Essays on technology and the labor market with search models

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ESSAYS ON TECHNOLOGY AND THE LABOR MARKET
WITH SEARCH MODELS

by

Soonhong Min

A Dissertation
Submitted to the University at Albany, State University of New York
in Partial Fulfillment of
the Requirements for the Degree of
Doctor of Philosophy

College of Arts and Sciences
Department of Economics
Spring 2022
To my family
ABSTRACT

This dissertation focuses on the impact of technological changes on workers based on the task-based model. In the first chapter, I first investigate the impacts of two types of technologies on employment and job choices in the directed search model. The relationship between technology and labor with respect to complementarity and substitutability defines technology as labor-augmenting and labor-saving. Progress of labor-augmenting technology mainly works in jobs hiring highly-skilled workers in positive ways while labor-saving technological development affects jobs with middle-skilled workers in destructive ways during the last two decades in KLIPS data. The consequence of technological advances intensifies the advantage of highly skilled workers relative to unskilled workers. Then, the second part examines how employment and the adoption of new technology are affected if workers raise their skill level in response to technological changes. Two possible scenarios predict the results of an increasing supply of high-skilled workers. When firms voluntarily control the skill requirements, it causes the incidence of overqualification that increases the earning inequality, and labor-saving technologies worsen the problem in routine task jobs. However, technology innovation is accelerated. The price adjustment can naturally correct the oversupply of the highly skilled by changing the incentive to move up the job ladder. It is carried out through the reduced dispersion of technical developments and therefore decreased earning gap across tasks.

In the second chapter, I examine how differently routine-biased technological changes affect unskilled workers by their innate ability and work experience. This chapter answers why some workers keep their jobs and others do not when labor-saving technologies take the worker’s role over. To focus on routine-biased technological changes, it covers high school graduates who might have either routine or manual tasks in the United States. In a random search model, workers follow the Nash bargaining wage to choose where to apply. Since the wage depends on productivity that varies by their innate ability and work experience, workers’ job search is delimited by their characteristics. The model simulates the impact of routine-biased technological changes with falling labor productivity in routine tasks, leading to wages dropping and routine jobs decreasing. From the lowest ability, those who were in the
routine task sector are crowded out. The unemployment rate of unskilled workers increases even though more manual jobs are created due to lower wages. Work experience makes those who are exposed to a risk of separation survive. It distinguishes the high unemployment rate of young workers who had opportunities to accumulate work experience from a relatively low one of old workers. Therefore, while the labor-saving technological influence curtails the welfare of unskilled workers, workers with high ability and/or experience can keep.
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# CONTENTS

<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>ABSTRACT</td>
<td>iii</td>
</tr>
<tr>
<td>ACKNOWLEDGMENT</td>
<td>v</td>
</tr>
<tr>
<td>LIST OF FIGURES</td>
<td>x</td>
</tr>
<tr>
<td>INTRODUCTION</td>
<td>xii</td>
</tr>
<tr>
<td>1. The Interaction of Technological Advances with Skills and the Impact of Increasing Supply of High Skills</td>
<td>1</td>
</tr>
<tr>
<td>1.1 Introduction</td>
<td>1</td>
</tr>
<tr>
<td>1.2 Model</td>
<td>8</td>
</tr>
<tr>
<td>1.2.1 Set-up</td>
<td>8</td>
</tr>
<tr>
<td>1.2.2 Firm’s problem</td>
<td>12</td>
</tr>
<tr>
<td>1.2.3 Worker’s problem</td>
<td>13</td>
</tr>
<tr>
<td>1.2.4 Equilibrium</td>
<td>14</td>
</tr>
<tr>
<td>1.3 Estimation</td>
<td>14</td>
</tr>
<tr>
<td>1.3.1 Functional Form and Distributional Assumptions</td>
<td>15</td>
</tr>
<tr>
<td>1.3.2 External Parameters</td>
<td>16</td>
</tr>
<tr>
<td>1.3.3 Estimated Parameters</td>
<td>17</td>
</tr>
<tr>
<td>1.3.3.1 Skill Distribution</td>
<td>18</td>
</tr>
<tr>
<td>1.3.3.2 The Cost of <em>machines</em></td>
<td>19</td>
</tr>
<tr>
<td>1.3.4 Calibrated Parameters</td>
<td>21</td>
</tr>
<tr>
<td>1.3.5 The Cost of <em>robots</em></td>
<td>23</td>
</tr>
<tr>
<td>1.3.6 Model Fit</td>
<td>27</td>
</tr>
<tr>
<td>1.4 Experiments</td>
<td>29</td>
</tr>
<tr>
<td>1.4.1 The Impact of Technological Changes on Workers</td>
<td>29</td>
</tr>
<tr>
<td>1.4.2 The Role of Skills in Technology Advances</td>
<td>31</td>
</tr>
</tbody>
</table>
2. Who is Hurt the Most
by the Routine-Biased Technological Changes:
a study of the impact of the RBTC on workers by their experience and ability

2.1 Introduction ............................................................................. 62

2.2 MODEL .................................................................................... 68
   2.2.1 Set up .............................................................................. 68
   2.2.2 Value functions ................................................................. 70
   2.2.3 Wage setting ..................................................................... 72
   2.2.4 Ability requirements for job application ............................. 73
   2.2.5 Unemployment Dynamics ................................................. 75
   2.2.6 Equilibrium ....................................................................... 76
   2.2.7 Characterizing the equilibrium .......................................... 77
      2.2.7.1 The job value and a wage ........................................... 77
      2.2.7.2 Ability requirements ................................................... 81
   2.2.8 Changes in steady state caused by RBTC shock ............... 82

2.3 MODEL SIMULATION .............................................................. 86
   2.3.1 Parameters ....................................................................... 86
   2.3.2 Model prediction ............................................................... 91
      2.3.2.1 Changes in ability requirements by the RBTC .......... 91
      2.3.2.2 Response of the routine and the manual job market to
              the RBTC ...................................................................... 91
      2.3.2.3 Changes in the composition of type of workers .......... 94
      2.3.2.4 The difference in the wage growth by occupational choices . 97

2.4 CONCLUSION ......................................................................... 99

APPENDIX B. This Is An Appendix .................................................. 101
   B.1 The share of employment by task ....................................... 101
      B.1.1 The share of employment by educational attainments ... 102
   B.2 Nash Bargaining wage .......................................................... 103
B.2.1 Wages for those who apply for the manual jobs only: $\epsilon \in [0, \epsilon^*_0]$  

B.2.2 Wages for those who apply both manual and routine jobs: $\epsilon \in [\epsilon^*_0, \epsilon^{**}]$  

B.2.2.1 The experienced workers: $\epsilon_1 \in [\epsilon^*_0, \epsilon^{**}]$  

B.2.2.2 The inexperienced workers  

B.2.3 Wages for those who apply for routine jobs only: $\epsilon^{**} \leq \epsilon \leq 1$  

B.3 Job value with Nash bargaining wages.
# LIST OF FIGURES

1.1 Gross Enrollment Rate for Tertiary Education ............................................. 3  
1.2 Required units of robots for automation. .................................................. 10  
1.3 Probability of Computerization ................................................................. 24  
1.4 Changes in Employment Share between 1999-2018, Data vs Model ................. 28  
1.5 Changes in Labor Complementary Technology, Data vs Model ..................... 28  
1.6 The Changes in the Employment Value and Wage ....................................... 30  
1.7 The Labor-augmenting Technological Advances over Worker’s Skills ............ 32  
1.8 Aggregate Benefit of Employment and Unemployment Rate .......................... 35  
1.9 The ratio of labor augmenting technology and skill to the initial skill distribution 37  
1.10 The Impact of Rising Skill Requirements on the Employment Value .............. 40  
1.11 The Impact of Price Adjustment on the Employment Value .......................... 47  
A.1 Percent Changes in the Employment Share (Base year = 2000) ...................... 52  
A.2 Percent Changes in the Real Wage (Base year = 2000) ............................... 53  
A.3 The Price of Robots during 1990-2005 from Graetz and Michaels (2018) ........ 57  
A.4 The Trend of Job Finding Rate and the Stock of Robots .............................. 57  
A.5 Skill Requirements ....................................................................................... 59  
A.6 Price Adjustments ....................................................................................... 59  
A.7 The Ratio of Labor-Augmenting Technology and Skills to the Initial Skill Distribution with Rising Skill Requirements .......................................................... 60  
A.8 The Ratio of Labor-Augmenting Technology and Skills to the Initial Skill Distribution with Price Adjustment ............................................................... 61
2.1 Ability Requirements for Job Application ........................................... 74
2.2 The Value of a Filled Manual Job (left) and Routine Job (right) ............ 78
2.3 Comparison of Job Values Before and After the RBTC Shock ............... 83
2.4 Ability Requirements across the Base Productivity ............................. 92
2.5 The Impact of the RBTC on Job Markets .......................................... 93
2.6 Changes in Unemployment by Types of Workers ............................. 96
2.7 The Gap of Log-Wage on the Distribution of the Worker’s Ability ....... 98
B.1 The share of employment by job tasks ............................................. 101
B.2 The share of employment by education attainment .......................... 102
B.3 Changes in wage for each task ..................................................... 107
B.4 The ability requirement for inexperienced workers .......................... 108
B.5 The ability requirements for experienced workers .......................... 110
INTRODUCTION

In this dissertation, I investigate the impact of technological changes on the labor market with the task-based model. Technological innovation has been a key driver of structural changes in the labor market since the 1980s. During the 1980s and the 1990s, the functionality of technologies operated by highly educated workers substantially developed, leading to an increase in the demand for highly skilled workers. Technological advances were thought of as a good accelerator for employment expansion in this era, especially for skilled workers. The new pattern since the late 1990s, however, has converted people’s thoughts toward technological developments. It has been observed that the employment of middle-paid workers decreases while technological progress continues. This change is tried to be explained with new types of technologies and the characteristics of job tasks done by middle-skilled workers in the task-based model. Because routine and repetitive features of middle-paid job tasks are easy to be replaced by automation and computerization, thus new labor-saving technological changes destroy the demand for middle-skilled labor. Since technological progress exponentially speeds up and so its influence on the labor market grows faster over time, I explore how technological changes affect workers’ decisions on job choices, qualifications, and employment.

I deal with workers’ characteristics to capture who the beneficiary or the sufferer under the influence of technological advances. Like technological innovation in the 1980s expanded the employment opportunities only for highly educated workers, educational attainment plays a critical role in job choice and job-finding rate of an individual worker. Considering that middle-skilled workers who face the destructive influence of automation technologies are mostly high-school graduates, determines the degree and the direction of technological influences are dependent on education attainment. Besides, within the education group, differences in innate ability are concluded in the variation of productivity. Since workers with lower productivity are vulnerable to technological unemployment, workers’ ability level is also considered in exploring how technological shock affects employment opportunities and job application decisions by worker’s characteristics. Essays’ findings show that highly skilled workers can take advantage of labor-complementary technologies and avoid the destructive
effects of automation. The results that allow us to interpret rising educational attainment as workers’ response to the structural changes in the labor market caused by technological progress are specified in chapter 1. Moreover, work experience, the other factor that can raise productivity, is discussed in chapter 2 for the competition for disappearing middle-skilled jobs. While the upper limit of middle-skilled workers’ job choices is already circumscribed by their skill level and automation technology shrinks the employment chances, accumulated work experience makes old workers more able to survive destructive technology shock. It adds an explanation of why changes in employment differ by age, a factor undiscussed in the thesis but observed in the data, under the growing influence of computerization.

I use the search and matching framework as a theoretical fundamental of this dissertation. This thesis aims to see how technological developments distort employment through changes in labor demand. Since the search model shows firms’ decisions on job openings, the model directly follows changes in the number of vacancies when technological shocks arrive. Moreover, the search model can explicitly split submarkets for job types and specific characteristics of workers. Technology mainly used in a sub-division of the labor market is dependent on job tasks, and the direction of technological impacts is the opposite according to whether technologies evolve in a skill-complementary or a labor-saving way. Considering that workers in my model search for a job in certain submarkets where they are qualifying, the rise or the fall of employment of a particular group of workers is explained by technological changes within the market, and it is tractable in the search model. Another advantage of the search model is the multiple wage determination methods. The Nash bargaining wage determination, used in chapter 2 and the traditional method in the random search model, explains why the wage growth rate of non-routine manual task occupations increases even though they are neutral to technological changes.

The first chapter “The interaction of technological advances and skills and the impact of increasing supply of high skills” studies how technological advances and workers’ skills are interconnected and what happens if workers raise their skill level in response to technological changes. I build a directed search model with two-sided heterogeneity in the labor market. Workers are heterogeneous in skills, while firms are heterogeneous in tasks they perform among manual, routine, or cognitive. Both labor-augmenting technology and labor-saving technology are considered to see the productivity effect and the replacement effect of tech-
nology that works oppositely on creating jobs. The first part of this chapter shows how two types of technologies are entangled with workers. It confirms that high-skilled workers benefit more from technological changes than unskilled workers, so technological progress can stimulate workers to raise their skills. In the second part, I then investigate the impact of the increasing supply of high-skilled workers under the growing influences of technologies. Findings show the benefit of high skills varies by the employment controlling method. Imposing skill requirements leads to increasing earning inequality and a larger disparity in technological development across tasks. On the other hand, allowing the market to adjust product prices reduces earnings inequality by shifting technological development initiatives from cognitive to manual tasks that induce technical gaps across tasks to decrease.

This second chapter “Who is hurt the most by the routine-biased technological changes: a study of the impact of the RBTC on workers by their experience and ability” focuses on the destructive impact of labor-saving technological development on routine task occupations. It targets those who used to hold routine task occupations and follows their occupation transition and flow in and out of the unemployment pool when technology shock lowers labor productivity in routine tasks. I construct the random search model and allow workers to look for both routine and non-routine manual jobs simultaneously. Workers determine where to apply based on the guidance of Nash bargaining wage that varies by innate ability and previous work experience in routine tasks. The model expects vacancies for routine task jobs to shrink as labor productivity to technology falls due to technological innovation and the ability requirement for the jobs to increase. This change explains why those who have a relatively low level of ability are firstly displaced or reallocated to manual task occupations. Furthermore, findings show that experienced workers are better at avoiding the threat of technological unemployment than workers who recently joined the labor market. It is consistent that the proportion of young workers in the routine tasks job market as the influence of labor-saving technology grows.
CHAPTER 1
The Interaction of Technological Advances with Skills and the Impact of Increasing Supply of High Skills

1.1 Introduction

A substantial body of research has shown how technological changes affect workers. They found labor-augmenting technologies raise wage inequality and create more jobs dealing with complex tasks, whereas labor-saving technologies induce wage polarization and automate some jobs. These changes have critical influences on the wage rate, job security, and other features related to job choices, but gains and losses incurred by technological development are unevenly spread across workers. While high-skilled workers are beneficiaries of technological progress, less-skilled workers are at a potentially high risk of technological unemployment. As the gap in benefits between skilled and unskilled workers expands by technological progress, workers are more eager to be beneficiaries. In addition, considering that raising skills through education and training is thought of as the primary solution to be prepared under the growing influence of technologies, workers are encouraged to be highly skilled as well (Marchant, Stevens, & Hennessy, 2014; Schlogl, Weiss, & Prainsack, 2021). If more workers pursue the advantage of high skills so that the supply of the high-skilled exceeds the demand, how does the oversupply of high-skilled workers initiated by technological changes affect, in turn, workers and technological advances? This paper answers this rarely discussed question.

As a key driver of changes in the labor market, technological progress has been studied to explain the changes in employment and wage. First, the skill-biased technological change

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model (SBTC hereafter) following Tinbergen (1974, 1975) explains an increase in the demand for highly educated workers and a rising skill premium (Katz & Murphy, 1992; Acemoglu, 1998; Autor, Katz, & Krueger, 1998; Goldin & Katz, 1998; Machin & Van Reenen, 1998; Acemoglu, 2002). Since the 1980s, technologies have exponentially expanded. This type of technology needs to be controlled and operated by those capable of doing. The nature of complementarity of technology and skills raises the demand for skilled workers rapidly along with technology innovation. The number of university graduates continued to rise at that moment, but the growth rate of the demand outweighed the supply. Thus, the skill shortage resulted in a rise in the skill premium (Card & DiNardo, 2002). Around the late 1990s, labor-saving technologies came to the fore. Since new technologies can solely operate in accomplishing tasks at a cheaper cost than labor, labor-saving technologies started to take over the role of workers. The substitution of technology for labor mainly has occurred in jobs that perform routine tasks, so phenomena induced by this technology are referred to as routine-biased technological changes (RBTC hereafter).² Routine task jobs employ middle-skilled workers, so the replacement of labor with technology polarizes the labor market (Autor, Levy, & Murnane, 2003; Acemoglu & Autor, 2011; Autor & Dorn, 2013; Jung & Mercenier, 2014). Because the large portion of less-educated workers employment relies on routine tasks, the destruction of routine jobs has pushed those workers toward less-paid and more insecure jobs or causes technological unemployment (Bárány & Siegel, 2018; Goos, Manning, & Salomons, 2009; Cortes, 2016; Salomons et al., 2018).

As technologies have increasing control over the demand for labor and economic returns, workers who want to avoid the displacement effect of automation and to take the benefit of skill-biased technological changes voluntarily invest in the development of skills to be highly skilled (Prettner & Strulik, 2020). Moreover, policies concerning the destructive effect of automation on less-skilled workers emphasize the importance of upskilling and retraining to make workers well prepared (Marchant, Stevens, & Hennessy, 2014; Schlogl, Weiss, & Prainsack, 2021). If more workers follow the voluntary motive and policy recommendation, educational attainment has persistently increased as long as technologies continue to advance.

²From the pioneering work by Autor, Levy, and Murnane (2003), RBTC research separates job tasks into four categories: nonroutine cognitive, routine cognitive, routine manual, and nonroutine manual. Routine tasks are characterized by repetitiveness and predictability, thus these tasks are suitable to be codified and programmed. Due to the features, occupations that mainly perform routine tasks such as repetitive production activities or clerical work are most susceptible to automation by labor-saving technology.
Indeed, over the last four decades, the gross enrollment ratio of tertiary education worldwide grew more than double as illustrated in Figure 1.1. The rate of developed countries, OECD, is two times greater than the world average. Some countries such as Canada or South Korea show above 90 percent of enrollment rate in recent years.⁴

![Figure 1.1: Gross Enrollment Rate for Tertiary Education](image)

**Note:** Gross enrollment ratio for tertiary school is calculated by dividing the number of students enrolled in tertiary education regardless of age by the population of the age group which officially corresponds to tertiary education, and multiplying by 100.


