concern is the relationship between social intelligence and cognitive skills; this measure of social skills may simply capture unmeasured cognitive skills. I find that the correlation between cognitive skill and social skill is about 0.13 in the analysis sample of NLSY79 and 0.07 in that of NLSY97, which shows very weak positive correlations. These results allow us to compare returns to cognitive skills and social skills across cohorts. Furthermore, I additionally used a measure of non-cognitive skills constructed by Deming (2017). Deming (2017) made this measure using the normalized average of the Rotter Locus of Control and the Rosenberg Self-Esteem Scale, following Heckman et al. (2006). The results may vary with the non-cognitive skills variables if my measure of social skills is an imperfect proxy.

Deming (2017) creates the task content of work using data from the 1998 Occupational Information Network (O*NET). The O*NET, developed and maintained by the U.S. Department of Labor, is an extensive survey containing data on 974 occupations and questions about abilities, skills, knowledge and work context as well as work activities required in an occupation. The procedure to construct measures of the task content of work is described in greater detail by Deming (2017) and thus I keep the presentation brief.

In particular, I focus on four of the indicators of task content: routine, social skills,

[3]Castex and Dechter (2014) who found that the correlation between the AFQT scores and years of schooling is 0.56 in the NLSY79 and 0.53 in the NLSY97 show the similar results.

information use and math. First, the O*NET variables to measure an occupation's routine is as follows - 1) degree of automation and 2) importance of repeating same tasks. Note that this definition of routineness differs from numerous other studies which distinguish routine-cognitive occupations (e.g., clerical, administrative, and sales) from routine-manual ones (e.g., production and operatives) (e.g. Autor and Dorn 2013; Acemoglu and Autor 2011). Second, the four variables in the O*NET module on an occupation's social skill intensity is as follows – 1) coordination; 2) negotiation; 3) persuasion; and 4) social perceptiveness. Third, information use is measured as the average of the following four work activity variables, 1) getting information needed to do the job, 2) identifying objects, actions and events, 3) processing information and 4) analyzing data or information. Lastly, math task intensity is defined as the average of three variables to capture mathematical competence, namely 1) mathematical reasoning ability, 2) mathematics knowledge and 3) mathematics skill. Those questions are re-scaled to fall between 0 and 10, and then averaged to create the composites. Following Autor & Dorn (2013), these composites are linked to the 1990 Census Occupation Classification (COC) codes using a crosswalk from the 1998 O*NET codes.

This is useful to understand task content of work. For instance, the mean of routine, social skills, information use and math task intensity for sales workers are 3.1, 6.2, 4.9 and 5.5 but those for the receptionist are 6.8, 4.1, 3.9 and 4.7, respectively. These results are line with expectations such that sales workers have social skills-intensive occupation, but receptionists have routine occupation.

A yearly unemployment rate is used as an indicator of macroeconomic conditions.

Both national unemployment rates as well as four census region (northeast, midwest, south and west) unemployment rates are employed (hereafter referred to as the national rate and the regional rate, respectively). Both national and regional rates are provided by the Bureau of Labor Statistics (BLS). I normalize each rate to have a mean zero and a standard deviation of one so that unemployment rates and skill measures have the same distribution.

The national rates show the variation from 1980 to 1998 in the NLSY79 and from 2003 to 2013 in the NLSY97 and therefore provide only 19 and 11 data points, respectively. This would raise other possibilities to explain my results such that changes in wage structure or deregulation during the 1980s could affect outcomes. An alternative method to provide more variation is to employ the regional unemployment rate. This approach has pros and cons. It provides more variation than the national rates; 76 and 44 data points in the NLSY79 and the NLSY97, respectively. However, effects of the regional rate may not be large compared to those of the national rate. Note that estimations will always have been adjusted for regional fixed effects.

To consider possible bias from unmeasured ability differences, I control for both potential work experience and a level of education in addition to a measure of cognitive skills. Potential work experience is defined as age minus schooling minus 6, following many other studies (e.g., Castex and Detcher 2014). There has been an increase in the schooling level over time; the average of years of schooling is 13.5 in the NLSY79 and 13.7 in the NLSY97. To deal with this problem, Castex and Dechter (2014) uses education dummy variables instead of years of schooling. Following them, I use education dummy variables in my estimation. Considering returns to potential experience and schooling level enables us to reduce ability bias.

Table 1.1 summarizes information of respondents. First, Table 1.1 demonstrates an increase in cognitive skills over time but a decrease in social skills across waves. This statistic, related to cognitive skills, is consistent with Altonji et al. (2012), which shows that the current generation is more skilled than the previous one. Second, Table 1.1 also documents information on the family background; parental education, the number of siblings and family structure. Parental education is measured in years of schooling. Family structure is an indicator as to whether participants live with both parents when they were 14 years old in the NLSY79 and 13-17 years old in the NLSY97. Third, Table 1 shows statistics on the schooling level, hourly wage rates (in 2013 dollars) and potential work experience. Both years of schooling and hourly wage increase over time. On the contrary, the average experience is somewhat lower for the NLSY97 cohort. This is partially related to the fact that the mean age is lower in NLSY97 due to a higher concentration of young workers and an increase in the schooling level in the NLSY97. Lastly, the mean of national and regional unemployment rate are higher in NLSY97 mainly due to the recent Great Recession. Note that the statistics are calculated using the BLS weights to achieve representativeness of the population[4].

[4]Castex and Dechter (2014) construct weights to match the age and family background distribution of NLSY97 to that of NLSY79. It turns out that changing demographics do not explain the results which assess the changes in wage structure between the 1980s and 2000s.

1.3 Estimation Results

I now turn to estimation of returns to both cognitive and social skills with consideration for the unemployment rate, using the NLSY79 and NLSY97.

1.3.1 Wage Regression

To investigate how the unemployment rate has affected returns to skills in the labor market over time, I regress log hourly wages on both measures of skills, controlling for a variety of other covariates. The equation is formally given by

$$ln\left(wage_{ijt}\right) = \beta_1^G U_t + \beta_2^G Cog_i + \beta_3^G SS_i + \beta_4^G U_t * Cog_i + \beta_5^G U_t * SS_i$$
$$+ \beta_6^G exp_{it} + \beta_7^G exp_{it}^2 + \beta_8^G Educ_i + \beta_9^G X_{ijt} + \zeta_j + \epsilon_{it} \quad (1.1)$$

where wage is the real log hourly wage rate paid to a worker i at time t, U_t is the unemployment rate, $Educ_i$ corresponds to a vector of education dummy variables, exp_{it} is the labor market experience, X_{it} controls for race-by-gender and four census regions, year and urbanicity fixed effect (indexed by j). Subscripts G on the coefficients denote the cohort, $G \in \{NLSY79, NLSY97\}$. The error term ϵ_{it}, clustered by individual, captures unobserved factors which could affect wages. Each observation is a person-year, and the data is a pooled sample of two cohorts of youth: NLSY79 and NLSY97.

The results are in columns (1) and (2) (Table 1.2) show the estimated effects of skills and the national unemployment rate on wages. The returns to cognitive skills display a significant decline over the past 20 years; one standard deviation increase in cognitive skills increases real hourly wages by 17.5 percent in the NLSY79 sample, compared to 7.3 percent in the NLSY97 sample. The difference between the coefficients on the cognitive skill is statistically significant at the 1 percent confidence level.

The return to social skills displays modest decreases over time, but there is no statistical difference between the coefficients on social skills. This implies that the returns to social skills in terms of wage have not changed very much across survey waves. This is inconsistent with Deming (2014), which finds that the returns to social skill among full-time workers have grown significantly across NLSY. I partly attribute this outcome difference to the fact that the social skills in the NLSY79 sample are differently measured. Firstly, Deming (2017) uses mean self-reported sociability at age 6 and as an adult to make social skill variables in the NLSY79. Mean self-reported sociability is 2.32 at age 6 and 2.88 as an adult, implying that respondents viewed themselves as less sociable in childhood than as adults. Secondly, I find that self-reported sociability at age 6 is somewhat influenced by the family background. When I replicate the same analysis using the measure of social skills in Deming (2017), the returns to social skills are about 20 percent smaller in the NLSY79; an increase in social skills of one standard deviation raises real hourly wages by 3.4 percent in the case of using my measure, compared to 2.4 percent in the case of using Deming's measure. See the Appendix Table A3 for details.

The sign on the national unemployment rate flips over time. For instance, the estimates imply a wage loss of 29.4 percent in the NLSY79 but a wage gain of 10 percent in the NLSY97 for an increase in the unemployment rate of one standard deviation. The relation between unemployment and wage rates has been one of the controversial topics in economics. On the one hand, a vast literature explains the existence of a negatively sloped relationship between wages and unemployment, following Phillips's work. The estimates in the NLSY79 are consistent with this conventional literature. On the other hand, Harris-Todaro (1970) argues that there is a positive relation between the regional wage level and the regional unemployment rate if a region's permanently high unemployment is compensated for by higher wages. Existing literature offers evidence on the positive association between wages and unemployment. For example, Blanchflower and Oswald (1994) find that the long-run relationship between wages and unemployment is positive in the US. Furthermore, Albæk et al. (2000) suggest that a higher degree of worker mobility combined with high speed of adjustment may produce a positive correlation between wages and the unemployment rate. My finding for the NLSY97 is consistent with their hypothesis[5].

I add an interaction between the unemployment rate and both skill measures. The interaction between skills and the unemployment rate allows me directly to test the hypothesis that the returns to skills vary with the unemployment rate. To begin with, the interaction between the cognitive skill and the unemployment rate is negative in the NLSY79 sample, while it is positive in the NLSY97 sample. It suggests that a one standard deviation increase in the unemployment rate lowers the wage return to cognitive skills from 17.5 percent to 15.9 percent in the NLSY79. In contrast, in the NLSY97, one standard deviation increase in the unemployment rate yields a wage gain from 7.3 percent to 9.2 percent. This evidence implies that, even though the returns to cognitive skills have declined over the past 20 years, there has been a growing emphasis on cognitive skills during recessions. In contrast, the interaction between social skills and the unemployment rate is negative but

[5] Another concern is that wage contract may be signed one year ago in some cases. To account for this time inconsistency, I estimate regression like equation 1.1 but with the lagged unemployment rate. The results in Appendix Table A1.1 are robust to using the lagged unemployment rate.

not statistically significant across the 1979 and 1997 waves of the NLSY, suggesting that the unemployment rate has not had a significant effect on the returns to social skills.

Taken together, returns to cognitive skills display a dramatic decrease, but cognitive skills become increasingly important when an unemployment rate is high. However, there have not been many changes on returns to social skills during normal times or recessions.

Column (3)-(8) reports estimation results of the wage equation controlling for additional characteristics. The decrease in return to cognitive skills is more pronounced when including family background controls, education level, and industry fixed effects. Moreover, the proportional declines in the cognitive skill coefficient also become more substantial. Unlike cognitive skills, the return to social skills have not varied very much across survey waves with and without control variables.

The interaction of the unemployment rate and cognitive skills is not statistically significant when including education level as a control variable in the NLSY79 sample. In the NLSY97, controlling the level of education or industry reduces the coefficient on the interaction between unemployment and cognitive skills, yet it remains statistically significant in the NLSY97. This also indicates that cognitive skills play more important role during recessions in the 2000s.

Equation (1.1) is estimated using the regional unemployment rate instead of the national rate. The results are in Appendix Table A1.2. In this specification, most results in both the NLSY79 and the NLSY97 are robust to using the regional unemployment. This means that the estimation results on skills and the interaction of the regional rate and skills do not vary significantly across survey waves regardless of the type of unemployment rate that is used. However, the effect of the regional unemployment rate on wage is small and insignificant in all cases. This stringent result is mainly because the region and year fixed effects absorb most of the variation.

Deming (2017) finds that cognitive skills and social skills are complements in the NLSY79. To test if the complementarity between cognitive skills and social skills affects main results, I add an interaction between cognitive and social skills. Column (2) in Appendix Table A1.4 shows that the interaction is positive, large (0.015), and statistically significant at the less than 1 percent level, which is consistent with Deming (2017), in the NLSY79. In contrast, Column (5) indicates that the interaction with the NLSY97 sample is negative and statistically insignificant. In spite of different results across survey waves, their inclusion barely changes the coefficients on cognitive and social skills and their interactions with the unemployment rate, suggesting that each measure contains independent information about productivity of workers. Columns (3) and (6) add controls for noncognitive skills to test whether my measure of social skills is an imperfect proxy for the underlying construct. Both Columns (3) and (6) suggest that noncognitive skills are highly predictive of wages across survey waves and have little impact on other estimates. Overall, the results are robust to accounting for the complementarity between cognitive skills and social skills or noncognitive skills.

In sum, comparing the returns to skills with consideration of an unemployment rate documents that higher cognitive skills are more beneficial in times of high unemployment. Furthermore, the results in this section consistently indicate that cognitive skill have gained growing importance across surveys when threatened by a high level of unemployment.

1.3.2 Full-time Employment Regression

I next examine how cognitive and social skills differently affect the full-time employment over a business cycle. I estimate:

$$Emp_{ijt} = \beta_1^G U_t + \beta_2^G Cog_i + \beta_3^T SS_i + \beta_4^G U_t * Cog_i + \beta_5^G U_t * SS_i + \beta_6^G exp_{it} + \beta_7^G exp_{it}^2 + \beta_8^G Educ_i + \beta_9^G X_{ijt} + \zeta_j + \epsilon_{it}. \quad (1.2)$$

The dependent variable Emp_{ijt} is a dummy for being employed and everything else is defined in the same way as equation (1.1).

The results are reported in Table 1.3. To begin with, it is clear that a high level of unemployment lowers employment rate by definition, and a negative sign of the coefficient on the unemployment rate in this specification is consistent with this. Furthermore, the impact of the unemployment rate on employment probability displays decreases over time. For instance, columns (1) and (2) show that one standard deviation increase in the unemployment rate is associated with a 3.5 percent decrease in full-time employment probability for the 1979 cohort, but only with a 0.5 percent decrease for the 1997 cohort.

Returns to cognitive skills display increases over time; column (1) shows that one standard deviation increase in cognitive skills increases the probability of full-time employment by 3.9 percentage point for the 1979 cohort, compared to 4.7 percent for the 1997 cohort. Column (3)-(8) additionally controls for family background and education level, which reduce the impact of cognitive skills overall. The proportional decline between the coefficients on cognitive skills for NLSY79 and NLSY97 cohorts become smaller as adding control variables.

The association between social skills and the probability of having full-time work has increased across surveys. A one-unit increase in social skills has relation to an increase in the probability of full-time employment of 0.9 percent for the NLSY79 sample, compared to 2.3 percent for the NLSY97 sample. Column (3)-(8) additionally controls for family background and education level, which reduce the impact of social skills overall. The results from Column (3)-(8) indicate that when including additional controls, the proportional decline in social skills coefficient does not change much.

Interestingly, estimation results which consistently show the growing importance of social skills contrast with results of wage function estimation which show few changes in return to social skills over time. This suggests that social skills have become a more important factor to increase the likelihood of being hired but a less important factor to raise wages.

I add an interaction between the unemployment rate and both skill measures to check whether the impacts of skills on the employment vary with the business cycle. The result shows that the interaction between cognitive skills and the unemployment rate is statistically significant for the NLSY79 cohort, while none of the interaction terms are statistically significant regardless of existence of control variables for the NLSY97 cohort. This evidence suggests that the relationship between both skill measures and the probability of full-time employment has not been significantly affected by the unemployment rate in the recent decade. These results also contrast with the wage estimation which documents the growing importance of cognitive skills during recessions.

To summarize, I firstly examine changes in returns to cognitive and social skills across NLSY waves. Wage returns to cognitive skills decrease while cognitive skills significantly have increased the employment probability over time. Social skills have gained growing importance with respect to employment as a dependent variable but show little change on wage return across surveys.

I also find that an unemployment rate alters this trend of the skill demand. For instance, the results document the growing importance of cognitive skills between 1980s and 2000s in terms of wages during recessions. However, these results vary depending on the outcome variables. The importance of cognitive skills regarding the employment probability have declined over time.

1.4 Occupational Sorting on Skills with the Unemployment Rate

Table 1.2 and 1.3 suggest that the business cycle differently affects labor markets, implying that demand for skills changes over the business cycle. For instance, if firms have a high demand for cognitive skills during recessions, then we would expect that workers are likely to sort into tasks which require cognitive skills. I explore this prediction in this section.

I exploit the variance of workplace tasks, constructed by Deming (2017) using data from the Occupational Information Network (O*NET). I test how the unemployment rate affects the task intensity of worker's occupation.

I focus on four of the indicators of task content; routine, social skills, information use and math (nonroutine analytical). There exists a negative correlation between the measures of routine and other three task intensities: social skills, information use and math.

Table 1.4 summarizes the Pearson correlation between four task measures. The occupation-level correlation between routine intensity and social skill, information use and math task intensity are -0.56, -0.19 and -0.26, respectively in the NLSY79. These are similar but less pronounced when using the NLSY97 sample; -0.51, -0.14 and -0.23, respectively.

Moreover, all measures, save for the measure of routine task intensity, are strongly positively correlated. For instance, the correlation between math task intensity and information use task intensity is about 0.94 (the highest) and the correlation between social skill task intensity and math task intensity is about 0.74 (the lowest). This suggests that routine occupations are less likely to require social skills, information use or math, and social skills-intensive occupations are related to information use or math tasks.

My regression specification is shown in equation (1.3).

$$Task_{it} = \beta_1^G U_t + \beta_2^G Cog_i + \beta_3^T SS_i + \beta_4^G U_t * Cog_i + \beta_5^G U_t * SS_i + \beta_6^G exp_{it} + \beta_7^G exp_{it}^2 + \beta_8^G Educ_i + \beta_9^G X_{it} + \zeta_j + \epsilon_{it} \quad (1.3)$$

Basically, this regression is analogous to the equation (1.1) but with the task content of occupations as the dependent variable. I control for the level of education, industry and year fixed effect and race-by-gender indicators and indicators for region and urbanicity.

Table 1.5 summarizes regression results from equation (1.3) for main dependent variables, task measures. Beginning with the first row, I find that only the routine task intensity coefficient on cognitive skill has a negative sign, while other task intensity coefficients on the cognitive skill have positive signs. I also find a similar pattern with social skills; only the routine task intensity has a negative coefficient on social skills, while other tasks do not. This pattern has not changed very much over time. These results imply that workers with higher cognitive skills and social skills have sorted into the information use, social skills or math-intensive occupations, rather than routine occupations.

Furthermore, Table 1.5 clearly shows that workers sort into occupations where their skills are more highly valued, and this pattern remains constant between the 1980s and 2000s. Workers having higher cognitive skills sort into information use or math-intensive occupations and those having higher social skills sort into social skills-intensive occupations. Only the magnitude of coefficients on both cognitive and social skills is somewhat different between the NLSY79 and the NLSY97. That is, the patterns that workers with higher cognitive skills sort into information use or math-intensive occupations display modest decrease over time, while the patterns that workers with higher social skills sort into social skills intensive jobs has been intensified.

The third row shows that in the NLSY79 sample, a one standard deviation increase in the unemployment rate increases the routine intensity of a worker's occupation by 2.16 percent, and the coefficient is statistically significant at the 1 percent level[6]. However, I do find that workers are less likely to sort into all but the routine occupation when the unemployment rate increases, and this effect persists at fairly similar magnitudes and significance levels; a one standard deviation increase in the unemployment rate decreases the information use intensity by 4.37 percent (the highest) and the social skills intensity by 3.35 percent (the lowest).

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[6]Following Deming (2017), the O*NET variables are transformed into percentiles, weighted by the 1980 labor supply distribution, and then divided by 10. Therefore, a one-unit increase in the task measures can be interpreted as a 10-percentage point increase in task intensity.

Interestingly, unlike the effect from both cognitive and social skills on occupational sorting, these patterns with respect to an unemployment rate in the NLSY79 are in stark contrast to the estimation results in the NLSY97. An increase in an unemployment rate decreases all task intensity of worker's occupation excluding routine intensity in the NLSY79 sample. However, more workers sort into social skills, information use and math-intensive occupations but not routine occupations, when the unemployment rate increases in the NLSY97 sample. Overall, this result shows that workers have been differentially influenced by labor market tightness and their own skills in terms of occupational sorting between the 1980s and 2000s.

1.5 Changes in the Relative Returns Across Occupations

In Table 1.5, we saw that workers move into occupations where their skills are highly valued, therefore estimating returns to occupational task might be biased if I control for occupations. To account for this concern, I estimate how the returns to occupation tasks changes with consideration of the unemployment rate, when the same worker switches occupations[7]. Also, Table 1.5 clearly shows that these patterns show significant difference between the NLSY79 and the NLSY97. We could expect that wage gains from sorting into routine, social skills, information use and math-intensive occupations have changed across survey waves.

I explore these predictions by estimating:

[7]The assumption such that labor market frictions prevent perfect sorting of workers to occupation allows us to estimate these patterns.

$$ln\,(wage_{it}) = \beta_1^G U_t + \beta_2^G Task_{ijt} + \beta_3^G U_t * Task_{ijt} + \beta_4^G X_{ijt} + \eta_i + \zeta_j + \delta_t + \epsilon_{ijt}. \quad (1.4)$$

The model includes controls for race-by-gender indicators, indicators for region and urbanicity and year (indexed by t) fixed effects. Note that I additionally control for worker fixed effects (indexed by i)[8]. The rest of the terms are defined as above.

The results are in Table 1.6. The row 2 shows that workers earn significantly higher wages when they sort into routine occupations. From row 4, 6 and 8, we can also observe the wage gains from switching into social skills, information use and math-intensive occupations. This pattern has not changed very much over time, although the magnitude of change has varied by task. In particular, workers who switch into a job that is 10 percentiles higher in the O*NET measure of social skill and information use intensity earn about 2 and 16 percent higher wages, respectively, in the 1980 to 1998 period, compared to 24 and 32 percent higher wages in the 2003 to 2013 period. On the contrary, wage returns from sorting into routine occupations has been almost constant across survey waves.

In the NLSY79 wages, row 3 shows that how the worker's wage return from sorting into routine task intensity changes with the unemployment rate; a wage return to a 10 percentile increase in routine task intensity is 9 percent but 12 percent when the unemployment rate increases by one standard deviation. Row 5, 7 and 9 shows the opposite estimation results. That is, one standard deviation increase in the unemployment rate lowers the wage gain of workers who switch into social skills, information use and math-intensive occupa-

[8]Regressions have also been estimated without a worker fixed effect. Results are very similar to those with a worker fixed effect, and are thus not reported.

tions by 4, 2 and 3 percent, respectively.

In contrast to results in the NLSY79, wage returns from sorting into routine occupation is decreasing in the unemployment rate in the NLSY97. For example, if the unemployment rate increases by one standard deviation, workers who sort into an occupation that is a 10 percentile higher in routine task intensity gain 2 percent lower wages. However, higher unemployment rate significantly increases wage returns from sorting into social skills, information use and math intensive occupation; wage returns to a 10 percentile increase in the measure of social skill, information use and math task intensities are 24, 32 and 22 percent, compared to 28, 37 and 25 when the unemployment rate increases by one standard deviation.

In sum, comparing the effects of occupational changes across survey waves clearly show that social skills, information processing abilities and math knowledge have become more important over time, and higher unemployment rates have precipitated this change.

1.6 Discussion

So far, I present the strong evidence that the boom-bust cycle has differentially affected the labor market outcomes and occupational sorting. Why does the business cycle matter? I argue that technological change provides one possible explanation.

Firms severely affected by the recession were induced to restructure their production, and recessions spur changes in labor inputs in a manner consistent with technological change. Many theoretical papers predict this phenomenon. For instance, this type of restructuring could often occur during recessions because opportunity costs or adjustment costs to new technology in boom times are relatively high (Hall 2005). Also, recessions may change managerial attention from growth to efficiency (Koenders and Rogerson 2005), the benefits and costs of making layoffs (Berger 2012), and a firm's incentive to invest in human capital (Jaimovich and Siu 2012). Lastly, in the Schumpeter cleansing model, low-productivity firms are replaced by high-productivity firms having modern production technologies (Caballero and Hammour 1991, 1996; Mortensen and Pissarides 1994). For our purposes, finding strong support for the specific model is unimportant. Instead, I want to suggest that these kinds of models could explain why the business cycle is closely linked to the accelerated adoption of new technologies.

If the firms restructure productions with new technology during recessions, we would expect that the type of technology employed may change the labor characteristics for the job. A vast literature in economics documents the complementarity between technology and labor. In particular, if there is the reallocation in the form of routine-biased technological change (RBTC), the technical change is biased towards replacing labor in routine tasks and in turn is complementary to high-skill cognitive jobs and substitute for middle-skill jobs which could be fully codified or automated. (Autor et al. 2003; Levy and Murnane 2004; Autor et al. 2008; Goos and Manning 2007; Autor and Dorn 2013). This suggests that an accelerated adoption of such technologies requires higher cognitive skills, computer skills or a higher level of education.

Indeed, from the wage function, I present strong evidence on the growing importance of cognitive skills during periods of recession. Comparing cohorts between the ages of 23 and 33, I find that cognitive skills are a significantly more important predictor of wages only in the NLSY97 cohort when the unemployment rate increases. Furthermore, an increase in the unemployment rate has induced more workers to sort into information use or math-intensive occupations over time. In particular, both information use and math task capture the abilities for processing the data and solving various problems which would require computer skills. Cognitive skills and computer skills are known to complement routine-biased technology (Autor et al. 2003; Brynjolfsson and McAfee 2011). These findings collectively raise the possibility that a structural shift in line with RBTC is occurring during recessions.

However, the regression results regarding the task content of occupations are puzzling in light of RBTC for two reasons. First, higher unemployment rates sort more workers into not only information use or math-intensive occupations but also social skill-intensive occupations. Second, workers with higher cognitive skills sort into social skill-intensive occupations, and workers having higher social skills sort into information use or math-intensive occupations. Considering that the cognitive skills and the social skills show the positive correlation, the results suggest that changes in technology require social skills as well as cognitive skills.

I argue that technical change is biased towards replacing labor in routine tasks and in turn is complementary to high-skill cognitive and social jobs. That is, machines do indeed substitute for labor, but also complement labor in areas where technology cannot easily automate; unlike routine tasks that are explicit and codifiable tasks, nonroutine tasks such as problem-solving capabilities, intuition, creativity, persuasion (tasks of professional, technical, and managerial occupations), situational adaptability, visual and language recognition, and in-person recognition (service and laborer occupations) cannot be easily substituted by automation. This force has amplified the comparative advantage of workers in supplying these skills (Autor 2015). This confirms the results that we see: recessions spur technological changes accompanied by an increased demand for both cognitive and social skills.

These results also can explain why employment and wages have not recently grown in high-skill occupations. Since 2000, the labor market shows evidence of smaller returns to cognitive skills or those in cognitive skill-intensive occupations (Beaudry et al. 2016; Castex and Dechter 2014). A rising importance of social skills in conjunction with cognitive skills can explain little or no growth in high-paying jobs. For instance, Deming (2017) argues that high-paying jobs increasingly require social skills.

One can readily find many cases in which technology has boosted workers in a manner of intensively supplying both cognitive skills and social skills. As a contemporary example, consider nurse technician occupations which require mastery of middle-skill mathematics, life sciences, and analytical reasoning as well as in-person interaction. That is, new technology enables them to increasingly perform diagnosing and prescribing tasks in lieu of physicians. Another example is automated teller machines (ATMs) and bank tellers (Bessen 2015). ATMs reduce the routine cash-handling tasks of bank tellers; simultaneously, information technology enables bank tellers to become involved in relationship banking such as forging relationships with customers or introducing additional bank services.