The effectiveness of high education to combat technological unemployment, however, needs to be assessed. The empirical evidence shows the high unemployment rate of young university graduates in South Korea, where the growth rate of tertiary education enrollment rate is the most rapidly rising and the level of enrollment itself is the highest in the world. For example, the unemployment rate for college degree earners ages 20 to 29 was 1.7 percent lower than the rate for high school graduates in 2000 (7.6 percent for high school graduates and 5.9 percent for college degree earners) but is 1.5 percent higher in 2017 (9.5 percent for high school graduates and 11 percent for college degree earners).⁴ Their job security is also

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³Gross enrollment ratio for tertiary school is calculated by dividing the number of students enrolled in tertiary education regardless of age by the population of the age group which officially corresponds to tertiary education, and multiplying by 100.

⁴Unemployment rate by age group and educational attainment in Economically Active Population Survey
under the expectation. More than twice the OECD average fraction of workers are engaged in a non-regular job like part-time or fixed-term contract job (Jung & Lee, 2016). It is not Korea specific problem. In East Asian countries - Taiwan, Hong Kong, Mainland China, and South Korea, university graduates have been experiencing difficulty in finding jobs matching their skill sets, and the university premium is stagnant or even slightly decreased (Mok & Jiang, 2018).

The undesired consequence in most educated workers comes from the imbalance between supply and demand for high-skilled workers. While the supply of highly educated workers rapidly rises, it is ambiguous whether the demand for them increases that much quickly or not. The innovation in skill-complementary technology could somewhat lead the demand for highly educated workers to increase. But, it is uncertain that the negative influence of labor-saving technology such as AI or machine learning on the demand for highly educated workers. If the productivity effect of labor-augmenting technology is insufficiently larger than the displacement effect of labor-saving technology, technology-driven demand for high-skilled workers grows slower than the supply. Then, the labor market faces a new problem, the oversupply of highly skilled workers. Although the results of a surge of highly educated workers inflow in the demand-supply framework have been discussed (McGuinness, 2006; Verhaest & Van der Velden, 2013), it rarely deals with the technology development as a cause of the surplus of high skills. It is anticipated that technological development continues to increase the benefit of high-skilled workers, and hence the supply of high-skilled workers persists in rising. Then, the effect of the increasing supply of high-skilled workers is worth investigating.

This paper aims to see the technological changes as the motive of the increasing supply of high-skilled workers and the impact of oversupply of highly skilled workers on labor and technological advances. To make technologies and skills interconnected, I set up the directed search model incorporating two-sided heterogeneity and two types of technologies. Workers are heterogeneous in their endowed cognitive skills. Firms are heterogeneous in tasks they perform, among manual, routine, and cognitive tasks (Acemoglu & Autor, 2011). I assume the complexity of tasks increases from manual to cognitive tasks, and the productivity increases in job complexity and skills. By the complementarity between the complexity of tasks

https://kosis.kr/statHtml/statHtml.do?orgId=101&tblId=DT_1DA7105S&conn_path=I2
and skills, a high-skilled worker is matched with a cognitive task job, a middle-skilled worker with a routine task job, and a low-skilled worker with a manual task job. Firms can use either labor-saving technology or labor-augmenting technology based on cost-effectiveness. Once deciding to use labor-saving technology, the firm exits the labor market. Otherwise, firms choose the level of labor-augmenting technology after being matched with a worker. Labor-saving technology is routine-biased. Labor-augmenting technology is skill-biased and is more efficient in complex tasks.

The model reproduces the changes in the share of employment in Korea from 1999 to 2018. Consistent with RBTC findings, the employment share of cognitive and manual tasks increases while routine tasks decrease. These changes in the model are drawn by technological advances solely. Labor-augmenting technology develops in all tasks, but its impact inclines toward the cognitive-highly skilled worker match. Labor-saving technology is estimated to work only in routine tasks. Since the growth of beneficial technical changes outweighs the differences in displacement effect over time, workers at the end period are paid better than those at the beginning due to sufficient technical support. However, within-cohort earning dispersion has persistently increased because technological influence works differently across tasks. Skill-biased labor-augmenting technology rapidly raises the value of employment in cognitive jobs while automation destroys the middle-paying routine jobs. It raises the 50/90 percentile gap in the employment value but flattens the 10/50 percentile gap. This rising inequality can justify why those who have observed it yearn to have the skilled worker’s advantageous position. Since this paper intends to see what happens in the labor market if more people realize their motive of being highly skilled under the profound impact of technologies, I set more people to receive higher education.

To explore the impact of the increasing supply of high skills on labor, I establish the new skill distributions with a higher proportion of workers with a bachelor’s or higher degree. If demand for each skill level is adjusted to meet the changes in the supply, workers can have a job as they desire. More workers are matched with a better-paying job, so the aggregate employment benefits rise. Overall labor-augmenting technology advances further with an upward shift in skill distribution, which consistent with findings of Caselli and Coleman (2001), Bresnahan, Brynjolfsson, and Hitt (2002), and Arvanitis (2005). Consequently, the influx of high-skilled workers can result in a virtuous circle of high skills and skill-driven
technological progress when the demand simultaneously evolves.

Suppose the demand for high skilled workers is fixed at the baseline model irrelevantly to the supply surge. To see what happens in the labor market with the oversupply of high-skilled workers, I simulate two scenarios: the rising skill requirements and the product price adjustment. First, I see the case of rising skill requirements. When skillful applicants are plentiful, firms want to select more productive workers with less recruiting efforts by asking applicants to meet the unnecessarily high qualification (Cappelli, 2015; Deming & Noray, 2020). Under new skill requirements, some workers who used to be qualified for a cognitive job are circumscribed to enter the cognitive task sector. Their migration toward routine tasks makes routine submarkets overcrowded, so the right-qualified workers in routine tasks are forced out sequentially. Thus, the oversupply of high-skilled workers causes the incidence of overqualification (McGuinness, 2006; Verhaest & Van der Velden, 2013). Overqualified workers experience a wage penalty, as Chevalier and Lindley (2009) and Green and Zhu (2010) found. In addition, some of the high skilled are exposed to the threat of automation. Contrary to the adverse effects on workers, firms can take advantage of the oversupply of high skills. A vacancy filled with a relatively skilled worker can install new technology more, and this change happens in cognitive tasks the most due to the benefit of skill-technology complementarity. The differences in productivity effect between cognitive and non-cognitive tasks increase the earning inequality, making the race for the job more competitive.

The second scenario uses the price adjustment mechanism. Concerning the case that cognitive task firms freely expand employment as more high-skilled workers are available, it causes the excess supply of cognitive task output and will lead to a reduction in prices if demand for the product is steady (Bessen, 2019). Since the decrease in the price lowers the revenue as well as the capacity to bear the cost of skill-enhancing technology, the adoption of technology becomes stagnant, and hence wage offers will go down. The opposite phenomenon happens in the sector where struggles to find a worker. This mechanism naturally lessens the earning inequality among skilled and unskilled workers, but it is hard to be thought of as positive outcomes, especially regarding technological advances. The rise or fall of product prices evens out the level of labor-augmenting technology across tasks. Considering that the productivity effect is largest in cognitive tasks, the growth in technology adoption rotated toward manual rather than cognitive tasks means that technology is used less efficiently.
Furthermore, a reduction in income inequality makes cognitive jobs less attractive, so workers are less likely to crave a cognitive job. If this process iterates, workers lose an incentive to raise their skills for higher remuneration, so the economy is possible to be caught in a relatively low-skill, low-growth trap (Galor & Tsiddon, 1997).

The simulation results recommend the effectiveness of education and training policy reconsidered, especially in countries where more than enough people already try to avoid technology-induced issues through education. Rather, it explains the importance of creating attractive but achievable jobs for all types of workers. If the model includes the role of high-skilled workers in creating new task jobs through technological innovation, the impact of the increasing supply of high-skilled workers could be more benign than the current consequences. But, even in this case, it is still crucial to create more ‘lovely’ jobs that stimulate the motivation of being highly skilled to promote technological developments and raise workers’ welfare.

This paper sheds light on the importance of the reciprocal interaction between technologies and the labor market. Existing research dealing with how the impacts change the labor market, not the opposite direction, predicts the positive consequences of raising skills. Because I merge the role of workers in technology use, it can bring some hints to explain why a highly educated economy with advanced technologies struggles with labor market challenges. The labor market frictions raise the understanding of employment trends induced by technology. The directed search model realizes differences in wage offers, job-finding rates, and possible job choices across heterogeneously skilled workers so that it can trace the difference in the job transition. Moreover, this paper helps explain a sudden increase in the adoption of labor-saving technology more plausible than a technological shock by quantifying the cost of automation and operation with labor based on the actual prices.

The paper is constructed as follows. In Section 1.2, I establish the model to construct the connection between technological advances and skills. In Section 1.3, I calibrate the model. I set up the functional forms and assumptions for the costs of using technology to estimate. In Section 1.4, I check the relation between technology and skill. After seeing any technological change is beneficial for skilled workers, I simulate the rising supply of high-skilled workers to see how the labor market and technological advances change. Lastly, I conclude in Section 1.5.
1.2 Model

1.2.1 Set-up

Time is discrete and continues forever. The labor market consists of a continuum of workers with measure one and a continuum of firms with positive measure. Both agents are risk-neutral with a discount factor of $\beta \in (0, 1)$. Workers are ex-ante heterogeneous with respect to skills, $s$, which are randomly drawn from a log-normal distribution, $\log(s) \sim N(\mu_s, \sigma^2_s)$, and $s \in [\underline{s}, \bar{s}]$. This represents the worker’s cognitive skills, learning ability or intelligence which is determined by an innate ability and educational attainment. The level is assumed to be determined when the worker enters the labor market and fixed over time. If a worker has a higher level of $s$, the worker has absolute advantage in performing a cognitively complex task.

Firms are characterized by a task $j$ that they specialize in. There are $J$ different tasks in the economy, which is denoted by $j \in [1, J]$. Tasks are categorized into manual (M), routine (R), and cognitive (C) tasks following Acemoglu and Autor (2011). As $j$ moves from 1 to $J$, the complexity of task increase. Note that $j_R$ and $j_C$ is the threshold to be classified as a routine and a cognitive task. Tasks $j \in [1, j_R)$ are manual tasks, $j \in [j_R, j_C)$ are routine tasks and $j \in [j_C, J]$ are cognitive tasks.

\[ \hspace{1cm} \begin{array}{c}
1 < \cdots < j_R < \cdots < j_C < \cdots < J \\
\text{Manual} \hspace{1cm} \text{Routine} \hspace{1cm} \text{Cognitive}
\end{array} \]

One firm hires one worker. All firms produce a homogeneous good, which is a numéraire good, by performing their own specific task. The production function $f(j, s)$ characterizes productivity of the pair of $j$ task and $s$ skill. A more complex task produces more output, a higher $s$ has both absolute and comparative advantage in more complex tasks. Simply, the

---

5Based on Autor, Levy, and Murnane (2003), Acemoglu and Autor (2011) actually separate tasks into four categories by a two-by-two matrix: Cognitive vs Manual, Routine vs Non-routine. Cognitive tasks are abstract and analytic so requires a high degree of intelligence to perform. Manual tasks take place in physical environments so is done by physical adaptability, dexterity and interpersonal engagement. Routine and non-routine feature involves in repetitiveness and predictability of a task. Instead of 4 categories, I merge routine manual and routine cognitive tasks into routine tasks. Manual and cognitive tasks mean non-routine manual or cognitive tasks in this paper. From manual to routine to cognitive tasks, the complexity of task is thought to increase so the required level of skill and wage paid to continue to rise as well. In this paper, as $j$ goes from 1 to $J$, the task is changing from manual to cognitive. From the end to the middle, tasks are getting routinized.
feature of the production function is described below.

\[
\begin{align*}
\frac{\partial f(j, s)}{\partial j} > 0, \quad \frac{\partial f(j, s)}{\partial s} > 0, \quad \frac{\partial^2 f(j, s)}{\partial j \partial s} > 0
\end{align*}
\]

Firms can increase units of output through technological advances. Adoption of new technology and improvement of its functionality raises the productivity of a worker the firm already employed, so the firm’s choice about using technology determines the productivity of a firm-worker pair. This labor-augmenting technology is delivered as a form of machines, computers and/or software, it will be called machines hereafter. The efficiency of labor complementary technology is indexed as \( z \). The firm selects \( z \) from \([1, \infty)\) then produces \( zf(j, s) \) units of output and pays \( r^j(z) \) units of machines at a given price of machine, \( p_k \). When a firm starts a business with \( z = 1 \), the firm pays \( r^j(1) \geq 0 \), as the cost of setting up a business or a kind of a fixed cost. The higher \( z \) is chosen, more innovative technology needs to be installed thus the required units of machines increases.

\[
\begin{align*}
r^j(1) \geq 0, \quad \frac{\partial r^j(z)}{\partial z} > 0, \quad \frac{\partial^2 r^j(z)}{\partial z^2} > 0,
\end{align*}
\]

Each unit of machines is rented at \( p_{kt} \) in period \( t \). The price is given at the beginning of the period and assumed to fall at a \( \rho_k \) rate per period: \( d_{kt} = -\rho_k p_{kt} dt \).

The firm has an option of production without a worker if it is more profitable. Robots hereafter describes any capital inputs or automation technologies that replace the role of labor in production. Suppose technologies can replace a worker’s job in any task. \( \kappa^j_R \) denotes units of robots required to replace one worker in \( j \) task. The units of robots are varied by tasks. Since features of routine tasks are well-suited for being executed by programmed instruction and simple mechanical system, routine tasks demand fewer units of robots than cognitive or manual tasks. I set \( \hat{j} \) as the task which uses robots the least among routine tasks. As task \( j \) is away from \( \hat{j} \), the amount of robots demanded increases (Frey & Osborne, 2017). Graphically, Figure 1.2 describes the U-shaped relationship between the required units of robots, \( \kappa^j_R \), and task complexity \( j \).\(^6\)

\(^6\)The difficulty of automation by tasks is consistent with findings of Frey and Osborne (2017). They find that workers in transportation and logistics occupations, office and administrative support workers, and labour in production occupations are highly susceptible to computerisation, those who have high educational attainment are employed in relatively low-risk occupations, and the computerisation in service occupations gradually diminishes the comparative advantage of human labour in manual tasks.
When a firm installs robots, the firm pays $p_r\kappa^j_R$ to have a robot, and can produce $f(j)$ units of output for $n$ periods. Assume that robots are as productive as the median worker. Once a firm chooses robots, that decision is irreversible until the installed robot is completely depreciated. The price of robots, $p_r$, is also given at the beginning of the period and declines $\rho_r$ per period: $\frac{dr_r}{dt} = -\rho_r p_r dt$.

Each period is divided into four stages: separation, search, matching and production.

During the separation stage, an existing match is destroyed because of an exogenous shock or the exit of a worker. When an exogenous shock arrives the economy at a rate of $\delta \in (0, 1)$. A worker leaves the labor market at a probability of $\lambda \in (0, 1)$ regardless of employment status. The exit of workers are filled with the same number of new entrants’ entry. New workers enter as unemployed.

In the search stage, workers and firms can direct their search without private information. Firms create vacancies under free entry condition. A $j$ task firm pays $c^j$ to post a vacancy which last one period. Each vacancy specifies the required skill $s$ and offers the wage rate $w$. This condition segments the labor market into submarkets that are indexed by $(j, w, s) \in \mathbb{N} \times \mathbb{R}_+ \times \mathbb{R}_+$. Assume that all jobs are full-time jobs. Workers choose the task $j$ and its wage offer $w$ to maximize their expected earnings. They can only visit one submarket in a period to apply for. No on-the-job search is assumed.

In the beginning of the search period, before posting new vacancies, each firm compares
the benefit of automation and the value of a vacancy in the submarket they are willing to be. The benefit of hiring a worker is evaluated on the level of technology $z$ which the firm will choose in the production process. When the expected benefit of automation lies below the benefit of using a worker, the firm starts the search process by opening vacancies in a submarket. Otherwise, the firm leaves the labor market and implements robots instead.

During the matching stage, participating workers and firms in each submarket at the period of $t$ consist market tightness as $\theta_t(j, w, s) = \frac{v_t(j, w, s)}{u_t(j, w, s)}$ where $v$ is the number of vacancies and $u$ is the number of unemployed workers. I define the probability at which workers meet firms as $p(\theta_t(j, w, s))$ at $t$, where $p : \mathbb{R}_+ \rightarrow [0, 1]$ is a twice-continuously differentiable, strictly increasing, strictly concave function such that $p(0) = 0$ and $p'(0) < \infty$. Similarly, vacancies meet workers with the probability $q(\theta_t(j, w, s))$, where $q : \mathbb{R}_+ \rightarrow [0, 1]$ is a twice-continuously differentiable, strictly decreasing, convex function such that $q(\theta) = p(\theta)/\theta$ where $q(0) = 1$ and $q'(0) < 0$, and $p(q^{-1}(\cdot))$ concave.\footnote{The assumption of the concavity of $p(q^{-1}(\cdot))$ is required to have the unique solution based on the worker’s search problem is strictly concave.}

Once matched, the firm-worker pair basically produces $f(j, s)$ units of output and pays $w$ to a worker matched in the $(j, w, s)$ submarket. Before starting production, the match picks the optimal level of technology $z$ over $[1, \infty)$ which results in the output $zf(j, s)$. The targeted $z$ is realized by installing $r^j(z)$ units of machines at a rental rate $p_k$, so the level of $z$ is determined by the direct cost of technology, $p_k r^j(z)$. The amount of machines, $r^j(z)$, to improve productivity is increasing in the level of $z$. Contrary to the actual limitation of technology in raising $z$, the model does not put the upper limit in $z$ in any task but a rapidly increasing amount of $r^j(z)$ along with $z$ reflects the difficulty in improving productivity by technological changes. $r^j(z)$ is varied by the characteristics of task $j$ as well. The rental price $p_k$ is drawn at the beginning of each period and firms can predict how much it falls in the future as well based on the trend of decline in the price (Graetz & Michaels, 2018). On average, the rental rate decreases at $\rho_k$ per period. In the real world, both functionality and the price of technology has been improved simultaneously so it is possible to use better technologies at cheaper price with time. However, for simplicity, I set the capability of each unit of technology constant and use a quality-adjusted price to reflect the improvement of functionality and a decline in the price of physical unit.
The aggregate state of the economy can be summarized by the tuple \( \psi = (p, u, e) \). The first component is the price of the product, which is fixed at one, and the set of the price of technologies, \( p = (1, p_k, p_r) \). Technology prices are drawn at the beginning of each period by Nature. The second component is the measure of unemployed workers holding \( s \) level of skills, \( u(s) \in [0,1] \). The third component is a function \( e : \mathbb{N} \times \mathbb{R}_+ \times \mathbb{R}_+ \rightarrow \mathbb{R}_+ \), where \( e(j, w, s) \) denotes the measure of employed workers in a submarket \((j, w, s)\).

### 1.2.2 Firm’s problem

Two major problems of a firm are the adoption of robots to substitute a worker and a decision on the implementation of new technologies for productivity. The first problem, the choice between a worker and robots, is determined in the search stage, but the firm has to compare the productivity of a firm-worker pair and the one of a firm-robots pair based on the rational choice of \( z \) which would be made in the production stage. Therefore, the firm’s choice is derived through a backward induction.

Suppose the firm is matched with a worker in the submarket \((j, w, s)\). Before production begins, the firm chooses \( z \) to maximize the expected sum of discounted profits. At a given rental rate of \( p_k \), the firm pays technology cost \( p_k r^j(z) \) to adopt \( z \). The decision produces \( zf(j, s) \) units of output. The unit price of output is assumed to be fixed at one.

The value of a filled job value with \( z \) is as below.

\[
J_t(j, w, s) = \max_z \left\{ zf(j, s) - w - p_k r^j(z) + \beta(1 - \lambda)(1 - \delta)J_{t+1}(j, w, s) \right\} 
\] (1.1)

If this firm decides to open vacancies, under free entry condition, the firm has the value of a vacancy \( V_t(j, w, s) \) as below.

\[
V_t(j, w, s) = -c^j + q(\theta_t(j, w, s))J_t(j, w, s) 
\] (1.2)

A job posting cost \( c^j \) is paid to each vacancy. It is assumed that \( c^j \) increases in complexity of a task \( j \) \((c^j < c^k \text{ for } j < k)\) to reflect the delicate hiring process for a position that will deal with a complex task. Each vacancy has a probability of \( q(\theta_t(j, w, s)) \) to be filled.

In any submarket visited by a positive measure of workers, the free entry condition
holds \( c^j \geq q(\theta_t(j, w, s))J_t(j, w, s) \) and \( \theta_t(j, w, s) \geq 0 \), with complementary slackness. Since firms enter the submarket \((j, w, s)\) when the expected profit can cover the job posting cost, the free entry condition holds, the equation (1.2) must be equal to zero with positive market tightness \( \theta_t(j, w, s) \) in equilibrium.

Before a decision on opening vacancies, it has to precede a comparison between the benefit of robots and the value of a job hiring a worker. When the firm automates its production process by installing \( \kappa^j_R \) units of robots at \( p_r \), then robots produce \( f(j) \) output for \( n \) periods. \( f(j) \) equals the median worker’s production. If the benefit of automation dominates the value of a job filled with a worker, the firm just purchases a robot instead of searching a worker. Under the assumption that installing a robot for automation takes one period, the equation (1.3) shows the condition that firms withdraw themselves from the labor market.

\[
V_t(j, s, w) \leq -p_r \kappa^j_R + \sum_{i=1}^{n} (\beta(1-\delta))^i f(j) \quad (1.3)
\]

Let \( R(j, s, w; z) = 0 \) if the equation (1.3) is satisfied and \( R(j, s, w; z) = 1 \) otherwise. The firm stays in the labor market conditional on \( R(j, s, w; z) = 1 \).

**1.2.3 Worker’s problem**

Consider an unemployed worker with \( s \) level of skills. The worker maximizes the expected discounted lifetime earnings by searching for jobs in submarket \((j, w, s)\) where the worker can satisfy the skill requirements. While unemployed, a worker has the value of unemployment as in the equation (1.4).

\[
U_t(s) = \max_{j, w} \left\{ p(\theta_t(j, w, s))W_t(j, w, s) \right\} + \left( 1 - p(\theta_t(j, w, s)) \right) \{ b(s) + \beta(1-\lambda)U_{t+1}(s) \} \quad (1.4)
\]

The unemployed with \( s \) skill receive \( b(s) \) that represents the value of leisure or home production where \( b'(s) > 0 \). If the unemployed worker who picked a submarket \((j, w, s)\) the best is matched with a job at a rate of \( p(\theta_t(j, w, s)) \), and the worker would get the value \( W_t(j, w, s) \) once employed as the equation (1.5).

\[
W_t(j, w, s) = w + \beta(1-\lambda) \{ (1-\delta)W_{t+1}(j, w, s) + \delta U_{t+1}(s) \} \quad (1.5)
\]
The earning of the match is based on the promised wage \( w \). The match is separated by the exogenous shock with a rate of \( \delta \) in the period \( t + 1 \), then the worker becomes unemployed and searches a new submarket as in the equation (1.4).

1.2.4 Equilibrium

*Block Recursive Equilibrium (BRE)* is a recursive equilibrium such that a market tightness function \( \theta_t(j, w, s) \), a set of value functions \( \{U_t(s), W_t(j, w, s), V_t(j, w, s), J_t(j, w, s)\} \) and optimal policy functions \( \{w(j, s), z(j, s), R(j, w, s)\} \) depend on the aggregate state of the economy \( \psi_t(p, u, e) \), only through a set of prices, and not through the distribution of workers across employment and unemployment state. The functions satisfy the following requirements:

1) The market tightness \( \theta_t(j, w, s) \) satisfies the free entry condition, \( V_t(j, w, s) = 0 \), for all submarkets such that \( R(j, w, s) = 1 \). Otherwise \( \theta_t(j, w, s) = 0 \).
2) The policy function \( z(j, s) \) is associated with \( J_t(j, w, s) \) for all submarkets.
3) The policy function \( w(j, s) \) solve the workers problems \( U_t(s), W_t(j, w, s) \) when \( \theta_t(j, w, s) \) is given.
4) Law of motion for the aggregate state is consistent with the policy functions, \( R(j, w, s), z(j, s) \) and \( w(j, s) \).

1.3 Estimation

In this section, I calibrate the model and evaluate its predictions. The model is estimated by the simulated method of moments. I follow the search and matching literature and previous studies regarding task-biased technological changes in choosing the moments to target. Mostly, the moments are chosen to make heterogeneous workers assign themselves to different tasks by following their benefits so the level of worker’s cognitive skills and the complexity of tasks are well aligned. I preset parameters for the baseline labor market \((\beta, \lambda, \delta, b(s))\) and price of capital \((p_{k0}, \rho_k, p_{r0}, \rho_r)\) in Section 1.3.2. The skill distribution and the cost of machines is estimated in Section 1.3.3.1 and 1.3.3.2. The remaining parameters, \((\mu_s, \sigma_s^2, r^j(z))\) are calibrated and discussed in Section 1.3.3 and the cost of robots, \(\kappa^j_R\), is derived in Section 1.3.5 based on parameters calibrated in previous sections.
1.3.1 Functional Form and Distributional Assumptions

The skill distribution is set to be a lognormal distribution, $\log(s) \sim N(\mu_s, \sigma_s^2)$. I assume $\mu_s = 0$ to make a median skilled worker has $s = 1$. I estimate the distribution with data in Section 1.3.3.1 and shift it by the measured mean.

For this, I first set the functional forms to those commonly used in the previous studies. I choose the production function $f(j, s) = A_j s^\alpha$. I preset the shape parameter of skill $\alpha = 0.66$ from the empirical estimates of Eden and Gaggl (2018), which is similar to common labor share. I assume task-specific productivity, $A_j$, is different by tasks. I use the matching function from Menzio and Shi (2010), I pick the CES contact rate function, which has a job-finding probability function bounded between 0 and 1 and $p(q^{-1}(\cdot))$ concave.

I use a canonical Cobb-Douglas production function to define the units of machines, $r^j(z)$, for the choice of labor-augmenting technology, $z$. Acemoglu (2003) and Jones (2005) show the technical change will be purely labor-augmenting in the long run. Following them, I use a Cobb-Douglas production function and denote it as $y_j = A_j s^\alpha k^\phi$. The first two components, $A_j s^\alpha$, correspond to the worker productivity in the model. The third term, $k^\phi$, can be interpreted as capital augmenting productivity, thus implies $z$ in the model. I assume that $\bar{k}_j$ is required as long as a $j$ task job is in operation. The firm’s problem with the Cobb-Douglas production function is equivalent to the model as follows.

$$
\text{max } \pi = k^\phi (A_j s^\alpha) - w - p_k k \\
\text{ s.t } k \geq \bar{k}_j
$$

It is defined that $z = 1$ if $k = \bar{k}$ and $z = k^\phi$ for task $j$ if $k > \bar{k}_j$. The minimum capital $\bar{k}$ in the Cobb-Douglas function is represented by $r^j(1) = B_j$ in the model. Thus, units of machines will be $r^j(z) = B_j z^{1/\phi}$. (See the Appendix A.3.3 for further details.

---

8Jones (2005) relaxes strong conditions of Acemoglu (2003) to take Cobb-Douglas production function to be the global production function and to get technical change to be labor-augmenting. However, the Cobb-Douglas function in their model needs to be CRS.

9In the Cobb-Douglas function, $y_j$ is per capita output, $A_j$ is $j$ task-specific productivity, $s$ is a worker’s skills, $k$ is capital stock per worker. $\alpha$ is labor share and $\phi$ is capital share where $0 < \alpha, \phi, \alpha + \phi \leq 1$. The subscript $j$ specifies task $j$. 

---
1.3.2 External Parameters

I preset or externally calibrate parameters from the previous literature. The time period is set to one month. To begin with, I set the discount factor $\beta$ to 0.9966 corresponding to 4% annual discount rate. I set the exogenous separation rate, $\delta = 1/(7 \times 12)$, to match the average job destruction rate from Cho, Chun, Kim, and Lee (2017). Matches are exogenously separated approximately once every 7 years. The exit rate of a worker, $\lambda$, was set to $1/360$ from Schauer (2018). It means the average expected duration of participation of workers would be 30 years. I assume the benefit of unemployment $b(s) = b \times s$ in the line with Flinn and Mullins (2015) and set $b = 0.7$ which is consistent with the empirical ratio of labor productivity at home and in the market measured by Hagedorn and Manovskii (2008) and Hall and Milgrom (2008).

The capital price in the initial period and the falling rates are set as follows. First, the price of machines, is set to 1.09 for the initial period and then declines at a rate of 1.05% per year. ($p_{k_0} = 1.09$ and $\rho_k = 0.088\%$). The initial value is set to the inverse value of the price of final goods relative to capital goods of Korea from Caselli and Feyrer (2007). The rate of capital price decline is derived from Karabarbounis and Neiman (2014) that show changes in the relative price of investment to consumption declines at a rate of roughly 10% every 10 years after 1980. Second, the price of robots is set to 1.851 in the beginning and falls 5% per year ($p_{r_0} = 1.851$ and $\rho_r = 0.426\%$). The initial price of robots is derived from the ratio of the price of industrial robots to the price of total output from the producer price index of Korea. The decline rate $\rho_r$ is set by IFR (2012) annual survey and Graetz and Michaels (2018). The price of robots in the data roughly halved from 1990 to 2005 and the quality-adjusted price fell by almost 80% (See the Appendix A.3.2 Figure A.3). I use the quality-adjusted price to reflect advances in robotics and improvements in technologies.

---

10Cho et al. (2017) use establishment-level data from the Census on Establishments in Korea from 2001 to 2011 and suggested job creation and destruction rate. The average job destruction rate of continuing establishments is 10.5 percent. It is lower than the mean job destruction rate of exit firms. This range is similar to Pyo, Hong, Kim, et al. (2016) which showed the job destruction rate caused by firm exit based on the firm size between 2003 and 2012 from the same data source.

11The decline rate is similar to Eden and Gaggl (2018). They derive the path of prices for ICT and Non-ICT assets relative to the GDP deflator and show the price index of ICT capital declines from 1 to 0.4 during 1980 to 2000 while the price index of Non-ICT is almost constant during 1950-2010.

12I calculate the price of capital to the price of output, $p_{k_0}$, with PPI to check the plausibility of using PPI. The calculated value with PPI is 1.076 in 1999, which is slightly smaller than the selected value of 1.09.

13The historic data and the robot manufacturer’s forecast for the price of robots is slightly higher than the IFR based estimates. ARK, one of the major industrial robot producing companies, anticipates the price
These preset parameters are summarized in Table 1.1.

<table>
<thead>
<tr>
<th>Category</th>
<th>Symbol</th>
<th>Value</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Discount factor</td>
<td>$\beta$</td>
<td>0.9966</td>
<td>Standard, 4% per year</td>
</tr>
<tr>
<td>Separation rate</td>
<td>$\delta$</td>
<td>1/84</td>
<td>Cho et al. (2017), 7 years average match duration</td>
</tr>
<tr>
<td>Exit probability</td>
<td>$\lambda$</td>
<td>1/360</td>
<td>Schauer (2018)</td>
</tr>
<tr>
<td>Value of leisure</td>
<td>$b(s)$</td>
<td>0.78</td>
<td>Flinn and Mullins (2015), Hall and Milgrom (2008)</td>
</tr>
<tr>
<td>Scale parameter of production</td>
<td>$\alpha$</td>
<td>0.66</td>
<td>Eden and Gaggl (2018), $f(j, s) = A_j s^\alpha$</td>
</tr>
<tr>
<td>Price of machines</td>
<td>$p_{k0}$</td>
<td>1.09</td>
<td>Caselli and Feyrer (2007)</td>
</tr>
<tr>
<td></td>
<td>$\rho_k$</td>
<td>0.088%</td>
<td>Karabarbounis and Neiman (2014), 1.05% per year</td>
</tr>
<tr>
<td>Price of robots</td>
<td>$p_{r0}$</td>
<td>1.85</td>
<td>PPI of Korea</td>
</tr>
<tr>
<td></td>
<td>$\rho_r$</td>
<td>0.426%</td>
<td>Graetz and Michaels (2018), 5% per year</td>
</tr>
</tbody>
</table>

### 1.3.3 Estimated Parameters

The remaining parameters are the mean and the variance of the skill distribution, $(\mu_s, \sigma_s^2)$, task specific productivity $A_j$, and job posting cost $c_j$, the cost of using machines, $r^j(z)$, and robots, $\kappa^j_R$. I first estimate the skill distribution and define the cost of machines. Then I move on to parameters of task-specific productivity and job posting cost jointly by the simulated method of moments. Since the number of parameters to be estimated is determined by task classification, I will mainly discuss manual (M), routine (R), and cognitive (C) tasks. However, I split routine tasks into three subgroups, $R_1, R_2, R_3$, each represents one of the routine task occupation groups, operator and fabricator, production craft, and office and admin, respectively. Subdivision of tasks is necessary when automation technology arrives but cannot replace all jobs within that task at once. I select routine tasks to split because routine task jobs are exposed to a threat of robotics the most while manual or cognitive tasks are yet far from the possibility of being fully automated. Three subgroups are the simplest version for it. Once parameters for the labor market are estimated, I would explain how to
construct the cost of robots relative to the job value and follow the effect of automation on the labor market.

1.3.3.1 Skill Distribution

Before estimating the remaining I first measure the skill distribution, \( \log(s) \sim N(\mu_s, \sigma^2_s) \). According to Iranzo, Schivardi, and Tosetti (2008), I estimate the parameters of \( \log(s) \) distribution by using the log wage based on the equation (1.6).

\[
 w_{it} = a_i + X_{it}\beta + \psi_{J(i,t)} + \epsilon_{it} \tag{1.6}
\]

The dependent variable, \( w_{it} \), is the log monthly income observed for individual \( i \) at period \( t \). The term \( a_i \) is the worker \( i \)'s fixed effect which captures unchanged personal attributes like the unobserved innate ability and years of schooling as well as sex and birth cohort. The second component, \( X_{it} \), is the effect of measured time-varying characteristics, years of experience, and its square. Other components, \( \psi_{J(i,t)} \) is the job fixed effect, where \( J(i,t) \) is the job task of a worker \( i \) working at time \( t \), such as occupational category, industry, job type, and location. \( \epsilon_{it} \) is the statistical residual, with the assumption that \( E(\epsilon_{it}|i, t, x) = 0 \) and orthogonal to all other effects in the model. By following Iranzo et al. (2008), I use the worker effect and the experience components as the proxy for a worker’s skills. Therefore, \( \log(s_{it}) = \hat{a}_i + X_{it}\hat{\beta} \).

The Korean Labor and Income Panel Study (KLIPS) allows me to identify firm and worker effects. I construct job mobility for variables such as years of experiences by occupational category but focus only on paid employees (For further details about KLIPS, see the Appendix A.1.1). Running the equation (1.6) draws the estimated value of \( \log(s_{it}) \) and it follows the normal distribution with parameters. The mean and the variance of the distribution is \((5.21, 0.447^2)\) for periods of 1999-2018. To make the median worker have \( s = 1 \), I shift the estimated normal distribution of \( \log(s) \) to have \( \mu_s = 0 \). Therefore, the skill distribution follows \( \log(s) \sim N(0, 0.447^2) \).

To check the robustness of the skill distribution, I construct the average monthly income from 1998 to 2018 for those who have been surveyed from the first wave of KLIPS. Since the average income over 20 years captures the changes in income caused by accumulated
job experiences, it could be thought that the difference in the average income is due to the
difference in workers’ observable and unobservable skills. The parameters estimated from
the average monthly log income are \((\mu_s, \sigma_s^2) = (5.22, 0.445^2)\) that are very similar to the
values estimated by the equation (1.6).

1.3.3.2 The Cost of Machines

A key factor in the choice of \(z\) by a \(j\) task firm is the units of machines, \(r^j(z)\). In Section
1.3.1, \(r^j(z)\) is defined as \(B_j z^{\varphi_j}\) from the firm’s problem with the Cobb-Douglas function,
\(y_j = A_j s^\alpha k^{\varphi_j}\). Because tasks are different in the degree of technology-skill complementarity
in the model, the parameter \(\varphi_j\) varies by the task. Thus, I estimate \(\varphi_j\) for each task \(j\),
manual, routine, and cognitive tasks, by running the specification (1.7) separately. It is
assumed that a constant returns to scale production function, \(\alpha + \varphi_j = 1\) along with Jones
(2005), and homogeneous workers with respect to skills at \(s = 1\).

\[
\ln y_t = \varphi \ln k_t + \beta_0 + \beta_d D_t + \beta_i D_i + u_t \tag{1.7}
\]

\(ln y_t\) and \(ln k_t\) are the natural logarithm of the per-worker output and capital, \(D_t\) is time
dummy, \(D_i\) is industry dummy within a task, and \(u_t\) is an error term. Data for manual
and cognitive tasks are constructed from the Survey of Business Activities of Korea from
2006 to 2019 at the industry level.\(^{15}\) Industry-level data is classified as either manual or
cognitive tasks based on the industry performs the most. Routine tasks intensely performed
in the Manufacturing and Construction industry obtain data from Mining and Manufacturing
Survey and Construction Survey because these surveys are available since 2000. Full details
are available in Appendix A.2.1 on Table A.1.