Although the results from occupational sorting regressions suggest that labor demand for social skills increases during recessions, wage and employment estimation show

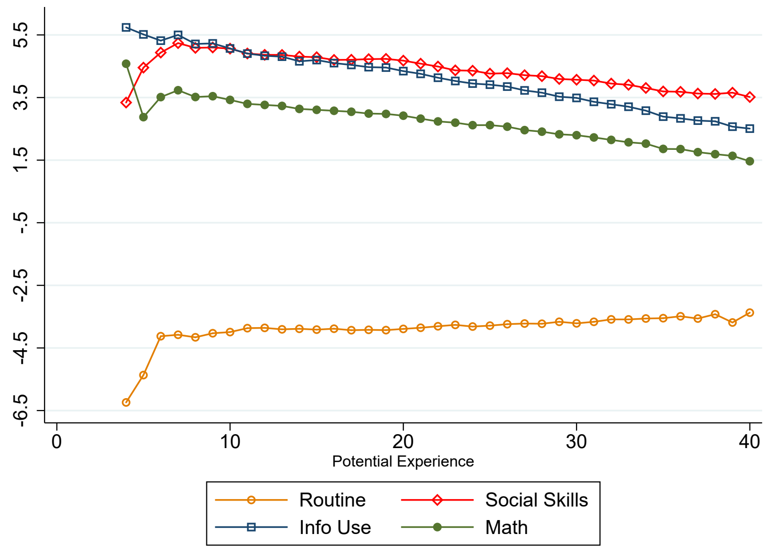

Figure 1.1: Occupation Task Intensity by Experience

Notes: Each line plots how routine, social skill, information use and math task intensity, as measured by the 1998 O*NET, vary by experience. Plotted values are coefficients in every experience year of equation (1.1). Consistent occupation codes for 19802012 are updated from Autor and Dorn (2013), Autor and Price (2013) and Deming (2017). See Deming (2017) for details on the construction of O*NET task measures and for examples of occupations in each of the four categories. Source: 19802000 census, 20052013 ACS.

conflicting results; market returns to social skills do not vary with the unemployment level. One hypothesis for these results is that social skills would gain importance in professional, technical, and managerial occupations which usually requires high education and long experience. For instance, many professions require both college and graduate degrees, so at least five to ten years in length are necessary to have new entrants. If this is the case, the baseline model may not capture the impact of social skills on labor market returns, wage and employment, because I limit my analysis to the 23-33 age group. This hypothesis would be compelling if more experienced workers were likely to sort into social skills intensive occupations.

The results from Figure 1.1 support this hypothesis. To observe how occupational task intensities vary by experience, I include all respondents above the age of 23 in the NLSY79 and estimate the equation (1.1) with experience fixed effects. Plotted values in Figure 1.1 depict the coefficients in every experience year. Overall, all task intensities except for routine have positive values with experience. In particular, social skills task intensities start to have the largest coefficients as experience level increases (about 15 years of experience). Considering that the mean of experience of workers in my sample is only 9.5 years, due to the fact that I restrict the age range to 23-33, this figure suggests that there is a possibility that results from the basic model reduce the effects of social skills on labor market outcomes.

Put together, experienced workers are likely to sort into the social skill intensive task and show relatively high social skill task intensities. These results support the hypothesis that my results may not capture the growing importance of social skills on labor market outcomes during recessions.

Therefore, I additionally investigate whether the returns to social skills vary with the unemployment rate for sufficiently experienced workers. I follow the baseline model in equations (1.1) and (1.2), but I include all respondents whose experiences are 15 years or more and over the age of 23, using only the NLSY79. 15 years of experience is chosen as a cut-off based on Figure 1.1, which shows the highest intensity of social skills at 15 years of experience. However, results are robust when using other years as a cut-off.

The results are in Table 1.7. Columns (1) through (4) show results for log hourly wage. When I focus only on experienced workers, the mean year of the sample is about

2002. Accordingly, estimation yields mixed results to those from the NLSY79 and the NLSY97 in Table 1.2. First, coefficients on the unemployment are negative, suggesting a negative relationship between the unemployment rate and wages. Second, the interaction of cognitive skills and the unemployment rate is positive, large and statistically significant at the less than one percent level. That is, an increase in the unemployment rate raises the returns to cognitive skills, implying the growing importance of cognitive skills during recessions. Lastly, the interaction of social skills and the unemployment rate is not significant even after restricting the experience range of workers.

Results from column (1) through (4) suggest that the high unemployment level is related to an increase in the wage returns to cognitive skills, yet the wage returns to social skills have not been significantly affected by the business cycle. This shows the rising demand only for cognitive skills labor during recessions. Unlike my hypothesis that the recessions induce firms to demand social skills of experienced workers, the interaction of social skills and the unemployment rate has little impact on the estimates.

Columns (5) through (8) study the impact of skills with the unemployment rate on the full-time employment and show results which are consistent with my hypothesis. The interaction of social skills and the unemployment rate is significant at the 1 percent confidence level in all specification, irrespective of controlling for education level or family background.

One possible explanation to interpret the different results between wages and employment probability is that social skills play important roles in finding jobs during recessions. Workers with higher social skills are likely to have more connections or networks and do better at the interview. These advantages may bring good results, especially in harsh economic climates. In the modern U.S. economy, recessions do not begin with a burst of layoffs. Unemployment rises because jobs are hard to find, not because an unusual number of people are thrown into unemployment (Hall 2005).

To support this argument, I estimate the equation (1) using different dependent variables; weeks worked per year, weeks tenure at current job and whether workers change job or not (hereafter collectively referred to as the college unemployment rates and individually as the weeks, tenure and the job change, respectively).

I predict that the coefficients of job change on interaction of unemployment rates and social skills are positive and statistically significant, if social skills are important to look for new jobs. However, if social skills figure high in keeping the current job, then the coefficients of weeks or tenure are positive and statistically important.

The results are in Table 1.8. The third column shows that a one standard deviation increase in the unemployment rate increases the returns to social skills with respect to the probability of changing jobs from 0.5 to 0.8 percentage points. That is, social skills become more important to find jobs as the unemployment rate increases. In contrast, the interaction of the unemployment rate and social skills are not statistically significant for weeks and tenure, suggesting that having higher social skills does not necessarily link to retaining current occupations.

This pattern has accelerated if using the sample of experienced workers. Social skills play a leading role in finding new jobs. A one standard deviation increase in social skills raises the probability of changing jobs by 0.8 percentage point, and a one standard deviation increase in the unemployment rate increases this probability from 0.8 to 0.14 percentage point. This effect is quite small in economic significance, considering the mean in the sample is 0.16. However, the coefficient on social skills as well as the interaction between the unemployment rate and social skills are statistically significant for neither weeks nor tenure.

Another way to interpret the different results between wage and employment probability in Table 1.7 is that recessions make social skills more important. Particularly, the previous literature looks at the significance of interpersonal linkages during recessions. For instance, Huang et al. (2011) show that social networks benefit firms in times of distress. This means that employers are likely to hire experienced workers with higher social skills in a bad economy.

In other words, social skills play a vital role in changing or switching jobs during recessions. However, this result is open to interpretation. We can have this result because employers prefer workers with higher social skills or because workers with higher social skills have more success in changing occupation based on their social skills. Either way, social skills are valuable in that they allow more respondents to be able to work in a bad economy.

Overall, cognitive skills are a significantly more important predictor of labor market success during recessions, and social skills play an important role for sufficiently experienced workers to increase employment probability.

1.7 Conclusion

In this paper, I draw upon the NLSY79 and the NLSY97 to presents comprehensive evidence of growing demand for cognitive and social skills when the economy suffers a recession. Using a cognitive skill measure captured by the ASVAB test and a social skill measure that reflects the extroversion factor from the Big 5 personality inventory, I show that wage returns to cognitive skills have experienced larger increases in recessions. Also, an increase in the unemployment rate increases returns to social skills, though only in terms on full-time employment and only in the case of sufficiently experienced workers.

I argue that the most probable explanation for these results is that recessions provide firms opportunities to optimally restructure and reallocate production according to a paradigm of routine-biased technological change. This suggests that labor demand is shifting in favor of more educated or highly-skilled workers. Moreover, such changes allow computers to substitute for workers in preforming routine tasks while amplifying the comparative advantage of workers who undertake tasks that require interpersonal interaction because at least so far, social interaction has proven difficult to automate (Autor 2015).

I show evidence to support my argument, using data from the Occupational Information Network (O*NET). I demonstrate that when the economy is in recession, more workers sort into social skill intensive occupations as well as several cognitive-related occupations which require high-level computer skills. Importantly, in contrast, routine occupations exhibit a sharp decline in task intensity during recessions. To put it shortly, shifts in labor market returns to both cognitive and social skills reflect technologically-driven changes during recessions.

I capture evidence that most work processes employ a multifaceted set of inputs, including cognitive skills and social skills. This perspective can provide a new insight into earlier literature that discusses the "great reversal" in demand for cognitive skills, such as Beaudry et al. (2014, 2016) and others. They document the slow growth in cognitive skill-intensive occupations in the U.S. during the 2000s. My results show that cognitive skills are still of great advantage to workers in conjunction with social skills. That is, even though the returns to cognitive skills appear to have declined over time, surviving workers become higher-skilled and supply tasks that only they can uniquely supply, such as interpersonal interaction or social skills. Therefore, my findings can help explain why there has been little employment growth in high-paying jobs over the past decade.

My results also suggest that adjustments to technological changes are episodic, concentrated during recessions, rather than occurring gradually. Whether adjustment to new technology is smooth or episodic is an important policy issue. If production shifts dramatically instead of gradually, then workers' skills become obsolete extremely quickly without enough time to retrain. Future policy makers should understand this mechanism and work on policy to raise the value of tasks where workers can maximize their comparative advantage around recessions.

Table 1.1: Summary Statistics

	NLSY79		NLSY97	
	Mean	SD	Mean	SD
Log hourly wage	2.08	0.65	2.59	0.70
National unemployment rate	6.60	1.13	6.97	1.96
Regional unemployment rate	6.61	1.32	6.98	2.03
Cognitive skills	165.63	30.92	167.20	31.08
Social skills	0.05	1.00	0.02	1.01
High school	0.57	0.49	0.46	0.50
Associate's	0.06	0.23	0.05	0.23
Bachelor's	0.16	0.37	0.18	0.39
Master's	0.03	0.18	0.03	0.18
Years of education	13.53	2.58	13.70	3.01
Age	27.74	3.08	26.75	2.68
Potential experience	9.32	3.78	6.54	3.68
Year	1988.80	3.67	2008.50	2.69
Siblings	3.36	2.32	4.01	2.95
Father's education	11.83	3.62	13.06	3.88
Mother's education	11.60	2.79	12.89	3.23
Family Intact	0.75	0.43	0.62	0.49

Notes: Log hourly wages are inflation adjusted to 2013 dollars. Cognitive skills are measured by the Armed Forces Qualifying Test (AFQT). Social skills are a standardized composite of two questions from the Big 5 personality inventory that measure extroversion. Both skills are normalized to have a mean of zero and a standard deviation of one. Education variables: high school=1 for high school graduates and 0 otherwise, associate's=1 for respondents with an associate degree, bachelor's=1 for bachelor's degree holders, and master's=1 for individuals with a master's degree or higher. Potential experience is defined as age minus schooling minus 6. Siblings capture the number of siblings. Parental education is measured in years of schooling. Family intact indicates family composition at 13-17 years old.

Table 1.2: Labor Market Returns to Skills in the NLSY79 vs NLSY97

(Outcome is Log Hourly Wage (in 2013 dollars))

	NLSY79	NLSY97	NLSY79	NLSY97	NLSY79	NLSY97	NLSY79	NLSY97
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Unemployment Rate	-0.294***	0.100***	-0.285***	0.099***	-0.234***	0.047***	-0.220***	0.044***
(National)	[0.014]	[0.006]	[0.015]	[0.007]	[0.015]	[0.007]	[0.014]	[0.007]
Cognitive Skills	0.175***	0.073***	0.161***	0.070***	0.142***	0.044***	0.111***	0.038***
	[0.008]	[0.009]	[0.009]	[0.010]	[0.008]	[0.009]	[0.008]	[0.009]
Social Skills	0.034***	0.028***	0.034***	0.025***	0.035***	0.029***	0.035***	0.028***
	[0.006]	[0.007]	[0.007]	[0.008]	[0.006]	[0.007]	[0.006]	[0.007]
Unemployment*Cognitive	-0.016***	0.019***	-0.016***	0.020***	-0.008	0.011***	-0.010*	0.012***
	[0.005]	[0.004]	[0.006]	[0.005]	[0.005]	[0.004]	[0.006]	[0.004]
Unemployment*Social	-0.006	-0.002	-0.005	-0.004	-0.006	-0.002	-0.005	-0.004
	[0.005]	[0.004]	[0.006]	[0.004]	[0.005]	[0.004]	[0.005]	[0.004]
Family background			○	○			○	○
Education level					○	○	○	○
Industry fixed effect							○	○
Observations	48,197	29,275	40,019	23,073	48,197	29,275	39,772	22,744
R-squared	0.271	0.124	0.273	0.132	0.289	0.156	0.377	0.267

Notes: Dependent variables are real log hourly wages. National unemployment rates are provided by the Bureau of Labor Statistics (BLS) and are normalized to have a mean zero and a standard deviation of one. Cognitive skills are measured by the Armed Forces Qualifying Test (AFQT), and are normalized to have a mean of zero and a standard deviation of one. Social skills are a standardized composite of two questions from the Big 5 personality inventory that measure extroversion. Education variables: high school=1 for high school graduates and 0 otherwise, associate's=1 for respondents with an associate degree, bachelor's=1 for bachelor's degree holders, and master's=1 for individuals with a master's degree or higher. Family background controls include parental education, intact family indicator and the number of siblings. The regression additionally controls for potential experience, quadratic in potential experience, racebygender indicator variables, year, census region and urbanicity fixed effects. Populations are weighted using the Bureau of Labor Statistics (BLS) weights. Standard errors are in brackets and clustered at the individual level. *** $p<0.01$, ** $p<0.05$, * $p<0.10$

Table 1.3: Labor Market Returns to Skills in the NLSY79 vs NLSY97

(Outcome is an indicator for being employed full-time

	NLSY79	NLSY97	NLSY79	NLSY97	NLSY79	NLSY97	NLSY79	NLSY97
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Unemployment Rate	-0.035***	-0.005**	-0.034***	-0.007**	-0.033***	-0.015***	-0.034***	-0.017***
(National)	[0.006]	[0.003]	[0.007]	[0.003]	[0.007]	[0.003]	[0.007]	[0.003]
Cognitive Skills	0.039***	0.047***	0.033***	0.040***	0.034***	0.037***	0.029***	0.031***
	[0.004]	[0.004]	[0.005]	[0.005]	[0.005]	[0.004]	[0.005]	[0.005]
Social Skills	0.009***	0.023***	0.006*	0.019***	0.008***	0.021***	0.005	0.018***
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
Unemployment*Cognitive	0.009***	0.001	0.010***	0.002	0.008***	0.002	0.009***	0.003
	[0.003]	[0.002]	[0.003]	[0.002]	[0.003]	[0.002]	[0.003]	[0.002]
Unemployment*Social	0.003	-0.001	0.002	-0.001	0.003	-0.001	0.002	-0.001
	[0.003]	[0.002]	[0.003]	[0.002]	[0.003]	[0.002]	[0.003]	[0.002]
Family background			○	○			○	○
Education level					○	○	○	○
Observations	61,905	43,645	50,913	33,926	61,905	43,645	50,913	33,926
R-squared	0.081	0.069	0.076	0.063	0.085	0.078	0.08	0.07

Notes: Dependent variable is an indicator for being employed full-time. National unemployment rates are provided by the Bureau of Labor Statistics (BLS) and are normalized to have a mean zero and a standard deviation of one. Cognitive skills are measured by the Armed Forces Qualifying Test (AFQT), and are normalized to have a mean of zero and a standard deviation of one. Social skills are a standardized composite of two questions from the Big 5 personality inventory that measure extroversion. Education variables: high school=1 for high school graduates and 0 otherwise, associate's=1 for respondents with an associate degree, bachelor's=1 for bachelor's degree holders, and master's=1 for individuals with a master's degree or higher. Family background controls include parental education, intact family indicator and the number of siblings. The regression additionally controls for potential experience, quadratic in potential experience, racebygender indicator variables, year, census region and urbanicity fixed effects. Populations are weighted using the Bureau of Labor Statistics (BLS) weights. Standard errors are in brackets and clustered at the individual level. *** $p<0.01$, ** $p<0.05$, * $p<0.10$

Table 1.4: Pearson Correlation Matrix for Occupation Task Intensity

NLSY79

	Routine	Social Skills	Information use	Math
Routine	1			
Social Skills	-0.5643	1		
Information use	-0.1956	0.7421	1	
Math	-0.2605	0.7922	0.9415	1

NLSY97

	Routine	Social Skills	Information use	Math
Routine	1			
Social Skills	-0.5124	1		
Information use	-0.1444	0.7473	1	
Math	-0.2302	0.7972	0.9448	1

Notes: I update O*NET task intensity measures, originally created by Deming (2017). The task measures are percentiles that range from 0 to 10 and are weighted by labor supply to conform to the 1980 occupation distribution.

Table 1.5: Occupational Sorting on Skills and the Unemployment rate in the NLSY79 vs the NLSY97

	NLSY79				NLSY97			
VARIABLES	Routine	Social Skills	Infor use	Math	Routine	Social Skills	Info use	Math
Cognitive Skills	-0.097***	0.426***	0.610***	0.580***	-0.085**	0.266***	0.375***	0.392***
	[0.034]	[0.032]	[0.033]	[0.035]	[0.037]	[0.031]	[0.033]	[0.036]
Social Skills	-0.176***	0.147***	0.077***	0.053**	-0.199***	0.159***	0.129***	0.116***
	[0.026]	[0.022]	[0.023]	[0.025]	[0.029]	[0.024]	[0.027]	[0.030]
Unemployment Rate	0.216***	-0.335***	-0.437***	-0.361***	-0.041*	0.087***	0.110***	0.064***
(National)	[0.065]	[0.056]	[0.058]	[0.064]	[0.025]	[0.020]	[0.022]	[0.024]
Unemployment*Cognitive	0.042*	-0.027	-0.029	-0.02	0.011	0.006	0.017	0.015
	[0.023]	[0.019]	[0.020]	[0.022]	[0.014]	[0.011]	[0.012]	[0.013]
Unemployment*Social	0.034	-0.013	0.018	0.023	0.005	0.015	0.006	0.009
	[0.023]	[0.020]	[0.022]	[0.024]	[0.014]	[0.011]	[0.012]	[0.014]
Observations	53,378	53,378	53,378	53,378	34,717	34,717	34,717	34,717
R-squared	0.228	0.297	0.404	0.321	0.212	0.34	0.432	0.326

Notes: Each column reports results from an estimate of equation (3) with the O*NET task intensity of an occupation as the dependent variables. The task measures are percentiles that range from 0 to 10 and are weighted by labor supply to conform to the 1980 occupation distribution. National unemployment rates are provided by the Bureau of Labor Statistics (BLS) and are normalized to have a mean zero and a standard deviation of one. Cognitive skills are measured by the Armed Forces Qualifying Test (AFQT), and are normalized to have a mean of zero and a standard deviation of one. Social skills are a standardized composite of two questions from the Big 5 personality inventory that measure extroversion. Education variables: high school=1 for high school graduates, associate's=1 for respondents with an associate degree, bachelor's=1 for bachelor's degree holders, and master's=1 for individuals with a master's degree or higher. The regression additionally controls for experience, quadratic in experience, racebygender indicator variables, census region, urbanicity and industry fixed effect. Populations are weighted using the Bureau of Labor Statistics (BLS) weights. Standard errors are in brackets and clustered at the individual level. *** p<0.01, **p<0.05, *p<0.10

Table 1.6: Changes in the Relative Returns across occupations

VARIABLES	NLSY79				NLSY97			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Unemployment Rate	-0.183***	-0.147**	-0.152***	-0.153***	-0.102***	-0.133***	-0.137***	-0.126***
(National)	[0.058]	[0.058]	[0.059]	[0.058]	[0.014]	[0.015]	[0.015]	[0.014]
Routine	0.009***				0.008***			
	[0.001]				[0.002]			
Unemployment * Routine	0.003**				-0.002**			
	[0.002]				[0.001]			
Social Skill		0.002				0.024***		
		[0.002]				[0.003]		
Unemployment * Social Skills		-0.004**				0.004***		
		[0.002]				[0.001]		
Information Use			0.016***				0.032***	
			[0.002]				[0.003]	
Unemployment * Information Use			-0.002				0.005***	
			[0.002]				[0.001]	
Math				0.016***				0.022***
				[0.002]				[0.003]
Unemployment * Math				-0.003*				0.003***
				[0.002]				[0.001]
Worker fixed effect	○	○	○	○	○	○	○	○
Observations	47,830	47,830	47,830	47,830	28,812	28,812	28,812	28,812
R-squared	0.251	0.284	0.31	0.293	0.198	0.233	0.245	0.226
Number of uniqueID	6413	6413	6413	6413	5557	5557	5557	5557

Notes: Dependent variables are real log hourly wages. Each column reports results from an estimate of equation (4). O*NET task intensity of an occupation are percentiles that range from 0 to 10 and are weighted by labor supply to conform to the 1980 occupation distribution. National unemployment rates are provided by the Bureau of Labor Statistics (BLS) and are normalized to have a mean zero and a standard deviation of one. The model includes controls for potential experience, quadratic in potential experience, race-by-gender indicators, indicators for region and unbanicity, age, year and worker fixed effects. Populations are weighted using the Bureau of Labor Statistics (BLS) weights. Standard errors are in brackets and clustered at the individual level. *** $p<0.01$, ** $p<0.05$, * $p<0.10$

Table 1.7: Labor Market Returns to Skills in the NLSY79

VARIABLES	Log Real Hourly Wage				Full-Time Employment			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Unemployment Rate	-0.234***	-0.218***	-0.228***	-0.133**	-0.227***	-0.214***	-0.229***	-0.217***
(National)	[0.030]	[0.041]	[0.030]	[0.054]	[0.039]	[0.048]	[0.039]	[0.048]
Cognitive Skill	0.219***	0.196***	0.186***	0.144***	0.046***	0.040***	0.041***	0.036***
	[0.010]	[0.012]	[0.011]	[0.011]	[0.005]	[0.005]	[0.005]	[0.006]
Social Skill	0.043***	0.043***	0.044***	0.039***	0.012***	0.010***	0.012***	0.010***
	[0.008]	[0.009]	[0.008]	[0.008]	[0.003]	[0.004]	[0.003]	[0.004]
Unemployment*Cognitive	0.016***	0.017***	0.015***	0.018***	0.011***	0.011***	0.011***	0.011***
	[0.004]	[0.004]	[0.004]	[0.004]	[0.002]	[0.002]	[0.002]	[0.002]
Unemployment*Social	-0.005	-0.005	-0.005	-0.004	0.005***	0.005***	0.005***	0.005***
	[0.004]	[0.004]	[0.004]	[0.004]	[0.002]	[0.002]	[0.002]	[0.002]
Family background		○		○		○		○
Education level			○	○			○	○
Industry fixed effect				○				○
Experience	15 years or more				15 years or more			
Observations	51,255	42,197	51,255	40,700	62,371	50,643	62,371	50,643
R-squared	0.243	0.237	0.25	0.338	0.058	0.056	0.065	0.062

Notes: Each column reports results from an estimate of equation (1), with real log hourly wages as the dependent variable in Columns 1 through 4. For an estimate of equation (2) in columns (5) through (8), equation (1) is used with an indicator for being employed full-time as the outcome. I include workers who have more than 15 years. Cognitive skills are measured by the Armed Forces Qualifying Test (AFQT), and are normalized to have a mean of zero and a standard deviation of one. Social skills are a standardized composite of two questions from the Big 5 personality inventory that measure extroversion. Education variables: high school=1 for high school graduates and 0 otherwise, associate's=1 for respondents with an associate degree, bachelor's=1 for bachelor's degree holders, and master's=1 for individuals with a master's degree or higher. The regression additionally controls for experience, experience2, racebygender indicator variables, census region, and urbanicity-plus controls as indicated. Populations are weighted using the Bureau of Labor Statistics (BLS) weights. Standard errors are in brackets and clustered at the individual level. *** $p<0.01$, **$p<0.05$, *$p<0.10$

Table 1.8: Labor Market Returns to Skills in the NLSY79

Experience	Weeks	Tenure	Job Change	Weeks	Tenure	Job Change
				15 years or more		
	(1)	(2)	(3)	(4)	(5)	(6)
Unemployment Rate	-0.010*	0.089***	0	-0.028	-0.088**	0.312***
(National)	[0.006]	[0.018]	[0.003]	[0.041]	[0.041]	[0.023]
Cognitive Skills	0.086***	0.135***	-0.014***	0.085***	0.184***	-0.011***
	[0.006]	[0.015]	[0.002]	[0.006]	[0.023]	[0.003]
Social Skills	0.009**	-0.002	0.005***	0.004	0.002	0.006***
	[0.004]	[0.010]	[0.002]	[0.005]	[0.017]	[0.002]
Unemployment*Cognitive	0	-0.007*	0.003*	0.002	0.017**	-0.001
	[0.003]	[0.004]	[0.002]	[0.004]	[0.007]	[0.002]
Unemployment*Social	0.002	-0.003	0.003*	0	-0.003	0.005***
	[0.003]	[0.004]	[0.002]	[0.003]	[0.006]	[0.002]
Observations	105,053	103,554	103,340	54,222	53,381	53,357
R-squared	0.048	0.225	0.012	0.038	0.112	0.009

Notes: Each column reports results from an estimate of equation (1), with weeks worked per year, tenure and an indicator for changing job as the dependent variable. In columns (1) through (4), I include workers who have more than 15 years. Cognitive skills are measured by the Armed Forces Qualifying Test (AFQT), and are normalized to have a mean of zero and a standard deviation of one. Social skills are a standardized composite of two questions from the Big 5 personality inventory that measure extroversion. Education variables: high school=1 for high school graduates and 0 otherwise, associate's=1 for respondents with an associate degree, bachelor's=1 for bachelor's degree holders, and master's=1 for individuals with a master's degree or higher. The regression additionally controls for experience, experience2, racebygender indicator variables, census region, and urbanicity-plus controls as indicated. Populations are weighted using the Bureau of Labor Statistics (BLS) weights. Standard errors are in brackets and clustered at the individual level. *** $p<0.01$, ** $p<0.05$, * $p<0.10$

CHAPTER 2
ENTRY LABOR MARKET CONDITIONS AND RETURNS TO COGNITIVE AND SOCIAL SKILLS

2.1 Introduction

Increasing evidence indicates that college graduates experience substantial earnings losses over the course of their careers from the adverse initial labor market conditions relative to their luckier counterparts (e.g., Kahn 2010; Oreopoulos et al. 2012; Altonji et al. 2016). Under the situation in which there exist fewer jobs to choose initially, they are more likely to suffer from underemployment, job mismatching or taking jobs at poorer quality firms (e.g., Reder 1955; Okun 1973, McLaughlin and Bils 2001). Furthermore, these disadvantages may even persist if a poor early start continuously leads college graduate to fewer training or promotion opportunities in the future (Topel and Ward 1992; Gibbons et al. 2005).

A long literature also suggests that skills or abilities of college graduates make a big difference in earnings. It is little wonder that workers differ widely in their own skills within the group of college graduates, and these differences could directly translate into finding good initial placements or a differential ability to upgrade from the negative impacts of entry conditions. Considering these facts, it is natural to ask then how labor market returns to skills interact with the business cycle.

In particular, many kinds of skills are relevant to success in the workplace. A vast literature in economics documents the labor market outcomes to noncognitive skills as well as cognitive skills. On the one hand, many papers found a positive association between cognitive skills and labor force outcomes. On the other hand, a growing body of work suggests that measured cognitive skills explain only a small portion of the variation in earnings (Heckman 1995), and noncognitive or soft skills explain important variation in adult labor outcomes (Heckman and Kautz 2012). Specifically, Deming (2017) recently shows that high-paying jobs increasingly require social skills which indicates the ability to work with others.

The advantages of having a high level of cognitive skills or social skills are apparent. It is known that cognitive skills could affect various aspects of educational achievement such as school score or attendance that directly and indirectly determine occupational achievement. Furthermore, employers highly value social skills. For instance, survey results from employers verify that teamwork, collaboration, and oral communication skills, which are related to social skills, have the highest priority among all other skills (e.g., Casner-Lotto and Barrington 2006; Jerald 2009). What is less clear is how these skills are related to determining factors of labor market outcomes, especially if experiencing early downturn.

In this paper, I analyze the short-, medium- and long-term career outcomes of college graduates as a function of economic conditions at graduation year and both cognitive and social skills. I address three main questions. First, what are the effects of cognitive and social skills on labor market outcomes and how these effects change over time? Second, how occupational sorting on skills and the the labor market returns to skills vary if graduating into a recession? Third, what are the channels through which a poor initial condition affects the labor market outcomes? To my knowledge no work has been done on both cognitive and social skills of college graduates.