Sales data is used for \(Y_t\), and the number of employees is for \(L_t\). \(K_t\) is constructed
from the stock value of the tangible and the intangible asset. I exclude land, structure
and buildings because changes in these assets rarely explain changes in productivity due to

\(^{15}\)Survey of Business Activities of Korea covers corporations that are doing business activities in Korea
as of the survey reference date, those with at least 50 full-time employees and 300 million KRW or more
capital stock. It provides basic information about the entity, number of workers, type of legal organization,
tangible and intangible assets, information on affiliated companies, transaction among domestic and overseas
enterprises, business management direction. The survey has been carried out since 2006 annually. For
details, see more information at Appendix A.1.2 and http://kostat.go.kr/portal/eng/surveyOutline/
3/8/index.static
improvement in labor-augmenting technology. I also eliminate vehicles in the transportation industry since the ratio of vehicles to drivers in the industry is mostly constant, and hence it does not cause a change in \( k_t \). To eliminate the effects of labor-saving technologies, I drop the value of robots in the manufacturing industry. The value of robots is calculated by the number of robots installed and the price of robots from International Federation of Robotics (IFR). Sales and assets are converted into real terms by price index with a value of 100 in 2015.

<table>
<thead>
<tr>
<th></th>
<th>Manual task</th>
<th>Routine task</th>
<th>Cognitive task</th>
</tr>
</thead>
<tbody>
<tr>
<td>Capital Share, ( \varphi )</td>
<td>0.172***</td>
<td>0.217***</td>
<td>0.225***</td>
</tr>
<tr>
<td></td>
<td>(0.0536)</td>
<td>(0.0243)</td>
<td>(0.0517)</td>
</tr>
<tr>
<td>Time dummy</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Industry dummy</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Observations</td>
<td>98</td>
<td>39</td>
<td>65</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.978</td>
<td>0.975</td>
<td>0.994</td>
</tr>
</tbody>
</table>

Note: Industry classification follows International Standard Industrial Classification Revision 4. Manual task includes Wholesale and retail, Transportation and storage, Accommodation and food service activities, Arts, entertainment, and recreation; Routine tasks include Manufacturing and Construction; Cognitive tasks include Information and communication, Finance, Education, Human health, and social work.

Results of regression are shown on Table 1.2. I use 0.172 and 0.225 for \( \varphi_j \) of manual and cognitive tasks separately, as shown in the table. I take 0.184 for \( R_1 \) that is the result of manufacturing industry data only. Other routine tasks, \( R_2 \) and \( R_3 \), use 0.217 as in the table. The value of \( \varphi_j \) increases as task \( j \) becomes more complex, from manual to cognitive tasks. It means the cost of labor-augmenting technology is relatively cheaper for more complex tasks, and thereby cognitive tasks are willing to adopt new technologies more than other tasks.

The parameter \( B_j \) can be interpreted as the existence of fixed costs thus it makes firms hire those who can at least bear the cost. By the first order condition of the equation (1.1) with respect to \( z \), \( B_j \) is a function of \( \varphi_j \), \( p_{k_0} \), and a match productivity, \( f(j,s) = A_j s^\alpha \).

\[
B_j = \left( \frac{\varphi_j A_j s^\alpha}{p_{k_0}} \right)^{\frac{\varphi_j}{1-\varphi_j}}
\]
I set $B_j$ by choosing a marginal worker who can bear the fixed cost of operation in the initial period. I target the marginal worker, $s$, for manual, routine, and cognitive tasks, which is the lower end, the 10th, and the 20th percentile value of the skill distribution, respectively. Thus, any workers are qualified for manual tasks while some low-skilled workers are excluded from routine or cognitive tasks. The skill distribution of those in cognitive tasks is shifted upward and less right-skewed than manual tasks because cognitive tasks demand relatively skilled workers than manual tasks. The cut-off trims those sparsely found on the left tail of cognitive tasks skill distribution. Similarly, routine tasks hire skilled workers more than manual tasks, but less than cognitive tasks, the cut-off of routine tasks is between cognitive and manual ones.

Based on the estimated skill distribution, I pick $s = (0.197, 0.612, 0.883)$ for cut-off of manual, routine, and cognitive tasks, respectively. Specific value of $B_j$ will be estimated in Section 1.3.4 together with task-specific productivity $A_j$.

### 1.3.4 Calibrated Parameters

The parameters left to estimate are following: the matching function parameter, $\gamma$, the task specific productivity, $A_j$, and the job posting cost, $c_j$ where $j = \{M, R_1, R_2, R_3, C\}$. I normalize $A_{R_2} = 1$. Ten parameters are estimated by matching the following moments: The share of employment in manual, routine, cognitive tasks in 1999. The wage ratio between manual to routine, cognitive to routine tasks use the average monthly income during 1999-2018 from Korean Labor and Income Panel Survey (KLIPS). The unemployment rate at 2000. The job-finding rates calculated from the average transition rate from unemployment to employment during 2000-2018 with Economically Active Population Survey. The ratio of $z$ between manual to routine, cognitive to routine tasks in 1999. The average job-filling rates from 2009 to 2018 measured in the Occupational Labor Force Survey at Establishments.

The parameters are jointly estimated using a simulated annealing algorithm in the parameter space that minimizes the distance between the empirical and simulated moments, with weights selected to yield relative errors of the same amplitude for each moment. Table

---

16 The mean skill of manual, routine, and cognitive tasks are (0.88, 1.08, 1.50) from the estimated skill distribution, and the skewness are (2.13, 1.63, 0.88), respectively.

17 Since Korea experienced the Asia Financial Crisis in 1997 and 1998. Due to the influence of the crisis, the unemployment rate in 1999 was still unusually high compared to the overall unemployment rate after 2000. Therefore, I target the unemployment rate in 2000 rather than 1999.

18 The transition rate between unemployment and employment follows the method of Shimer (2012), but only labor force participants are targeted in order to fit the model.
1.3 summarizes the parameter values that result from the calibration. From the estimated task-specific productivity, $A_j$, the values of $B_j$ are derived. The complete set of machines costs, $r^j(z) = B_j z^{\varphi_j}$, is now calculated by $B_j$ from Table 1.3 and $\varphi_j$ from Table 1.2.

Table 1.3: Calibrated Model Parameters

<table>
<thead>
<tr>
<th>Category</th>
<th>Symbol</th>
<th>Value</th>
<th>Derived value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Matching function parameter</td>
<td>$\gamma$</td>
<td>0.692</td>
<td></td>
</tr>
<tr>
<td>Task specific Productivity &amp; Job Posting Cost</td>
<td>$A_M, c_M$</td>
<td>0.918, 0.22</td>
<td>$B_M = 0.094$</td>
</tr>
<tr>
<td></td>
<td>$A_{R_1}, c_{R_1}$</td>
<td>0.955, 0.28</td>
<td>$B_{R_1} = 0.115$</td>
</tr>
<tr>
<td></td>
<td>$A_{R_2}, c_{R_2}$</td>
<td>1.000, 0.56</td>
<td>$B_{R_2} = 0.142$</td>
</tr>
<tr>
<td></td>
<td>$A_{R_3}, c_{R_3}$</td>
<td>1.081, 0.56</td>
<td>$B_{R_3} = 0.231$</td>
</tr>
<tr>
<td></td>
<td>$A_C, c_C$</td>
<td>1.120, 1.02</td>
<td>$B_C = 0.265$</td>
</tr>
</tbody>
</table>

Table 1.4 shows the fit of the model with the targeted moments. The fit is, overall, quite satisfactory.

Table 1.4: Targeted Moments

<table>
<thead>
<tr>
<th>Moments</th>
<th>Data</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Employment Share</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Manual</td>
<td>33.45</td>
<td>32.87</td>
</tr>
<tr>
<td>Routine</td>
<td>47.19</td>
<td>48.32</td>
</tr>
<tr>
<td>Cognitive</td>
<td>19.36</td>
<td>18.80</td>
</tr>
<tr>
<td>Wage ratio</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$w_M/w_R$</td>
<td>0.67</td>
<td>0.64</td>
</tr>
<tr>
<td>$w_C/w_R$</td>
<td>1.59</td>
<td>1.60</td>
</tr>
<tr>
<td>$z$ ratio</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$z_M/z_R$</td>
<td>0.845</td>
<td>0.973</td>
</tr>
<tr>
<td>$z_C/z_R$</td>
<td>1.089</td>
<td>1.090</td>
</tr>
<tr>
<td>Unemployment rate</td>
<td>4.60</td>
<td>4.56</td>
</tr>
<tr>
<td>Job finding rate</td>
<td>0.320</td>
<td>0.324</td>
</tr>
<tr>
<td>Job filling rate</td>
<td>0.864</td>
<td>0.856</td>
</tr>
</tbody>
</table>
1.3.5 The Cost of Robots

Firms can operate with Robots. A decision about whether and when to adopt automation depends on the decision rule, $R(j, s, w)$. The rule compares the value of vacancy under the free entry condition and the value of a job operated by robots. To estimate the value of a job operated by robots, the productivity and the cost of using robots, $f(j)$ and $p_r\kappa^j_R$ in the equation (1.3), need to be identified. However, there have been only a few previous studies to refer to how to estimate the cost of automation. Humlum (2019) estimates the path of common adoption costs which the robot diffusion curve fits the S-shape diffusion curve, but he limits his interest to a manufacturing sector. Adachi (2021) constructs a novel data set that tracks the cost of robots by occupation in manufacturing industry, but he follows the price of robots, not establishing the entire cost of utilizing the robotic system itself. So far, the differences in automation costs across occupations are understood based on the trial that shows how easy a certain occupation can be automated. As the cost of automation in the model needs to be defined at the task level, I use the probability of computerization of Frey and Osborne (2017) to understand the easiness of being automated at the broad occupation level. The benefit of using robots is then calculated by comparing the total cost of a robotic system and labor costs.

As I assumed, robots can produce as much as the median skilled worker, $f(j) = f(j, 1)$. By following Björkman (2010), the operational life time $n$ is set to 8 years. Since the price of robots, $p_r$, is preset in Section 1.3.2, the key to estimating the cost of using robots is to find $\kappa^j_R$, the number of robots to perform $j$ task. To estimate $\kappa^j_R$, I figure out which task could be automated first. Figure 1.3 shows the probability of computerization of Frey and Osborne (2017) for 9 broad occupation groups in the order of the level of cognitive ability required to perform the jobs. The shape of the figure is consistent with the inverse shape of Figure 1.2 in the model, except craft and repair occupations, so substitution of robots for workers will occur from routine task occupations as expected. Since operators and fabricators (“operate” in the figure) are at the highest risk of automation, I begin with this routine-manual task job to estimate the cost of using robots relative to labor cost and expand the estimate to other tasks. The tasks operators frequently perform are defined as $R_1$ among routine tasks.

The cost of using robots is calculated from the actual price of a robot provided by IFR. Since an industrial robot is typically not stand-alone hardware, the cost of robotic system
Figure 1.3: Probability of Computerization

Note: The probability of computerization is calculated based on Frey and Osborne (2017). They rank 702 occupations according to their probability of computerisation and I classify occupations into 9 broad occupation categories by Acemoglu and Autor (2011); managers, professionals, technicians (Cognitive task jobs) / office and admin, production and craft, operators and fabricators (Routine task jobs) / sales, food prep, cleaning service and laborers, personal care service (Manual task jobs). 9 broad occupations on x-axis are arranged in the order of the level of cognitive ability required to perform tasks from the lowest (personal care service) to the highest (professionals).

includes expenditures for installation and integration. Hence, the cost of a robotic system is recommended to multiply the robot’s price by a minimum of three (Klump, Jurkat, & Schneider, 2021). Thus, the total cost of the robotic system is to be three times the average price of a robot. The labor cost is derived from the monthly income of operators and fabricators from KLIPS. I take median wages and convert it into an annual compensation by multiplying 13, 12 monthly wages and one month wage as a retirement allowance, and adding 22.7% of it for fringe benefits. In Table 1.5, the total cost of the robotic system decreases over time while annual compensation increases. It makes a robot is cost-effective.

19The fringe benefit rate of 22.7% is the average ratio of the fringe benefits to workers’ wages among Korean Stock market listed companies from 1999 to 2018. The price of a robot is measured in US dollars, and workers’ annual compensation is measured in Korean Won. To match the measurement unit, the average annual exchange rate is applied to convert the annual compensation to dollar values. Both price and compensation are real values.
than a worker after 7 years the economy begins. I estimate $\kappa_{R}^{\text{oper}}$ by targeting the period that the value of a job using robots is greater than the job value filled with a worker around $t = 85$, 7 years after the economy begins.

Table 1.5: The Comparison of Cost of Robots versus Labor in Operation Jobs

<table>
<thead>
<tr>
<th>Year</th>
<th>Robot Price</th>
<th>Annual Compensation</th>
<th>Total Cost of Robot system</th>
<th>Labor Cost</th>
<th>R/L Select</th>
</tr>
</thead>
<tbody>
<tr>
<td>1999</td>
<td>96,221</td>
<td>17,613</td>
<td>288,664</td>
<td>147,463</td>
<td>L</td>
</tr>
<tr>
<td>2000</td>
<td>89,005</td>
<td>15,506</td>
<td>267,014</td>
<td>154,294</td>
<td>L</td>
</tr>
<tr>
<td>2001</td>
<td>82,329</td>
<td>15,923</td>
<td>246,988</td>
<td>159,126</td>
<td>L</td>
</tr>
<tr>
<td>2002</td>
<td>76,155</td>
<td>17,142</td>
<td>228,464</td>
<td>163,660</td>
<td>L</td>
</tr>
<tr>
<td>2003</td>
<td>70,443</td>
<td>18,146</td>
<td>211,329</td>
<td>168,266</td>
<td>L</td>
</tr>
<tr>
<td>2004</td>
<td>65,160</td>
<td>21,609</td>
<td>195,480</td>
<td>172,949</td>
<td>L</td>
</tr>
<tr>
<td>2005</td>
<td>60,273</td>
<td>21,823</td>
<td>180,819</td>
<td>176,370</td>
<td>L</td>
</tr>
<tr>
<td>2006</td>
<td>55,752</td>
<td>25,305</td>
<td>167,257</td>
<td>179,969</td>
<td>R</td>
</tr>
<tr>
<td>2007</td>
<td>51,571</td>
<td>24,514</td>
<td>154,713</td>
<td>179,771</td>
<td>R</td>
</tr>
</tbody>
</table>

Note: Robot Price is the average selling price for industrial robots sourced by IFR. Annual compensation is the sum of wage, fringe benefit, and retirement benefit paid to median workers in production operation and fabrication. Total Cost of Robot system is 3 times the robot price to include expenditures for installation and integration, and other components to make the robotic system work. Labor Cost is the sum of the present value of annual compensation over 8 years, the average lifespan of a robot. All prices and costs are dollar values in real terms. R/L Select column marks R if robots are cost-effective than workers.

From the estimated value of $\kappa_{R}^{\text{oper}}$, I calculate the penetration of robots in other tasks with the probability of computerization and the applicability of automation technology. Even after operation and fabrication jobs are fully automated, because a heterogeneous mix of tasks in each occupation generates a difference in the ease of automation across occupations, there will be occupations that mainly carry out routine tasks such as craft/repair works or admin/office support that are defined as $R_2$ and $R_3$. I measure the value of $\kappa_{R}^{j}$ of the remaining four tasks ($j = M, R_2, R_3, C$) relative to $\kappa_{R}^{\text{oper}}$ with the probability of computerization from Frey and Osborne (2017). I use the inverse ratio of the probability of a task to that of operation occupations. However, considering the attainability of automation technology, I also take the interactive tasks score. Even though Frey and Osborne’s work is widely cited, there are arguments about the explanatory power of their predictions for actual employment changes, especially in tasks involving face-to-face interaction. Tasks that neces-
situate interpersonal activity remain a highly challenging domain from a technological point of view, so the automatability of occupations in admin/office and sales category in Figure 1.3 is upward-biased (Arntz, Gregory, & Zierahn, 2016).\textsuperscript{20} I adjust it with an interpersonal task score from Acemoglu and Autor (2011). With a distance between task $j$ and $R_1$ in addition to the inverse ratio of the automation probability, I calculate $\kappa^j_R$ in a quadratic form.

$$\kappa^j_R = \kappa^\text{oper} R \times \left( \frac{\text{prob(oper)}}{\text{prob}(j)} + \text{Distance in interpersonal task score} \right)^2$$

Table 1.6: The Relative Amount of Robots

<table>
<thead>
<tr>
<th>Task $j$</th>
<th>Probability of Computerization</th>
<th>Distance in Interact. Score</th>
<th>$\kappa^j_R / \kappa^R_{R_1}$</th>
<th>Robot units.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Manual</td>
<td>0.594</td>
<td>0.322</td>
<td>3.353</td>
<td>131.96</td>
</tr>
<tr>
<td>Routine - $R_1$</td>
<td>0.897</td>
<td>-</td>
<td>1.000</td>
<td>38.90</td>
</tr>
<tr>
<td>Routine - $R_2$</td>
<td>0.596</td>
<td>0.231</td>
<td>3.013</td>
<td>117.22</td>
</tr>
<tr>
<td>Routine - $R_3$</td>
<td>0.848</td>
<td>0.713</td>
<td>3.137</td>
<td>122.05</td>
</tr>
<tr>
<td>Cognitive</td>
<td>0.267</td>
<td>1.729</td>
<td>25.910</td>
<td>1008.12</td>
</tr>
</tbody>
</table>

Note: The Probability of Computerization is calculated from Frey and Osborne (2017) by Acemoglu and Autor (2011) broad occupational category and task classification. Interpersonal Score is also from Acemoglu and Autor (2011). The distance is derived from the gap between task $j$ and $R_1$ that is the task related to operation and fabrication occupations.

The amount of robots required for each task relative to $R_1$ task is illustrated on Table 1.6 in the column of $\kappa^j_R / \kappa^R_{R_1}$. The challenges to automation of other tasks require at least three times more inputs than the base task $R_1$. As many previous studies predict, cognitive tasks jobs are least susceptible to automation. The ratio of manual and other two routine tasks looks similar, but the causes are different. Craft and repair jobs, $R_2$ tasks, look similar to operation jobs because these jobs are usually operating in the manufacturing industry but demand for specialized ‘finger dexterity’ and unstructured features of craft and repair job tasks impede automation. $R_3$ tasks of admin/office jobs are relatively easy to computerize.

\textsuperscript{20}Arntz, Gregory, and Zierahn (2016) analyze the probability of automation in 21 OECD countries on the approach of Frey and Osborne (2017) but find only 9% of jobs are at risk of automation, which is much lower than Frey and Osborne’s results, 7%. They explain that it is because of challenges in automation for some tasks, such as interactive tasks. For example, the occupation “Bookkeeping, Accounting, and Auditing Clerks” (SOC code: 43-3031) receives 98% probability of automation from Frey and Osborne (2017) but only 24% is estimated by Arntz et al. (2016). Similarly, 92% probability of computerization of “Retail Salesperson” (SOC code 41-2031) is lowered to 4%.
but the importance of interpersonal activity deters automation. The last column, Robot units, calculates units of robots measured in units of output. I set the sum of the present value of output over 8 years by the median worker in $R_1$ tasks as a basis (Björkman, 2010). To make the cost-effectiveness of automation equals labor at $t = 85$, the first period $R_1$ task converts to automation, I let $p_{t=85} \kappa_{R_1}^{R_1}$ equal the sum of the present value of output. Applying $p_{t=85} = 1.2925$, then $\kappa_{R_1}^{R_1} = 38.90$ is calculated. I estimate $\kappa_j^R$ of other tasks by $\kappa_{R_1}^{R_1}$ multiplying $\kappa_j^R / \kappa_{R_1}^{R_1}$ and show the results on Robots units column. This estimation will be compared with robots’ productivity to make a decision on automation.

### 1.3.6 Model Fit

Results from the model for the trends in employment share by tasks in aggregate to data from 1999 to 2018 are represented in Figure 1.4. It reflects both influences of labor-augmenting technology and labor-replacing technology on employment. As targeted, job destruction of $R_1$ tasks occurs in 2006 in the model, but it does not happen in the other tasks. An increasing share of employment in manual tasks is due to the job transition of middle-skilled workers from routine to manual task jobs. Cognitive tasks, on the other hand, expand their employment because of the productivity effect. Although technology-driven productivity has continued to grow over time across all tasks, the productivity improvement by technology advances is rapidly rising in cognitive tasks because the efficiency of machines in the model increases in the complexity of tasks. The higher technical productivity can compensate for the lower labor productivity, cognitive jobs can hire relatively low-skilled workers. As the advantage of technology flows into workers with a higher wage offer, it attracts some middle-skilled workers who were previously near the border of routine and cognitive tasks to move to cognitive tasks. Due to the productivity effect of cognitive tasks and the displacement effect of routine tasks, the employment share of routine tasks is squeezed from both sides.

Figure 1.5 shows how labor-complementary technology, which means machines, changes over time. The growth rates of $z$ relative to 1999 are derived from data, which was used for measuring capital share parameter $\varphi$ in Section 1.3.3.2, as well as the model estimation results. The model outcomes use the average value of $z$ within each task. Unfortunately, the fit of the trend of $z$ cannot explain as much as the employment share trend. Overall,
Figure 1.4: Changes in Employment Share between 1999-2018, Data vs Model

Note: Model outcomes are illustrated with dashed lines. Data are shown with connected lines. The data source is Korean Labor Income Panel Study (KLIPS) from 1999 to 2018.

Figure 1.5: Changes in Labor Complementary Technology, Data vs Model

Note: Trends show the growth rate of labor-augmenting technology-driven productivity between 1999 to 2019. Model outcomes are denoted with dashed lines. Data are shown with connected lines and its sources are Survey of Business Activities of Korea (Manual and Cognitive tasks) and Mining and Manufacturing Survey and Construction Survey of Korea.
the model explains the growth rate of technology adoption in the data around 45 percent for manual and routine tasks and 62 percent for cognitive tasks. The adoption decision in the model follows the path of technology prices that is deterministic and calculates the cost of technology with fixed units of machines. Because of the lack of non-price factors, such as investment promotion policy, firm-specific or industry-specific investment strategies, it is rarely realized that explosive increases in technology in the model.

1.4 Experiments

In this section, I investigate the relationship between technological changes and workers’ skills in the model. I first discuss how technological changes affect the value of employment and change workers’ job choice. Secondly, I verify how the worker’s skill plays a critical role in technological changes. After establishing the link between technology and skill, I develop the model to see what happens if the overall skill level in the economy rises.

1.4.1 The Impact of Technological Changes on Workers

Two types of technologies work differently in the creation of jobs. Labor-saving technologies destroy jobs while labor-augmenting technologies create jobs, denoted as the displacement effects and the productivity effects (Acemoglu & Restrepo, 2019). If both technologies develop simultaneously, how do technological changes affect the labor market? To see the overall impact of technological changes, I investigate which types of jobs are created or destroyed, as well as which jobs are the most affected.

The adoption of technologies is facilitated by the decrease in the price of technology. In the model, the price of labor augmenting technology decreases by 1% per year. It leads to the increase in adoption of technologies so that production increases by 16 percent, 25 percent, and 49 percent in manual, routine, and cognitive tasks respectively over 20 years.

The technology-driven productivity effect results in the increase in the benefits to workers. Figure 1.6 shows the changes in employment value and wages. It represents the difference of employment values (left side) or wages (right side) between those who entered at the beginning and 20 years later. The advantages of technological improvements are from two parts: (1) the increase in the productivity of task a worker selected at the beginning
and (2) task transition due to the expansion of more complex task jobs which take more advantage of using technologies. The first productivity effect is represented by the red line. The value of technologically enhanced productivity grows as a worker’s skill level rises. The value of employment increases rapidly for workers above 80 percentile because job tasks those workers are matched with, cognitive tasks, are cost-effective in adopting new technologies and their relatively high skill level accelerates the installation. The second job transition effect is represented by the dashed black line. Because the productivity effect raises the value of a filled job that increases the job-finding rate and allows to offer a better wage, workers in between tasks have an incentive to apply for more complex task jobs that were hard to be matched. As workers move up the job ladder toward more complex tasks, the benefit of employment increase.

Technological innovation not only benefits but also harms workers. The price of labor-saving technologies falls by 5% per year, so robots take the routine manual task jobs. Once automation technologies perfectly replace workers’ roles, those who were to select that task will be unable to apply for the job, thus they will have to move on to the next best offer. The influence of automation is depicted in the shaded area in Figure 1.6. Even though automation takes away the best-fit job from workers, those who need to switch a job experience labor complementary technological benefit in any job. However, they are deprived of 3.7% of
increases of the value they potentially have if there were no threats of automation. In terms of earnings, some workers seem to be better off. Among workers who faced the consequence of automation directly, the relatively high (low) skilled workers switch to a job with more (less) complex tasks. Given that the degree of wage offer is determined by the complexity of jobs, the direction of job transition explains the wage gain or loss among individuals who were displaced by automation. This trend of occupational mobility and the difference in wage growth is consistent with what Cortes (2016) have observed, but it is hard to say some workers are benefited from automation. Even though switchers who move to a more complex task are paid more, a decline in job-finding rate offsets the benefit of a higher wage.

When paying more attention to the dispersion of the employment value, the labor market inequality looks changing. In Figure 1.6, the changes in the value of employment are exponentially expanding above the 50th percentile while the lower half is reasonably smooth. The pattern of these changes, based on the dispersion of the value at the beginning period, indicates the 50/90 percentile gap is soared, while the 10/50 percentile gap is somewhat slanted. When focusing on a certain time period, workers who look for a job at that moment have a bigger earning inequality than those who did previously. Even though technological advancements improve the lives of all workers over time, the increased disparity between workers can encourage workers to strive for a higher rank in the skill distribution.

1.4.2 The Role of Skills in Technology Advances

Labor augmenting technology works as a pair with a worker, so workers who use the technology more efficiently can expedite the adoption of technologies. This positive relationship between technology and workers’ skills is depicted in Figure 1.7. It shows changes in the level of technologies across skill levels over two decades. Even though the rate of technological change varies depending on the degree of technology-skill complementarity of tasks, technological progress accelerates as worker skill improves.

The economy begins with the average level of labor-augmenting technology, $z$ at 1.110 in manual tasks, 1.139 in routine tasks, and 1.213 in cognitive task jobs. A decline in the price of machines drives the adoption of new technologies, the average level of labor-augmenting technology in cognitive tasks increases by 4.94%, in routine tasks by 3.60%, and manual tasks by 3.45% over two decades in the model. These changes could be raised up to 4.67% for
manual tasks, 5.36% for routine tasks and 6.31% for cognitive tasks if changes in skill level employed in tasks are not considered. Because the labor-saving technology is affected by the cost-effectiveness of technology rather than overall skill in the labor market, the influence of workers on automation technology is not discussed.

1.4.3 The Effect of the Increasing Supply of High-skills

This section investigates how the increasing supply of high skills and skill-induced technological advances interacts. In the previous section, I verified that labor-augmenting technology raised the value of employment and showed that technology development depends on a matched worker’s skill. However, workers who observed the rising income inequality have an incentive to have the skilled worker’s advantageous position under the profound impact of technologies. Suppose the overall skill level in society increases. In that case, it is predictable that higher skills lead to the rise of labor-complementary technologies, and thus the benefit of technological advances goes to workers, in turn. To see the impact of the increasing skill on workers through technological changes, I adjust the proportion of the highly skilled workers. When the supply of high-skilled workers increases, I first focus on how it changes the firm’s decision on technology use and job openings without any restriction.
that demand for labor can cause. After then, I add the assumption of the relatively constant demand for the product. The condition is expected to alter the firm’s willingness to employ and to use technologies, so I investigate how the controlled firm’s outcome affects workers.

1.4.3.1 The Shift in Skill Distribution

To see the impact of the increasing supply of skills, I make the different skill distributions with various proportions of highly skilled workers. I use educational attainment as a proxy of skills and change the proportion of highly educated workers. I raise a fraction of workers with a bachelor’s or higher degree from 26% at the beginning, as in the initial skill distribution, up to 35%, 50% or 80% at the end period. Contrarily, a fraction of workers with a high school diploma or less than a high school diploma has decreased. By educational attainment, the number of workers calculated from these new fractions is drawn from their education group skill distribution, then are summed up to get the entire skill distribution. The mean and the standard deviation of new skill distributions are in Table 1.7. As the proportion of highly educated workers increases, the average skill is higher than the initial skill distribution.21

Table 1.7: The Mean and Standard Deviation of Simulated Skill Distributions

<table>
<thead>
<tr>
<th></th>
<th>Benchmark</th>
<th>Univ35</th>
<th>Univ50</th>
<th>Univ80</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0</td>
<td>0.060</td>
<td>0.115</td>
<td>0.218</td>
</tr>
<tr>
<td>S.D</td>
<td>0.447</td>
<td>0.450</td>
<td>0.461</td>
<td>0.458</td>
</tr>
</tbody>
</table>

1.4.3.2 Skill-driven Technological Changes in Balanced Labor Market

I examine how the increasing supply of high-skilled workers drives technological advances in the balanced labor market. This section assumes the labor demand across skills also changes to catch up with the pace of changes caused by the increasing supply of high-skilled workers. Since I do not add other factors that can alter skill choice, the job choice

---

21The skill distribution of each education group is measured by the method that estimates initial skill distribution in Section 1.3.3.1. The skill distribution of each education group follows the lognormal distribution. The mean and the standard deviation of logarithm skill for each group is as below: Less than high school (−0.322, 0.313), High school graduate (−0.08, 0.365), Some college or associate degree (0.07, 0.399), Bachelor’s degree (0.267, 0.435), Master’s or doctoral degree (0.467, 0.466)
of an individual worker with a certain level of skills does not change regardless of the skill distribution, but the number of matches in each submarket is determined by the labor supply.

Overall employment benefits grow as the skill-biased inflow of workers in the new skill distributions can be absorbed by the demand. It is due to the increasing (decreasing) share of employment in cognitive (manual) tasks. Table 1.8 summarizes these changes. In all cases, the share of employment in cognitive tasks increases while the one in manual tasks decreases. It means that more people get better-paid jobs. Besides, cognitive tasks take advantage of technological advances more than other tasks. The growing portion of cognitive jobs explains higher benefits from technological progress. Thus the aggregate employment value expands as shown in Figure 1.8. Even though unemployment rates on the other side of the figure get higher as more workers apply for a cognitive job, it does not mean the economy is in poor shape. It is because job finding rates dwindle from manual to cognitive jobs. The difficulty of being matched will be compensated by higher remuneration, so workers are willing to bear lower job-finding rates.

Table 1.8: The Employment Share with/without Labor-saving Technology

<table>
<thead>
<tr>
<th>Task</th>
<th>Benchmark</th>
<th>Univ35</th>
<th>Univ50</th>
<th>Univ80</th>
</tr>
</thead>
<tbody>
<tr>
<td>Manual</td>
<td>w/o</td>
<td>23.44</td>
<td>19.60</td>
<td>17.19</td>
</tr>
<tr>
<td></td>
<td>w/</td>
<td>35.36</td>
<td>30.03</td>
<td>26.43</td>
</tr>
<tr>
<td></td>
<td>(Δ)</td>
<td>(11.92)</td>
<td>(10.43)</td>
<td>(9.24)</td>
</tr>
<tr>
<td>Routine</td>
<td>w/o</td>
<td>51.74</td>
<td>50.74</td>
<td>48.32</td>
</tr>
<tr>
<td></td>
<td>w/</td>
<td>39.81</td>
<td>40.28</td>
<td>39.05</td>
</tr>
<tr>
<td></td>
<td>(Δ)</td>
<td>(-11.93)</td>
<td>(-10.46)</td>
<td>(-9.27)</td>
</tr>
<tr>
<td>Cognitive</td>
<td>w/o</td>
<td>24.83</td>
<td>29.66</td>
<td>34.49</td>
</tr>
<tr>
<td></td>
<td>w/</td>
<td>24.85</td>
<td>29.69</td>
<td>34.52</td>
</tr>
<tr>
<td></td>
<td>(Δ)</td>
<td>(0.02)</td>
<td>(0.03)</td>
<td>(0.03)</td>
</tr>
</tbody>
</table>

*Note:* In the row of Manual, Routine and Cognitive, w/o and w/ means the employment share without or with the displacement effect of labor-saving technology, respectively. Δ counts the difference in the employment share with or without the effect.

In addition, the number of workers who are at the risk of automation are decreasing as the skill distribution becomes increasingly negative-skewed. Table 1.8 compares the employment share without (w/o) and with (w/) the effect of labor-saving technology, and the rows in (Δ) represent how many workers are affected. For example, 12% of workers in Bench-
Figure 1.8: Aggregate Benefit of Employment and Unemployment Rate

Note: Figure compares the aggregate employment benefit and unemployment rate by skill distributions. The graphs on the lower side reflect the impact of automation of R1 routine tasks.

Mark are reallocated by automation while 7% of workers changed their jobs if 80 percent of workers are university graduates. Given that automation eliminates the best job for middle-skilled workers, a reduction in the number of middle-skilled workers in routine tasks lowers the displacement effects. The graphs in the lower side of Figure 1.8 contrast the impact of automation. Once automation occurs, the employment value plummets immediately in all cases, but, as more high-skilled workers stay in the labor market, the degree of decline gets smaller, and the speed of recovery is faster. It is because fewer workers are exposed to the impact of automation.
As a proportion of relatively high-skilled workers within each task sector grows, the level of labor-augmenting technologies in the economy increases. The positive link between technological changes and skills is described in Figure 1.9 and Table 1.9. Figure 1.9 shows changes in the level of labor-augmenting technology and skills in the simulated skill distributions relative to the initial skill distribution, denoted as Benchmark. The growth rate of the average skills is higher in the complexity of tasks, and the effect of higher skills on the adoption of technologies is amplified in cognitive tasks more than in other tasks due to the degree of technology-skill complementarity.

Table 1.9: The Average Level of Skill and Labor-augmenting Technology

<table>
<thead>
<tr>
<th>Task</th>
<th>Benchmark</th>
<th>Univ35</th>
<th>Univ50</th>
<th>Univ80</th>
</tr>
</thead>
<tbody>
<tr>
<td>Manual</td>
<td>s</td>
<td>0.592</td>
<td>0.595</td>
<td>0.597</td>
</tr>
<tr>
<td></td>
<td>z</td>
<td>1.149</td>
<td>1.150</td>
<td>1.151</td>
</tr>
<tr>
<td></td>
<td>Emp.%</td>
<td>23.44</td>
<td>19.60</td>
<td>17.19</td>
</tr>
<tr>
<td>Routine</td>
<td>s</td>
<td>0.985</td>
<td>0.998</td>
<td>1.006</td>
</tr>
<tr>
<td></td>
<td>z</td>
<td>1.179</td>
<td>1.180</td>
<td>1.181</td>
</tr>
<tr>
<td></td>
<td>Emp.%</td>
<td>51.74</td>
<td>50.74</td>
<td>48.32</td>
</tr>
<tr>
<td>Cognitive</td>
<td>s</td>
<td>1.876</td>
<td>1.887</td>
<td>1.934</td>
</tr>
<tr>
<td></td>
<td>z</td>
<td>1.273</td>
<td>1.275</td>
<td>1.280</td>
</tr>
<tr>
<td></td>
<td>Emp.%</td>
<td>24.83</td>
<td>29.66</td>
<td>34.49</td>
</tr>
</tbody>
</table>

Note: In the row of Manual, Routine and Cognitive, s means the average level of skill, z shows the level of labor-augmenting technology use in the task, and Emp.% represents the share of employment in each task without the displacement effect of labor-saving technology at the end period, 20 years after the economy begins.

Unlike the decision on labor-augmenting technologies, the adoption of labor-saving technologies does not depend on workers’ skills. In the model, a firm operates its task with robots if automation is cheaper than human workers. The free entry condition sets the value of a vacancy for workers to be zero, the adoption of robots relies on the cost-benefit of automation, which is defined by how easily the task can be autonomously operated and the price of robots, not by the skill level of those who the firm might choose to employ. Therefore, the task and the timing of replacing workers with robots are indifferent across skill distributions. Due to the restriction of empirical evidence, no findings explicitly prove the difference in workers’ skills within the task changes that task’s decision on automation.
Note: The figure compares the average level of labor complementary technology and skills across skill distribution to the initial skill distribution ('benchmark' in the figure). The range of skills for each task across all distributions are identical but the proportion of relatively high skilled workers within the task continuously increases from benchmark to Univ80 distribution.
However, there are some clues consistent with the results in the model. Aghion, Antonin, Bunel, and Jaravel (2020) reveal that the impact of automation on employment within the firm is not different across skill groups and Riddell and Song (2017) show that education does not influence the use of labor-replacing technologies.\textsuperscript{22}

As a result, as long as the labor market is well-balanced with an expanding supply of skilled workers, the benefits of increasing skills are passed on to workers in the form of more decent jobs and fewer risky jobs. Workers have an incentive to grow skills if they can be matched with a more complex task job that pays a better income as they improve their skills through higher educational attainment or training unless the cost of education exceeds the increase in benefit.

1.4.3.3 Skill-driven Technological Changes in Unbalanced Labor Market

If the labor demand for skilled workers does not grow as fast as the supply of skilled workers increases, how will technology adoption and the worker’s benefits change? In the previous section, I explore the effects of the increasing supply of high skills without excess demand or supply in the labor market. However, the consequences can be understood only if the demand for each task product grows at a pace of the supply growth under the new skill distribution. Suppose the demand for cognitive task products, for example, is not responsive to the excess supply incurred by higher productivity as a result of the increasing supply of high-skilled workers and skill-induced technological changes. In that case, the output price decreases, or firms preemptively control the quantity supplied to keep the revenue stable. Indeed, firms control the demand for labor based on the demand for their product more than the changes in the supply of labor, and the demand in the product market is not that much affected by the labor market condition.\textsuperscript{23} I add conditions that make the effects of increasing skilled workers more realistic. Under the assumption of the stable demand for each task output and consequently the constant demand for labor in each task sector, I simply target the employment share in each task at the level in the initial skill distribution. To

\textsuperscript{22}Previous research regarding the automation decision is more interested in differences in cost-benefit of automation across countries or industries that are caused by the higher bargaining power of labor under labor-friendly institutions (Acemoglu & Restrepo, 2018; Presidente, 2019) or by additional training cost to use workers (Feng & Graetz, 2020).