I use the National Longitudinal Survey of Youth 1979 (NLSY79) to study labor market outcomes for cohorts who graduated college between 1979 and 1989. This sample allows me to analyze workers who experience the recession of the early 1980s directly and indirectly, measured by the national unemployment rate. I analyze hourly wages, labor supply, occupation quality and job mobility. Specifically, following the previous literature, I focus only on college graduates to better understand how short-term labor market conditions affect long-term labor market outcomes. The advantages of studying this group is that they start to search the job by the time of graduation and enter the labor market almost simultaneously. This is typically not the case with other samples of workers. Moreover, studying college graduates reduces the concern such that individuals with higher cognitive skills are likely to be more educated.

This is the first study to document the overall magnitude and heterogeneity of various labor market outcomes to cognitive and social skills. I find that returns to cognitive and social skills are positive and statistically significant; one standard deviation increase in cognitive and social skills increases hourly wages by 11.9% and 3.6%, respectively. Both cognitive and social skills gain increasing importance over time so that returns to both skills also constantly increase across the first 15 years of experience. However, adverse labor market conditions have short- and long-term effects that vary dramatically across types of skills. One standard deviation increase in the unemployment rate lowers the wage returns to cognitive skills from 12.2% to 11.88% but it increases the returns to social skills from 3.5% to 3.62%. These results imply that the costs of labor market shock depend on the type of skills. The experience profile is also surprising in that there are different patterns in the effects of both skills during a recession; if workers experience adverse labor market at the initial place, returns to cognitive skills gradually diminish over time, while the wage returns to social skills almost double the magnitude by 15 years out.

In this study, my results also paint an intricate picture of the effect of skills on occupational sorting that vary dramatically across types of skills. Since it is not easy to directly measure the variance of tasks, I use empirical analogs using data from Occupational Information Network (O*NET). I show that workers with higher social skill sort into social skill-intensive occupations, while workers with higher cognitive skill sort into cognitive skill-intensive occupations. Moreover, my findings show evidence of complementarity between cognitive and social skills for sufficiently experienced workers in information use and social skill-intensive occupations. They lie well below Deming (2017) who finds the complementarity between cognitive skills and social skills.

However, the impacts from graduating in recessions lead to different results depending on types of tasks. As the college unemployment rate increases, workers are more likely to sort into in information use and social skill-intensive occupations based on their skills. In contrast, an increase in the college unemployment rate discourages occupational sorting on skills for workers in routine, math and social interaction-intensive occupations. Moreover, complementarity between cognitive and social skills in information use and social skill-intensive occupations does not hold with an increase in the national unemployment rate at college graduation. This implies that initial labor market conditions for college graduates play significant roles in determining task content of occupations.

Regarding the third question, I examine the mechanisms how the adverse labor market conditions for college graduates affect labor market outcomes. First of all, my results highlight the separate roles of each skill. It seems that the roles of cognitive skills and social skills on labor market outcomes display a high degree of heterogeneity. Workers with higher cognitive skills are more likely to be employed, find job more quickly and have higher-quality employment. Workers with high social skills are likely to voluntarily change jobs more often.

Graduating into a recession magnifies these roles of both cognitive and social skills, suggesting that recessions could set the stage for displaying skills of workers. For instance, I find that in recessions workers with higher cognitive skills are more likely to be employed, find jobs more quickly, and find more attractive employers. Workers with a higher level of social skills are likely to change jobs voluntarily more often in spite of the poor initial economic condition. These effects from each skill persist at least first 10 years after graduation in most cases. Specifically, workers with higher cognitive and social skills are more likely to be working full-time if graduating from college in times of higher unemployment, although this effect from social skills fades away over the first 3 years.

Overall, cognitive skills account for initial job placement and social skills are related to a subsequent job mobility so that these heterogeneities in skills likely drives a substantial portion of the wage effects. It is true that the estimates of social skills on wages are substantially smaller in magnitude than those of cognitive skills, and cognitive skills are also of benefit to college graduates who need to get through a thin market right after graduation. However, plenty of evidence document that workers who change jobs voluntarily receive significant wage boosts on average, especially in the first ten years of workers' careers (Topel and Ward 1992). In other words, the catch-up process appears to occur in experiencing improvements in their employers through job mobility. Therefore, the fact that workers with higher social skills have tendency to change jobs voluntarily may explain much of the wage effects. That is, job mobility toward better firms plays an important role in the recovery process. Furthermore, the wage returns to social skills increases in response to an increase in the college unemployment rate and they continue to increase over time, suggesting that graduating during a recession strengthens the role of social skills. In contrast, a rise in the college unemployment rate decreases the wage returns to cognitive skills.

This paper finds that entering the labor market in recession leads to unequal wage effects in labor market outcomes across workers' skill distribution. It negatively affects graduates at the top of cognitive skill distribution. These losses imply substantial reductions in the financial returns to cognitive skills after a bad start. However, this crisis could turn into opportunity for workers in the upper-brackets of social skills, mostly by voluntarily switching jobs.

This paper adds to previous work in two areas. First, this paper is relevant to the literature on noncognitive skills such as leadership skills or social skills, which find that noncognitive skills explain an important fraction of variation in labor market outcomes. In particular, Deming (2017) shows that the labor market increasingly rewards social skills. Second, my work is closely related to Kahn (2010), Oreopoulos et al. (2012) and Altonji et al. (2016), who study the labor market consequences of graduating in times of higher unemployment and commonly find strong initial negative effects which remain persistent for up to ten to fifteen years before fading out.

A key contribution of this paper is to document the complex patterns in the timing and heterogeneity of the skill effects from early labor market conditions. To the best of my knowledge, it is the only paper to examine the differential impacts of cognitive and social skills on labor market outcomes and how these are dramatically varied by initial market conditions. I focus on college graduates experiencing the early 1980s recession directly or indirectly and find that there is a large degree of heterogeneity in the costs of recessions even within the group of college graduates depending on the level and types of skills.

2.2 Data

The main data set used in this paper is the National Longitudinal Survey of Youth (NLSY79) to estimate the impacts of entry conditions for college graduates on labor market outcomes. The NLSY79 is a nationally representative sample of youths between the ages of 14 and 22 in 1979. The survey was conducted annually from 1979 to 1993 and biannually from 1994 thereafter. The NLSY79 contains detailed information on each respondent, including education, work history, measures of pre-market skills and other personal characteristics.

The main goal of this paper is to estimate the short-, medium and long-term effects of initial economic conditions on various labor market outcomes. I restrict the analysis to workers with at least a college degree. That is, the data set used in this paper contains only college graduates who graduated between 1979 and 1989 to better align the length of time and avoid selection issues, because the data are not balanced across time or across year of experience and are instead heavily skewed towards these cohorts. Lastly, I focus on workers between 0 and 15 years out of college mainly due to the fact that all cohorts can be observed for this length of time. I provide a description of the sample by college graduation year in Table A2.1.

In subsequent sections, I measure the impacts of the unemployment rate on wage, employment, labor supply, occupation quality and job mobility. My main outcome is the real log hourly wage (indexed to 2006 dollars) at main job, excluding respondents who are enrolled in school in that year. Following Altonji et al. (2016), the bottom and top wages are coded to be between \$5 and \$250 per hour. Not only employment but also full-time employment, which can be defined as working at least 30 hours per week, are analyzed, because it is known that employers have created an increasing portion of part-time workers in an attempt to cut labor costs (Nardone 1995). Occupation quality is measured by the prestige score taken from the Duncan Socioeconomic Index that asks many different questions about the prestige of occupations, the average income and educational requirements. Lastly, I disaggregate job mobility into two different variables: weeks tenure at current main job and a dummy for changing occupations. The NLSY79 provides an unusually complete history of employment experiences including analyses of why workers separate from their employers and frequencies of these separations. From this information it is possible to construct the job mobility related variables.

I use both national and four census region (northeast, midwest, south and west) unemployment rate in the year of college graduation as an indicator of the economic condition, taken from Bureau of Labor Statistics (BLS). Hereafter collectively referred to as the college unemployment rates and individually as the national rate and the regional rate, respectively. In prior studies, the national unemployment rate is commonly used as a measure of economic condition (e.e, Kahn 2010; Oreopoulos et al. 2012; Altonji et al. 2016). Table A2.1 shows values and means of the unemployment rate for each cohort. Substantial variation exists in the national unemployment rate from 1979 to 1989; the unemployment rate is relatively high in 1982-1983 and relatively low in 1988-1989.

The national rates show the variation from 1979 to 1989 in the NLSY79 and therefore provide only 11 data points. This would raise other possibilities to explain results. For instance, changes in wage structure or deregulation during the 1980s could affect labor market outcomes. An alternative method to provide more variation is to employ the regional unemployment rate. These rates are measured in four census region in which an individual has her residence in the year she graduated from college. All regression using regional rates will always have been adjusted for year and region of college graduation fixed effects. This approach has pros and cons. It provides more variation than the national rates, potentially 44 data points. However, effects of the regional rate may not be large compared to those of the national rate, because the census region effects would absorb considerable variation.

As a proxy for cognitive skills, I use respondents' standardized scores on the Armed Forces Qualifying Test (AFQT). The AFQT scores are widely used in the literature as a measure of cognitive achievement, aptitude, and intelligence. Following Deming (2017), I take the raw scores from Altonji et al. (2012) and normalize them to have mean 0 and standard deviation 1. Note that Altonji et al. (2012) account for idiosyncrasies such as different test format or ages when taking a test.

Deming (2017) constructed a pre-market measure of social skills, which is used as a proxy for social skills. Since NLSY79 does not include psychometrically valid and field-tested measures of social skills, Deming (2017) instead constructs a measure of social skills that measures behavioral extroversion and pro-social orientation as an alternative. For instance, a measure of social skills in the NLSY79 uses the following four variables: (i) self-reported sociability in 1981 (ii) self-reported sociability in 1981 at age 6 (iii) the number of clubs in which the respondent participated in high school (iv) participation in high school sports.

Regarding this measure in Deming (2017), I address two important concerns. First, personality may change as one grows up. Many studies argue that during the early years of life, mean-level changes in traits are obvious and dramatic, while mean-level changes in traits are less extreme later in life (e.g. Borghans et al. 2008). This means that self-reported sociability at age 6 is likely to change after childhood. I find that the correlation between the two variables that measure social skills in the NLSY79, the self-reported sociability as adults and at age 6, is about 0.39 in the analysis sample. It indicates that these two variables show somewhat weak association, and therefore caution should be taken in constructing a composite variable. Second, family background characteristics may play an important role in determining children's social and emotional development (e.g., Blau 1999). In that case, there could be measurement error in the variables indicating sociability at age 6.

To account for the possible bias mentioned above, I reconstruct a new measure of social skills using the following two variables: (i) self-reported personality scale: extroverted or enthusiastic (disagree strongly, disagree moderately, disagree a little, neither agree nor disagree, agree a little, agree moderately, agree strongly) (ii) self-reported personality scale: reserved or quiet. These questions capture the extroversion factor from Big 5 personality traits (e.g. Goldberg 1993; Judge and et al. 1999; Barrick and Mount 1991), which is a taxonomy for personality traits. These questions are included in the recent survey at 2014 and therefore conducted in adulthood. This reduces the possibility that the measure of social skills is largely affected by other variables such as family income or years of parental education. Each variable is normalized to have a mean of zero and a standard deviation of one. Then, I take the average and then re-normalize it so that cognitive skills and social skills have the same distribution.

Another concern is the relationship between social intelligence and cognitive skills; this measure of social skills may simply capture unmeasured cognitive skills. I find that the correlation between cognitive skill and social skill is about -0.02 in the analysis sample of NLSY79 which shows very weak association between variables of two skills. These results allow us to compare returns to cognitive skills and social skills across cohorts.

I also study how the task content of work changes using data from O*NET. O*NET is a survey periodically conducted by the U.S. Department of Labor to a random sample of workers in each occupation. The O*NET survey contains various questions about the abilities, skills, knowledge and work activities required to perform tasks in each occupation, with specific examples to better respondent's understanding on the scale value of each number. Each question is originally measured on an ordinal scale and re-scaled to fall between 0 and 10 before being averaged to create the composite. The O*NET variables are transformed into percentiles weighted by the 1980 labor supply distribution. Following Autor & Dorn (2013), these composites are linked to the 1990 Census Occupation Classification (COC) codes using a crosswalk from the 1998 O*NET codes. Especially, I use 5 composite variables that describe tasks performed in an occupation provided by Deming (2017). The detailed procedure is described in more detail in Deming (2017). Note that the initial 1998 release of the O*NET is used mainly because it provides the most precise and accurate information on the task content of occupations in earlier years.

Among 10 composite variables, I focus on five indicators of task content: routine, social skills, information use, math and social interaction. First, the O*NET variables to measure an occupation's routine is as follows - 1) degree of automation and 2) importance of repeating same tasks. Note that this definition of routineness differs from numerous other studies which distinguish routine-cognitive occupations (e.g., clerical, administrative, and sales) from routine-manual ones (e.g., production and operatives) (e.g., Autor and Dorn 2013; Acemoglu and Autor 2011). Second, the four variables in the O*NET module on an occupation's social skill intensity is as follows – 1) coordination; 2) negotiation; 3) persuasion; and 4) social perceptiveness. Third, information use is measured as the average of the following four work activity variables, 1) getting information needed to do the job, 2) identifying objects, actions and events, 3) processing information and 4) analyzing data or information. Fourth, math task intensity is defined as the average of three variables to capture mathematical competence, namely 1) mathematical reasoning ability, 2) mathematics knowledge and 3) mathematics skill. Lastly, an occupation's social interaction task intensity is measured by a single work context variable, job-required social interaction.

Table 2.1 summarizes the key variables for non-enrolled workers. Average log hourly rate of pay is \$2.91 in 2006 dollars, and the employment rates and the full-time employment rates are 90% and 75%, respectively. On average, workers tend to work slightly more than 11 months per year and stay at one job 3.9 years. College graduates have higher cognitive and social skills than other degree groups; the average cognitive skills are 0.82 and the average social skills are 0.16, both of which are above the mean 0. Especially, cognitive skills of college graduates are considerably higher than the average. As noted above, the sample is restricted to individuals who graduated from college between 1979 and 1989 and had a minimum of 15 years post-college graduation. Therefore, the average graduation year is 1983 and the average year is 1991. The regional unemployment rate vary more than the national unemployment rate; the mean of regional rate is 7.5, but the mean of national rate is 7.

2.3 Econometric Model and Results

2.3.1 Labor Market Returns to Skills by Year of Experience

It is reasonable to expect that the effects of labor market outcomes on cognitive and social skills change over time as potential experience increases. For instance, if sufficiently experienced worker were promoted to a management position which requires a high level of social skills, then returns to social skills must be increasing. To examine this prediction, I regress various labor market outcomes on both measures of skills and their interaction with potential experience, controlling for a variety of other covariates:

$$Y_{ict} = \alpha + \beta_1 Cog_i + \beta_2 Cog_i * Exp_{it} + \beta_3 Soc_i + \beta_4 Soc_i * Exp_{it} + \gamma' X_{it} + \epsilon_{ict} \quad (2.1)$$

In equation (2.1), Y_{ict} is a labor market outcome measured in year t for an individual i, in college graduation graduation cohort c. As described above, the dependent variables are log hourly wage, the probability of being employed, the probability of full-time employment, working weeks per year, the occupation prestige score, weeks tenure at current job and a dummy for changing jobs. The baseline model includes controls for potential experience, quadratic and cubic in potential experience[1], gender, race/ethnicity, gender interacted with race/ethnicity and year and region fixed effects. Note that Exp_{it} is potential experience rather than actual experience and defined as the number of years since college graduation. This is because actual experience could be potentially endogenous with respect to the college unemployment rate and is also noisily observed in the data set.

The coefficients β_1 and β_3 represent the direct effects of cognitive and social skills on a labor market outcome. By interacting each skill measure with potential experience, β_2 and β_4 show how the effect changes over time. The error term is clustered by year of college graduation in the national rate regressions and by region-year in the regional rate regressions[2].

The results are in Table 2.2. Panel A shows the coefficients for skills and its inter-

[1] Results are not sensitive to the functional form of the potential experience term.

[2] Although clustering is done at the level of variation for identifying the college unemployment rate, clustering by individual could be desirable as well because of possible correlation across observations on the same person. Results are similar no regard to clustering. In this paper, I present results clustered by year rather than individual due to the fact that clustering by year is a higher level of aggregation and thus provides a more conservative specification.

action with potential experience. Panel B provides insights for long-run effects by showing these values fitted for 1,3,7,10 and 15 years since college graduation. Columns (1) and (2) summarize wage regression results. I find that the returns to cognitive and social skills are positive and statistically significant. A one standard deviation increases in cognitive and social skills increase real hourly wages by 11.9% and 3.6%, respectively. The estimates lie well below the results of Deming (2017), who finds a 1 percentage point increase in cognitive and social skills increase in log hourly wage by 20.6% and 5.5%, respectively, using all cohorts who are above 23 years old in NLSY79.

Each year these wage effects of cognitive and social skills persist by 0.4% and 0.2%, respectively. The subsequent rows in panel B report the experience profile starting with a large 0.12 and 0.038 log points wage increases in the first year out of school. The effect does not fade away over the next full 15 years but increases over time; this effect increases to 0.18 and 0.07 log points after 15 years and remains statistically significant at 1% level for both cognitive and social skills, respectively. These estimates could be evidence that cognitive and social skills play an important role in determining initial wage and become even more crucial as experience increases. Furthermore, although cognitive skills yield larger effects in magnitude than social skills, the gap between cognitive and social skills gradually shrink over time.

The remainder of Table 2.2, columns (3)-(6), summarizes regression results for labor supply. Turning first to the probability of being employed, column (3) shows modest impact of cognitive skills on the probability of being employed. That is, the probability of being employed is raised by approximately 0.04 in response to a one standard deviation increase only in cognitive skills. However, this effect is quite small in economic significance, considering the mean in the sample is 0.9, and falls to 0.02 points after 3 years of experience. The effect is gone by year 7 but then negatively affects 15 years out. The effect of social skills is even smaller in magnitude and not significant.

Columns (5) and (6) show estimates the effects for the probability of full-time employment. I estimate small effects of both cognitive and social skills, though most of these are not significant.

Overall, labor supply with respect to employment is small in economic significance and the magnitudes are also quite small. These results are not surprising in that the sample contains workers with at least a college degree. In this sample, 90% were employed and 75% were employed full-time, indicating that this group is unlikely to be unemployed with high probability and has relatively inelastic labor supply compared to other demographic groups.

The effects for weeks worked are shown in columns (7) and (8). I find that only cognitive skills are useful to obtain working hours. The effect is one and a half longer week for one standard deviation increase in cognitive skills but dissipates by 0.2 weeks every year.

The significant role of finding the first employment likely drives a substantial portion of working hours effects. Higher cognitive skills will help alleviates some of the difficulties finding employment at the initial place so that those with higher cognitive skills are likely to work slightly more than others. I estimate statistically significant impacts of cognitive skills on working hours in the only first year out. This result supports that a substantial part of weeks worked could be explained by the ability to find new jobs, which are closely related to cognitive skills.

Turning next to occupation-related outcomes in Table 2.3, columns (1)-(6), I report the effects of skills on the occupation prestige score, weeks of tenure at the current employer and changing status of occupation. To begin with, the occupational prestige score provides an indirect measure of the quality of jobs. This is valuable to check because having higher-quality jobs is no less important than just being employed. Column (1) shows that the occupation prestige score increases by more than 2.6 points in response to one standard deviation increase in cognitive skills. This effect is modest compared to the mean of the prestige score in this sample, 48.8, but statistically significant and remains fairly constant throughout the entire period studied. That is, worker having higher cognitive skills is able to fully shift into better jobs over the first 15 years of a career. On the other hand, the effects of social skills are small, negative (-0.08) and insignificant. Overall, it seems that cognitive skills are more crucial in determining the quality of jobs.

Tenure indicates how often each individual changed employers. I find that both cognitive and social skills have no initial effect on job tenure and its impact are not statistically significant at least over the first 15 years of their careers. On the contrary, column (6) shows that the probability of changing jobs is raised by approximately 1.9% in response to one standard deviation increase in social skills. The subsequent rows in panel B report that the effect of social skills on job change is substantial, 0.017, in the first year out and this is significant at the 1% level. This effect halves by 7 years out and become small and insignificant thereafter. On the contrary, I do not find any significant initial and long-term impact of cognitive skills on the outcome variable of changing jobs. In other words, workers with higher level of social skills tend to change their jobs more often.

The above results suggest that job mobility seems to be related to social skills of workers. Thus, it is reasonable to ask why workers with a higher level of social skills are inclined to be mobile. Do they have a better outside opportunities thanks to their social skills? However, not all job separations are worker-initiated; high job mobility can also be related to a high frequency of involuntary discharges and/or a tenuous attachment to the workforce. So, it is also important to focus on issues linked to involuntary job displacements.

To better understand if skills differently affect voluntary (employee-initiated) and involuntary (employer-initiated) job changes, I additionally construct two separate mobility variables: voluntary job changes and involuntary job changes. The NLSY79 provides extensive information on each respondent's work history which allows an analysis of voluntary "quitting" and involuntary mobility such as layoffs or firings. In particular, for every job separation the respondent is asked reasons for leaving. The possible responses to this question can be classified as (1) a layoff, (2) a discharge, (3) a quit for pregnancy or other family-related reason, and (4) a quit for any other reason, although each survey contains different response categories.

The results are in Table 2.4. I find a sizable effect of social skills on the probability of voluntary job change. The estimates in column (2) imply that a one standard deviation increase in social skills increased the probability of changing job voluntarily by 0.004. This effect is quite big in economic significance, considering the mean of voluntary job change variable in the sample is 0.008. This effect almost halves but is still significant by 3 years out. In contrast, the effect of both cognitive and social skills on involuntary job change is negative and not significant (Table 2.4, columns (3)-(4)).

A possible concern is that career-change variables are noisy compared to other outcome variables. To account for this problem, I have also looked at the question on the most recent reason leaving the main job. This is valuable to check in that this question includes the very detailed reasons for leaving jobs, allowing me to disaggregate the voluntary job change variable into economic quits and family-related quits. This disaggregation is useful because economic quits and family-related quits would have different effects on labor market outcomes. For instance, Keith and Mcwilliams (1995) find that economic quits positively affect subsequent wages, but discharges and lay-offs negatively affected subsequent wages, using the data from the NLSY79.

Results in Table 2.4 show that workers with high social skills are likely to change jobs more often voluntarily. Similarly, we predict that workers with higher social skills will change occupations owing to economic reasons (e.g., quit because wages too low) rather than family reasons (e.g., quit for pregnancy or family reasons). I explore these predictions by estimating equation (1), allowing dependent variables to be either an indicator switching jobs for economic reasons or family reasons to study the role of skills in changing occupations.

The results are in Table A2.2. It turns out that results are very similar to those in Table 2.4. That is, one standard deviation increase in social skills increases the probability of job change due to the economic reason by 1.1%, suggesting that a worker with higher social skills might leave a job for a better one. But I find that involuntarily changing jobs or switching occupation because of family reasons are not associated with social skills of workers.

The results in Table 2.4 and Table A2.2 suggest that workers with higher social skills could shift into other jobs more often. One possible explanation for these results is that social skills play an important role in the process of finding jobs, because workers with higher social skills are likely to have more connections or networks and do better at the interview. Given previous results that job changes are associated with wage growth (Topel and Ward 1992), and the effects of social skills is statistically limited only to voluntary job change, this could explain some of the wage effect as well.

Overall, cognitive and social skills appear to be affecting labor market outcomes differently. To begin with, both cognitive and social skills commonly allow workers to have higher wages and these returns increase with experience. On the other hand, cognitive skills may be mainly related to initial employment placement and occupation quality, but social skills seem to play a key role in changing jobs in the short- and medium- term.

2.3.2 Occupational Sorting on Skills

Previous results show clearly that workers sort into occupations where their skills are more rewarded. I next examine the match quality of occupation depending on the type and level of skills. Specifically, I explore if workers with higher level of cognitive or social skills sort into cognitive or social skills-intensive occupations, respectively. I estimate regressions like (2.1) above but with the task content of occupations, measured using O*NET and constructed by Deming (2017), as the dependent variable. The baseline model is identical to equation (1).

The results are in Table 2.5. Columns (1) and (2) show that a one standard deviation increase in cognitive increases the routine task intensity of a worker's occupation by 5.13 percentiles, and the coefficient is highly statistically significant. Each year this effect dissipates by 0.29 percentiles. Considering that routine occupation captures automating repetitive tasks, this result suggests that workers with higher level of cognitive skills are less likely to sort into simple repetitive occupations at higher experience years. However, columns (2) shows that a one standard deviation increase in social skills decreases the routine task intensity by 2.78 percentiles. Panel B suggests persistent effects of social skills for all experience years. This result highlights that workers with higher levels of social skill sort into nonroutine-intensive occupations, which is consistent with results in Deming (2017).

Columns (3) and (4) in Table 2.5 show estimates for social skills-intensive occupations. I find that workers in social skill-intensive occupations have higher social skills (0.161, p ¡ 0.005), which is consistent again with Deming (2017). Workers with higher cognitive skills start to sort into social skill-intensive occupation at experience years 7, although the initial effect of cognitive skills is statistically insignificant. This result could be the evidence of complementarity between cognitive skills and social skills in social skill-intensive occupation at later experience.

Columns (5) and (6) estimate parallel specifications but with the information use intensity of a worker's occupation as the outcome. The results are generally similar but opposite in skills. That is, I find a positive coefficient on cognitive skills, and the dynamic effects of cognitive skills indicate persistence for all experience years. This indicates that workers in cognitive-intensive occupation have higher cognitive skills for most of the experience years. A coefficient on social skills is not statistically significant, but this effect of social skills on task intensity become important and significant after ten years of experience, suggesting that cognitive skill and social skill become complements with later experience years.

Turning next to the math intensity of a worker's occupation, I find that a one standard deviation increase in cognitive skills significantly increases the math task intensity by 7.85 percentiles. In contrast, social skills indicate insignificant effects on math task intensity for the full 15 years after college graduation. This suggests that workers with higher cognitive skills sort into math-intensive occupations, but complementarity between cognitive skills and social skills does not emerges in math-intensive occupations.

Columns (7) and (8) show results for occupations which require social interaction. First, looking at the cognitive skills, I find a big negative cognitive skill effect that is persistent over the first fifteen years of a career accumulate. In contrast, workers with higher social skills sort into social interaction-intensive occupation and its impact remains fairly constant throughout the entire period studied.

Overall, the results in Table 2.5 suggests that workers sort into occupations where their skills are more rewarded. In particular, workers with higher cognitive skills sort into cognitive skill-intensive occupation, while workers with higher social skills sort into social skill-intensive occupation. In addition, I find evidence for growing complementarity between cognitive skills and social skills after a couple of years of labor market experience in both information use and social skill-intensive occupation. Professional, technical, and managerial occupations are categorized as the highest skill and highest paid groups, and tasks of these jobs contains communications ability, inductive reasoning, analytical capability and expert mastery, which lie well below social skills and information use task measures (Autor 2015). Arguably, workers in highest categories with a sufficiently long career performs a variety of tasks which require both cognitive and social skills. It implies that occupations require different skills with experience and task intensity.

2.3.3 The Effects of Entry Conditions on Labor Market Outcomes

In this section, I discuss how the impacts of entry conditions on the labor market outcomes varies depending on cognitive and social skills. In particular, to estimate the effect of the unemployment rate at graduation on labor market outcomes and how this varies across skills of workers, I use the following specification:

$$Y_{ict} = \lambda_0+\lambda_1 U_c+\lambda_2 U_c*Exp_{it}+\alpha_1 Cog_i+\alpha_2 Cog_i*U_c+\alpha_3 Cog_i*Exp_{it}+\alpha_4 Cog_i*U_c*Exp_{it}$$

$$+ \beta_1 Soc_i + \beta_2 Soc_i * U_c + \beta_3 Soc_i * Exp_{it} + \beta_4 Soc_i * U_c * Exp_{it} + \gamma' X_{it} + \epsilon_{ict} \quad (2.2)$$

Where U_c indexes the national unemployment rate in the year of college graduation and the rest of the terms are defined as above. The interaction between skills and the college unemployment rate allows me to directly test the hypothesis that the returns to skills have changed by the poor entry conditions. I also include the three-way interaction $Skills_i * U_c * Exp_{it}$ to allow the differential effect to vary with experience. The error term is also clustered by year of college graduation.

Table 2.6 addresses regression results for the skill effects of graduating in a bad economy on labor market outcomes. Panel A shows regression coefficients for skills and its interaction with the unemployment rate. Panel B shows these variables fitted for 0, 1, 3, 7, 10 and 15 years since college graduation. These values equal to $\alpha_1 + \alpha_2 + \alpha_4 * Exp_{it}$ for cognitive skills and $\beta_1 + \beta_2 + \beta_4 * Exp_{it}$ for social skills, respectively.

Looking first at the wage effect, I find that the college unemployment rate does indeed have negative effects of wage returns to cognitive skills. A one standard deviation increase in the college unemployment rate lowers real hourly wages to cognitive skills from 12.22% to 11.88%. Each year this tendency dissipates by 0.34% but statistically significant through at least 15 years after college graduation, as panel B indicates.

In contrast, college graduates with higher social skills face the opposite and more persistent effects when graduating into a recession. A one standard deviation increase in the college unemployment rate is associated with an increased wage returns to social skills from 3.51% to 3.62%. The subsequent rows in panel B report the experience profile starting with a larger 3.74% wage gains in the first year out of school. This effect increases to 5.48% even after 15 years of experience and remains significant at the 1% level.

Overall, interestingly, it seems that graduating in the bad economy differently affects labor market returns to cognitive skill and social skill. Table 2.2 shows that there are positive returns, in terms of hourly wages, to both cognitive and social skills. However, the coefficient on the interaction between the college unemployment rate and cognitive skill is negative, while the coefficient on the interaction between the college unemployment rate and social skill is positive. That is, in response to the increase in the college unemployment higher unemployment raises the returns to social skills but reduces the returns to cognitive skills, although returns to cognitive skills are larger in magnitude than those to social skills.

Moreover, graduating in a time of high unemployment seems to alter how effects of skills on outcomes varies over time. Table 2.2 indicates that the estimates on both cognitive and social skills become larger in magnitude as experience grow, suggesting that both skills grow in importance over time and accordingly returns to both cognitive and social skills increase. In contrast, the results in Table 2.6 differently move around somewhat, depending on types of skills. If there is an increase in the college unemployment rate, the returns to cognitive skills decline over time but the returns to social skills grow as potential experience increases.

To sum up, workers who have higher social skills are less sensitive to initial economic conditions and they may recover from early setbacks using their social skills, resulting in some catch up for the full 15 years after college graduation.

Figure 2.1 and 2.2 plot the returns to cognitive and social skills, respectively, for high and average college unemployment rates. The solid lines show the returns to skills for those graduating in a recession for our sample (the college unemployment rate is 9.7), and the dotted lines show an average economy (the college unemployment rate is 7). The orange lines show returns for workers with high skills (e.g., skills = 1.5). The green lines show returns for workers with average skills (e.g., cognitive skills = 0.91, social skills = 0.16). Finally, the red lines show returns for workers with low skills (e.g., skills = -1.5).

These figures clearly show how graduating in a time of high unemployment rate alters the returns to skills and how it varies across types and levels of skills. First, when skills of workers are sufficiently high, a bad economy negatively affects returns to cognitive

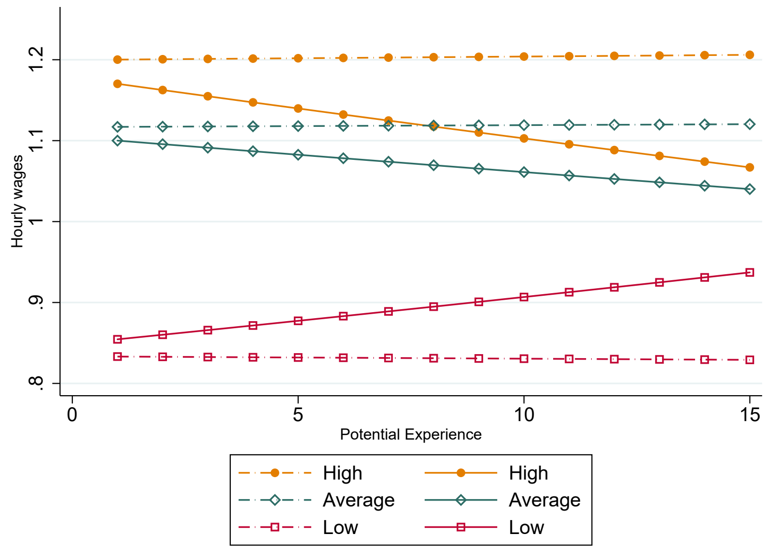

Figure 2.1: Wage Returns to Cognitive Skills

Notes: This figure plots the wage profiles for different values of cognitive skills and the unemployment rates at graduation for an easier comparison of outcomes. The solid lines show the returns to skills for those graduating in a recession (the national unemployment rate at graduation is 9.7), and the dotted lines show an average economy (the national unemployment rate at graduation is 7). The orange lines show returns for workers with high skills (cognitive skills = 1.5). The green lines show returns for workers with average skills (cognitive skills = 0.91). Finally, the red lines show returns for workers with low skills (cognitive skills = -1.5).

skills, while it increases the returns to social skills. Especially, during recessions, the gap between workers having high and low level of social skills are large and widen with experience, indicating the significant role of social skills. Second, when skills of workers are sufficiently low, I find the opposite results; unemployment conditions at college graduation negatively affect returns to social skills but positively affect returns to cognitive skills.

Figure 2.3 plots profiles of real hourly wage for different levels of cognitive and social skills and the college unemployment rate for a comparison of outcomes among different groups. The solid line shows hourly wages for those graduating in the bad economy for our sample (the college unemployment rate is 9.7); the dotted lines fit for those gradu-

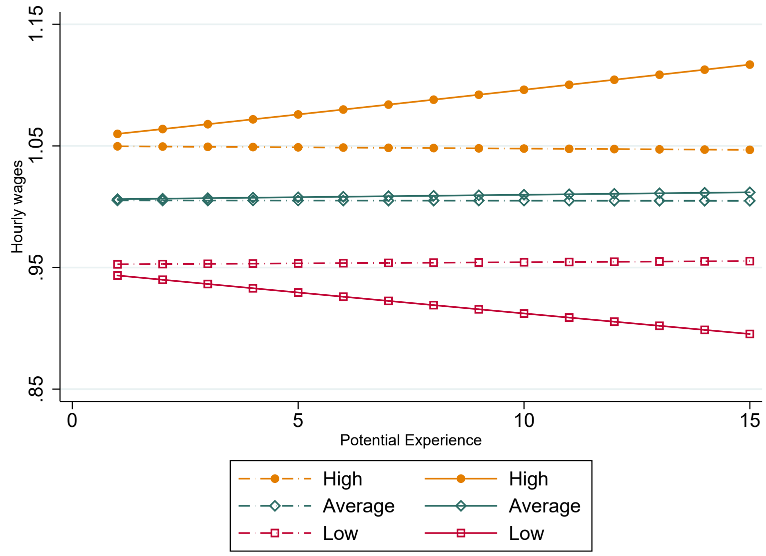

Figure 2.2: Wage Returns to Social Skills

Notes: This figure plots the wage profiles for different values of social skills and the unemployment rates at graduation for an easier comparison of outcomes. The solid lines show the returns to skills for those graduating in a recession (the national unemployment rate at graduation is 9.7), and the dotted lines show an average economy (the national unemployment rate at graduation is 7). The orange lines show returns for workers with high skills (social skills = 1.5). The green lines show returns for workers with average skills (social skills= 0.16). Finally, the red lines show returns for workers with low skills (social skills = -1.5).

ating in the average economy (the college unemployment rate is 7). From the top, the first two lines show high cognitive and high social skills group, the next two lines show high cognitive and low social skills group, the next two lines show low cognitive and high social skills group and the last two on the bottom show low cognitive and low social skills group.

Several interesting features stand out in this graph. First, cognitive skills result in rewards of greater magnitude; the high cognitive and low social skills groups have higher wages than low cognitive and high social skills groups. Second, the returns to social skills have higher reward in a bad economy rather than an average economy; in most cases, graduating into a large recession negatively affects the wages so that the solid line, indicating

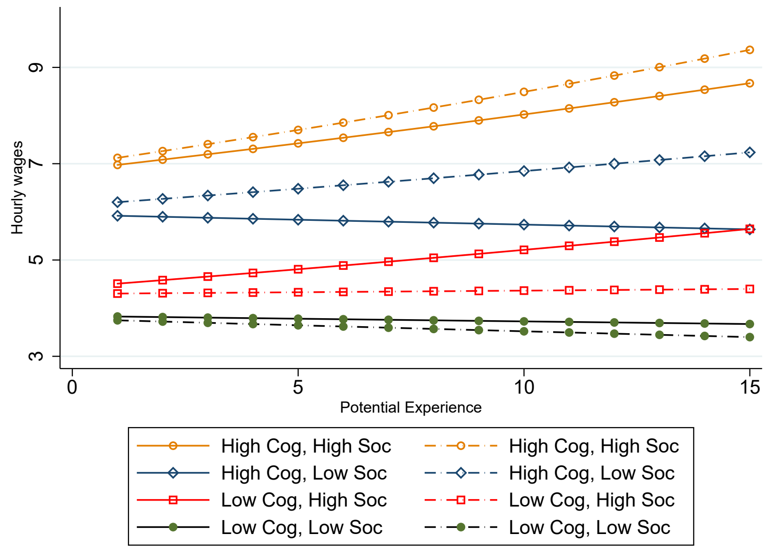

Figure 2.3: Wages by Experience, Entry Conditions, and Skills

Notes: This figure plots profiles of real hourly wage for different levels of cognitive and social skills (high skills = 1.5, low skills = -1.5) and the college unemployment rate for a comparison of outcomes among different groups. The solid line shows hourly wages for those graduating in the bad economy (the unemployment rate at graduation is 9.7). The dotted lines fit for those graduating in the average economy (the unemployment rate at graduation is 7). From the top, the first two lines show high cognitive and high social skills group, the next two lines show high cognitive and low social skills group, the next two lines show low cognitive and high social skills group and the last two on the bottom show low cognitive and low social skills group.

an average unemployment rate, is below the dotted line, indicating a recession. However, the low cognitive and high social skills groups show the opposite result. That is, workers who have low cognitive and high social skills have higher wages if they graduate in a bad economy. Note that we can find the similar results for the low cognitive and low social skills groups as well. Returns to cognitive skills mainly causes this result, given the result from figure 1 such that high unemployment increases returns to cognitive skills for low skill workers. Third, social skills are important as potential experience increases as well as graduates in a worse economy. This can be inferred from the fact that the gap between the high cognitive and low social skills groups and the low cognitive and high social skills groups gradually narrow as workers accumulates experience, considering only the high unemployment case (the blue solid line and red solid line).

Regarding the probability of being employed from the results in columns (3) and (4) in Table 2.6, I find only cognitive skills have initial effect on the employment probability, suggesting that college graduates with higher cognitive skills are more likely to be hired. Furthermore, graduating from college in a bad economy drives the growing importance of cognitive skills; the impact of cognitive skills on the probability of employment has increased from 3.72% to 5.45% when there is a one standard deviation increase in the college unemployment rate. This effect constantly persists over the first 10 years of a career.

Columns (5) and (6) show that neither cognitive nor social skills have initial effects on full-time employment, but these effects become positive, large and statistically significant in response to an increase in the college unemployment rate. For instance, a one standard deviation increase in the college unemployment rate raises the returns, with respect to the full-time employment, to cognitive from 3.03% to 6.87% and to social skills from 0.86% to 3.72%, respectively. The effects of social skills on full-time employment become smaller and fades within seven experience years, while cognitive skills have persistent effects in the accumulation of experience.

The effects for weeks worked show the growing importance of cognitive skills, and this effect is statistically significant and sizable. The initial effect of cognitive skills for weeks worked is about one week more work. When the unemployment rate increases by one standard deviation, workers are likely to work two week and a half longer. The positive effect of cognitive skills on labor supply could be evidence that workers who graduate in worse economies and have higher cognitive skills may find the job faster so that they could work somewhat more. The pattern is much more pronounced for college graduates in adverse labor market conditions. Column (7) in Table 2.2 indicates that the effect of cognitive skills on weeks fades within one year. However, these effects are persistent at least fifteen experience years if individuals graduate in a recession as column (7) in Table 2.6 suggests.

Overall, it seems that graduating into a recession would add the importance of skills regarding labor supply, especially cognitive skills. In other words, cognitive skills are useful to overcome a difficulty of being hired when the unemployment rises, and thus they could obtain more working hours. Interestingly, the association between social skills and full-time employment becomes statistically positive as we consider the college unemployment rate. This implies that social skills as well as cognitive skills come into the picture to have full-time jobs when economies are tough. But social skills still have insignificant effects on employment probability of college graduates who experience adverse labor market conditions, suggesting that employment and full-time employment should be approached differently.

High unemployment is favorable for high cognitive workers in terms of finding "better" jobs. Column (1) in Table 2.7 shows that one standard deviation increase in the unemployment rate raises the occupation prestige score by 2.52 points. Each year dissipates this effect. The fitted college unemployment rate effect of cognitive skills on the prestige score was 3.00 at the first year and small by 15 years out (1.56). However, it is large in magnitude and statistically significant at the 1% level through the fifteenth year after college graduation.

Social skills have no initial effect on the occupational prestige scores, but its impact becomes positive and statistically significant starting 10 years after graduating in a worse economy. This effect, which is less than 1 point, is small in magnitude if considering the sample mean for the prestige scores at 15 years of a career. It is likely to be the case that the small differences in the prestige scores that are driven by social skills and the unemployment rate accumulate over the ten years after graduation and become significant later on. The fact that social skills have no impacts on the prestige scores in the baseline model (column (4) in Table 2.3) considered, it seems that high unemployment makes social skills more important in terms of improving occupation quality.

Columns (5) and (6) in Table 2.7 show results for job changes. To begin with, cognitive skills have no initial effects, however, 10 years after college graduation, the effects become negative and statistically significant at the 10% level. Namely, the estimates become large over time. This suggests that workers with higher cognitive skills are less likely to switch careers later in their life when graduating into a time of higher unemployment.

In contrast, column (6) in Table 2.7 indicates that social skills positively affects career changes, and this tendency is deepen with higher college unemployment rate. That is, a one standard deviation increase in the unemployment rate increases the possibility of changing jobs from 1.7 to 3.31 percentage points. This effect is statistically significant at 5% level and remains fairly constant throughout the entire period studied.

This is partly consistent with results on tenure (columns (3) and (4) in Table 2.7) in that workers with higher cognitive skills are more likely to stay at the current job but those with higher social skills tend to stay shorter periods of weeks. However, it is important to bear in mind that the tenure effects are small in magnitude and not statistically significant in most cases.

Other factors rather than skills may affect the decision of changing occupations. For instance, Wagner (1997) shows that small firms offer worse jobs than large firms on average. Specifically, in small firms compared to large firms, wages are lower, non-wage incomes are lower, job security is lower, and opportunities for skill enhancement are worse. This implies that workers in small firms are more likely to switch to large firms. I explore this issue by controlling for the firm size, measured by following two questions: (1) the number of employers and (2) whether the firm has more than one location.

Column (8) in Table 2.7 presents that the effect of social skills on changing jobs is robust to including firm size variables, although the coefficients become smaller. However, interestingly, cognitive skill is an important channel through which stay at the current jobs. Workers with higher level of cognitive skills are less likely to change jobs, and this effect of cognitive skills appear to persist over the first 15 years of a career. Overall, these results suggest that workers' decision on changing jobs is not mainly driven by firm size.

Looking at another possibility to explain job mobility, it could be affiliated with wage growth. However, results should be interpreted with caution because employee-initiated and employer-initiated separation might have different effects, as shown in Table 2.4. Therefore, I construct voluntary and involuntary variables based on the responses of workers who experience job separation and then check how estimates varies depending on whether workers voluntarily change jobs or not, if college graduates experience poor initial labor markets.

Column (2) in Table 2.8 shows that the probability of voluntarily changing jobs is raised by approximately 0.4 percentage points in response to a one standard deviation increase in social skills. Workers are more affected by exposure to adverse initial shock; one standard deviation increase in the unemployment rate reinforces this effect even further from 0.4 to 0.51 percentage points. This effect is persistent and significant at the 10% level over the first seven years since graduation, and it becomes insignificant thereafter. In contrast, column (2) in Table 2.8 suggests that social skills do not affect involuntary job changes initially. However, these impacts become negative and statistically significant starting 15 years after college graduation, implying that workers with higher social skills are less likely to change their jobs due to discharges or lay-offs. In contrast, the estimates to cognitive skills remain small and insignificant in all cases.

Overall, cognitive and social skills appear to be affecting labor market outcomes differently, and these patterns varied in response to adverse labor market shocks. Firstly, I find that graduating into a time of high unemployment results in modest wages losses to cognitive skills but leads to an increase in wage returns to social skills. Early in a career, labor market returns to cognitive and social skills reduce by 0.3% but increase by 0.1%, respectively, relative to their luckier counterparts. These patterns are much more pronounced later in a career.

Second, workers are likely to work more in response to an increase in the unemployment rate. This result is driven partially by an ability to obtain jobs more easily in a bad economy based on their cognitive (and social skills in the case of full-time employment). In other words, it could be construed as an evidence that college graduates, entering labor market in recessions, try to catch up wage difference by working more hours.

Third, it seems that workers with higher cognitive skills initially move into better jobs a little easier, if they graduate in a bad economy. However, this effect is gradually diminished over time instead social skills become important to shift to other occupations. Workers having higher social skills are likely to change jobs more often over the first 15 years if graduating into a time of high unemployment. Considering that changing employers does affect a worker's subsequent wage, workers with higher social skills could catch up more quickly from poor initial conditions.

2.3.4 Occupational Sorting on Skills and Entry Labor Market Conditions

In this section, I use the data to show that higher initial unemployment rate conditions affect occupational sorting on both cognitive and social skills. I use a linear regression model such as equation (2) above but with the task content of occupations (measured using O*NET) as dependent variable. To make the result comparable with that of luckier peers, I consider the same task content of occupations in Table 5; routine, social skills, information use, math and social interaction.

The results are in Table 2.5. Column (1) shows that the national unemployment rate has no initial effect of cognitive skills on the routine task intensity of a worker's occupation but its impact becomes positive and statistically significant starting 7 years after college graduation. It seems that small differences which are driven by cognitive skills in the routine task intensity become important later on. Column (2) indicates that a worker with higher social skills are less likely to sort into routine occupations, however, the national rate has the opposite effect. That is, the routine task intensity of a worker's occupation is increased by 3.13 percentiles in response to a one standard deviation increase in a national unemployment rate. This effect persists at all experience level.

Columns (3) and (4) replace routine with social skill task intensity. Columns (4) shows that a one standard deviation increase in the national rate increases the social skill task intensity from 1.57 percentiles to 1.72 percentiles. This effect remain fairly constant throughout the entire period studied. Thus, it suggests that workers who graduate from college in bad economies have higher social skills in social skill-intensive occupations. In contrast, column (3) suggests that the effect of cognitive skills on social skill task intensity is insignificant at least in the fifteen year out.

Columns (5) and (6) estimate parallel specifications but with the information use intensity of a worker's occupation as the dependent variable. Column (5) displays that a one standard deviation increase in the national rate increases the information use task intensity of a worker's occupation by 0.6 percentiles. This effect of cognitive skills then dissipates slowly, but is still significant at the 1% level. However, column (6) shows the insignificant effect of the social skills on occupational sorting into information use-intensive occupations in response to an increase in the national unemployment rate.

Columns (3)-(6) in Table 2.5 and Table 2.9 suggest that the unemployment rate yields different results of occupational sorting on skills. Columns (3)-(6) in Table 5 show evidence of complementarity between cognitive skills and social skills among experienced workers. That is, sufficiently experienced workers in social skills and information use-intensive occupations have a higher level of both cognitive and social skills. However, the effects of recession shocks for young workers do not allow to hold complementarity between cognitive and social skills for the first fifteen years of potential experience. Workers with higher levels of social skill sort into social skill-intensive occupations, but those with higher levels of cognitive skill sort into information use-intensive occupations.

Turning next to math task intensity of a worker's occupation. Unlike workers in information use-intensive occupations, I find a negative unemployment effect that slowly diminishes but persists for 15 years after college graduation. That is, an adverse initial labor market shock reduces the math task intensity for at least 15 years of experience. Not surprisingly, workers with high social skills do not sort into math-intensive occupations.

The remainder of Table 2.6 shows results on social interaction-intensive task measures. A one standard deviation increase in the national unemployment rate at college graduation increases the effect of cognitive skills but decreases the effect of social skills on social interaction task intensity. In other words, workers with higher cognitive skills are less likely to switch into social interaction-intensive occupations, but a thin market at the time of college graduation slows this trend so that more workers with a high level of cognitive skills move into social-interaction occupation than their luckier counterparts. Similarly, workers in social interaction-intensive occupations have higher social skills, but the national unemployment rate lowers this level of social skills.

Overall, this result highlights that the economic conditions at the beginning of one's labor market career appears to differently influence the task intensity of a worker's occupation. Specifically, as the national rate increases, workers in social skills and information use-intensive occupations have higher social skills and higher cognitive skills, respectively. That is, the adverse entry condition improves the matching quality of workers to occupation. In contrast, an increase in the national rate at graduation hampers sorting of workers to occupations in routine, math and social interaction-intensive occupations.

2.4 Conclusion

In this paper, I estimate the labor market outcomes of graduating from college in times of higher unemployment and measure how those effects vary with the one's level of cognitive and social skills. Pooling information on the graduating cohorts from 1979 to 1989 in the NLSY79, I find that graduating from college in a recession decreases wages to cognitive skills, while it increases wages to social skills. For college graduates, I estimate that labor market outcomes to cognitive skills decline by 2.69% and those to social skills gain by 3.42%, indicating that there is a large degree of heterogeneity in the costs of initial adverse conditions depending on skill types, even within the same cohort of college graduates. These effects do not fade out but more persist over the first 15 years of a career. A main contribution of this paper is to explore and untangle complex patters in heterogeneity of skills from initial labor market shocks.

Another main contribution of this paper is the analysis of the mechanisms behind these persistent and heterogeneous skill effects of the early labor market conditions. I find that occupation quality and match quality account for a substantial portion of the heterogeneous wage effects of cognitive and social skills. Workers with high cognitive skills are likely to be 'more employed' 'at faster speed' and have 'higher-quality' jobs, compared to lower-cognitive skilled workers. Workers with high social skills are likely to voluntarily change jobs more often.

Remarkably, graduating into a recession magnifies the role of both cognitive and social skills. I find that workers who enter the labor market in a recession with higher cognitive skills to be employed with higher probability, and start to work at more attractive employers, relative to their luckier counterparts. Social skills allow workers to actively move into other jobs even in worse economies. Clearly, the effects of cognitive skills on wages are larger in magnitude than those of social skills. However, given that a crucial part of wage catch-up occurs by means of moving to higher paying firms, and that workers are more mobile early in their careers than later in their careers, social skills rather than cognitive skills are more helpful for faster recovery. These patterns could partially explain the wage effects of cognitive and social skill in the case of graduating in recessions.

Considering that various theories bring out different predictions about the long-term effects of a poor early experience, the analysis that focuses on cognitive and social skills, which has received little attention in this literature, lends substantial added-value to this question. Theory about the long-lasting effects of graduating in a recession is ambiguous; on the one hand, workers who graduate in bad economies are able to overcome the loss such as initial unemployment or job mismatching, if they could quickly switch to the "correct" job when the economy improves. On the other hand, the effects of poor labor market condition will be quite persistent if workers accumulate disparities in human capital, because workers who enter labor markets in downturns would have spent more time in bad matches or investing in the wrong types of human capital (Jovanovic 1979b; Neal 1999; Gibbons and Waldman 2004).

We could gain meaningful insight by looking at this question in the context of cognitive and social skills. That is, workers with higher social skills are able to move into to the "correct" job quite quickly, allowing them to work through the initial misfortune. In this case, job shopping is beneficial and common, and we will not observe the long-lasting effects of graduating in a bad economy. On the contrary, individuals who entered in a thin market and may have spent more time in bad matches will be continuously less productive than their luckier counterparts. This is because higher cognitive skills would yield better performance by leading workers to learn faster, but workers in wrong types of tasks continue to lose chances of learning. It suggests that it is much more important to train workers with high cognitive skills in good matches to begin with. In this case, the effects of a poor early experience could be quite persistent.

Furthermore, my results present evidence of the skill effects on occupational sorting of workers. Workers with higher levels of cognitive skills sort into jobs that involve more cognitive skills such as routine, information use and math-intensive occupations. In contrast, an increase in social skills increases social skills or social interaction task intensity of a worker's occupation.

This occupational sorting of workers graduating from college in times of higher unemployment vary with occupation task intensity. An increase in the college unemployment rate allows workers in social skills and information use-intensive occupations sort into these occupations where their skills are more rewarded. In contrast, I find that the college unemployment rate impedes sorting to occupations in other types of tasks. For instance, workers with higher cognitive skills originally select into math or routine-intensive occupations, but they are less likely to sort into those jobs as the college unemployment rate increases.

This paper provides direct evidence that the business-cycle effects of labor market entrants that vary with cognitive and social skills have the capacity to capture the main patterns in this sample. For further study, it is worth focusing on the differential impacts of cognitive and social skills using other cohorts graduating in different recessions. This may yield a better understanding of business-cycle effects on skills.

Table 2.1: Summary Statistics

Variable	Mean	SD	Min	Max
Graduation year	1983.73	2.65	1979	1989
Graduation unemployment rate (National)	7.45	1.30	5.30	9.70
Graduation unemployment rate (Regional)	7.50	1.48	4.10	11.10
Year	1991.90	5.38	1979	2004
Log hourly wage	2.91	0.55	1.61	5.52
Employed	0.90	0.30	0	1
Full-time employed	0.75	0.43	0	1
Weeks per year	44.73	14.70	0	52
Occupation prestige score	48.96	13.23	7	82
Tenure	188.66	188.09	1	1230
Job change	0.18	0.39	0	1
Cognitive skills	0.82	0.75	-2.42	1.89
Social skills	0.16	0.95	-2.37	2.01
Potential experience	8.17	4.42	0	15
Highest grade completed	16.43	0.92	16	20
Age	30.87	4.85	22	47
Black	0.17	0.38	0	1
Hispanic	0.08	0.27	0	1
Male	0.48	0.50	0	1

Notes: The sample includes unenrolled workers who graduate between 1979 and 1989, with potential experience 0-15 and with valid outcome variables in the previous year's observations. Potential experience is defined as years since graduation. Log hourly wages are inflation adjusted to 2006 dollars. Cognitive skills are measured by the Armed Forces Qualifying Test (AFQT), and are normalized to have a mean of zero and a standard deviation of one. Social skills are a standardized composite of two questions from the Big 5 personality inventory that measure extroversion. Full-time employment indicates workers who work at least 30 hours per week. Weeks per year are weeks worked in the past calendar year but tenure is weeks tenure at current and main job. Job change is a dummy for changing job.