\textsuperscript{23}Autor and Dorn (2013) investigate whether the rising income of highly skilled workers stimulates demand for in-person service. They cannot find a strong relationship between the shift in the labor supply of high-skill workers and the employment growth of manual task occupations.
control oversupplied high-skilled workers, I first put the rising skill requirements in Section 1.4.3.4 and secondly use the output price adjustment mechanism in Section 1.4.3.5.

1.4.3.4 Rising Skill Requirements

When the supply of skilled workers exceeds its demand, firms select workers more rigorously. They ask workers to meet minimum qualifications that are rising as available workers become more skillful. Some previous studies prove that the skill requirements such as education and experience requirements increase when job seekers are more plentiful (Beaudry, Green, & Sand, 2016; Modestino, Shoag, & Ballance, 2019) and this change is strengthened by technological changes within a firm (Hershbein & Kahn, 2018; Spitz-Oener, 2006). I set the skill requirements to make the number of jobs within each task equal to those in the initial skill distribution. Assuming that all firms executing the same task agree to this condition, I will treat the skill requirements as if given exogenously. As more highly skilled workers enter the labor market, the minimum skill level for cognitive, and routine tasks rises compared to a least skilled worker in the initial skill distribution. (For further details about how the minimum skill level evolves, see the Appendix A.4.1)

Growing skill requirements restrict the worker’s job choice. For example, a worker with $s=1.5$ can have a cognitive task job in the initial skill distribution. But, that worker cannot hold the job under the Univ80 distribution where the minimum qualification is around $s=1.75$ at the end period. For the worker, a routine job is the next best option, but they will be overqualified in the routine sector. As more high-skilled workers who are crowded out from cognitive tasks by rising skill requirements make routine task submarkets congested, and the matter of qualified workers being crowded out by the rising skill requirements is repeated in routine tasks. Like this, some workers are limited to their job choice by new skill requirements. It results in a decrease in the employment value of those who are crowded out from the best choice job. Figure 1.10 shows the changes in the employment value caused by rising skill requirements due to the increasing supply of skilled workers. It measures the log difference in the employment value with and without skill requirements at the end period in the initial skill distribution represented as Benchmark in the figure, and other skill distribution with 35%, 50%, and 80% university graduates, Univ35, Univ50, and Univ80, respectively. As the supply of skilled workers grows faster, the qualification requirements...
Figure 1.10: The Impact of Rising Skill Requirements on the Employment Value

Note: The figure measures the log difference in the employment value at the end period relative to the initial skill distribution. Benchmark denotes the initial skill distribution, Univ35, Univ50, and Univ80 represent a skill distribution with 35%, 50%, and 80% university graduates, respectively. The blue lines describe the impact of changing tasks pushed by skill requirements. The skill requirements of each skill distribution are set to match the share of employment in manual, routine and cognitive task jobs of the initial skill distribution. The orange dashed lines show the impact of automation of R1 task, the routine manual tasks.

for cognitive and routine task jobs are rising further. The blue lines indicate changes in the employment benefit. Under the influence of the skill requirements, the range of workers gets wider and the decrease in the value of employment becomes deeper.

An involuntary shift in job choice changes those who face the risk of automation. In Benchmark, the skill level between 0.6 and 0.9 holds R1 routine task jobs that replace workers with robots the easiest. The orange dashed lines in this range show how much the employment value decreases due to automation. Despite skill requirements were not imposed in the initial status, job destruction caused by automation deprives workers in this range.
of the best job. From Univ35 to Univ80 distribution, the range of workers who experience the influence of automation widens as the rapidly increasing supply of skilled workers makes the available workers at the bottom of distribution sparse. In the Univ80 distribution, even workers with greater than the skill level of a median worker in the initial skill distribution are vulnerable to automation. These workers need not be worried about the threat of automation when they were in the initial skill distribution, however, because of harsh skill requirements along with the sufficient number of high-skilled workers, they are crowded out from where this level of workers used to work toward a job that will almost certainly replace a worker with robots in the near future.

The overall technology adoption within one task sector increases as the skill requirements control the range of qualifying skills. Even though the decision on labor-augmenting technology of each submarket is not changed, the increasing supply of skills that brings about the rising skill requirements pushes up the average skill level within each task, so the weighted average of labor-augmenting technology grows faster. Changes in the average skill level and the average labor-augmenting technology in each task across skill distribution over time are illustrated in Appendix A.4.2 Figure A.7. The positive relationship between skills and technological advances and its growth patterns look similar to findings in the previous section, but the rate of growth is much faster. Without qualification requirements, the average skill level of new skill distribution relative to the benchmark increases by 0.5 to 5 percent, which raises overall technological growth by 0.1 to 1 percent. Adding skill requirements raise the average skill ratio by 6.8 to 17 percent in manual tasks, 8 to 24 percent in routine tasks, and 7 to 22 percent in cognitive tasks from Univ35 to Univ80 distribution. This change accelerates the adoption of technologies thus, relative to the baseline model, the average labor augmenting technology grows 1 to 4 percent more. Table 1.10 summarizes the overall changes in the average skill and technology.

In short, workers who sharpen their skills enough to accomplish the desired job could be

---

24The average skill level increases by 1 to 3% in manual tasks, 1.5 to 4.5% in routine tasks, and 0.5 to 5% in the cognitive task from Univ35 to Univ80 distribution relative to the initial skill distribution.

25In the initial skill distribution, the average technology level increases by 3.4% (manual), 3.5%(routine), and 4.6% (cognitive) over two decades. This result can explain 45%, 62% maximum, of the growth rate of capital stock in the data that is around 7.6% (manual), 9.0% (routine), and 7.9% (cognitive). The growing supply of skilled workers and the rising skill requirements reinforce the explanation ability. Univ50 distribution can explain almost all of the growth rate of capital in the data. Routine and manual task technologies cannot increase as fast as cognitive tasks do because of the lower degree of skill-technology complementarity. However, the ability to explain the data rises above 60 percent with Univ80 distribution.
crowded out if the rising skill requirement controls the oversupply of the high-skilled. When the rewards for an overqualified worker are insufficient to offset their human capital investment, those workers suffer from costs of human capital investment and lower compensation. When more workers develop their skills to reach a higher rank in the distribution but the demand for them falls behind, the investment rather causes inefficiency in the economy. Since the model does not consider the cost of increasing skills before entering the labor market, it is hard to measure the size of the inefficiency caused by the oversupply of high skills directly. However, considering that the most frequently suggested solution for technology-driven job loss is training or education, the human capital investment may end up costing more than it saves if rising workforce skills are not fully supported by the sufficiently rising demand. Because the model does not include the role of cognitive tasks in technology innovation, the model might underestimate the demand toward skilled workers. Indeed, research shows technical innovation pulls the skilled workers, and workforce skills and technological improvement mutually reinforce (machin1998technologykim2002statetoner2011workforce). However, although a strong correlation between technical innovation and human capital is confirmed, it is not well identified that the increasing supply of the skilled can spur R&D activity and therefore bring about a reinstatement effect by creating new task jobs. Therefore, it remains unclear whether a policy-driven supply of highly educated workers can stimulate

Table 1.10: The Average Level of Skill and Technology with Skill Requirements

<table>
<thead>
<tr>
<th>Task</th>
<th>Benchmark</th>
<th>Univ35</th>
<th>Univ50</th>
<th>Univ80</th>
</tr>
</thead>
<tbody>
<tr>
<td>Manual</td>
<td>s 0.592</td>
<td>0.635</td>
<td>0.651</td>
<td>0.691</td>
</tr>
<tr>
<td></td>
<td>z 1.149</td>
<td>1.161</td>
<td>1.165</td>
<td>1.175</td>
</tr>
<tr>
<td></td>
<td>Emp.% 23.44</td>
<td>25.28</td>
<td>25.31</td>
<td>25.05</td>
</tr>
<tr>
<td>Routine</td>
<td>s 0.985</td>
<td>1.069</td>
<td>1.126</td>
<td>1.232</td>
</tr>
<tr>
<td></td>
<td>z 1.179</td>
<td>1.190</td>
<td>1.197</td>
<td>1.222</td>
</tr>
<tr>
<td></td>
<td>Emp.% 51.74</td>
<td>49.88</td>
<td>49.73</td>
<td>50.36</td>
</tr>
<tr>
<td>Cognitive</td>
<td>s 1.876</td>
<td>1.986</td>
<td>2.127</td>
<td>2.294</td>
</tr>
<tr>
<td></td>
<td>z 1.273</td>
<td>1.288</td>
<td>1.305</td>
<td>1.325</td>
</tr>
<tr>
<td></td>
<td>Emp.% 24.83</td>
<td>24.84</td>
<td>24.96</td>
<td>24.59</td>
</tr>
</tbody>
</table>

*Note:* In the row of Manual, Routine and Cognitive, s means the average level of skill, z shows the level of labor-augmenting technology use in the task, and Emp.% represents the share of employment in each task without the displacement effect of labor-saving technology at the end period, 20 years after the economy begins.
more innovative activities and hence increase employment in the real economy.

1.4.3.5 Price Adjustment Mechanism

In this section, I verify the role of the endogenously adjusted product prices in the effect of the rising supply of highly-skilled workers on firms and workers. Like the previous section, I use skill distributions with different proportions of university graduates and aim to keep the employment share of each task at the level in the initial skill distribution. Since the constant demand for labor implies the demand for the product in each manual, routine, and cognitive task sector is unaffected by the supply, there will be excess demand or supply if the changes in skill composition in the economy alter the supply of product. Contrary to the model that all goods as the numéraire, the price of each task output can deviate from one when there is excess demand or supply in the product market. The price adjustment process in this section plays a role in stabilizing the employment share regardless of the skill distributions.

In the model, at the beginning of the period $t$, the price of task $j$ output is given as $p_{jt}$. To make the analysis simple, I assume firms perfectly know how the skill supply will change and forecast the fluctuation of prices derived by changes in the skill distribution. The equation (1.8) is the value of a matched job that reflects the role of a price of task $j$. I use a middle routine task (R2) as the numéraire and make the prices of other tasks change relative to it.

$$J_t(j, w, s; p_t) = p_{jt}zf(j, s) - w - p_kr^j(z) + \beta(1 - \lambda)(1 - \delta)J_{t+1}(j, w, s; p_t) \quad (1.8)$$

Once the constant price assumption is relaxed, the product market adjusts the gap between the stable demand of the product and the varying supply induced by the growing number of high skilled workers. As firms performing cognitive tasks increase their employment when more highly-skilled workers are available, cognitive task products increase temporarily but that increase will be corrected by the decreasing price of the product. However, this paper uses the price adjustment mechanism is to keep the number of jobs of each task at the level in the initial skill distribution rather than the amounts of products. Refer to Table 1.9, in the row of Emp%, it is expected that employment in cognitive tasks needs to
be suppressed and employment in manual tasks needs to be spurred as more highly skilled workers enter the labor market. To incur the change, on the basis of the numéraire, R2, the prices of manual and R1 tasks should increase while the prices of cognitive and R3 should decrease. Table 1.11 summarizes how prices change by the skill distribution. The degree of price changes is determined by the scale of the supply of high-skilled workers. In addition, because the set of prices rotate downward at R2 as a pivot, the volatility in submarkets for routine tasks is relatively weak compared to manual or cognitive.

Table 1.11: The Average Level of Skill and Technology with Price Adjustment

<table>
<thead>
<tr>
<th>Task</th>
<th>Benchmark</th>
<th>Univ35</th>
<th>Univ50</th>
<th>Univ80</th>
</tr>
</thead>
<tbody>
<tr>
<td>Manual</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$p_M$</td>
<td>1</td>
<td>1.002</td>
<td>1.003</td>
<td>1.006</td>
</tr>
<tr>
<td>$s$</td>
<td>0.592</td>
<td>0.619</td>
<td>0.637</td>
<td>0.707</td>
</tr>
<tr>
<td>$z$</td>
<td>1.149</td>
<td>1.157</td>
<td>1.162</td>
<td>1.180</td>
</tr>
<tr>
<td>$(\Delta z%)$</td>
<td>(-)</td>
<td>(0.034%)</td>
<td>(0.068%)</td>
<td>(0.130%)</td>
</tr>
<tr>
<td>Emp.%</td>
<td>23.44</td>
<td>23.57</td>
<td>23.15</td>
<td>23.90</td>
</tr>
<tr>
<td>Routine</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$p_R$</td>
<td>1</td>
<td>(1.001, 0.998)</td>
<td>(1.002, 0.995)</td>
<td>(1.003, 0.992)</td>
</tr>
<tr>
<td>$s$</td>
<td>0.985</td>
<td>1.051</td>
<td>1.112</td>
<td>1.253</td>
</tr>
<tr>
<td>$z$</td>
<td>1.179</td>
<td>1.192</td>
<td>1.204</td>
<td>1.225</td>
</tr>
<tr>
<td>$(\Delta z%)$</td>
<td>(-)</td>
<td>(0.019%, -0.060%)</td>
<td>(0.043%, -0.133%)</td>
<td>(0.076%, -0.233%)</td>
</tr>
<tr>
<td>Emp.%</td>
<td>51.74</td>
<td>51.35</td>
<td>51.82</td>
<td>51.33</td>
</tr>
<tr>
<td>Cognitive</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$p_C$</td>
<td>1</td>
<td>0.996</td>
<td>0.992</td>
<td>0.987</td>
</tr>
<tr>
<td>$s$</td>
<td>1.876</td>
<td>1.980</td>
<td>2.124</td>
<td>2.308</td>
</tr>
<tr>
<td>$z$</td>
<td>1.273</td>
<td>1.286</td>
<td>1.302</td>
<td>1.321</td>
</tr>
<tr>
<td>$(\Delta z%)$</td>
<td>(-)</td>
<td>(-0.104%)</td>
<td>(-0.223%)</td>
<td>(-0.390%)</td>
</tr>
<tr>
<td>Emp.%</td>
<td>24.83</td>
<td>25.08</td>
<td>25.02</td>
<td>24.77</td>
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</table>

Note: In the row of Manual, Routine and Cognitive, $p_j$ is the price level (two values in $p_R$ means $(p_{R_1},p_{R_3})$ where $p_{R_2} = 1$), $s$ means the average level of skill, $z$ shows the level of technology use in the task, and Emp.% represent the share of employment in the task at the end period. $(\Delta z\%)$ shows the percentage change of $z$ relative to $z$ value at the reference product price ($p_{R_2} = 1$) in each submarket for the task.

New product prices directly affect the revenue of each job and therefore get involved in technology choice. The decision on labor-augmenting technology takes the capability of the job in bearing the cost of new technology into account. Since the price of output is given before the technology adoption decision, by the direction of price changes, manual tasks can advance technology more than what it used to do in the initial distribution. On
the other hand, cognitive tasks slow down the adoption of new technology. $\Delta z\%$ in Table 1.11 measures the percentage change of the level of technology relative to the one selected in the initial skill distribution. Cognitive tasks in the Univ80 distribution, for instance, have $-0.39\%$ for $\Delta z\%$, which means that all pairs performing cognitive tasks decrease the level of technology by $-0.39$ percentage due to $-0.13$ percentage decline in prices. On the contrary, the manual tasks raise the level of labor augmenting technology by $0.13$ percentage more thanks to a $0.6$ percent increase in price. The falling and the rising rate of technological changes is identically applied to all firms within the sector, and hence the dispersion of labor-augmenting technology level in manual tasks increases while in cognitive tasks decreases.

The installation of automation is also affected by the outcomes of price adjustments. The changes in the price of products alter the firm’s revenue regardless of who made that product, so the benefit of using robots also depends on the new prices. By the fall or the rise of product prices, firms will accelerate or delay the time of the adoption of automation. In the model, only the R1 routine task is automated seven years after the economy began. Because the cost of using robots is independent of the skill distributions, as the inflow of highly skilled workers raises the price of R1 products, the higher profit of automation advances the timing of automation adoption. The simulation results show the automation replaces a worker one month earlier at Univ50 and Univ80 distribution. The decision on automation for other tasks such as manual is not realized in the twenty years long experiments. If expanding the periods, however, the simulation reveals that the adoption of robots to perform manual tasks is moved up one or two months in Univ50 distribution or Univ80 distribution, respectively. Because the simulated prices are not drastically changed, it seems automation decisions are fundamentally different. However, this experiment can imply that the consequence of the race for high skills to get a good job, which means the oversupply of high skills, advances the arrival of automation, and thereby those who fall behind the competition encounter the risk of losing the right job earlier.

The combination of the new product prices and the adjusted decisions on technology adoption affects the value of a filled job, thereby altering the submarket where workers search for a job. The negative price effects of cognitive and R3 tasks on revenue and technological improvement depreciate the value of a filled job. The depreciation, first of all, leads to the lower market tightness within each submarket for cognitive and R3, the job-finding rates of
these jobs fall. Moreover, drops in the job value reduce the wage offer. Both the reduced wage offer and the lower job-finding rate shrink the value of employment in a cognitive job, so some workers are less inclined to prefer the cognitive job. In particular, workers on the border of R3 and cognitive tasks choose R3 routine jobs over cognitive tasks. Although R3 undergoes price drops, the decrease in the value of employment in R3 for such workers may be lesser than cognitive because the degree of depreciation is lower than cognitive. The positive price effects in manual and R1 tasks work oppositely, thus some workers who chose R1 tasks at the fixed price are willing to switch to a manual job.

Figure 1.11 shows changes in the value of employment derived from price adjustments. The blue lines show the total effects of price change. It merges the pure price effect and the task change effect. The pure price effect is illustrated in the yellow areas. If workers keep the job matched at level one fixed price, changes in the product prices raise the value of employment in manual tasks and lower the value in cognitive tasks. The grey areas measure the impact of the task change. Because the pure price effects distort the gap in the employment value between tasks, workers can receive higher values when moving toward a less complex task job. The positive spikes of grey areas explain why some workers voluntarily hold a manual or a routine job. The effect is growing as the proportion of skilled workers increases. For that reason, the changes are most conspicuous in Univ80 distribution. This total effect varies with skill, but as previously stated, workers around the bottom of the distribution undoubtedly enjoy higher values while those who near the top struggle in shabby conditions. As a result, the economic inequality between workers is lessened.