Table 2.2: Labor Market Returns to Cognitive and Social Skills in the NLSY79

	Log wage		Employed		Full-time employed		Weeks per year	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Cognitive	Social	Cognitive	Social	Cognitive	Social	Cognitive	Social
A: Regression coefficients								
Skills	0.119***	0.036***	0.040**	0.008	0.035	0.012	1.280**	0.296
	[0.026]	[0.005]	[0.014]	[0.011]	[0.020]	[0.013]	[0.563]	[0.533]
Skills * Exp	0.004	0.002	-0.005***	0	-0.007**	-0.001	-0.199**	0.001
	[0.002]	[0.001]	[0.001]	[0.001]	[0.002]	[0.002]	[0.083]	[0.068]
B: Fitted marginal effects of skills								
Experience								
1	0.1217***	0.0381***	0.0338**	0.0076	0.0274	0.0097	1.0413**	0.2586
	[0.0246]	[0.0038]	[0.0135]	[0.0106]	[0.0182]	[0.0117]	[0.5153]	[0.5078]
3	0.1299***	0.0427***	0.0234*	0.0070	0.0150	0.0076	0.6609	0.2688
	[0.0218]	[0.0039]	[0.0124]	[0.0094]	[0.0160]	[0.0101]	[0.4474]	[0.4614]
7	0.1462***	0.0519***	0.0027	0.0058	-0.0098	0.0035	-0.1000	0.2891
	[0.0188]	[0.0081]	[0.0114]	[0.0098]	[0.0142]	[0.0109]	[0.4827]	[0.4866]
10	0.1585***	0.0589***	-0.0129	0.0048	-0.0284	0.0004	-0.6707	0.3043
	[0.0194]	[0.0121]	[0.0120]	[0.0121]	[0.0158]	[0.0144]	[0.6329]	[0.5952]
15	0.1789***	0.0705***	-0.0389**	0.0033	-0.0593**	-0.0049	-1.6218	0.3297
	[0.0251]	[0.0190]	[0.0151]	[0.0179]	[0.0223]	[0.0223]	[0.9758]	[0.8601]

Notes: Each column reports results from an estimate of equation (1), with log hourly wages, employment, full-time employment, weeks worked per year, prestige score, tenure and job change as outcome. The data source is the National Longitudinal Survey of Youth 1979 cohort (NLSY79). The sample is restricted to workers who graduated from college between 1979 and 1989 and have valid skill measures and outcome variables within 15 years of college graduation who are not enrolled in school. Cognitive skills are measured by each respondent's score on the Armed Forces Qualifying Test (AFQT), and social skills is a standardized composite of two variables (i) self-reported personality scale: extroverted or enthusiastic (ii) self-reported personality scale: reserved or quiet. Both skill measures are normalized to have a mean of 0 and a standard deviation of 1. Regression includes year fixed effects, plus additional controls such as potential experience, a quadratic and a cubic in potential experience, gender, race/ethnicity and gender interacted with race/ethnicity. Standard errors are in brackets and are clustered by year of college gradation. ***p<.01, **p<05, *p<10.

Table 2.3: Labor Market Returns to Cognitive and Social Skills in the NLSY79

	Prestige score		Tenure		Job change	
	(1)	(2)	(3)	(4)	(5)	(6)
	Cognitive	Social	Cognitive	Social	Cognitive	Social
A: Regression coefficients						
Skills	2.581***	-0.051	6.375	2.537	-0.016	0.019***
	[0.354]	[0.344]	[6.208]	[3.641]	[0.011]	[0.005]
Skills * Exp	0.031	0.057	0.072	-0.568	0.001	-0.002***
	[0.054]	[0.049]	[0.823]	[0.705]	[0.001]	[0.000]
B: Fitted marginal effects of skills						
Experience						
1	2.5997***	-0.0045	6.3729	1.9018	-0.0151	0.0171***
	[0.3376]	[0.3068]	[5.6088]	[3.1544]	[0.0102]	[0.0051]
3	2.6657***	0.1113	6.5481	0.7825	-0.0131	0.0139**
	[0.3227]	[0.2415]	[4.6712]	[2.4778]	[0.0076]	[0.0044]
7	2.7976***	0.3430	6.8986	-1.4562	-0.0092**	0.0075*
	[0.3920]	[0.2116]	[4.3512]	[3.2368]	[0.0039]	[0.0034]
10	2.8966***	0.5168	7.1614	-3.1352	-0.0063	0.0027
	[0.5013]	[0.2922]	[5.5775]	[4.9188]	[0.0049]	[0.0031]
15	3.0615***	0.8064	7.5995	-5.9335	-0.0014	-0.0052
	[0.7276]	[0.4998]	[8.8723]	[8.1848]	[0.0108]	[0.0037]

Notes: Each column reports results from an estimate of equation (1), with prestige score, tenure and job change as outcome. The data source is the National Longitudinal Survey of Youth 1979 cohort (NLSY79). The sample is restricted to workers who graduated from college between 1979 and 1989 and have valid skill measures and outcome variables within 15 years of college graduation who are not enrolled in school. Cognitive skills are measured by each respondent's score on the Armed Forces Qualifying Test (AFQT), and social skills is a standardized composite of two variables (i) self-reported personality scale: extroverted or enthusiastic (ii) self-reported personality scale: reserved or quiet. Both skill measures are normalized to have a mean of 0 and a standard deviation of 1. Regression includes year fixed effects, plus additional controls such as potential experience, a quadratic and a cubic in potential experience, gender, race/ethnicity and gender interacted with race/ethnicity. Standard errors are in brackets and are clustered by year of college gradation. ***p<.01, **p<.05, *p<.10.

Table 2.4: Voluntary and Involuntary Job Change in the NLSY79

	Job chage (voluntary)		Job change (involuntary)	
	(1)	(2)	(3)	(4)
	Cognitive	Social	Cognitive	Social
A: Regression coefficients				
Skills	-0.004	0.004*	-0.002	-0.003
	[0.005]	[0.002]	[0.002]	[0.002]
Skills * Exp	0.001	-0.000*	0	0
	[0.000]	[0.000]	[0.000]	[0.000]
B: Fitted marginal effects of skills				
Experience				
1	-0.0034	0.0036*	-0.0008	-0.0019
	[0.0050]	[0.0019]	[0.0020]	[0.0016]
3	-0.0024	0.0028*	-0.0007	-0.0015
	[0.0042]	[0.0015]	[0.0016]	[0.0012]
7	-0.0004	0.0012	-0.0006	-0.0006
	[0.0025]	[0.0008]	[0.0010]	[0.0005]
10	0.0011	0.0000	-0.0004	0.0000*
	[0.0014]	[0.0003]	[0.0008]	[0.0000]
15	0.0036*	-0.0020*	-0.0002	0.0010
	[0.0014]	[0.0009]	[0.0014]	[0.0009]

Notes: Each column reports results from an estimate of equation (1), with voluntary and involuntary job change as outcome. The data source is the National Longitudinal Survey of Youth 1979 cohort (NLSY79). The sample is restricted to workers who graduated from college between 1979 and 1989 and have valid skill measures and outcome variables within 15 years of college graduation who are not enrolled in school. Cognitive skills are measured by each respondent's score on the Armed Forces Qualifying Test (AFQT), and social skills is a standardized composite of two variables (i) self-reported personality scale: extroverted or enthusiastic (ii) self-reported personality scale: reserved or quiet. Both skill measures are normalized to have a mean of 0 and a standard deviation of 1. Regression includes year fixed effects, plus additional controls such as potential experience, a quadratic in potential experience, gender, race/ethnicity and gender interacted with race/ethnicity. Standard errors are in brackets and are clustered by year of college gradation. ***p<.01, **p<.05, *p<.10.

Table 2.5: Occupational Sorting on Skills in the NLSY79

	Routine		Social skills		Information use		Math		Social Interaction	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(7)	(8)
	Cognitive	Social	Cognitive	Social	Cognitive	Social	Cognitive	Social	Cognitive	Social
A: Regression coefficients										
Skills	0.513***	-0.278*	0.088	0.161**	0.658***	-0.016	0.785***	-0.062	-0.482***	0.213**
	[0.146]	[0.131]	[0.089]	[0.071]	[0.087]	[0.053]	[0.120]	[0.062]	[0.127]	[0.092]
Skills * Exp	-0.029**	-0.005	0.015**	0.007	-0.001	0.014**	-0.011	0.010**	0.013*	0.001
	[0.012]	[0.010]	[0.005]	[0.007]	[0.009]	[0.005]	[0.008]	[0.004]	[0.007]	[0.010]
B: Fitted marginal effects of skills										
Experience										
1	0.4836***	-0.2829**	0.1024	0.1678**	0.6571***	-0.0022	0.7736***	-0.0525	-0.4696***	0.2145**
	[0.1361]	[0.1234]	[0.0873]	[0.0660]	[0.0828]	[0.0519]	[0.1206]	[0.0606]	[0.1227]	[0.0871]
3	0.4257***	-0.2930**	0.1316	0.1811**	0.6560***	0.0259	0.7509***	-0.0331	-0.4439***	0.2170**
	[0.1169]	[0.1081]	[0.0845]	[0.0580]	[0.0780]	[0.0503]	[0.1222]	[0.0590]	[0.1154]	[0.0799]
7	0.3100***	-0.3132***	0.1902**	0.2077***	0.6538***	0.0821	0.7057***	0.0058	-0.3927***	0.2221**
	[0.0865]	[0.0828]	[0.0831]	[0.0516]	[0.0809]	[0.0526]	[0.1306]	[0.0595]	[0.1048]	[0.0787]
10	0.2231**	-0.3284***	0.2341**	0.2277***	0.6522***	0.1242*	0.6718***	0.0350	-0.3542***	0.2259**
	[0.0769]	[0.0723]	[0.0858]	[0.0570]	[0.0931]	[0.0586]	[0.1408]	[0.0630]	[0.1013]	[0.0894]
15	0.0784579	-0.3536***	0.3074***	0.2610***	0.6495***	0.1945**	0.6153***	0.0837	-0.2902***	0.2322*
	[0.0955]	[0.0791]	[0.0966]	[0.0796]	[0.1247]	[0.0741]	[0.1634]	[0.0737]	[0.1048]	[0.1212]

Notes: Each column reports results from an estimate of equation (1), with the indicated 1998 O*NET task intensity of an occupation as the dependent variables and person-year as the unit of observation. Following Deming(2017), the task measures are percentiles that range from 0 to 10 and are weighted by labor supply to conform to the 1980 occupation distribution. The O*NET task measures that are used here are routine, social skills, information use, math and require social skills. The data source is the National Longitudinal Survey of Youth 1979 cohort (NLSY79). The sample is restricted to workers who graduated from college between 1979 and 1989 and have valid skill measures and outcome variables within 15 years of college graduation who are not enrolled in school. Cognitive skills are measured by each respondent's score on the Armed Forces Qualifying Test (AFQT), and social skills is a standardized composite of two variables (i) self-reported personality scale: extroverted or enthusiastic (ii) self-reported personality scale: reserved or quiet. Both skill measures are normalized to have a mean of 0 and a standard deviation of 1. Regression includes year fixed effects, plus additional controls such as potential experience, a quadratic and a cubic in potential experience, gender, race/ethnicity and gender interacted with race/ethnicity. Standard errors are in brackets and are clustered by year of college gradation. ***p<.01, **p<.05, *p<.10.

Table 2.6: Labor Market Returns to Skills and Labor Market Conditions in the NLSY79

	Log wage		Employed		Full-time employed	
	(1)	(2)	(3)	(4)	(5)	(6)
	Cognitive	Social	Cognitive	Social	Cognitive	Social
A: Regression coefficients						
Skills	0.122***	0.035***	0.037**	0.007	0.03	0.009
	[0.027]	[0.005]	[0.014]	[0.011]	[0.018]	[0.010]
Skills * Unemploy	-0.003	0.001	0.017	0.007	0.038*	0.029**
	[0.021]	[0.010]	[0.014]	[0.006]	[0.019]	[0.009]
B: Fitted marginal effects of skills						
Experience						
0	0.1188***	0.0362**	0.0545***	0.0142	0.0687**	0.0372***
	[0.0282]	[0.0118]	[0.0154]	[0.0114]	[0.0257]	[0.0063]
1	0.1163***	0.0374***	0.0532***	0.0143	0.0673**	0.0345***
	[0.0273]	[0.0107]	[0.0148]	[0.0107]	[0.0245]	[0.0077]
3	0.1114***	0.0399***	0.0507***	0.0145	0.0646**	0.0290**
	[0.0261]	[0.0086]	[0.0140]	[0.0101]	[0.0223]	[0.0109]
7	0.1015***	0.0449***	0.0457***	0.0150	0.0593**	0.0182
	[0.0267]	[0.0056]	[0.0140]	[0.0121]	[0.0198]	[0.0178]
10	0.0941**	0.0486***	0.0419**	0.0154	0.0553**	0.0100
	[0.0296]	[0.0058]	[0.0155]	[0.0155]	[0.0201]	[0.0231]
15	0.0817*	0.0548***	0.0357	0.0160	0.0486*	-0.0036
	[0.0377]	[0.0103]	[0.0200]	[0.0226]	[0.0241]	[0.0320]

Notes: Each column reports results from an estimate of equation (2), with log hourly wages, employment, full-time employment and weeks worked per year as outcome. The data source is the National Longitudinal Survey of Youth 1979 cohort (NLSY79). The sample is restricted to workers who graduated from college between 1979 and 1989 and have valid skill measures and outcome variables within 15 years of college graduation who are not enrolled in school. Cognitive skills are measured by each respondent's score on the Armed Forces Qualifying Test (AFQT), and social skills is a standardized composite of two variables (i) self-reported personality scale: extroverted or enthusiastic (ii) self-reported personality scale: reserved or quiet. Both skill measures are normalized to have a mean of 0 and a standard deviation of 1. The unemployment rate is the national yearly unemployment rate from BLS. Regression includes year fixed effects, plus additional controls such as potential experience, a quadratic in potential experience, gender, race/ethnicity and gender interacted with race/ethnicity. Standard errors are in brackets and are clustered by year of college gradation. ***p<.01, **p<.05, *p<.10.

Table 2.7: Labor Market Returns to Skills and Labor Market Conditions in the NLSY79

	Prestige score		Tenure		Job change		Job change	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Cognitive	Social	Cognitive	Social	Cognitive	Social	Cognitive	Social
A: Regression coefficients								
Skills	2.525***	-0.064	5.682	2.854	-0.017	0.017***	-0.032*	0.011*
	[0.372]	[0.353]	[6.142]	[3.720]	[0.011]	[0.004]	[0.015]	[0.005]
Skills * Unemploy	0.58	0.218	2.901	-0.78	0.012	0.017***	-0.006	0.009**
	[0.472]	[0.364]	[4.061]	[5.038]	[0.009]	[0.003]	[0.007]	[0.004]
B: Fitted marginal effects of skills								
Experience								
0	3.1049***	0.1537	8.5834	2.0741	-0.0059	0.0331***	-0.0387**	0.0199***
	[0.5580]	[0.4999]	[5.6390]	[6.0274]	[0.0121]	[0.0044]	[0.0168]	[0.0062]
1	3.0025***	0.2089	9.1057	0.9514	-0.0075	0.0322***	-0.0385**	0.0197***
	[0.5398]	[0.4792]	[5.6945]	[5.7430]	[0.0116]	[0.0043]	[0.0164]	[0.0060]
3	2.7977***	0.3193	10.1505	-1.2940	-0.0107	0.0305***	-0.0381**	0.0193***
	[0.5134]	[0.4415]	[6.1290]	[5.2531]	[0.0109]	[0.0042]	[0.0156]	[0.0056]
7	2.3881***	0.5401	12.2400	-5.7848	-0.0171	0.0271***	-0.0373**	0.0185***
	[0.5069]	[0.3860]	[7.9592]	[4.6967]	[0.0106]	[0.0044]	[0.0145]	[0.0054]
10	2.0808***	0.7057*	13.8071	-9.1529*	-0.0219*	0.0245***	-0.0366**	0.0179**
	[0.5428]	[0.3674]	[9.8111]	[4.7423]	[0.0113]	[0.0049]	[0.0141]	[0.0057]
15	1.5688**	0.9817**	16.4190	-14.7664**	-0.0300*	0.0202***	-0.0356**	0.0169**
	[0.6626]	[0.3880]	[13.3026]	[5.6512]	[0.0141]	[0.0062]	[0.0144]	[0.0068]
Firm size							X	X

Notes: Each column reports results from an estimate of equation (2) with prestige score, tenure and job change as outcome. The data source is the NLSY79. The sample is restricted to workers who graduated from college between 1979 and 1989 and have valid skill measures and outcome variables within 15 years of college graduation who are not enrolled in school. Cognitive skills are measured by each respondent's score on the Armed Forces Qualifying Test (AFQT), and social skills is a standardized composite of self-reported personality scale (i) extroverted or enthusiastic (ii) reserved or quiet. The unemployment rate is the national yearly unemployment rate from BLS. Regression includes year fixed effects, plus additional controls such as potential experience, a quadratic in potential experience, gender, race/ethnicity and gender interacted with race/ethnicity. As indicated, the firm size, measured by the number of employees in the firm and whether the employer has more than one location, is also controlled. Standard errors are in brackets and are clustered by year of college gradation. ***p<.01, **p<.05, *p<.10.

Table 2.8: Voluntary and Involuntary Job Change and Labor Market Conditions in the NLSY79

	Job chage (voluntary)		Job change (involuntary)	
	(1)	(2)	(3)	(4)
	Cognitive	Social	Cognitive	Social
A: Regression coefficients				
Skills	-0.004	0.004*	-0.003	-0.003
	[0.005]	[0.002]	[0.002]	[0.002]
Skills * Unemploy	-0.003	0.001	0.001	0.002
	[0.004]	[0.002]	[0.002]	[0.002]
B: Fitted marginal effects of skills				
Experience				
0	-0.0069	0.0051	-0.0006	-0.0004
	[0.0053]	[0.0028]	[0.0035]	[0.0021]
1	-0.0066	0.0049*	-0.0006	-0.0006
	[0.0052]	[0.0027]	[0.0033]	[0.0020]
3	-0.0060	0.0046*	-0.0007	-0.0010
	[0.0050]	[0.0025]	[0.0029]	[0.0018]
7	-0.0048	0.0040*	-0.0008	-0.0017
	[0.0050]	[0.0021]	[0.0023]	[0.0016]
10	-0.0039	0.0035	-0.0010	-0.0023
	[0.0053]	[0.0020]	[0.0021]	[0.0015]
15	-0.0024	0.0027	-0.0011	-0.0033*
	[0.0060]	[0.0020]	[0.0023]	[0.0016]

Notes: Each column reports results from an estimate of equation (2) with voluntary and involuntary job change as outcome. The data source is the National Longitudinal Survey of Youth 1979 cohort (NLSY79). The sample is restricted to workers who graduated from college between 1979 and 1989 and have valid skill measures and outcome variables within 15 years of college graduation who are not enrolled in school. Cognitive skills are measured by each respondent's score on the Armed Forces Qualifying Test (AFQT), and social skills is a standardized composite of two variables (i) self-reported personality scale: extroverted or enthusiastic (ii) self-reported personality scale: reserved or quiet. Both skill measures are normalized to have a mean of 0 and a standard deviation of 1. The unemployment rate is the national yearly unemployment rate from BLS. Regression includes year fixed effects, plus additional controls such as potential experience, a quadratic in potential experience, gender, race/ethnicity and gender interacted with race/ethnicity. Standard errors are in brackets and are clustered by year of college gradation. ***p<.01, **p<.05, *p<.10.

Table 2.9: Occupational Sorting on Skills and Labor Market Conditions in the NLSY79

	Routine		Social skills		Information use		Math		Social Interaction	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Cognitive	Social	Cognitive	Social	Cognitive	Social	Cognitive	Social	Cognitive	Social
A: Regression coefficients										
Skills	0.5726***	-0.2849*	0.072	0.1577*	0.6603***	-0.0317	0.8016***	-0.0702	-0.4901***	0.2133*
	[0.1220]	[0.1314]	[0.0930]	[0.0729]	[0.0923]	[0.0559]	[0.1127]	[0.0651]	[0.1314]	[0.0964]
Skills * Unemploy	-0.3747**	0.0313	0.1415	0.015	0.0635	0.0947	-0.045	0.0388	0.0935	-0.025
	[0.1357]	[0.0872]	[0.0941]	[0.0575]	[0.0782]	[0.0687]	[0.1037]	[0.0512]	[0.1598]	[0.0920]
B: Fitted marginal effects of skills										
Experience										
0	0.1979	-0.2537*	0.2135	0.1726*	0.7239***	0.0630	0.7566***	-0.0314	-0.3967*	0.1883
	[0.1751]	[0.1322]	[0.1200]	[0.0842]	[0.0967]	[0.0861]	[0.1514]	[0.0726]	[0.2055]	[0.1186]
1	0.2192	-0.2582*	0.2019	0.1804*	0.7127***	0.0608	0.7489***	-0.0309	-0.4019*	0.2066*
	[0.1732]	[0.1304]	[0.1177]	[0.0815]	[0.0957]	[0.0846]	[0.1490]	[0.0705]	[0.1987]	[0.1088]
3	0.2616	-0.2672*	0.1786	0.1958**	0.6905***	0.0563	0.7334***	-0.0299	-0.4123*	0.2431**
	[0.1705]	[0.1283]	[0.1136]	[0.0776]	[0.0945]	[0.0821]	[0.1447]	[0.0682]	[0.1859]	[0.0919]
7	0.3464*	-0.2851*	0.1321	0.2267**	0.6460***	0.0474	0.7023***	-0.0280	-0.4331**	0.3163***
	[0.1696]	[0.1294]	[0.1079]	[0.0765]	[0.0952]	[0.0791]	[0.1374]	[0.0708]	[0.1639]	[0.0761]
10	0.4100**	-0.2986*	0.0972	0.2499**	0.6127***	0.0407	0.6790***	-0.0266	-0.4488**	0.3711***
	[0.1730]	[0.1349]	[0.1060]	[0.0815]	[0.0984]	[0.0785]	[0.1335]	[0.0785]	[0.1516]	[0.0863]
15	0.5161**	-0.3210*	0.0390	0.2886**	0.5571***	0.0295	0.6402***	-0.0242	-0.4748***	0.4625***
	[0.1856]	[0.1517]	[0.1076]	[0.0987]	[0.1083]	[0.0811]	[0.1300]	[0.0989]	[0.1421]	[0.1310]

Notes: Each column reports results from an estimate of equation (2), with the 1998 O*NET task intensity of an occupation as the dependent variables. Following Deming(2017), the task measures are percentiles that range from 0 to 10 and are weighted by labor supply to conform to the 1980 occupation distribution. The data source is the National Longitudinal Survey of Youth 1979 cohort (NLSY79). The sample is restricted to workers who graduated from college between 1979 and 1989 and have valid skill measures and outcome variables within 15 years of college graduation who are not enrolled in school. Cognitive skills are measured by each respondent's score on the Armed Forces Qualifying Test (AFQT), and social skills is a standardized composite of two variables (i) self-reported personality scale: extroverted or enthusiastic (ii) self-reported personality scale: reserved or quiet. Both skill measures are normalized to have a mean of 0 and a standard deviation of 1. Regression includes year fixed effects, plus additional controls such as potential experience, a quadratic and a cubic in potential experience, gender, race/ethnicity and gender interacted with race/ethnicity. Standard errors are in brackets and are clustered by year of college gradation. ***p<.01, **p<.05, *p<.10.

CHAPTER 3
SELLING A LEMON UNDER DEMAND UNCERTAINTY

3.1 Introduction

Consider a seller who wishes to sell a used car. Due to her experience with the car, she is likely to be better informed about the car than buyers. This adverse selection produces risks for buyers, thereby complicating their purchase decisions. On the other hand, the seller is likely to have uncertainty about her demand. She may not have precise information about the aggregate state of the economy or the general popularity of her car. This is arguably the reason why most used car sellers refer to price information services such as Kelly Blue Book. There is an extensive literature both on adverse selection and on demand uncertainty. The goal of this paper is to understand the interplay between adverse selection and demand uncertainty, which, to our knowledge, has not been investigated in the literature yet, in a tractable dynamic trading environment.

We consider a dynamic pricing problem facing a seller who wishes to sell an indivisible object. She sets a price and can adjust it at any point in time at no cost. Buyers arrive sequentially, observe the posted price, and decide whether to purchase the good or not. The seller has private information about the quality of the good, which is either high or low. On the other hand, she faces uncertainty about demand. Specifically, she is uncertain whether the arrival rate of buyers is high or low.

For each case, we characterize a class of equilibria in which the seller insists on a constant price if her good is of high quality. The assumption about the high-quality seller's pricing behavior implies that at any point in time, the low-quality seller can choose only between two prices, one which is charged by the high-quality seller and the other which is optimal conditional on her type being revealed. This mitigates severe equilibrium multiplicity, which results from the signaling nature of the model, as well as gives tractability to the analysis. Still, there is a continuum of prices that can be employed as the high price. Instead of selecting a particular equilibrium, we characterize all such equilibria.

We first consider the case where buyers are also uncertain about demand (symmetric demand uncertainty). In that case, we show that the low-quality seller's optimal pricing strategy is a simple switching-down strategy: she begins with the high price and switches down to the low price once she fails to trade for a while. This is a familiar result in the literature on demand uncertainty (experimentation). Intuitively, as she continues to fail to trade, she becomes more pessimistic about demand and eventually switches to the low price, which speeds up trade and, therefore, is optimal with low demand.

The difference from the existing literature is that in our model, the low-quality seller always begins with the high price, no matter how small the initial probability of high demand is. This is because effective demand is endogenously determined by the presence of adverse selection in our model. To see this more clearly, suppose the low-quality seller never offers the high price. If so, upon observing the high price, buyers believe that the seller is the high type for sure and, therefore, accepts the price. This, of course, provides an incentive for the low-quality seller to deviate and offer the high price. This shows that the low-quality seller must offer the high price with a positive probability. Combining this with the fact that she becomes more pessimistic over time, it follows that the low-quality seller always plays a switching-down pricing strategy.

We also show that symmetric demand uncertainty is always beneficial to the low-quality seller: her expected payoff is strictly higher with symmetric demand uncertainty than without demand uncertainty[1]. This is counterintuitive in light of the conventional wisdom that (demand) uncertainty inhibits a seller's complete optimization and, therefore, learning is always valuable. This is, again, due to endogenous demand. Buyers adjust their purchase behavior, depending on whether there is demand uncertainty or not. Therefore, the conventional wisdom, which applies to a seller's optimal decision problem, does not apply to our strategic environment. The payoff dominance under symmetric demand uncertainty is due to the fact that, although the seller faces the same constraint as buyers initially, she has the advantage to learn about demand and adjust her price over time. Notice that this shows that (private) learning is still valuable in our environment.

We then study the case where buyers are informed about demand (asymmetric demand uncertainty) and demonstrate that the results are markedly different from those with symmetric demand uncertainty. Asymmetric demand uncertainty has no effect on the seller's expected payoff: both seller types' expected payoffs in each state are identical to those without demand uncertainty. In addition, the low-quality seller's switching-down pricing strategy can never be a part of equilibrium. We show that there exists an equilibrium in which the low-quality seller adopts a switching-up-and-down pricing strategy: she begins with the low price, switches up to the high price at some point, and finally reverts

[1]The effect of symmetric demand uncertainty on the high-quality seller's expected payoff is ambiguous: it may or may not increase her expected payoff. This shows that the low-quality seller's gain is not driven by the high-quality seller's loss.

back to the low price.

The payoff result is, again, due to endogenous demand. We show that if buyers know the demand state, then in equilibrium they adjust their purchase strategies, so that the low-quality seller is indifferent between the high price and the low price in both demand states. This implies that, although the seller still learns about demand over time, learning is simply of no value to her. Notice that this can never arise with exogenous demand, unless the decision problem itself is trivial. More intuitively, the seller does not enjoy an informational advantage over buyers and, therefore, cannot extract more surplus.

The necessity of a complicated structure of equilibrium pricing strategy highlights the strategic aspect of our model. In the model with asymmetric demand uncertainty, as argued above, the low-quality seller is indifferent between the high price and the low price in both states, and thus any pricing strategy is the low-quality seller's best response to buyers' equilibrium purchase strategies. However, equilibrium imposes a restriction on the set of feasible pricing strategies, because the pricing strategy affects buyers' incentives, which must be adjusted so that they play a particular purchase strategy. The resulting set of restrictions can be jointly resolved only by a rather sophisticated form of pricing strategy, such as a switching-up-and-down strategy.

Our paper mainly contributes to the literature on demand uncertainty (experimentation). A non-exhaustive list of seminal contributions includes Rothschild (1974); McLennan (1984); Easley and Kiefer (1988); Balvers and Cosimano (1990); Aghion et al. (1991); Mirman, Samuelson and Urbano (1993); Rustichini and Wolinsky (1995); Keller and Rady (1999). All existing studies we are aware of in this literature consider an agent's dynamic decision problem with exogenous demand and do not endogenize demand through adverse selection, as we do in this paper. Our paper is particularly close to Mason and Välimäki (2011). They consider a similar dynamic problem under demand uncertainty, but with exogenous demand (more precisely, in their model, each buyer has private value for the seller's good and accepts any price below his value). As explained above, this leads to various different results. For example, if the probability of high demand is sufficiently small, then the seller in their model immediately settles on the low price, while the low-quality seller in our model still begins with the high price. Nevertheless, we significantly benefit from their analysis. In particular, in the model with symmetric demand uncertainty, given buyers' purchase strategies, the low-quality seller's optimal pricing problem is formally identical to their problem, and thus their explicit solution to the binary case applies unchanged to our environment (see Proposition 3.2).