The displacement effects by automation in Figure 1.11 are substantially smaller and uniform in comparison to the scenario with skill requirements. The orange dashed lines in the figure represent who are displaced by automation and how much they are supposed to lose their employment values. Job task switching is less effective because price adjustments already minimize disparities in the value of employment across tasks. The comparable depth of orange lines across graphs in Figure 1.11 confirms that the impact of automation is similar to all distributions. When the labor market is under the control of skill requirements, the influence of automation ranges from 0.03 to 0.6 percent, depending on the distribution. Because of the enormous disparities in employment value between jobs, the risk of losing a job due to automation is more painful to workers. Consequently, the natural market control
Figure 1.11: The Impact of Price Adjustment on the Employment Value

Note: The figure measures the log difference in the employment value at the end period relative to the initial skill distribution. Benchmark denotes the initial skill distribution, Univ35, Univ50, and Univ80 represent a skill distribution with 35%, 50%, and 80% university graduates, respectively. The blue line shows the effect of the adjustment in the price of each task product. This effect is decomposed into two parts, the first part is the effects of changes in employment value itself at task selected at the benchmark price at one as shown in the yellow area, and the second part is the effects of task selection that is changed by new values of employment in the grey area. The orange dashed lines show the impact of automation of R1 task, the routine manual tasks.

through the pricing mechanism improves the benefit of working in manual tasks, the impact of automation is mitigated.

In summary, price adjustments distort incentives to improve technologies and decrease the advantage of holding a more complex task job. New prices are calculated to compensate for a shortfall or surplus caused by the oversupply of highly-skilled workers. For manual jobs which strive to find a worker, prices are to increase. At the same time, cognitive jobs which have sufficient applicants withstand the declining prices. Thanks to the benefit of
price effect, the manual task jobs spur technological advancements, allowing for better pay and matching rates. The cognitive task jobs, on the contrary, slow down the technology improvement as a result of falling prices, so that the wage offers and the matching rates worsen. These changes incur the gap in the value of employment between tasks to diminish. Unlike circumstances under skill requirements, adjusted employment values induce workers to be willing to stay where they used to search for a job, even though the benefits of the technology-driven productivity effect are still greater for more complex tasks. Additionally, it could relieve the motivation to earn a university degree. Workers will likely lose interest in holding a cognitive job if it is not sufficiently profitable, and wealth disparity will decrease, thus they will not need to pursue higher education. Then, it’s possible that the incentive system will finally correct the labor market imbalance.

1.5 Conclusion

In this paper, I try to identify the interaction between technological advances and workers’ skills based on the task-based framework. First of all, I check the effects of technological change on workers. Second, I investigate the role of skills in advancing technological changes. After that, I examine how the growing availability of highly skilled workers affects labor and technological changes.

I build the directed search model with two sided heterogeneity. Workers are characterized by their endowed skills and firms are classified by tasks among manual, routine, and cognitive tasks. The complexity of task and worker’s skills are assumed to be complementary, and hence the workers search for a job of which complexity corresponds to their skills. Firms can choose the labor augmenting technology at the given technology price that continues to fall over time. This type of technology is skill complementary and functions more efficiently in cognitive tasks. Rather than employing a worker, firms can install labor-saving technology on the basis of the cost-effectiveness and ease of automation. Automation is not affected by skills in the labor market but affects the risk of unemployment for workers performing routine tasks.

The model first examines the impact of technological advances on workers. As the cost of technology decreases, all firms use labor-augmenting technology more and routine tasks adopt automation technology. Labor-augmenting technological advancements increase
productivity which is largest in cognitive tasks because of the efficiency of utilizing labor-augmenting technology. It increases the value of employment for all workers but the increment is biased toward the high-skilled workers in cognitive tasks. By the size of the productivity effect, the share of employment in cognitive tasks rises. On the other hand, labor-saving technology starts to occur in the routine task jobs in my findings. Thereby middle-skilled workers who normally operate routine tasks are relocated. Secondly, I examine the role of skills in technology improvement. High-skilled workers stimulate technological advances because of the complementarity between labor-augmenting technology and skills. Among firms executing the same task, a firm matched with a relatively highly skilled worker raises the technology more than a match with a low-skilled worker. As a result of this reciprocal interaction between skills and technology, the gap in the technical benefits between the match of cognitive tasks and a high-skilled worker and the match of manual tasks and a low-skilled worker widens.

I explore the impact of the growing supply of highly skilled workers driven by technological advances on workers and technological changes, in turn. Under the profound influence of technologies, workers have an incentive to raise their skills to take advantage of the productivity effect as well as to avoid being displaced as a result of technological advancements. When the changes in skill proportion by the increasing supply of high-skilled workers are satisfied with the demand, the shift in skill distribution can raise the benefit of workers and increase the overall labor-augmenting technological changes. However, since the demand for high-skilled labor is unrelated to the supply, I experiment with what happens if there is an excess supply of highly skilled workers in the labor market. To control the demand-supply imbalance, I establish the rising skill requirement and use the price adjustment mechanism. The skill requirements upward shift the scope of skills in cognitive and routine tasks. It leads to the incidence of overqualification. The displacement effect of labor-saving technology crowds out some overqualified workers, so the overqualification problem would be severer by technological changes. The higher skill level accelerates labor-augmenting technological advances that are skill-biased. Thus, skill requirements raise the earning inequality between cognitive and non-cognitive tasks. The price adjustment mechanism corrects the differences in the difficulty of finding workers by tasks. Prices favorable to manual tasks improve the gap in profits, so reduce the dispersion of technical developments across tasks. The earning gap between tasks decreases, adjusting the willingness to raise the job ladder.
My findings give a question about making more workers highly skilled through education and training can persistently be effective under the growing influence of technologies. Higher-skilled workers are undoubtedly more likely to benefit from technology and less vulnerable to the threat of automation than low-skilled workers. But, if the demand for the high-skilled is already fulfilled, the rising supply of high-skilled workers brings about overqualification, increasing earning inequality, or sluggish technology development. Therefore, to improve the welfare of workers, not only raising workers’ skills but creating more jobs that workers are willing to hold must come together.

The model remains many possible future works. It is conceivable to evaluate the inefficiency of an overstock of high skilled workers if the model incorporates the endogenous schooling decision. Incorporating the contribution of skilled workers to innovation into the model can result in the creation of new tasks and the demand for labor. Furthermore, allowing on-the-job searching or unilateral contract termination would accurately depict the uncertain condition of workers under the impact of technology.
APPENDIX A

A.1 Data

A.1.1 The Korea Labor and Income Panel Study (KLIPS)

The Korea Labor and Income Panel Study (KLIPS) is the panel survey related to labor. The first wave was carried out in 1998 with an original 5,000 households in urban areas. From the 12th wave, the scope of the survey is expanded to rural areas to make the sample more nationally representative, so additional 1,415 households were added in 2009. The most recent 23rd wave was completed in 2020, but this paper covers up to 2018.

The survey tracks households and individual respondents annually. Information about the demographic characteristics and job characteristics of individuals aged above 15 in the household was collected retrospective in the first survey, and annual changes have been followed. When an individual within a surveyed household turned 15, or if an individual aged above 15 joined sampled households, the individual is covered in the survey. Retrospective information of new respondents was collected in the first year the member joined the survey.

The KLIPS contains a wide variety of information, including household demographics, economic activities and labor market mobility, income, education, and other social and economic factors. The Work History Dataset intensively gathers all jobs ever held by an individual. It provides employment type, job type, job position, start and end month and year of employment, occupation and industry, work hours, job-seeking activities, labor market mobility, wage, and income. I follow an individual’s career path and sort jobs into cognitive, routine, and manual task jobs based on the Korean occupation code in the survey and Acemoglu and Autor (2011) occupation classification. The Work History Dataset also renders education, vocational and on-the-job training history. I build the education group based on the most recently attained level of schooling, receipt of diploma/degree, the highest level attained by those without diploma or degree, years of formal education. I use wages to measure the skill distribution. The KLIPS provides monthly wage (paid) and income (unpaid), overtime payment (paid), and working days per month and year. Since I only cover paid workers, wages paid to employees are selected. I calculate the total annual and monthly
average earnings by the monthly wage and the number of months worked in each wave.

A.1.1.1 Percent Changes in Employment and Real Wage in KLIPS

Based on the occupation code in KLIPS, I classify each employment into Broad Occupational Group of Acemoglu and Autor (2011). Figures below show percent changes in employment and wages based on the values in 2000 as a reference year. From (a) to (d), each occupational group represents Non-routine Cognitive tasks (a), Routine Cognitive and Interpersonal tasks (b), Routine Manual tasks (c), and Non-routine manual tasks (d). The conversion from Korea Occupational Classification to US Occupational Classification that Acemoglu and Autor is made by International Occupational Classification (ISCO-08) as an intermediary.

Figure A.1: Percent Changes in the Employment Share (Base year = 2000)
A.1.2 Industry-level Business Activity Data

This paper uses surveys to establish sales per worker and capital per worker to estimate the parameter $\varphi$ that shows the effect of using labor-augmenting technology in Section 1.3.3.2.

A.1.2.1 The Survey of Business Activities of Korea

The survey has been conducted since 2006 annually to grasp the various business activities such as basic information of corporation, number of workers, type of legal organization, tangible and intangible assets, information on affiliated companies, transaction among domestic and overseas enterprises, business management direction for the purpose of providing basic data required for economic policies. It covers the corporations doing business activities in Korea as of the survey reference date, those with at least 50 full-time employees and 300
million KRW or more capital stock. For an industry like Wholesale and Retail Trade, the scope is delimited by companies with capital stock of 1 billion KRW or more rather than the number of employees.

I bring the sales amounts, the total amount of assets (tangible and intangible assets), and the number of regular employees from the survey. The survey provides the number of employees in total, by gender, and by employment type (regular/temporary). Among all information related to assets, I select the values of Machines and Equipment, Other tangible assets, and/or Vehicles in addition to Intangible assets based on needs. Since Land, Structure, and Buildings in the tangible asset category do not improve workers’ productivity, these assets are not included in the analysis.

### A.1.2.2 Mining and Manufacturing Survey

Mining and Manufacturing Survey is conducted since 2002 but its origin went back to 1968. Compared to The Survey of Business Activities, this survey deals with information in mining and manufacturing industry in more detail and covers a smaller scale of entities. According to the Korean Standard Industrial Classification, establishments with at least 10 employees in the category of B.Mining and C.Manufacturing are interviewed. The survey provides the type of legal organization, number of employees, labor cost, annual sales and value of shipment, operating expenses, assets, and inventories. The value of assets is reported the year-end value of assets at item level as in The Survey of Business Activities, and changes in asset value by item during a year additionally. Workers are classified into regular/temporary employees or self-employed.

### A.1.2.3 Construction Survey / Business Analysis of the Construction Industry

Construction Survey has been conducted since 1968, but the survey after 1993 was released lately. It covers companies that are registered as construction-related businesses and have conducted construction activities as their key or sub-business in the given year. The survey provides information the Survey of Business Activities does. Moreover, Business Analysis of the Construction Industry provides the industry-level financial statement. Thus the value of assets is reported at a specific item level. Due to the characteristics of the construction industry, I separate fixed assets, Work-in-Progress, and inventories more
thoroughly. Not only the number of total/regular/temporary workers but employees in production and administration are reported.

### A.2 Classification of Tasks

#### A.2.1 Standard Industrial Classification

<table>
<thead>
<tr>
<th>Sec</th>
<th>Section Description</th>
<th>ISIC Rev.4</th>
<th>KSIC Ver.10</th>
<th>Skill Group*</th>
</tr>
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<tbody>
<tr>
<td>A.</td>
<td>Agriculture; forestry and fishing</td>
<td>01-03</td>
<td>01-03</td>
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<td>B.</td>
<td>Mining and quarrying</td>
<td>05-09</td>
<td>05-08</td>
<td>Middle</td>
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<tr>
<td>C.</td>
<td>Manufacturing</td>
<td>10-33</td>
<td>10-34</td>
<td>Middle</td>
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<tr>
<td>D.</td>
<td>Electricity; gas, steam and air conditioning supply</td>
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<td>High</td>
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<tr>
<td>E.</td>
<td>Water supply; sewerage, waste management and remediation activities</td>
<td>36-39</td>
<td>36-39</td>
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</tr>
<tr>
<td>F.</td>
<td>Construction</td>
<td>41-43</td>
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<tr>
<td>G.</td>
<td>Wholesale and retail trade</td>
<td>45-47</td>
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<td>H.</td>
<td>Transportation and storage</td>
<td>49-53</td>
<td>49-52</td>
<td>H/L**</td>
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<td>I.</td>
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<td>J.</td>
<td>Information and communication</td>
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<tr>
<td>K.</td>
<td>Financial and insurance activities</td>
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<td>64-66</td>
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<tr>
<td>L.</td>
<td>Real estate activities</td>
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<tr>
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<td>Professional, scientific and technical activities</td>
<td>69-75</td>
<td>70-73</td>
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<td>N.</td>
<td>Administrative and support service activities</td>
<td>77-82</td>
<td>74-76</td>
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<td>Public administration and defence; compulsory social security</td>
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<tr>
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<td>Education</td>
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<tr>
<td>S.</td>
<td>Other service activities</td>
<td>94-96</td>
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<td>Low</td>
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Note: ISIC Rev.4 refers International Standard Industrial Classification Revision 4. Revision 4 was adopted from 2006. Sector T (Activities of households as employers; undifferentiated goods- and services- producing activities of households for own use) and U (Activities of extraterritorial organizations and bodies) are excluded. KSIC refers Korean Standard Statistical Classification, 10th version (revised at 2017) and 9th version (at 2008). The KSIC was based on the International Standard Industrial Classification (ISIC) adopted by the UN.

Skill Group* follows Bárány and Siegel (2018) Categorization of industries in Appendix Section A2. Instead of Middle-skilled, they classified Mining, Manufacturing and Construction industry as Manufacturing. Transportation** is classified as low-skilled category for Land transport and transport via pipelines (49) and Warehousing and support activities for transportation (53)- and as high-skilled for remaining divisions. This classification is similar to Sector Grouping by Salomons et al. (2018) in Table 1B.
A.3 Cost of Technology

A.3.1 The Cost of Machines with a Cobb-Douglas Production Function

A firm produces with one worker and capital stock which is at least $\bar{k}$. The production function is a Cobb-Douglas function so the match produces $y_j = k^{\varphi_j}(A_j s^\alpha)$ if the worker has $s$ level of skills, where $y_j$ is per capita output, $A_j$ is total factor productivity, $k$ is capital stock per worker, and $\alpha, \varphi_j$ are capital share and labor share in task $j$ which satisfy $0 < \alpha, \varphi, \alpha + \varphi \leq 1$. The rental rate of capital stock is given as $p_k$ and the worker is paid $w$. The $j$ task firm maximizes its profit as follows.

$$\max \pi_j = k^{\varphi_j}(A_j s^\alpha) - w(j, s) - p_k k \quad \text{s.t } k \geq \bar{k}_j$$  \hspace{1cm} (A.1)

The first order condition to find the optimal amount of $k_j^*$ is shown as below.

$$\frac{\partial \pi_j}{\partial k} = \varphi_j k^{\varphi_j-1}(A_j s^\alpha) - p_k = 0 \quad \rightarrow \quad k_j^* = \left( \frac{\varphi_j A_j s^\alpha}{p_k} \right)^{\frac{1}{1-\varphi_j}} \geq \bar{k}_j$$  \hspace{1cm} (A.2)

The optimal $k_j^*$ must be equal or greater than $\bar{k}_j$. I find the skill level that makes $k_j^* = \bar{k}_j$ and let the level as $s_j^*$. 

$$\left( \frac{\varphi_j A_j s^\alpha}{p_k} \right)^{\frac{1}{1-\varphi_j}} = \bar{k}_j \quad \rightarrow \quad s = \left( \frac{p \bar{k}_j^{-\varphi_j}}{\varphi_j A_j} \right)^{\frac{1}{\alpha}}$$  \hspace{1cm} (A.3)

The firm matched with a worker with $s > s_j^*$ adopts $k_j^* > \bar{k}_j$ if the skill level $s$ that makes zero profit at $\bar{k}_j$ in the Equation (A.1) is assumed to be lower than $s_j^*$.

Applying the results with the Cobb-Douglas production function to the model, the level of labor-augmenting technology $z$ is corresponding to $k^{\varphi_j}$. Let $z = 1$ if $k = \bar{k}_j$ and $r^j(1) = B$ which is equivalent to $\bar{k}_j$. If $k > \bar{k}_j$, $z = (k/\bar{k}_j)^{\varphi_j}$ thus $r^j(\bar{k}_j) = Bz^{\frac{1}{\varphi_j}}$. 

56
A.3.2 Price of robots

Figure A.3: The Price of Robots during 1990-2005 from Graetz and Michaels (2018)

A.3.3 Robot Installation and Job Finding Rates

As the price of Robots decreases, it incurs the rise of robot installation. Figure A.4 shows the stock of operational robots and the pattern of job finding rate of routine task jobs and the stock of operational robots.

Figure A.4: The Trend of Job Finding Rate and the Stock of Robots

Note: The job-finding rates are derived from the job-filling rates in Occupational Employment Survey. Occupational classification follows Acemoglu and Autor (2011). The source of the stock of operational robots is IFR.
Considering that robots are a kind of labor-saving technology, the increasing number of robots in the workplace changes the labor market. In a broad classification of job tasks, among routine tasks, I draw the pattern of job finding rates of administration, craft and operation job and the changes in the stock of operation robots in manufacturing industry. The job finding rates continue to decline over time in any tasks, but reductions in job finding rates of routine manual task job, craft and operation jobs, is notable than routine cognitive task jobs. Considering that workers in manufacturing industry are more likely to be exposed to threats of automation than workers in other sectors, the difference in decreases in job finding rates is related to the degree of automation that is represented by the stock of installed robots.

The job-finding rates are derived from the job-filling rates in Occupational Employment Survey from 2009. The survey includes the number of vacancies and the number of filled jobs by occupational classification. Based on occupation information, each occupation is assigned to broad 3 level task groups and broad occupational categories defined by Acemoglu and Autor (2011). The job-filling rates are first calculated based on the survey data and the job-filling rate are converted from the job-finding rates along with the model matching function and the estimated parameter. A data source of the stock of operational robots is IFR.
A.4 Experiments

A.4.1 Skill Thresholds in Unbalanced Labor Market

Figure A.5: Skill Requirements

Figure A.6: Price Adjustments
A.4.2 Rising Skill Requirements

Figure A.7: The Ratio of Labor-Augmenting Technology and Skills to the Initial Skill Distribution with Rising Skill Requirements
A.4.3 Price Adjustment

Figure A.8: The Ratio of Labor-Augmenting Technology and Skills to the Initial Skill Distribution with Price Adjustment
CHAPTER 2

Who is Hurt the Most
by the Routine-Biased Technological Changes:
a study of the impact of the RBTC on workers by their experience and ability

2.1 Introduction

Rapid advances in technology carry both gains and losses to the economy, but workers in the Rust Belt might disagree that technological revolution benefits them. Actually, in the United States, there has been a decrease in middle-skilled jobs such as manufacturing production assembly jobs relative to the high- or the low-skilled jobs over the past four decades. According to seminal research, it is mainly due to the evolution of technology (Acemoglu & Autor, 2011; Autor, Levy, & Murnane, 2003). Considering that either capital or labor could perform a certain task, firms decide the input factor based on the comparative advantage (Roy, 1951). As technological developments raise the capabilities of computers and machines, workers become relatively unproductive, so they are more likely to be replaced by capital inputs in the era of computerization. These tasks are generally concentrated in the middle of the skill distribution. Thus, the increase in unemployment of middle-skilled workers is connected to technological advances.