Our paper also contributes to the fast-growing literature on dynamic adverse selection. See Evans (1989); Vincent (1989, 1990); Taylor (1999); Janssen and Roy (2002); Deneckere and Liang (2006); Horner and Vieille (2009); Moreno and Wooders (2010); Daley and Green (2012) for some seminal contributions. Most papers in this literature consider the case where uninformed players make price offers to informed players, mainly to avoid equilibrium multiplicity due to signaling. We are aware of three exceptions, Lauermann and Wolinsky (2011), Palazzo (2015), and Gerardi, Hörner and Maestri (2014), each of which studies the opposite case where informed players make price offers to uninformed players. The first two focus on undefeated equilibria (Mailath, Okuno-Fujiwara and Postlewaite, 1993), while the last one characterizes the set of all equilibrium payoffs. To our knowledge, we are the first to introduce demand uncertainty into a dynamic trading environment with adverse selection.

The rest of the paper is organized as follows. We introduce the model in Section 3.2 and studies the benchmark model without demand uncertainty in Section 3.3. We then analyze the model with symmetric demand uncertainty in Section 3.4 and the model with asymmetric demand uncertainty in Section 3.5. We conclude in Section 3.6.

3.2 The Model

3.2.1 Physical Environment

A seller wishes to sell an indivisible object. Time is continuous and indexed by t. The time the seller arrives at the market is normalized to 0. At each point in time, the seller posts a price. Buyers arrive sequentially according to a Poisson process of rate λ. Upon arrival, each buyer observes the posted price and decides whether to purchase the good or not. If the buyer purchases, then trade takes place between the buyer and the seller, and the game ends. If not, the buyer leaves, while the seller continues the game. The common discount rate is given by $r > 0$.

The seller's good is either of high quality (H) or of low quality (L). If the good is of quality $a = H, L$, then it yields flow payoff rc_a to the seller (while she retains it) and flow payoff rv_a to a buyer (once he purchases it). Note that this means that the (reservation) value of the good is c_a to the seller and v_a to a buyer. A high-quality unit is more valuable to both the seller and buyers (i.e., $v_H > v_L$ and $c_H > c_L$). There are always positive gains from trade (i.e., $v_a > c_a$ for both $a = H, L$), but the quality of the good is known only to the seller. It is common knowledge that the seller's good is of high quality with probability q_0 at the beginning of the game. Without loss of generality, we normalize c_L to 0.

The seller is uncertain about the arrival rate of buyers, which is either λ_h (high demand) or λ_l (low demand), where $\lambda_h > \lambda_l > 0$. It is commonly known that the good is in high demand (i.e., $\lambda = \lambda_h$) with probability μ_0 at the beginning of the game, and the realization of the demand state is independent of the quality of the good. We consider two cases that differ in terms of buyers' knowledge about the demand state. We say that demand uncertainty is *symmetric* if the demand state is also unknown to buyers, and refer to the opposite case as *asymmetric* demand uncertainty.[2]

All agents are risk-neutral and maximize their expected utility. If a buyer purchases the good at price p at time t and the good is of quality a, then the buyer receives payoff $v_a - p$, while the seller obtains $(1 - e^{-rt})c_a + e^{-rt}p$. All other buyers receive zero payoff.

3.2.2 Strategies and Equilibrium

We consider the following information structure:[3] the seller does not observe the arrival of buyers, while each buyer observes only the price posted at the time of his arrival. The former implies that the seller cannot tell whether the failure of sale is due to no arrival of buyers or due to buyers' refusal to accept the posted price. The latter implies that buyers' beliefs and strategies are independent of their arrival time and, therefore, stationary over

[2] In Appendix A, we analyze another asymmetric case in which the demand state is known to the seller, but not to buyers.

[3] It is well-known that uninformed players' (buyers') information about informed players' (sellers') histories plays a crucial role in dynamic environments. See, e.g., Swinkels (1999), Taylor (1999), Hörner and Vieille (2009), and Kim (2015).

time from the seller's viewpoint.[4] Both assumptions give tractability to the analysis.

Under the information structure, the seller's (pure) offer strategy is a function $p : \{L, H\} \times \mathcal{R}_+ \to \mathcal{R}_+$, where $p(a, t)$ represents the price the type-a seller posts at time t. For buyers' beliefs and strategies, denote by Λ the information set of buyers regarding the demand state. The set Λ is a singleton with symmetric demand uncertainty (i.e., if buyers cannot distinguish between high demand λ_h and low demand λ_l), while it is isomorphic to the set $\{\lambda_h, \lambda_l\}$ with asymmetric demand uncertainty. Then, buyers' beliefs about the seller's type are represented by a function $q : \Lambda \times \mathcal{R}_+ \to [0, 1]$, where $q(\lambda, p)$ denotes the probability that buyers assign to the high type conditional on demand state λ and price p. Similarly, their (mixed) purchase strategies are a function $\sigma_B : \Lambda \times \mathcal{R}_+ \to [0, 1]$, where $\sigma_B(\lambda, p)$ denotes the probability that buyers accept p in state λ.

A tuple (p, q, σ_B) is a (perfect Bayesian) equilibrium of the dynamic trading game if the following conditions hold:

- Seller optimality: for each $a = H, L$, the type-a sellers' pricing strategy $p(a, \cdot)$ maximizes her expected payoff, that is,

$$p(a, \cdot) \in argmax_{p'(a,\cdot)} E[(1 - e^{-r\tau})c_a + e^{-r\tau} p'(a, \tau)],$$

  where τ is the (random) time at which a buyer purchases the good.

- Buyer optimality: for each $\lambda \in \Lambda$ and $p \in \mathcal{R}_+$, each buyer accepts price p only when his expected payoff by doing so is non-negative. In other words, $\sigma_B(\lambda, p) > 0$ only

[4] This is a common modeling assumption in the literature on dynamic adverse selection (see, e.g., Zhu, 2012; Lauermann and Wolinsky, 2015). For different approaches, which give rise to non-stationary dynamics, see, e.g., Hörner and Vieille (2009) and Kim (2015).

when

$$q(\lambda, p)v_H + (1 - q(\lambda, p))v_L - p \geq 0.$$

- Belief consistency: for each $\lambda \in \Lambda$ deand $p \in \mathcal{R}_+$, $q(\lambda, p)$ is obtained from p and σ_B by Bayes' rule whenever possible.

3.2.3 Assumptions

We focus on the case where adverse selection is so severe that inefficiency is unavoidable. Specifically, we maintain the following assumption, which is common in the literature.

Assumption 3.1.

$$q_0 v_H + (1 - q_0)v_L < c_H.$$

The left-hand side is buyers' unconditional expected value of the good, while the right-hand side is the high-type seller's reservation value. This assumption ensures that there does not exist an equilibrium in which both seller types always offer a price in $[c_H, q_0 v_H + (1 - q_0)v_L]$ and buyers always accept the price, which is an efficient market outcome. Note that, since $v_H > c_H$, the assumption implies that v_L is strictly less than c_H and q_0 is sufficiently small.

Because of its signaling nature, the game suffers from severe equilibrium multiplicity. In order to focus on economic insights stemming from the model, as well as for tractability, we restrict attention to the equilibria of the following structure:

Assumption 3.2. *The high-type seller always offers a price $p_H \in [c_H, v_H)$.*

This strategy of the high-type seller can be supported, for example, by assuming that buyers believe that all other prices are offered only by the low-type seller. This assumption excludes the trivial equilibria in which the high-type seller always offers a losing price (above v_H). In addition, it does not allow the high-type seller to dynamically adjust her price. As shown shortly, in the absence of demand uncertainty, this incurs no loss of generality in characterizing the set of equilibria. For the cases of demand uncertainty in Sections 3.4 and 3.5, this significantly simplifies the analysis.

Finally, for equilibrium existence, we make the following assumption:

Assumption 3.3. *Buyers accept v_L with probability* 1.

Notice that it is a strictly dominant strategy for a buyer to accept $p < v_L$, because his expected value is bounded below by v_L. Therefore, the seller can ensure trade with the next arriving buyer by posting a price arbitrarily close to v_L. For equilibrium existence, it is necessary that buyers accept v_L even if they assign probability 1 to the low type and, therefore, are indifferent between accepting and rejecting v_L.

Assumptions 3.2 and 3.3 imply that there are effectively two prices, v_L and p_H: the high type always offers p_H, while the low type chooses between v_L and p_H at each point in time. With a slight abuse of notation, in what follows, we describe the low-type seller's offer strategy by a function $\sigma_S : \mathcal{R} \to [0, 1]$, where $\sigma_S(t)$ denotes the probability that the low-type seller offers p_H at time t. In addition, we use σ_B to denote the probability that each buyer accepts p_H (i.e., $\sigma_B(\lambda) \equiv \sigma_B(\lambda, p_H)$ from now on).

3.3 No Demand Uncertainty

We first study the benchmark case where there is no demand uncertainty (i.e., λ is commonly known). This allows us to identify the effects due to demand uncertainty as well as explain some basic concepts and tools used in the following sections.

3.3.1 Buyers' Beliefs

In our model, buyers' beliefs about the seller's type depart from their prior belief q_0 for two reasons. First, the very fact that a buyer meets the seller provides information about the seller's type. The low-type seller trades relatively faster than the high-type seller, because the former may offer v_L (which is accepted with probability 1), while the latter insists on p_H (which is not accepted with probability 1 in equilibrium). This means that the high type stays relatively longer than the low type, and thus the seller who is still available on the market is more likely to be the high type. We denote by q^I buyers' beliefs at this stage and refer to them as their *interim* beliefs. Second, the posted price also conveys information about the seller's type. Since buyers' beliefs (and optimal purchase decisions) following v_L are trivial, we focus on their beliefs conditional on p_H. We refer to those beliefs as buyers' *ex post* beliefs and denote by q^*.

Given $\sigma_S(t)$ and σ_B, the trading (exit) rate of the high-type seller is equal to $\lambda\sigma_B$, while that of the low-type seller is equal to $\lambda(\sigma_S(t)\sigma_B + 1 - \sigma_S(t))$. This means that the probability that the high-type seller stays on the market until time t is equal to $e^{-\int_0^t \lambda\sigma_B dt}$, while that of the the low-type seller is equal to $e^{-\int_0^t \lambda(\sigma_S(t)\sigma_B+1-\sigma_S(t))dt}$. Since a seller can be interpreted to be randomly drawn from the space $\{L, H\} \times \mathcal{R}_+$ (i.e., the areas below the

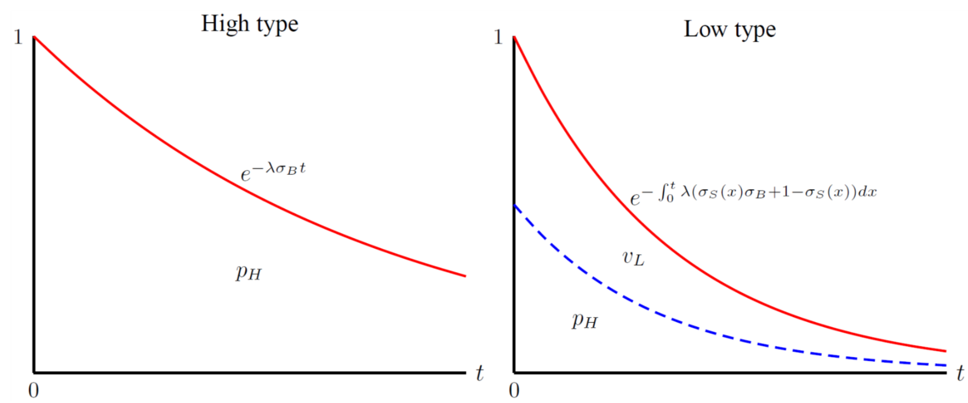

Figure 3.1: The probability that each seller type does not trade by time t.

Notes: The probability that each seller type does not trade by time t. The dashed line in the right panel depicts the probability that the low-type seller does not trade by time t and offers p_H at time t (i.e., $\sigma_S(t)e^{-\int_0^t \lambda(\sigma_S(x)\sigma_B+1-\sigma_S(x))dx}$). The right panel is drawn for the case where $\sigma_S(t)$ is independent of t.

solid lines in Figure 3.1, with total weights q_0 to the high type and $1-q_0$ to the low type), buyers' interim beliefs can be calculated as follows:

$$q^I = \frac{q_0 \int_0^\infty e^{-\int_0^x \lambda\sigma_B dx} dt}{q_0 \int_0^\infty e^{-\int_0^x \lambda\sigma_B dx} dt + (1-q_0)\int_0^\infty e^{-\int_0^t \lambda(\sigma_S(x)\sigma_B+1-\sigma_S(x))dx}},$$

which is equivalent to

$$\frac{q^I}{1-q^I} = \frac{q_0}{1-q_0} \frac{\int_0^\infty e^{-\int_0^t \lambda\sigma_B dx} dt}{\int_0^\infty e^{-\int_0^t \lambda(\sigma_S(x)\sigma_B+1-\sigma_S(x))dx} dt}. \tag{3.1}$$

Notice that q^I is necessarily larger than q_0. As explained above, this is because the low-type seller trades faster than the high-type seller ($\sigma_S(t)\sigma_B + 1 - \sigma_S(t) \geq \sigma_B$ at any t), and thus a seller who is available is more likely to be the high type.

Now we incorporate the signaling aspect of posted price and derive buyers' ex post beliefs q^*. The high-type seller insists on p_H, while the low-type seller offers p_H with probability $\sigma_S(t)$ at time t. Since time t is not observable to buyers, it is necessary to derive the probability that the low-type seller offers p_H unconditional on t.[5] Applying the fact that that a seller is randomly drawn from the entire population (i.e., the space $\{L, H\} \times \mathcal{R}_+$) and the probability that the seller has not traded by time t is equal to $e^{-\int_0^t \lambda(\sigma_S(x)\sigma_B + 1 - \sigma_S(x))dx}$, the unconditional probability that the low-type seller offers p_H is equal to

$$\frac{\int_0^\infty \sigma_S(t) e^{-\int_0^t \lambda(\sigma_S(x)\sigma_B + 1 - \sigma_S(x))dx} dt}{\int_0^\infty e^{-\int_0^t \lambda(\sigma_S(x)\sigma_B + 1 - \sigma_S(x))dx} dt}.$$

It then follows that buyers' ex post beliefs are given by

$$\frac{q^*}{1-q^*} = \frac{q^I}{1-q^I} \frac{1}{\frac{\int_0^\infty \sigma_S(t) e^{-\int_0^t \lambda(\sigma_S(x)\sigma_B + 1 - \sigma_S(x))dx} dt}{\int_0^\infty e^{-\int_0^t \lambda(\sigma_S(x)\sigma_B + 1 - \sigma_S(x))dx} dt}}. \tag{3.2}$$

Notice that q^* is always greater than q^I. Intuitively, the high-type seller always offers p_H, while the low-type seller may offer v_L. Therefore, the seller who offers p_H is more likely to be the high type.

Combining (3.1) and (3.2) yields

$$\frac{q^*}{1-q^*} = \frac{q_0}{1-q_0} \frac{\int_0^\infty e^{-\int_0^t \lambda \sigma_B dx} dt}{\int_0^\infty \sigma_S(t) e^{-\int_0^t \lambda(\sigma_S(x)\sigma_B + 1 - \sigma_S(x))dx} dt}. \tag{3.3}$$

This equation gives a unique value of q^* as a function of the low-type seller's pricing strategy σ_S and buyers' purchase strategies σ_B. In other words, the equilibrium requirement that buyers' beliefs must be consistent with a strategy profile reduces to this equation.

---

[5]If time t were observable by buyers, then the probability would be simply $\sigma_S(t)$, and thus buyers' ex post beliefs would be equal to

$$\frac{q^*}{1-q^*} = \frac{q^I}{1-q^I} \frac{1}{\sigma_S(t)}.$$

Notice the similarities between this expression and equation (3.2).

3.3.2 Equilibrium Characterization

We complete equilibrium characterization by deriving two other equilibrium conditions and combining them with condition (3.3).

The two other equilibrium conditions are (i) buyers must randomize between accepting and rejecting p_H (i.e., $\sigma_B \in (0,1)$), and (ii) the low-type seller must offer both v_L and p_H with positive probabilities. To understand the first condition, suppose that buyers always accept p_H. Then, clearly, the low-type seller strictly prefers offering p_H to v_L. Since both seller types play an identical strategy, $q^* = q^I = q_0$. But then, Assumption 3.1 implies that buyers' expected payoffs are strictly negative. Now suppose that buyers always reject p_H. If so, the low-type seller strictly prefers offering v_L to p_H. This implies that buyers would believe that the seller who offers p_H is the high type with probability 1 (i.e., $q^* = 1$) and, therefore, accept $p_H(< v_H)$ with probability 1, which is a contradiction. The same argument can be used for the second equilibrium condition that the low-type seller must randomize between v_L and p_H.

Formally, the two equilibrium conditions are

$$q^*(v_H - p_H) + (1-q^*)(v_L - p_H) = 0 \Leftrightarrow \frac{q^*}{1-q^*} = \frac{p_H - v_L}{v_H - p_H},$$

and

$$\int_0^\infty e^{-rt} p_H d(1 - e^{-\lambda\sigma_B t}) = \frac{\lambda\sigma_B}{r+\lambda\sigma_B} p_H = \int_0^\infty e^{-rt} v_L d(1-e^{-\lambda t}) = \frac{\lambda}{r+\lambda} v_L.$$

The first equation corresponds to buyers' indifference between accepting and rejecting p_H, while the second one corresponds to the low-type seller's indifference between p_H (left) and v_L (right).

We combine and summarize all the results so far in the following proposition.

Proposition 3.1. *For each $p_H \in [c_H, v_H)$, there exists a continuum of payoff-equivalent equilibria. In any equilibrium, $q^* = (p_H - v_L)/(v_H - v_L)$ and $\sigma_B = rv_L/((r+\lambda)p_H - \lambda v_L)$, while the low-type seller's strategy $\sigma_S(t)$ supports an equilibrium if and only if it satisfies equation* (3.3)*. The low-type seller's expected payoff is equal to $\lambda v_L/(r + \lambda)$, while the high-type seller's (net) expected payoff is equal to $\lambda\sigma_B(p_H - c_H)/(r + \lambda\sigma_B)$.*

Observe that the low-type seller's expected payoff is independent of p_H, while the high-type seller's expected payoff strictly increases in p_H. This is due to a standard single crossing property: the high-type seller, due to her higher reservation value, is more willing to trade off slower trade for a higher price. Since the low-type seller is indifferent among different p_H's, the high-type seller obtains a higher expected payoff as p_H increases. Notice that this implies that the two seller types cannot be simultaneously indifferent between two different prices (that can be accepted by buyers with positive probabilities). Therefore, the two-price restriction (Assumption 3.2) incurs effectively no loss of generality in the model without demand uncertainty.

To see equilibrium multiplicity more concretely, consider the following three simple pricing strategies:

- Stationary strategy: the low-type seller randomizes between p_H and v_L with a constant probability over time (i.e., $\sigma_S(t)$ is independent of t).
- Switching-down strategy: the low-type seller begins with p_H, and switches down to v_L at a certain time T_D (i.e., $\sigma_S(t) = 1$ if $t < T_D$ and $\sigma_S(t) = 0$ otherwise).
- Switching-up strategy: the low-type seller begins with v_L, and switches up to p_H at

a certain time T_U (i.e., $\sigma_S(t) = 0$ if $t < T_U$ and $\sigma_S(t) = 1$ otherwise).

It is easy to see that each of these pricing strategies can be supported as an equilibrium strategy (by identifying proper values of σ_S, T_D, and T_U). In the next two sections, we show that the introduction of demand uncertainty has a dramatic impact on equilibrium multiplicity and the structure of equilibrium pricing strategy.

3.4 Symmetric Demand Uncertainty

We now introduce demand uncertainty into the model: the arrival rate of buyers is λ_h with probability μ_0 and λ_l with probability $1 - \mu_0$. We begin with the case of symmetric demand uncertainty, namely the case in which both the seller and buyers are uncertain about the demand state.

3.4.1 Optimal Pricing

In the presence of demand uncertainty, the seller learns about demand over time, and thus her problem is no longer stationary. In particular, conditional on no trade, she becomes increasingly more pessimistic. Naturally, it is optimal for her to begin with the high price p_H, which yields higher profits if accepted but has a lower acceptance probability. Once she becomes sufficiently pessimistic, she switches to the lower price v_L, which results in lower profits but guarantees faster trade.

To systematically analyze the low-type seller's optimal pricing problem, let $\mu(t)$ denote the probability that she assigns to demand state h at time t. The evolution of $\mu(t)$ depends on her pricing strategy as well as buyers' purchase strategies. Suppose buyers accept p_H with probability σ_B. If the low-type seller offers p_H, then $\mu(t)$ evolves according to

$$\mu(t+dt) = \frac{\mu(t)e^{-\lambda_h \sigma_B dt}}{\mu(t)e^{-\lambda_h \sigma_B dt} + (1-\mu(t))e^{-\lambda_l \sigma_B dt}},$$

which can be reduced to

$$\dot{\mu}(t) = -\mu(t)(1-\mu(t))(\lambda_h - \lambda_l)\sigma_B. \tag{3.4}$$

Similarly, if the offer is v_L, then trade occurs as long as a buyer arrives, and thus

$$\mu(t+dt) = \frac{\mu(t)e^{-\lambda_h dt}}{\mu(t)e^{-\lambda_h \sigma_B dt} + (1-\mu(t))e^{-\lambda_l \sigma_B dt}}.$$

As before, this expression can be reduced to

$$\dot{\mu}(t) = -\mu(t)(1-\mu(t))(\lambda_h - \lambda_l). \tag{3.5}$$

Clearly, the low-type seller's belief decreases faster in the latter case. Intuitively, when the price is v_L, a sale does not occur only when no buyer has arrived, while with price p_H, it may also be because of a buyer's refusal to accept the price. Therefore, no sale is a stronger signal about low demand when the price is v_L.

The seller's optimal pricing strategy is a standard cutoff rule: there is a threshold belief $\overline{\mu}$ such that the low-type seller offers p_H if and only if her belief exceeds $\overline{\mu}$. Since $\mu(t)$ necessarily decreases over time, this means that there exists a cutoff time at which the low-type seller switches from p_H to v_L, and the low-type seller never reverts back to p_H. Clearly, the cutoff time is the point at which the seller's belief is equal to $\mu(t) = \overline{\mu}$.

To explicitly derive the low-type seller's optimal pricing strategy, let $V(\mu)$ denote her expected payoff when her belief is equal to μ. If $\mu > \overline{\mu}$, then her optimal price is p_H.

Therefore, the continuous-time Bellman equation is given as follows:[6]

$$rV(\mu) = (\mu\lambda_h + (1-\mu)\lambda_l)\sigma_B(p_H - V(\mu)) + \dot{V}(\mu).$$

Combining this equation with equation (3.4) yields

$$rV(\mu) = (\mu\lambda_h + (1-\mu)\lambda_l)\sigma_B(p_H - V(\mu)) - V'(\mu)\mu(1-\mu)(\lambda_h - \lambda_l)\sigma_B.$$

If $\mu \leq \overline{\mu}$, then the low-type seller offers v_L. Since her belief constantly decreases, she never switches to p_H and continues to offer v_L, *as if* she commits to v_L. It follows that

$$V(\mu) = \mu\int_0^\infty e^{-rt}v_L d(1-e^{-\lambda_h t}) + (1-\mu)\int_0^\infty e^{-rt}v_L d(1-e^{-\lambda_l t}) = \mu\frac{\lambda_h}{r+\lambda_h}v_L + (1-\mu)\frac{\lambda_l}{r+\lambda_l}v_L.$$

This form of optimal stopping problem is familiar in the literature on experimentation. In particular, given buyers' purchase strategies σ_B, the problem is effectively identical to the binary case in Mason and Välimäki (2011). They study a dynamic pricing problem in which buyers have private values (implying no inference problem on the seller's type) and the distribution of their values is exogenously given (i.e., in the context of our model, σ_B is exogenously given). We translate their solution into our context and report all the results in the following proposition.

Proposition 3.2. *Given buyers' purchase strategies σ_B, the low-type seller's optimal pric-*

[6]Heuristically, this Bellman equation can be obtained from the following recursive equation:

$$V(\mu(t)) = (\mu(t)\lambda_h + (1-\mu(t))\lambda_l)\sigma_B dt p_H + (1-(\mu(t)\lambda_h + (1-\mu(t))\lambda_l)\sigma_B dt)e^{-rdt}V(\mu(t+dt)).$$

It suffices to subtract $e^{-rdt}V(\mu(t))$ and divide both sides by dt after appropriately arranging the terms.

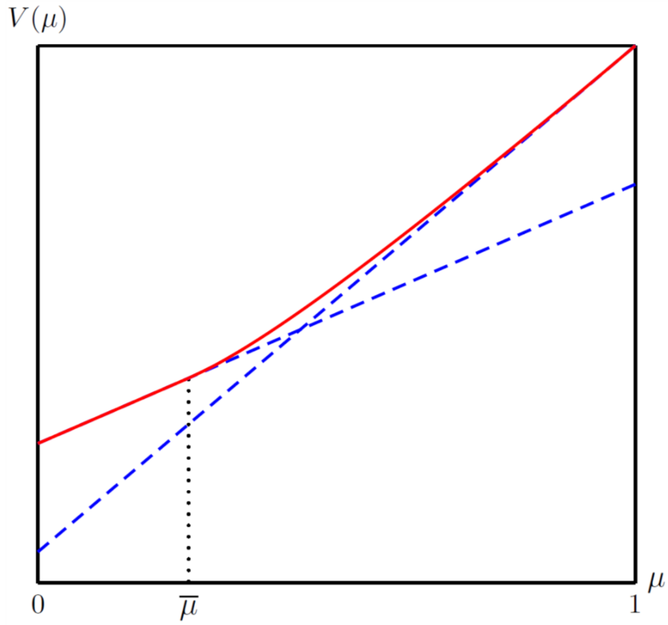

Figure 3.2: The low-type seller's expected payoff

Notes: The low-type seller's expected payoff as a function of her belief about the demand state, given buyers' purchase strategies σ_B.

ing strategy is to offer p_H if his belief exceeds $\overline{\mu}$ and offer v_L otherwise, where

$$\overline{\mu} = \begin{cases} 1, \; \textit{if} \; \frac{\lambda_h \sigma_B p_H}{r+\lambda_h \sigma_B} \leq \frac{\lambda_h v_L}{r+\lambda_h}, \\ 0, \; \textit{if} \; \frac{\lambda_l \sigma_B p_H}{r+\lambda_l \sigma_B} \geq \frac{\lambda_l v_L}{r+\lambda_l}, \\ \frac{-\lambda_l (r+\lambda_h)(\sigma_B \lambda_l (p_H - v_L) + r(\sigma_B p_H - v_L))}{(\lambda_h - \lambda_l)(r(\sigma_B \lambda_l (p_H - v_L) + r(\sigma_B p_H - v_L)) + \sigma_B \lambda_h (p_H - v_L)(r+\lambda_l))}, \; \textit{otherwise}. \end{cases}$$

The low-type seller's expected payoff as a function of her belief is equal to

$$V(\mu) = \begin{cases} \left(\mu \frac{\lambda_h \sigma_B}{r+\lambda_h \sigma_B} + (1-\mu) \frac{\lambda_l \sigma_B}{r+\lambda_l \sigma_B}\right) p_H + C(1-\mu) \left(\frac{1-\mu}{\mu}\right)^{\frac{r+\lambda_L \sigma_B}{(\lambda_H - \lambda_L)\sigma_B}}, & \textit{if } \mu > \overline{\mu}, \\ \left(\mu \frac{\lambda_h}{r+\lambda_h} + (1-\mu) \frac{\lambda_l}{r+\lambda_l}\right) v_L, & \textit{if } \mu \leq \overline{\mu}, \end{cases}$$

where

$$C = \frac{\overline{\mu}(\lambda_h - \lambda_l)\sigma_B}{\overline{\mu}(\lambda_h - \lambda_l)\sigma_B + \lambda_l \sigma_B} \left(\frac{r(\lambda_h - \lambda_l)\sigma_B p_H}{(r+\lambda_h \sigma_B)(r+\lambda_l \sigma_B)} - \frac{r v_L (\lambda_h - \lambda_l)}{(r+\lambda_h)(r+\lambda_l)} \right) \left(\frac{1-\overline{\mu}}{\overline{\mu}}\right)^{-\frac{r+\lambda_L \sigma_B}{(\lambda_H - \lambda_L)\sigma_B}}.$$

[h!]

Figure 3.2 depicts the value function $V(\mu)$. The two dashed lines represent the low-type seller's expected payoffs when she posts only v_L (the line that coincides with $V(\mu)$ when $\mu \leq \overline{\mu}$) or p_H (the line that meets $V(\mu)$ when $\mu = 1$). As is well-known, the flexibility to adjust the price (in particular, the option to decrease the price from p_H to v_L) is valuable to the seller, which is reflected in the fact that $V_B(\mu)$ uniformly stays above the two dashed lines.

For later use, let $T(\sigma_B)$ denote the length of time it takes for the low-type seller's belief to reach $\overline{\mu}$, assuming that she follows the optimal pricing strategy in Proposition 3.2. The following result provides an explicit solution for $T(\sigma_B)$.

Corollary 3.1. *Given buyers' purchase strategies σ_B, the low-type seller offers p_H until time $T(\sigma_B)$ and v_L thereafter, where*

$$T(\sigma_B) = \max\left\{0, \frac{1}{(\lambda_h - \lambda_l)\sigma_B} ln\left(\frac{\mu_0}{1-\mu_0}\frac{1-\overline{\mu}}{\overline{\mu}}\right)\right\}.$$

3.4.2 Buyers' Beliefs

We now derive buyers' equilibrium beliefs q^* (the probability that each buyer assigns to the high type conditional on observing p_H). As shown in the previous section, the trading rates of each seller type affect q^*. Since the trading rates also depend on the demand state, it is necessary to determine buyers' beliefs about the demand state, although those beliefs do not directly influence their purchase decisions. We denote by μ^* buyers' (ex post) beliefs about the demand state (conditional on observing p_H). We first take μ^* as given and determine q^*.

Given μ^* and σ_B, buyers' beliefs about the seller's type q^* can be derived as in the previous section. As shown above, given σ_B, the low-type seller's optimal pricing strategy is uniquely determined. Therefore, unlike in Section 3.3, it suffices to derive q^* that corresponds to the low-type seller's pricing strategy in Proposition 3.2: the low-type seller offers p_H until time $T(\sigma_B)$ and switches to v_L.

Following the same steps as in the previous section (and skipping the derivation of q^I),

$$\begin{aligned} \frac{q^*}{1-q^*} &= \frac{q_0}{1-q_0} \frac{\mu^* \int_0^\infty e^{-\lambda_h \sigma_B t} dt + (1-\mu^*) \int_0^\infty e^{-\lambda_l \sigma_B t} dt}{\mu^* \int_0^{T(\sigma_B)} e^{-\lambda_h \sigma_B t} dt + (1-\mu^*) \int_0^{T(\sigma_B)} e^{-\lambda_l \sigma_B t} dt} \\ &= \frac{q_0}{1-q_0} \frac{\frac{\mu^*}{\lambda_h \sigma_B} + \frac{1-\mu^*}{\lambda_l \sigma_B}}{\frac{\mu^*(1-e^{-\lambda_h \sigma_B T(\sigma_B)})}{\lambda_h \sigma_B} + \frac{(1-\mu^*)(1-e^{-\lambda_l \sigma_B T(\sigma_B)})}{\lambda_l \sigma_B}}. \end{aligned} \tag{3.6}$$

Now, q^* departs from q_0 for three reasons. First, the high-type seller stays on the market relatively longer than the low-type seller (which pushes up q^I above q_0). Second, the high-type seller is more likely to offer p_H than the low-type seller (which pushes up q^* above q^I). Finally, buyers' beliefs about the demand state also influence q^*. This last effect is unclear at this stage, because μ^* is also an endogenous variable.

We now determine μ^*. Similarly to the relationship between q^* and q_0, there are two reasons why μ^* departs from μ_0. First, trade occurs faster in demand state h than in demand state l. Therefore, the very fact that the seller is still available makes buyers assign a relatively lower probability to the high demand state. Second, for a given length of time, the seller meets relatively more buyers in demand state h than in demand state l. Therefore, a buyer is more likely to arrive (i.e., be born) in demand state h than in demand state l, which increases the probability of the high demand state.

Applying similar arguments to those used to derive q^* above,

$$\begin{aligned}\frac{\mu^*}{1-\mu^*} &= \frac{\mu_0}{1-\mu_0}\frac{\lambda_h}{\lambda_l}\frac{q_0\int_0^\infty e^{-\lambda_h\sigma_B t}dt + (1-q_0)\int_0^{T(\sigma_B)} e^{-\lambda_h\sigma_B t}dt}{q_0\int_0^\infty e^{-\lambda_l\sigma_B t}dt + (1-q_0)\int_0^{T(\sigma_B)} e^{-\lambda_l\sigma_B t}dt} \\ &= \frac{\mu_0}{1-\mu_0}\frac{q_0+(1-q_0)(1-e^{-\lambda_h\sigma_B T(\sigma_B)})}{q_0+(1-q_0)(1-e^{-\lambda_l\sigma_B T(\sigma_B)})}.\end{aligned} \tag{3.7}$$

The second term in the right-hand side (λ_h/λ_l) captures the second effect in the previous paragraph, while the last term represents the first effect. From the final expression, it follows that buyers' beliefs about demand μ^* exceed their prior beliefs μ_0 (which means that the second effect necessarily dominates the first effect), as long as $T(\sigma_B)$ is finite.

Combining equations (3.6) and (3.7) yields the following result.

Lemma 3.1. *Given buyers' purchase strategies σ_B (and the low-type seller's optimal response to σ_B, as characterized in Proposition 3.1), buyers' ex post beliefs about the seller's type q^* is uniquely determined by*

$$\frac{q^*}{1-q^*} = \frac{q_0}{1-q_0}\frac{\frac{\mu_0}{\lambda_h}(q_0+(1-q_0)\kappa_h(\sigma_B)) + \frac{1-\mu_0}{\lambda_l}(q_0+(1-q_0)\kappa_l(\sigma_B))}{\frac{\mu_0}{\lambda_h}\kappa_h(\sigma_B)(q_0+(1-q_0)\kappa_h(\sigma_B)) + \frac{1-\mu_0}{\lambda_l}\kappa_l(\sigma_B)(q_0+(1-q_0)\kappa_l(\sigma_B))},$$

where

$$\kappa_d(\sigma_B) = 1-e^{-\lambda_d\sigma_B T(\sigma_B)}, \textit{ for each } d = h, l.$$

3.4.3 Equilibrium Characterization

We complete equilibrium characterization by endogenizing buyers' purchase strategies σ_B. A necessary condition, once again, comes from the fact that in equilibrium, buyers must be indifferent between accepting and rejecting p_H. If they always accept p_H, then the low-type seller prefers offering p_H to v_L, independently of her belief about the demand state. In this case, $q^* = q_0$, but then buyers' expected payoffs become strictly negative, due to Assumption 3.1. To the contrary, if buyers always reject p_H, then the low-type seller always prefers v_L to p_H. In this case, $q^* = 1$, and thus buyers strictly prefer accepting p_H to rejecting it, which is a contradiction. This leads to the last equilibrium condition:

$$q^*(v_H - p_H) + (1 - q^*)(v_L - p_H) = 0 \Leftrightarrow \frac{q^*}{1 - q^*} = \frac{p_H - v_L}{v_H - p_H}. \tag{3.8}$$

Given Proposition 3.2, Lemma 3.1, and equation (3.8), equilibrium characterization reduces to finding a value of σ_B that satisfies

$$\frac{q_0}{1-q_0} \frac{\frac{\mu_0}{\lambda_h}(q_0 + (1-q_0)\kappa_h(\sigma_B)) + \frac{1-\mu_0}{\lambda_l}(q_0 + (1-q_0)\kappa_l(\sigma_B))}{\frac{\mu_0}{\lambda_h}\kappa_h(\sigma_B)(q_0 + (1-q_0)\kappa_h(\sigma_B)) + \frac{1-\mu_0}{\lambda_l}\kappa_l(\sigma_B)(q_0 + (1-q_0)\kappa_l(\sigma_B))} = \frac{p_H - v_L}{v_H - p_H}. \tag{3.9}$$

Proposition 3.3. *For each $p_H \in [c_H, v_H)$, there exists a unique equilibrium in the model with symmetric demand uncertainty. In the equilibrium, the probability that each buyer accepts p_H, σ_B, is such that $\overline{\mu}(\sigma_B) < \mu_0$ (i.e., $T(\sigma_B) > 0$).*

Proof. See Appendix B. □

Proposition 3.3 implies that under symmetric demand uncertainty, the low-type seller necessarily plays a switching-down strategy: she offers p_H until time $T(\sigma_B)(> 0)$ and then switches down to v_L. Importantly, this property holds even if the prior probability of high demand μ_0 is sufficiently small. This is in stark contrast to the result in Mason and Välimäki (2011): in their model with exogenous demand, the cutoff belief $\overline{\mu}$ is independent of the prior probability μ_0, and thus the seller immediately offers the low price v_L as soon as μ_0 is below $\overline{\mu}$. In our environment with endogenous demand, the cutoff belief $\overline{\mu}$ depends on μ_0. In particular, if μ_0 is small, then $\overline{\mu}$ becomes even smaller, and thus the low-type seller always begins with the high price p_H.

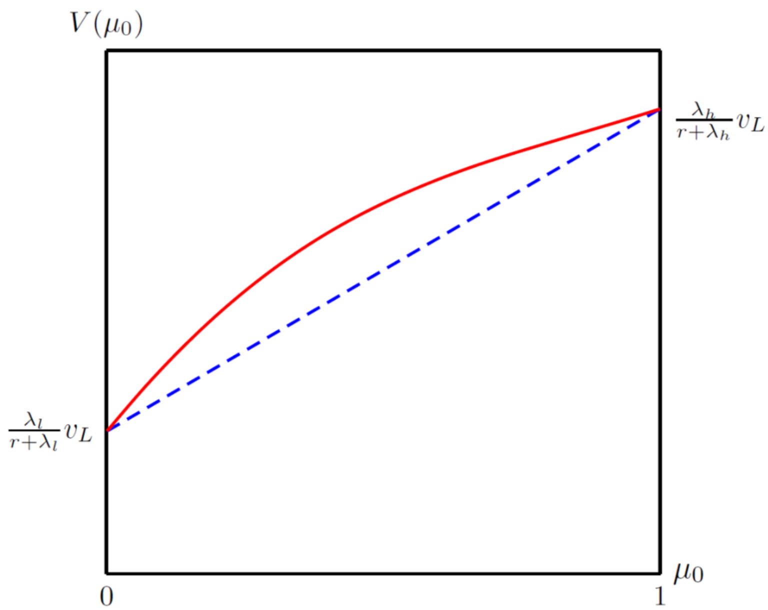

Figure 3.3: The low-type seller's ex ante expected payoffs

Notes: The low-type seller's ex ante expected payoffs with symmetric demand uncertainty (solid) and without demand uncertainty (dashed).

Proposition 3.3 also implies that symmetric demand uncertainty is necessarily beneficial to the low-type seller: her expected payoff under symmetric demand uncertainty $V(\mu_0)$ is strictly higher than that under no demand uncertainty.[7] See Figure 3.3 for a graphical representation. A key to understanding this counterintuitive result, again, lies in the fact that demand is endogenously determined in our model. With exogenous demand, demand uncertainty always lowers the seller's expected payoff for the standard reason, namely that it creates the possibility that the seller takes a wrong action. With endogenous demand, demand uncertainty also influences buyers' purchase strategies, and thus the standard ar-

[7]The payoff result for the high-type seller depends on parameter values. Symmetric demand uncertainty tends to increase the high-type seller's expected payoff if p_H is rather small, while the opposite is true if p_H is rather large.

gument no longer applies.

Note that the payoff result does not deny the value of learning. In fact, as shown in Figure 3.2, given σ_B, the low-type seller's value function $V(\mu)$ is convex, and thus learning is always valuable to the seller. It is crucial to distinguish between *ex ante* demand uncertainty (corresponding to initial belief μ_0) and *interim* demand uncertainty (corresponding to the seller's updated belief $\mu(t)$ over time). The payoff result (that demand uncertainty increases the low-type seller's expected payoff) is concerned with the former, while the learning result (that the value function $V(\mu)$ is convex in Proposition 3.2, and thus learning is valuable) is related to the latter. With exogenous demand, the distinction between the two is inconsequential: the seller's expected payoff is the same whether she begins with belief μ_0 or reaches the same level μ_0 after some time. With endogenous demand, the distinction is crucial, because ex ante demand uncertainty affects buyers' purchase strategies σ_H, while interim demand uncertainty does not. To put it differently, public learning (reducing ex ante demand uncertainty) is not valuable to the seller, while private learning (learning about demand over time) is always valuable.

3.5 Asymmetric Demand Uncertainty

In this section, we analyze the case of asymmetric demand uncertainty: the seller is still uninformed about the demand state, while buyers know whether the arrival rate of buyers is high or low.

For notational simplicity, we use σ_d to denote the probability that each buyer accepts p_H and q_d^* to denote buyers' beliefs about the seller's type conditional on price p_H when the demand state is $d = h, l$. In other words, $\sigma_d = \sigma_B(\lambda_d)$ and $q_d^* = q(\lambda_d, p_H)$ for each $d = h, l$.

3.5.1 Buyers' Beliefs

We begin by deriving buyers' ex post beliefs about the seller's type in each demand state. Fix the low-type seller's pricing strategy $\sigma_S(\cdot)$ and buyers' purchase strategies (σ_h, σ_l). Following the same steps as in Section 3.3.1, for each demand state $d = h, l$,

$$\frac{q_d^*}{1 - q_d^*} = \frac{q_0}{1 - q_0} \frac{\int_0^\infty e^{-\int_0^t \lambda_d \sigma_d dx} dt}{\int_0^\infty \sigma_S(t) e^{-\int_0^t \lambda_d(\sigma_S(x)\sigma_d + 1 - \sigma_S(x))dx} dt}. \tag{3.10}$$

There is no general relationship between q_h^* and q_l^*: each can be larger than the other, depending on agents' strategies. For example, suppose the low-type seller plays a simple switching-down pricing strategy with cutoff time T_D. In that case, for each $d = h, l$,

$$\frac{q_d^*}{1 - q_d^*} = \frac{q_0}{1 - q_0} \frac{\frac{1}{\lambda_d \sigma_d}}{\frac{1 - e^{-\lambda_d \sigma_d T_D}}{\lambda_d \sigma_d}} = \frac{q_0}{1 - q_0} \frac{1}{1 - e^{-\lambda_d \sigma_d T_D}}.$$

Therefore, $q_h^* < q_l^*$ if $\lambda_h \sigma_h > \lambda_l \sigma_l$, while the opposite is true if $\lambda_h \sigma_h > \lambda_l \sigma_l$. If buyers' purchase strategies were independent of the demand state (i.e., $\sigma_h = \sigma_l$), then the former would be necessarily the case (because $\lambda_h > \lambda_l$). However, there is no priori reason why buyers play an identical purchase strategy in both states. Indeed, as shown shortly, in equilibrium buyers' purchase strategies do depend on the demand state (i.e., $\sigma_h \neq \sigma_l$).

3.5.2 Buyers' Equilibrium Purchase Strategies

For the same reason as in the previous sections, it cannot be an equilibrium that the low-type seller offers only one price. Under asymmetric demand uncertainty, this means that there are only the following three possibilities:

- The seller's optimal price is p_H in demand state h and v_L in demand state l:

$$\frac{\lambda_h \sigma_h}{r+\lambda_h \sigma_h} p_H > \frac{\lambda_h}{r+\lambda_h} v_L, \text{ while } \frac{\lambda_l \sigma_l}{r+\lambda_l \sigma_l} p_H < \frac{\lambda_l}{r+\lambda_l} v_L.$$

- The seller's optimal price is v_L in demand state h and p_H in demand state l:

$$\frac{\lambda_h \sigma_h}{r+\lambda_h \sigma_h} p_H < \frac{\lambda_h}{r+\lambda_h} v_L, \text{ while } \frac{\lambda_l \sigma_l}{r+\lambda_l \sigma_l} p_H > \frac{\lambda_l}{r+\lambda_l} v_L.$$

- The seller is indifferent between p_H and v_L in both demand states:

$$\frac{\lambda_h \sigma_h}{r+\lambda_h \sigma_h} p_H = \frac{\lambda_h}{r+\lambda_h} v_L, \text{ and } \frac{\lambda_l \sigma_l}{r+\lambda_l \sigma_l} p_H = \frac{\lambda_l}{r+\lambda_l} v_L.$$

The following proposition establishes that only the last case can arise in equilibrium.

Proposition 3.4. *In the model with asymmetric demand uncertainty, buyers' equilibrium purchase strategies must be given by*

$$\overline{\sigma}_d = \frac{r v_L}{(r+\lambda_d) p_H - \lambda_d v_L}, \textit{ for each } d = h, l.$$

Proof. See Appendix B. □

To understand the result, consider the first case, which is a natural case given its similarities to the equilibrium under symmetric demand uncertainty. In this case, the low-type seller's optimal pricing strategy is a simple switching-down strategy: she offers p_H and drops the price to v_L at some T_D. But then, as explained above, buyers assign a lower probability to the high type in demand state h than in demand state l (i.e., $q_h^* < q_l^*$), which makes the low-type seller's optimal price in each state reversed (i.e., the optimal price becomes v_L in demand state h and p_H in demand state l). Intuitively, both seller types trade faster in demand state h than in demand state l. However, the low-type seller offers p_H only until time T_D, while T_D is independent of the demand state. This makes, conditional on p_H, the seller to be more likely to be the low type in demand state h than in demand state l.[8]

In the second case, the opposite reasoning applies. Given the low-type seller's optimal price in each state, she plays either a switching-up pricing strategy or a version of stationary strategy.[9] In both cases, it can be shown that buyers assign a higher probability to the high type in demand state h than in demand state l (i.e., $q_h^* > q_l^*$) and, therefore, it cannot be that the low-type seller's optimal price is v_L in demand state h and p_H in demand state l.

Proposition 3.4 implies that the low-type seller is indifferent between p_H and v_L, independent of her belief about demand. The following result is then immediate.

Corollary 3.2. *In the model with asymmetric demand uncertainty, conditional on each demand state $d = h, l$, the low-type seller's expected payoff is equal to $\lambda_d v_L/(r + \lambda_d)$, while the high-type seller's (net) expected payoff is equal to $\lambda_d \overline{\sigma}_d (p_H - c_H)/(r + \lambda_d \overline{\sigma}_d)$.*

Together with Proposition 3.3, this result demonstrates the subtlety of the effects of demand uncertainty on the seller's expected payoff. If buyers are symmetrically unin-

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[8]Observe that if either $T_D = \infty$ or T_D depends on the demand state (in particular, $\lambda_d \sigma_d T_D$ is identical between the two states), then $q_h^* = q_l^*$.

[9]As shown in the proof of Proposition 3.4, the former case arises if $\lambda_h \sigma_h \geq \lambda_l \sigma_l$, while the latter case arises if $\lambda_h \sigma_h < \lambda_l \sigma_l$. The necessity of a stationary strategy is due to the fact that if $\lambda_h \sigma_h < \lambda_l \sigma_l$, then the low-type seller's belief, conditional on no trade, increases when the price is p_H, while it necessarily decreases when the price is v_L.

formed about demand, then demand uncertainty necessarily increases the low-type seller's expected payoff. It may or may not increase the high-type seller's expected payoff. If buyers are informed about demand, then demand uncertainty has no impact on the seller's expected payoff: each seller type obtains the same expected payoff as in the model without demand uncertainty.

3.5.3 Equilibrium Pricing Strategy

Proposition 3.4 suggests that any pricing strategy is the low-type seller's best response to buyers' equilibrium purchase strategies. This does not mean that any pricing strategy can be a part of equilibrium (thus, *equilibrium* pricing strategy, rather than *optimal* pricing strategy). Recall that in the model without demand uncertainty, the low-type seller is also indifferent between p_H and v_L, but there is a equilibrium restriction on her pricing strategy $\sigma_S(t)$:

$$\frac{q_0}{1-q_0}\frac{\int_0^\infty e^{-\int_0^t \lambda\sigma_B dx}dt}{\int_0^\infty \sigma_S(t)e^{-\int_0^t \lambda(\sigma_S(x)\sigma_B+1-\sigma_S(x))dx}dt}=\frac{q^*}{1-q^*}=\frac{p_H-v_L}{v_H-p_H}.$$

The following proposition provides a necessary and sufficient condition for the low-type seller's equilibrium pricing strategy in the model with asymmetric demand uncertainty. The result follows from Proposition 3.4 and equation (3.10).

Proposition 3.5. *In the model with asymmetric demand uncertainty, a strategy profile* $(\sigma_S(\cdot),\sigma_h,\sigma_l)$ *is an equilibrium if and only if for both* $d=h,l$, $\sigma_d=\overline{\sigma}_d$ *and*

$$\frac{q_d^*}{1-q_d^*}=\frac{q_0}{1-q_0}\frac{\int_0^\infty e^{-\int_0^t \lambda_d\sigma_d dx}dt}{\int_0^\infty \sigma_S(t)e^{-\int_0^t \lambda_d(\sigma_S(x)\sigma_d+1-\sigma_S(x))dx}dt}=\frac{p_H-v_L}{v_H-p_H}. \tag{3.11}$$

We first show that a simple pricing strategy cannot support an equilibrium.

- Stationary strategy: suppose $\sigma_S(t) = \widehat{\sigma}_S$ for all t. Then,

$$\frac{q_d^*}{1-q_d^*} = \frac{q_0}{1-q_0}\frac{\frac{1}{\lambda_d\overline{\sigma}_d}}{\frac{\widehat{\sigma}_S}{\widehat{\sigma}_S\overline{\sigma}_d+1-\widehat{\sigma}_S}} = \frac{q_0}{1-q_0}\frac{\widehat{\sigma}_S\overline{\sigma}_d+1-\widehat{\sigma}_S}{\widehat{\sigma}_S\overline{\sigma}_d}.$$

Notice that

$$\overline{\sigma}_h = \frac{rv_L}{rp_H+\lambda_h(p_H-v_L)} < \frac{rv_L}{rp_H+\lambda_l(p_H-v_L)} = \overline{\sigma}_l.$$

Applying this to the above equation, it follows that $q_h^* > q_l^*$.

- Switching-down strategy: suppose for some $T_D \geq 0$, $\sigma_S(t) = 1$ if $t < T_D$, while $\sigma_S(t) = 0$ if $t \geq T_D$. Then, as shown above,

$$\frac{q_d^*}{1-q_d^*} = \frac{q_0}{1-q_0}\frac{1}{1-e^{-\lambda_d\overline{\sigma}_d T_D}}.$$

Notice that $\lambda_h\overline{\sigma}_h > \lambda_l\overline{\sigma}_l$, because

$$\frac{\lambda_h\overline{\sigma}_h}{r+\lambda_h\overline{\sigma}_h}p_H = \frac{\lambda_h}{r+\lambda_h}v_L > \frac{\lambda_l}{r+\lambda_l}v_L = \frac{\lambda_l\overline{\sigma}_l}{r+\lambda_l\overline{\sigma}_l}p_H.$$

It is then immediate that $q_h^* < q_l^*$.

- Switching-up strategy: suppose for some $T_U \geq 0$, $\sigma_S(t) = 0$ if $t < T_U$, while $\sigma_S(t) = 1$ if $t \geq T_U$. Then,

$$\frac{q_d^*}{1-q_d^*} = \frac{q_0}{1-q_0}\frac{\frac{1}{\lambda_d\overline{\sigma}_d}}{\frac{e^{-\lambda_d T_U}}{\lambda_d\overline{\sigma}_d}} = \frac{q_0}{1-q_0}\frac{1}{e^{-\lambda_d T_U}}.$$

Therefore, it is necessarily the case that $q_h^* > q_l^*$.

The following proposition presents one form of equilibrium pricing strategy, which has a relatively simple structure but contrasts well with the unique equilibrium pricing strategy under symmetric demand uncertainty. We note that there are many other equilibria, because the function $\sigma_S(t)$ can be adjusted in various ways to satisfy equation (3.5).

Proposition 3.6. *In the model with asymmetric demand uncertainty, there exists a (switch-up-and-down) equilibrium in which the low-type seller begins with v_L, switches up to p_H at some $T_U(>0)$, and reverts back to v_L at some $T_D(>T_U)$.*

Proof. Given T_D and T_U, buyers' beliefs, conditional on p_H, are as follows: for each $d = h, l$,

$$\frac{q_d^*}{1-q_d^*} = \frac{q_0}{1-q_0}\frac{\frac{1}{\lambda_d\overline{\sigma}_d}}{\frac{e^{-\lambda_d T_U}(1-e^{-\lambda_d\overline{\sigma}_d T_D})}{\lambda_d\overline{\sigma}_d}} = \frac{q_0}{1-q_0}\frac{1}{e^{-\lambda_d T_U}(1-e^{-\lambda_d\overline{\sigma}_d T_D})}.$$

For each $T_U \geq 0$, let $\phi(T_U)$ be the value such that

$$\frac{q_l^*}{1-q_l^*} = \frac{q_0}{1-q_0}\frac{1}{e^{-\lambda_l T_U}(1-e^{-\lambda_l\overline{\sigma}_l\phi(T_U)})} = \frac{p_H-v_L}{v_H-p_H}.$$

The function $\phi(T_U)$ is well-defined as long as

$$\frac{q_0}{1-q_0}\frac{1}{e^{-\lambda_l T_U}} \leq \frac{p_H-v_L}{v_H-p_H}. \tag{3.12}$$

It is clear that the function is continuous and strictly increasing over the relevant range.

Now notice that if $T_U = 0$, then (as in the switching-down case above)

$$\frac{q_h^*}{1-q_h^*} = \frac{q_0}{1-q_0}\frac{1}{1-e^{-\lambda_h\overline{\sigma}_h\phi(0)}} < \frac{q_0}{1-q_0}\frac{1}{1-e^{-\lambda_l\overline{\sigma}_l\phi(0)}} = \frac{q_l^*}{1-q_l^*}.$$

To the contrary, if T_U is the maximal value that satisfies the inequality (3.12), then $\phi(T_U) = \infty$, and thus (as in the switching-up case above)

$$\frac{q_h^*}{1-q_h^*} = \frac{q_0}{1-q_0}\frac{1}{e^{-\lambda_h T_U}} > \frac{q_0}{1-q_0}\frac{1}{e^{-\lambda_l T_U}} = \frac{q_l^*}{1-q_l^*}.$$

By the continuity and monotonicity, there exists a unique value of T_U that satisfies

$$\frac{q_h^*}{1-q_h^*} = \frac{q_0}{1-q_0}\frac{1}{e^{-\lambda_l T_U}(1-e^{-\lambda_l\overline{\sigma}_l\phi(T_U)})} = \frac{p_H-v_L}{v_H-p_H}.$$

□

3.6 Conclusion

In this paper, we studied a dynamic pricing problem with two prominent features, demand uncertainty and adverse selection. Demand uncertainty introduces a non-stationary component (seller learning) into an otherwise stationary environment, which is new to the literature on adverse selection. Adverse selection forces demand to be endogenously determined, rather than exogeneously given as typically assumed in the literature on demand uncertainty.

We demonstrated that this exercise generates a rich set of novel economic implications. If the demand state is also unknown to buyers, then it induces the low-type seller to adopt an intuitive pricing strategy in which she begins with a high price and eventually switches down to a low price. Demand uncertainty is also beneficial to the low-type seller: she obtains a higher expected payoff with symmetric demand uncertainty than without it. If the demand state is known to buyers, then both results change significantly. Demand uncertainty does not affect the seller's expected payoff. In addition, the low-type seller's equilibrium pricing strategy cannot take a simple form. We showed that a switching-down pricing strategy can never be a part of equilibrium, while there exists an equilibrium in which the low-type seller employs a more sophisticated switching-up-and-down pricing strategy.

APPENDIX A
APPENDIX TO CHAPTER 1

Table A1.1: Labor Market Returns to Skills in the NLSY79 vs NLSY97

	NLSY79	NLSY97	NLSY79	NLSY97	NLSY79	NLSY97	NLSY79	NLSY97
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lagged Unemployment Rate	-0.298***	0.104***	-0.288***	0.102***	-0.239***	0.047***	-0.216***	0.025***
(National)	[0.015]	[0.005]	[0.016]	[0.006]	[0.016]	[0.006]	[0.015]	[0.006]
Cognitive Skill	0.176***	0.076***	0.163***	0.074***	0.143***	0.046***	0.113***	0.040***
	[0.008]	[0.009]	[0.009]	[0.010]	[0.008]	[0.009]	[0.009]	[0.009]
Social Skill	0.035***	0.029***	0.035***	0.024***	0.036***	0.029***	0.036***	0.027***
	[0.006]	[0.007]	[0.007]	[0.008]	[0.006]	[0.007]	[0.006]	[0.007]
Unemployment*Cognitive	-0.014***	0.020***	-0.016***	0.019***	-0.006	0.011***	-0.011**	0.012***
	[0.005]	[0.004]	[0.006]	[0.004]	[0.005]	[0.004]	[0.005]	[0.004]
Unemployment*Social	-0.006	-0.004	-0.006	-0.005	-0.005	-0.005	-0.007	-0.004
	[0.005]	[0.004]	[0.005]	[0.004]	[0.005]	[0.004]	[0.005]	[0.004]
Family background			○	○			○	○
Education level					○	○	○	○
Industry fixed effect							○	○
Observations	48,197	29,275	40,019	23,073	48,197	29,275	39,772	22,744
R-squared	0.271	0.124	0.273	0.132	0.289	0.156	0.378	0.267

Notes: Dependent variables are real log hourly wages. The lagged national unemployment rate is used. Cognitive skills are measured by the Armed Forces Qualifying Test (AFQT), and are normalized to have a mean of zero and a standard deviation of one. Social skills are a standardized composite of two questions from the Big 5 personality inventory that measure extroversion. Education variables: high school=1 for high school graduates and 0 otherwise, associate's=1 for respondents with an associate degree, bachelor's=1 for bachelor's degree holders, and master's=1 for individuals with a master's degree or higher. Family background controls include parental education, intact family indicator and the number of siblings. The regression additionally controls for experience, experience2, racebygender indicator variables, census region and urbanicity fixed effects. Populations are weighted using the Bureau of Labor Statistics (BLS) weights. Standard errors are in brackets and clustered at the individual level. *** p<0.01, **p<0.05, *p<0.10

Table A1.2: Labor Market Returns to Skills in the NLSY79 vs NLSY97

(Outcome is Log Hourly Wage (in 2013 dollars))

	NLSY79	NLSY97	NLSY79	NLSY97	NLSY79	NLSY97	NLSY79	NLSY97
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Unemployment Rate	0.012	0.002	0.013	-0.013	0.008	0.006	0.008	-0.007
(Regional)	[0.012]	[0.021]	[0.013]	[0.023]	[0.012]	[0.021]	[0.011]	[0.022]
Cognitive Skill	0.174***	0.073***	0.159***	0.071***	0.141***	0.044***	0.110***	0.038***
	[0.008]	[0.009]	[0.009]	[0.010]	[0.008]	[0.009]	[0.008]	[0.009]
Social Skill	0.034***	0.029***	0.034***	0.025***	0.035***	0.029***	0.035***	0.028***
	[0.006]	[0.007]	[0.007]	[0.008]	[0.006]	[0.007]	[0.006]	[0.007]
Unemployment*Cognitive	-0.009*	0.020***	-0.008	0.020***	-0.001	0.012***	-0.003	0.013***
	[0.005]	[0.004]	[0.006]	[0.005]	[0.005]	[0.004]	[0.005]	[0.004]
Unemployment*Social	-0.007	-0.004	-0.006	-0.006	-0.007	-0.004	-0.004	-0.005
	[0.005]	[0.004]	[0.005]	[0.004]	[0.005]	[0.004]	[0.005]	[0.004]
Family background			○	○			○	○
Education level					○	○	○	○
Industry fixed effect							○	○
Observations	48,197	29,275	40,019	23,073	48,197	29,275	39,772	22,744
R-squared	0.271	0.124	0.273	0.132	0.289	0.156	0.377	0.267

Notes: Dependent variables are real log hourly wages. Four census region (northeast, midwest, south and west) unemployment rate is used. Cognitive skills are measured by the Armed Forces Qualifying Test (AFQT), and are normalized to have a mean of zero and a standard deviation of one. Social skills are a standardized composite of two questions from the Big 5 personality inventory that measure extroversion. Education variables: high school=1 for high school graduates and 0 otherwise, associate's=1 for respondents with an associate degree, bachelor's=1 for bachelor's degree holders, and master's=1 for individuals with a master's degree or higher. Family background controls include parental education, intact family indicator and the number of siblings. The regression additionally controls for experience, experience2, racebygender indicator variables, census region, and urbanicity-plus controls as indicated. Populations are weighted using the Bureau of Labor Statistics (BLS) weights. Standard errors are in brackets and clustered at the individual level. *** $p<0.01$, ** $p<0.05$, * $p<0.10$

Table A1.3: Labor Market Returns to Skills in the NLSY79 vs NLSY97

(Outcome is an indicator for being employed full-time)

	NLSY79	NLSY97	NLSY79	NLSY97	NLSY79	NLSY97	NLSY79	NLSY97
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Unemployment Rate	-0.195***	-0.021	-0.189***	-0.028	-0.178***	-0.103***	-0.176***	-0.106***
(Regional)	[0.032]	[0.018]	[0.032]	[0.018]	[0.031]	[0.018]	[0.031]	[0.018]
Cognitive Skill	0.516***	0.410***	0.473***	0.390***	0.434***	0.304***	0.407***	0.294***
	[0.045]	[0.032]	[0.046]	[0.033]	[0.050]	[0.035]	[0.051]	[0.035]
Social Skill	0.101***	0.191***	0.096***	0.186***	0.098***	0.179***	0.094***	0.176***
	[0.033]	[0.029]	[0.033]	[0.029]	[0.033]	[0.029]	[0.033]	[0.029]
Unemployment*Cognitive	0.032	-0.004	0.033	-0.004	0.032	-0.01	0.032	-0.01
	[0.032]	[0.015]	[0.032]	[0.015]	[0.031]	[0.015]	[0.031]	[0.015]
Unemployment*Social	0.027	-0.017	0.025	-0.017	0.024	-0.017	0.022	-0.018
	[0.029]	[0.015]	[0.029]	[0.015]	[0.029]	[0.015]	[0.029]	[0.015]
Family background			○	○			○	○
Education level					○	○	○	○
Observations	61,905	43,644	61,801	43,644	61,905	43,644	21,169	25,216

Notes: Dependent variables are real log hourly wages. Four census region (northeast, midwest, south and west) unemployment rate is used. Cognitive skills are measured by the Armed Forces Qualifying Test (AFQT), and are normalized to have a mean of zero and a standard deviation of one. Social skills are a standardized composite of two questions from the Big 5 personality inventory that measure extroversion. Education variables: high school=1 for high school graduates and 0 otherwise, associate's=1 for respondents with an associate degree, bachelor's=1 for bachelor's degree holders, and master's=1 for individuals with a master's degree or higher. Family background controls include parental education, intact family indicator and the number of siblings. The regression additionally controls for experience, experience2, racebygender indicator variables, census region, and urbanicity-plus controls as indicated. Populations are weighted using the Bureau of Labor Statistics (BLS) weights. Standard errors are in brackets and clustered at the individual level. *** p<0.01, **p<0.05, *p<0.10

Table A1.4: Labor Market Returns to Skills in the NLSY79 vs NLSY97 with Additional Controls

VARIABLES	NLSY79			NLSY97		
	(1)	(2)	(3)	(4)	(5)	(6)
Unemployment Rate	-0.294***	-0.294***	-0.309***	0.100***	0.100***	0.099***
(National)	[0.014]	[0.015]	[0.015]	[0.006]	[0.006]	[0.006]
Cognitive Skill	0.175***	0.176***	0.152***	0.073***	0.072***	0.076***
	[0.008]	[0.008]	[0.008]	[0.009]	[0.009]	[0.008]
Social Skill	0.034***	0.031***	0.028***	0.028***	0.029***	0.020***
	[0.006]	[0.006]	[0.006]	[0.007]	[0.007]	[0.007]
Cognitive Skill * Social Skill		0.015***			-0.001	
		[0.006]			[0.007]	
Non-cognitive Skill			0.058***			0.073***
			[0.007]			[0.007]
Unemployment*Cognitive	-0.016***	-0.015***	-0.017***	0.019***	0.019***	0.018***
	[0.005]	[0.005]	[0.005]	[0.004]	[0.004]	[0.004]
Unemployment*Social	-0.006	-0.006	-0.007	-0.002	-0.002	-0.001
	[0.005]	[0.005]	[0.005]	[0.004]	[0.004]	[0.004]
Observations	48,197	48,197	48,168	29,275	29,275	29,268
R-squared	0.214	0.215	0.217	0.086	0.086	0.099

Notes: Dependent variables are real log hourly wages. Cognitive skills are measured by the Armed Forces Qualifying Test (AFQT), and are normalized to have a mean of zero and a standard deviation of one. Social skills are a standardized composite of two questions from the Big 5 personality inventory that measure extroversion. Measure of ”noncognitive” skills is the normalized average of the Rotter and Rosenberg scores in the NLSY. Education variables: high school=1 for high school graduates and 0 otherwise, associate's=1 for respondents with an associate degree, bachelor's=1 for bachelor's degree holders, and master's=1 for individuals with a master's degree or higher. Family background controls include parental education, intact family indicator and the number of siblings. The regression additionally controls for experience, experience2, racebygender indicator variables, census region, and urbanicity-plus controls as indicated. Populations are weighted using the Bureau of Labor Statistics (BLS) weights. Standard errors are in brackets and clustered at the individual level. *** $p<0.01$, ** $p<0.05$, * $p<0.10$

APPENDIX B
APPENDIX TO CHAPTER 2

Table A2.1: Sample sizes of college graduation cohorts

Year of college graduation	Frequency	Unemployment rate	
		National	Region (Mean)
1979	7.32	5.8	5.8
1980	8.04	7.1	7.0
1981	9.66	7.6	7.6
1982	10.95	9.7	9.6
1983	10.97	9.6	9.7
1984	13.51	7.5	7.6
1985	12.72	7.2	7.2
1986	12.64	7	7.0
1987	7.81	6.2	6.3
1988	3.61	5.5	5.5
1989	2.79	5.3	5.4
Total	100	7.14	7.2

Notes: The sample is college graduates in NLSY79 who graduated between 1979 and 1989, with aged 23-59 and with potential experience 0-15 years. I exclude enrolled people. Both national and four census regional unemployment rates are calculated using the BLS.

Table A2.2: Reasons for the Most Recent Job Change in the NLSY79

	Voluntary job changes				Involuntary job change	
	Family reasons		Economic reasons			
	(1)	(2)	(3)	(4)	(5)	(6)
	Cognitive	Social	Cognitive	Social	Cognitive	Social
Regression coefficients						
Skills	0.005*	0.001	0.004	0.011**	0.004	-0.001
	[0.003]	[0.001]	[0.007]	[0.004]	[0.013]	[0.011]
Skills * Exp	0	0	0	-0.001*	0.001	0
	[0.000]	[0.000]	[0.000]	[0.000]	[0.002]	[0.001]
Observations	8422		8559		9,249	
R-squared	0.006		0.008		0.009	

Notes: Each column reports results from an estimate of equation (1), with reasons of the most recent job change as outcome. The data source is the National Longitudinal Survey of Youth 1979 cohort (NLSY79). The sample is restricted to workers who graduated from college between 1979 and 1989 and have valid skill measures and outcome variables within 15 years of college graduation who are not enrolled in school. Cognitive skills are measured by each respondent's score on the Armed Forces Qualifying Test (AFQT), and social skills is a standardized composite of two variables (i) self-reported personality scale: extroverted or enthusiastic (ii) self-reported personality scale: reserved or quiet. Both skill measures are normalized to have a mean of 0 and a standard deviation of 1. Regression includes four census regions and year fixed effects, plus additional controls such as potential experience, a quadratic in potential experience, gender, race/ethnicity and gender interacted with race/ethnicity. Standard errors are in brackets and are clustered by year of college gradation. ***p<.01, **p<.05, *p<.10.

APPENDIX C
APPENDIX TO CHAPTER 3

Appendix 3.1: The Case when λ is Known Only to the Seller

In this appendix, we consider another asymmetric case where the demand state is known to the seller, but not to buyers. The setup is straightforward to interpret, and thus we avoid its detailed description.

We begin with a lemma that characterizes the low-type seller's best response to buyers' purchase strategies σ_B. The values of $\overline{\sigma}_h$ and $\overline{\sigma}_l$ are as defined in Proposition 3.4. Recall that $\overline{\sigma}_h < \overline{\sigma}_l$.

Lemma C.1. *Suppose each buyer accepts p_H with probability σ_B.*

- *If $\sigma_B \leq \overline{\sigma}_h$, then the low-type seller weakly prefers offering v_L to p_H in demand state h and strictly prefers v_L to p_H in demand state l.*
- *if $\sigma_B \in (\overline{\sigma}_h, \overline{\sigma}_l)$, then the low-type seller strictly prefers offering p_H to v_L in demand state h and strictly prefers v_L to p_H in demand state l.*
- *If $\sigma_B \geq \overline{\sigma}_l$, then the low-type seller strictly prefers offering p_H to v_L in demand state h and weakly prefers p_H to v_L in demand state l.*

Proof. The result is straightforward given that the low-type seller knows the demand state and for each $d = h, l$, she is indifferent between p_H and v_L in demand state d when each buyer accepts p_H with probability $\overline{\sigma}_d$. □

For the same reason as in the other cases, it cannot be an equilibrium that the low-type seller offers only one price in both states. Therefore, in equilibrium, buyers' purchase strategies must be such that $\sigma_B \in [\overline{\sigma}_h, \overline{\sigma}_l]$.

We focus on one particular pricing strategy where the low-type seller offers only p_H in demand state h and v_L in demand state l and identify a condition under which that pricing strategy can be an equilibrium. The condition is then used to identify the parameter range in which $\sigma_B = \overline{\sigma}_h$ and the parameter range in which $\sigma_B = \overline{\sigma}_l$.

Given the seller's pricing strategy, as in Section 3.4.2, buyers' beliefs about the seller's type, conditional on p_H, are given by

$$\frac{q^*}{1-q^*} = \frac{q_0}{1-q_0}\frac{\frac{\mu^*}{\lambda_h\sigma_B}+\frac{1-\mu^*}{\lambda_l\sigma_B}}{\frac{\mu^*}{\lambda_h\sigma_B}} = \frac{q_0}{1-q_0}\left(1+\frac{1-\mu^*}{\mu^*}\frac{\lambda_h}{\lambda_l}\right).$$

Buyers' beliefs about the demand state, conditional on p_H, are given by

$$\frac{\mu^*}{1-\mu^*} = \frac{\mu_0}{1-\mu_0}\frac{\frac{q_0}{\lambda_h\sigma_B}+\frac{1-q_0}{\lambda_h\sigma_B}}{\frac{q_0}{\lambda_l\sigma_B}} = \frac{\mu_0}{1-\mu_0}\frac{\lambda_l}{q_0\lambda_h}.$$

Combining the two equations and imposing another equilibrium condition that $q^*(v_H - p_H) + (1-q^*)(v_L - p_H) = 0$,

$$\frac{p_H - v_L}{v_H - p_H} = \frac{q_0}{1-q_0}\left(1+\frac{1-\mu_0}{\mu_0}q_0\frac{\lambda_h^2}{\lambda_l^2}\right). \tag{C.1}$$

Since the right-hand side is strictly decreasing from infinity to $q_0/(1-q_0)$ as μ_0 increases from 0 to 1, under Assumption 3.1 (which ensures that the right-hand side is smaller than the left-hand side when μ_0 is sufficiently close to 1), there exists a unique interior value of μ_0 that satisfies the equation.

The following result follows from the characterization above.

Proposition C.1. *Let $\overline{\mu}_0$ denote the unique value of μ_0 that satisfies equation* (C.1).

- *If $\mu_0 < \overline{\mu}_0$, then in equilibrium each buyer accepts p_H with probability $\overline{\sigma}_l$, and the low-type seller offers only p_H in demand state h but both p_H and v_L in demand state l.*

- *If $\mu_0 = \overline{\mu}_0$, then in equilibrium each buyer accepts p_H with with probability $\sigma_B \in [\overline{\sigma}_h, \overline{\sigma}_l]$, and the low-type seller offers only p_H in demand state h and v_L in demand state l.*

- *If $\mu_0 > \overline{\mu}_0$, then in equilibrium each buyer accepts p_H with probability $\overline{\sigma}_h$, and the low-type seller offers both p_H and v_L in demand state h, but only v_L in demand state l.*

Proof. If $\mu_0 < \overline{\mu}_0$, then $q^* > (p_H - v_L)/(v_H - v_L)$ whenever the low-type seller offers v_L with a positive probability in demand state h (which implies that she offers only v_L in demand state l). Therefore, she must offer only p_H in demand state h. Given this, it is clear that she must offer both p_H and v_L in demand state l, which can be the case only when $\sigma_B = \overline{\sigma}_l$.

If $\mu_0 = \overline{\mu}_0$, then, as shown above, $q^* = (p_H - v_L)/(v_H - v_L)$ when the low-type seller offers only p_H in demand state h and v_L in demand state l. This can be the case if and only if $\sigma_B \in [\overline{\sigma}_h, \overline{\sigma}_l]$.

If $\mu_0 > \overline{\mu}_0$, then, opposite to the first case, $q^* < (p_H - v_L)/(v_H - v_L)$ whenever the low-type seller offers p_H with a positive probability in demand state l (which implies that she offers only p_H in demand state h). Therefore, she must offer only v_L in demand state l. Given this, she must offer both p_H and v_L in demand state h, which can be the case only when $\sigma_B = \overline{\sigma}_h$. □

In each case, the equilibrium condition $q^* = (p_H - v_L)/(v_H - v_L)$ imposes a restriction on the behavior of the low-type seller's pricing strategy. The restriction can be derived as in the other models and, therefore, omitted.

Proposition C.1 implies that the seller's expected payoff may or may not be larger than in the model without demand uncertainty, depending on whether μ_0 is above or below $\overline{\mu_0}$, as formalized in the following corollary.

Corollary C.1. *Suppose the demand state is known to the seller, but not to buyers.*

- *If $\mu_0 < \overline{\mu}_0$, then in any equilibrium, the low-type seller's expected payoff is equal to*

$$\mu_0 \frac{\lambda_h \overline{\sigma}_l}{r + \lambda_h \overline{\sigma}_l} p_H + (1 - \mu_0) \frac{\lambda_l}{r + \lambda_l} v_L \left(> \mu_0 \frac{\lambda_h \overline{\sigma}_h}{r + \lambda_h \overline{\sigma}_h} p_H + (1 - \mu_0) \frac{\lambda_l}{r + \lambda_l} v_L \right),$$

and the high-type seller's expected payoff is equal to

$$\left(\mu_0 \frac{\lambda_h \overline{\sigma}_l}{r + \lambda_h \overline{\sigma}_l} + (1 - \mu_0) \frac{\lambda_l \overline{\sigma}_l}{r + \lambda_l \overline{\sigma}_l} \right) (p_H - c_H)$$
$$\left(> \left(\mu_0 \frac{\lambda_h \overline{\sigma}_h}{r + \lambda_h \overline{\sigma}_h} + (1 - \mu_0) \frac{\lambda_l \overline{\sigma}_l}{r + \lambda_l \overline{\sigma}_l} \right) (p_H - c_H) \right).$$

- *If $\mu_0 > \overline{\mu}_0$, then in any equilibrium, the low-type seller's expected payoff is equal to*

$$\mu_0 \frac{\lambda_h}{r + \lambda_h} v_L + (1 - \mu_0) \frac{\lambda_l}{r + \lambda_l} v_L,$$

and the high-type seller's expected payoff is equal to

$$\left(\mu_0 \frac{\lambda_h \overline{\sigma}_h}{r + \lambda_h \overline{\sigma}_h} + (1 - \mu_0) \frac{\lambda_l \overline{\sigma}_h}{r + \lambda_l \overline{\sigma}_h} \right) (p_H - c_H)$$
$$\left(< \left(\mu_0 \frac{\lambda_h \overline{\sigma}_h}{r + \lambda_h \overline{\sigma}_h} + (1 - \mu_0) \frac{\lambda_l \overline{\sigma}_l}{r + \lambda_l \overline{\sigma}_l} \right) (p_H - c_H) \right).$$

Appendix 3.2: Omitted Proofs

Proof of Proposition 3.3. Let $\underline{\sigma}_B$ be the value such that $\overline{\mu}(\underline{\sigma}_B) = \mu_0$ (i.e., the maximal value of σ_B such that $T(\sigma_B) = 0$). In addition, let $\overline{\sigma}_B$ be the value such that $\overline{\mu}(\overline{\sigma}_B) = 0$ (i.e., the minimal value of σ_B such that $T(\sigma_B) = \infty$). We show that equilibrium σ_B necessarily lies in $(\underline{\sigma}_B, \overline{\sigma}_B)$. Whenever $\sigma_B \leq \underline{\sigma}_B$, $k_d(\sigma_B) = 0$ for both $d = h, l$. Therefore, the left-hand side is necessarily larger than the right-hand side in equation (3.9). To the contrary, if $\sigma_B \geq \overline{\sigma}_B$, then $\kappa_d(\sigma_B) = 1$ for both $d = h, l$. This implies that the left-hand side in equation (3.9) reduces to $q_0/(1 - q_0)$, which is strictly less than the right-hand side by Assumption 3.1. Finally, the left-hand side is continuous and strictly decreasing on $(\underline{\sigma}_B, \overline{\sigma}_B)$. Therefore, there exists a unique value of σ_B that satisfies (3.9) on $(\underline{\sigma}_B, \overline{\sigma}_B)$. □

Proof of Proposition 3.4. In demand state a, the low-type seller is indifferent between offering p_H and v_L when $\sigma_d = \overline{\sigma}_d$. Therefore, she strictly prefers p_H to v_L if $\sigma_d > \overline{\sigma}_d$, while the opposite is true if $\sigma_d < \overline{\sigma}_d$.

We divide the proof into three cases. The first case is when the low-type seller prefers p_H in demand state h and v_L in demand state l, while the latter two cases correspond to the case where the low-type seller prefers v_L in demand state h and p_H in demand state l

(i) $\sigma_h > \overline{\sigma}_h$, while $\sigma_l < \overline{\sigma}_l$.

In this case, there exists a belief level $\overline{\mu}$ such that the seller's optimal price is p_H if and only if $\mu > \overline{\mu}$. In addition, $\lambda_h\sigma_h > \lambda_l\sigma_l$, because

$$\frac{\lambda_h\sigma_h}{r + \lambda_h\sigma_h} > \frac{\lambda_h}{r + \lambda_h}v_L > \frac{\lambda_l}{r + \lambda_l}v_L > \frac{\lambda_l\sigma_l}{r + \lambda_l\sigma_l}p_H.$$

This means that conditional on no trade, the seller's belief decreases over time, whether she offers p_H or v_L. It follows that the low-type seller's optimal pricing strategy is a simple switching-down strategy: she begins with p_H and then switches down to v_L at some $T_D(\geq 0)$. But then,

$$\frac{q_h^*}{1-q_h^*} = \frac{q_0}{1-q_0}\frac{1}{1-e^{-\lambda_h\sigma_h T_D}} < \frac{q_0}{1-q_0}\frac{1}{1-e^{-\lambda_l\sigma_l T_D}} = \frac{q_l^*}{1-q_l^*}.$$

This implies that either $\sigma_h = 0$ (if $\sigma_l = \overline{\sigma}_l$) or $\sigma_l = 1$ (if $\sigma_h = \overline{\sigma}_h$), which is a contradiction to the supposition that $\sigma_h > \overline{\sigma}_h$, while $\sigma_l < \overline{\sigma}_l$.

(ii) $\sigma_h < \overline{\sigma}_h$, $\sigma_l > \overline{\sigma}_l$, and $\lambda_h\sigma_h \geq \lambda_l\sigma_l$.

In this case, there exists a belief level $\overline{\mu}$ such that the seller's optimal price is p_H if $\mu < \overline{\mu}$ and v_L if $\mu > \overline{\mu}$. In addition, since $\lambda_h\sigma_h > \lambda_l\sigma_l$, conditional on no trade, the seller's belief decreases according to

$$\dot{\mu} = -\mu(1-\mu)(\lambda_h\sigma_h - \lambda_l\sigma_l) \leq 0,$$

while she offers p_H. It follows that the low-type seller's optimal pricing strategy is a simple switching-up strategy: she begins with v_L and then switches up to p_H at some $T_U(\geq 0)$. But then,

$$\frac{q_h^*}{1-q_h^*} = \frac{q_0}{1-q_0}\frac{1}{e^{-\lambda_h T_U}} > \frac{q_0}{1-q_0}\frac{1}{e^{-\lambda_l T_U}} = \frac{q_l^*}{1-q_l^*}.$$

Therefore, either $\sigma_h = 1$ (if $\sigma_l = \overline{\sigma}_l$) or $\sigma_l = 0$ (if $\sigma_h = \overline{\sigma}_h$), which is a contradiction to the supposition that $\sigma_h < \overline{\sigma}_h$, while $\sigma_l > \overline{\sigma}_l$.

(iii) $\sigma_h < \overline{\sigma}_h$, $\sigma_l > \overline{\sigma}_l$, and $\lambda_h\sigma_h < \lambda_l\sigma_l$.

In this case, as in (ii), there exists $\overline{\mu}$ such that the seller's optimal price is p_H if $\mu < \overline{\mu}$ and v_L if $\mu > \overline{\mu}$. Different from (ii), conditional on no trade, the seller's belief strictly increases according to

$$\dot{\mu} = -\mu(1-\mu)(\lambda_h\sigma_h - \lambda_l\sigma_l) > 0,$$

while she offers p_H. Since her belief conditional on no trade strictly decreases while she offers v_L, this means that her belief stays constant once it reaches $\overline{\mu}$ (i.e., $\overline{\mu}$ is an absorbing state). For this to happen, the low-type seller must offer p_H at rate

$$\sigma_S(t) = \widehat{\sigma}_S = \frac{\lambda_h - \lambda_l}{(\lambda_h - \lambda_l) - (\lambda_h\sigma_h - \lambda_l\sigma_l)} < 1.$$

In other words, every time she offers v_L, she needs to offer p_H $(\lambda_h - \lambda_l)/(\lambda_l\sigma_l - \lambda_h\sigma_h)$ times.[1]

Suppose $\mu_0 \leq \overline{\mu}$. In this case, the low-type seller offers p_H until some T and then follows the above pricing strategy. Then, for each $d = h, l$,

$$\frac{q_d^*}{1-q_d^*} = \frac{q_0}{1-q_0}\frac{\frac{1}{\lambda_d\sigma_d}}{\frac{1-e^{-\lambda_d\sigma_d T}}{\lambda_d\sigma_d} + \frac{e^{-\lambda_d\sigma_d T}\widehat{\sigma}_S}{\lambda_d(\widehat{\sigma}_S\sigma_d+1-\widehat{\sigma}_S)}} = \frac{q_0}{1-q_0}\frac{1}{1-e^{-\lambda_d\sigma_d T}\frac{1-\widehat{\sigma}_S}{\widehat{\sigma}_S\sigma_d+1-\widehat{\sigma}_S}}.$$

Since $\lambda_l\sigma_l > \lambda_h\sigma_h$, it follows that $q_h^* > q_l^*$. As in (ii), this implies that either $\sigma_h = 1$ or $\sigma_l = 0$, which contradicts the supposition that $\sigma_h < \overline{\sigma}_h$, while $\sigma_l > \overline{\sigma}_l$.

Now suppose $\mu_0 > \overline{\mu}$. In this case, the low-type seller offers v_L until some T and then follows the above pricing strategy. Then, for each $d = h, l$,

$$\frac{q_d^*}{1-q_d^*} = \frac{q_0}{1-q_0}\frac{\frac{1}{\lambda_d\sigma_d}}{\frac{e^{-\lambda_d T}\widehat{\sigma}_S}{\lambda_d(\widehat{\sigma}_S\sigma_d+1-\widehat{\sigma}_S)}} = \frac{q_0}{1-q_0}\frac{e^{\lambda_d T}(\widehat{\sigma}_S\sigma_d+1-\widehat{\sigma}_S)}{\widehat{\sigma}_S\sigma_d}.$$

Therefore, again, $q_h^* > q_l^*$, which leads to same contradiction as above.

□

[1] This means that in discrete time, the low-type seller's belief asymmetrically oscillates around $\overline{\mu}$.

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