However, although previous studies have succeeded in figuring out the link between the observed job polarization and the influence of technological changes, it is still ambiguous why some middle-skilled workers are displaced from their job and others are not, and which factors cause this difference. This paper is to show how technological advances change the worker’s position in the labor market and who is affected the most. For this purpose, I add the inherent ability of workers and their work experience. Moreover, to focus on the negative impact of technological progress on labor markets, I restrict the scope of workers to those who were likely to be holding or applying for routine task jobs, specifically workers without a college degree, and the scope of jobs to routine task jobs and non-routine manual task jobs.

The occupational classification such as routine task jobs or non-routine manual task
jobs is following the task model of Autor, Levy, and Murnane (2003, ALM hereafter) because the input substitutability (or complementarity) between capital and labor depends on the job tasks. The task model of ALM separates tasks into four categories - cognitive versus manual, routine versus non-routine, and classifies occupations according to tasks it performs. Non-routine cognitive tasks are analytic, problem-solving, and creative tasks in which high-skilled professional, managerial, and technical occupations are specialized. Non-routine manual tasks use physical dexterity and interpersonal adaptability for activities like serving, cleaning, in-person health assistance, and other low-skilled jobs. Routine (cognitive and manual) tasks carry out repetitive, predictable, and well-defined procedures such as book-keeping and manufacturing assembly operations. These characteristics of routine tasks are programmable and codifiable, so routine task jobs are more likely to be performed by computers or program-controlled equipment as technological developments increase the capability of these capital inputs.\footnote{On the contrary, non-routine cognitive task jobs are rather complemented by computers in accessing, organizing, and manipulating information, so technological developments raise the productivity of capital inputs as well as workers’ productivity. Thus, employment in non-routine cognitive jobs expands while routine task jobs are hollowed out. Non-routine manual task jobs are neither substituted nor complemented by computers, so the impact of technological progress on non-routine manual jobs is limited. More details about changes in the share of employment by occupational tasks are in the Appendix B.}

Seeing that middle-skilled occupations are specialized in routine tasks, disappearing middle-skilled jobs observed in the data could be understood in terms of their job tasks characteristics operated by computers and machines. Compared to the impact of technological changes on cognitive jobs, which is beneficial, or on manual jobs, which is neutral, routine task jobs are most affected by the technology advances, thus workers holding routine jobs are exposed to a higher probability of being unemployed than other workers with non-routine task jobs. Therefore, routine jobs workers are mainly discussed in this paper to understand the disadvantage of technological change. The recent technological change is biased toward routine tasks, it is called the routine biased technological change (the RBTC hereafter).

This paper covers only routine and manual occupations and includes all less-educated workers. If workers are separated from routine jobs due to technological progress, they might want to have a non-routine task job to avoid being unemployed. However, their alternative is confined to manual jobs because of qualification. Since non-routine cognitive jobs usually require a bachelor’s degree or a higher degree, routine job workers, mostly high school graduates, are not qualified for non-routine cognitive jobs, so cognitive jobs are
unnecessary to trace occupational transitions of less-educated workers who do not hold a bachelor’s degree. Moreover, all less-educated workers are analyzed regardless of current employment status. Since all workers in the model are homogeneous in terms of educational attainment, the job allocation between manual or routine tasks is affected by the differences in individual-specific ability and work experience among workers as long as they still prefer routine to manual tasks. If the allocation is changed as technology develops, the model can observe how technological changes alter the role of worker-specific skills and therefore trace the impact of technological developments on the job allocation.

The analysis begins with a random search model. There are two labor markets, one for routine tasks and the other for manual tasks. Firms choose where to open vacancies, and firms within the market are assumed to be homogeneous. Workers are heterogeneous in terms of inborn ability and work experience, and these characteristics determine the productivity of a match. Due to the properties of routine tasks, productivity increases as work experience is accumulated and the level of ability of the worker is higher. I build that the productivity of routine jobs consists of the base productivity that is indifferent to all workers and the additional part comprised of the worker’s specific ability and experience. On the contrary, the productivity of manual jobs is supposed to be invariable regardless of whoever performs because manual tasks are simple and easy to be done without special skill or training. Therefore, the productivity of the manual job is normalized in the model. While the unemployed search for a job, they could apply for both a routine and a manual task job simultaneously but choose to drop the one, which gives the negative surplus. Since the surplus is determined by the probability that a worker meets a vacancy, the productivity of the match, and its wage determined by Nash bargaining, the job application decision depends on workers’ characteristics and the market conditions. In given market conditions, the experienced worker with a high level of ability matched with the manual job cannot generate a positive surplus because the wage paid to the worker is too high relative to the fixed productivity of the manual job. Similarly, the routine job is unprofitable to a worker who never experienced and has the lowest level of ability if the base productivity of the routine job is lower than the productivity of the manual job. Therefore, workers at the lower end of the ability distribution are more likely to apply for only manual jobs, workers at the upper end are more likely to apply for only routine jobs, and workers in the middle are expected to be in both markets concurrently. It implies that, given the productivity and
market tightness, a certain level of ability is acceptable to the routine jobs or the manual jobs by worker’s experience. These endogenous ability requirements are used as criteria for forming the mat.

The impact of RBTC in this model is described as the decrease in the base productivity of routine jobs to show the disadvantage of using workers instead of computers regardless of worker characteristics. The drop in the base productivity of routine tasks immediately incurs changes in routine task jobs and indirectly affects manual task jobs. First of all, the new productivity entirely lowers wages and the value of routine jobs. Some existing pairs are separated if a matched worker’s ability and/or experience cannot fill the loss of the base productivity. Besides, firms holding positions for routine tasks cut their vacancies to cope with reductions in the match surplus and the decreased number of available workers. It decreases the routine market tightness so finding a routine job becomes challenging under the influence of the RBTC. On the other hand, the productivity of manual jobs remains the same. However, if the job is matched with a worker staying in both markets, the job value increases as the wage falls because of the decreased value of an outside option. Correspondingly, firms open more vacancies. Thus the market tightness rises, although those who are separated from the routine jobs flow into the manual market. Unlike routine jobs, manual jobs are easily accessible than before, but it is not enough to offset the difficulty of getting routine jobs. Consequently, technological changes lead the unemployment rate to rise and the share of employment in routine tasks to decrease in the model.

Based on the structural changes in labor markets incurred by the RBTC, the model can trace who is hurt the most: inexperienced young workers. At the moment the productivity shock hits the economy, workers in the routine job market are clearly worse off than those in the manual job market. In terms of the risk of being unemployed, the likelihood of unemployment increases as the ability is close to the ability thresholds. It is, of course, higher to the inexperienced. Since routine jobs demand individual-specific productivity from ability and experience to compensate for the decrease in the base productivity, the match is sustained only if a worker satisfies the new ability requirement that is higher than before. Hence, those who have ability less than the new threshold are laid off then deprived of the qualification for routine tasks. Under the assumption that work experience augments per unit ability productivity, the level of ability asked inexperienced workers to have is stricter.
than the experienced workers, so the likelihood of losing a job is higher for inexperienced workers. Furthermore, those workers suffer from not only unemployment itself but a longer duration of unemployment. Previously, they applied for a routine job and a manual job simultaneously and accepted either one that came first. They, however, now should wait until a manual job offer arrives, so a spell of unemployment stochastically lengthens. Young workers seem to be damaged more severely in that they have less opportunity of being experienced, although the current market condition is equally bad to all workers. To be experienced, young workers need firstly to be qualified for, secondly to be matched with, and finally to be promoted in a routine job. However, because the ability threshold young workers should hurdle is higher than the old one, fewer workers could get qualified. Besides, a low market tightness, which leads to a lower job-finding rate, makes entrants struggle to get a job. Even though the probability of getting a promotion is unchanged, young workers are harder to be experienced because of a limited chance of working for routine tasks. Briefly, the benefit of workers searching for a job after the RBTC arrived (young workers) relative to those in the labor market prior to the change (old workers) shows how the RBTC hurts young workers more than old workers.

Simulations confirm model prediction numerically. Basic parameters are chosen from data of the U.S. in 1980 when the labor markets were not disturbed by technological development to set the economy without the RBTC. Parameters for workers are matched with key features of the male workers without a college degree. Thus, the model begins with 6.9% of the unemployment rate, 69% of experienced workers and 79% of routine jobs conditional on employment. The workers are assumed to be uniformly distributed over the range of [0,1]. The ability level of 0.12 is required to enter the routine market at the beginning. Once the technological shock is given, for example, a 40% decrease in the base productivity (from 0.7 to 0.42) raises the unemployment rate up to 7.4%, decreases the proportion of the experienced workers by 14 percentage points (from 69% to 55%), and shrinks the share of routine jobs conditional on employment by 15 percentage point (from 79% to 64%). This result is consistent with the employment share in routine tasks of non-college graduates in 2005, so we could conjecture the difficulty of getting into the routine market in recent years from the differences between 1980 and 2005. While the economy is verging on the consequence corresponding to 2005, simulations specify how the ability thresholds are shifted. The inexperienced currently needs at least 0.29 level of ability. For the experienced, 0.2 is required.
Both are much greater than the initial level of 0.12, but the gap between 0.2 and 0.29 allows an old and experienced worker whose ability is in these ranges keeps the position while a young worker with the same level of ability, on the contrary, cannot get in, and an old but inexperienced worker is ousted from the routine market. In the circumstances that technologies continue to progress, workers who joined the labor market in the past took advantage of low qualification, thus the routine job market is largely occupied by old workers as Autor and Dorn (2009) figure out that routine job is getting old.

Like Autor and Dorn (2009), several recent articles emphasize the role of worker characteristics to see the impact of the RBTC on the labor market. Autor and Dorn (2009), Gordo and Skirbekk (2013), Cortes (2016) and Cortes, Jaimovich, and Siu (2017) show the importance of age, ability or sex to explain the difference of the influence of the technological change across workers. Autor and Dorn (2009), in particular, focus on changes in age structure to analyze the transition between employment and unemployment across occupations. They hypothesize that growing occupations are typically more likely to hire young workers while declining occupations cannot. Authors analyze changes in the age composition of employment within the local labor market in the U.S. and prove, first, routine task jobs are declining, and second, routine task jobs are getting old. Gordo and Skirbekk (2013) describes how less-educated workers are weak to the new labor market demands rather than showing the virtue of age. When a worker is asked to do a new task that is mostly cognitive intensive, workers in their 50s seem to perform cognitively intense new tasks more than those in their 30s, but those who adapt new tasks successfully generally have a college degree rather than take the virtue of age. Cortes (2016) also describes the role of unobservable ability in occupational mobility. By following individual workers’ transitions between different types of jobs, he finds that workers with a low level of ability who had a routine task job move toward manual jobs under the influence of the RBTC. He also shows that RBTC lowers the participation rate leading to the decline in the share of routine employment. Recently, Cortes et al. (2017) further investigate why workers are less likely to enter or stay in routine occupations with demographic characteristics.²

²Workers could find a job in a non-routine cognitive task sector rather than a non-routine manual task, but it is hard to hold because cognitive occupations ask workers to have college degrees or long-term experience. Moreover, although the non-routine cognitive task occupations expand, a growing number of college graduates offsets its impact on the labor market. Cortes et al. (2017) investigate changes in demographic compositions and then show workers who lose routine task occupations could not get in non-routine cognitive occupations.
The plan of the paper is as follows. In the next section, I describe the model and characterize its equilibrium and properties. Section 3 simulates the model to measure the impact of the changes in routine task productivity and then draw a conclusion.

2.2 MODEL

2.2.1 Set up

Time is continuous with an infinite horizon. There are two labor markets, one for routine tasks and the other for manual tasks. Two types of agents, workers and firms, search for each other to be matched in the market where they decide to enter.

There is a unit mass of workers in the model. Workers are heterogeneous in terms of inborn ability and experience. They are risk-neutral and discount the future at a rate $r$. At each unit of time, existing workers exit the labor market at a rate $\delta$, and new young workers enter to replace those who exit.

Workers are unemployed or employed in either a routine or a manual job. Only unemployed workers could be job seekers (no on-the-job search). Job seekers can apply for both routine task jobs and manual task jobs simultaneously without any extra cost. Some workers, however, choose to apply for only either manual jobs or routine jobs when one of them seems not to provide a positive surplus. Those who applied for both jobs are matched with a job that first arrives. At that time, an application in the opposite market is withdrawn immediately.\(^3\)

Workers are characterized by their innate ability and previous work experience in routine jobs. Each worker was endowed with an ability $\epsilon$ that is fixed at a given level over time. Workers recognize their absolute ability and relative position on the distribution of ability which follows the uniform distribution over a range of $[0, 1]$.\(^4\) By work experience in routine jobs in the past, workers are classified as the experienced or the inexperienced. A worker

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\(^3\)I do not consider those who are not in the labor force.

\(^4\)“Ability” in this paper does mean the ability to satisfy job-specific requirements, not only intelligence. Recently, a new survey, the Occupational Requirements Survey, provides job-related requirements like dealing with “a degree of uncertainty or complexity”, keeping “very heavy strength level” or coping with “rapid pace of work”. If a worker is very strong or able to cope with the rapid pace of work, that worker performs the job better than those who do not satisfy the requirements. Thus, a highly “able” worker who could fill routine task occupational requirements is expected to remain in a routine task job longer. (Source: the Bureau of Labor Statistics: https://www.bls.gov/ncs/ors/home.htm)
who was hired to perform routine tasks but did not achieve the required skills yet is labeled as an inexperienced worker. An experienced worker is a worker who has already attained appropriate skills for routine tasks through many years of experience. The inexperienced worker could become experienced through promotion within the same employer at a rate $\gamma$. Once being experienced, the worker could keep their title regardless of present occupation or unemployment. Hereafter, a superscript $i$ indicates worker type, where 0 denotes the inexperienced worker and 1 denotes the experienced, and $\epsilon$ represents the level of ability.

These worker characteristics are adopted for the routine tasks in this model. Due to the feature of routine tasks, workers are preferred if they have the ability to understand the routinized process so get used to tasks quickly. Therefore, individual-specific ability decides units of output in a routine task job. Hence, the productivity of routine tasks is supposed to increase proportionally to the worker’s ability. Also, experience performing routine tasks in the past raises the productivity of a routine job. Since routine tasks are performed repeatedly, a worker who has done the tasks for a long time is more likely to have better skills than a worker who was never doing it before. For this reason, I assume that experienced workers are more productive than inexperienced workers at a given level of ability. Meanwhile, output in manual jobs are assumed to be constant regardless of worker characteristics because simple tasks of manual jobs do not require special skills, knowledge, or cognitive ability. Thus, all workers matched with a vacancy for manual tasks generate constant units of output.

There is a continuum of risk-neutral firms that discount the future at the rate $r$. Firms choose which job market to enter, and all firms within the market are homogeneous with respect to production technology. After firms select the market, they create vacancies as many as they want. When a firm opens vacancies, a vacancy incurs a flow of cost $c_j$ to the firm depending on the types of work $j \in \{r, m\}$ they open, where $r$ indicates routine tasks and $m$ indicates manual tasks.

Production occurs if a vacancy for $j$ task is matched with an unemployed worker type $i$ with $\epsilon$. This pair generates $p_{ji}(\epsilon)$ units of output. Specifically, manual jobs produce $p_m$ units of output; a routine job generates $p_r + \alpha \epsilon$ if a worker is inexperienced or $p_r + \beta \epsilon$ with experienced worker where $p_r$ is the base productivity of a routine job that is assumed to be
smaller than \( p_m \). Additionally, by the assumptions, \( \beta \) is greater than \( \alpha \).\(^5\) Each pair splits the match surplus according to the Nash bargaining solution. Jobs are destroyed if hit by exogenous separation shock according to a Poisson process with parameter \( \lambda \).

According to the matching function \( M(u_j, v_j) \), vacancies are matched with unemployed workers in a market \( j \in \{r, m\} \), where \( v_j \) and \( u_j \) is the number of vacancies and unemployed workers in a market \( j \). The function \( M(\cdot, \cdot) \) is assumed to exhibit constant returns to scale, be twice differentiable, increasing in both arguments and concave. The rate at which unemployed workers meet vacancies is then \( M(u_j, v_j)/u_j = M(1, \theta_j) \) where \( \theta_j = v_j/u_j \) is called the labor market tightness. It is convenient to define \( m(\theta_j) \equiv M(1, \theta_j) \) so that \( m(\cdot) \) inherits concavity from \( M(\cdot, \cdot) \). The rate at which vacancies meet unemployed workers is then \( M(u_j, v_j)/v_j = m(\theta_j)/\theta_j \). I further assume that \( m(0) = 0 \), \( \lim_{\theta_j \to 0} m'(\theta_j) = \infty \) and \( \lim_{\theta_j \to \infty} m'(\theta_j) = 0 \).

2.2.2 Value functions

Workers in the model can be in any one of six possible states: unemployed inexperienced \((U^0)\), unemployed experienced \((U^1)\), employed experienced \((E^1_r)\) or inexperienced \((E^0_r)\) in routine job, employed experienced \((E^1_m)\) or inexperienced \((E^0_m)\) in manual job.

The value functions for each state for a type \( i \) with the ability level of \( \epsilon \) are as follows:

\[
(r + \delta)U^0(\epsilon) = b + m(\theta_r)\max\{\mathbb{E}\{E^0_r(\epsilon) - U^0(\epsilon)\}, 0\} + m(\theta_m)\max\{\mathbb{E}\{E^0_m(\epsilon) - U^0(\epsilon)\}, 0\} \quad (2.1)
\]

\[
(r + \delta)U^1(\epsilon) = b + m(\theta_r)\max\{\mathbb{E}\{E^1_r(\epsilon) - U^1(\epsilon)\}, 0\} + m(\theta_m)\max\{\mathbb{E}\{E^1_m(\epsilon) - U^1(\epsilon)\}, 0\} \quad (2.2)
\]

\(^5\)Before a firm and a worker agree to produce, they decide either to form a match or to remain separate when they meet. However, firms might misjudge the productivity of the match because the productivity of the pair is entirely determined by worker characteristics, but the level of ability is not easily observable to firms, unlike experience. Experience is observable and measurable because workers share their work histories, such as years of work and previous job positions on their job applications. The ability could be checked up if references or recommendations are available, but it is not clearly discernible. To avoid asymmetric information problems between firms and workers, I assume that firms could distinguish all information about workers, including ability, at the moment of meeting. Therefore, both firms and workers could observe the true productivity of the match.
First, the value of unemployment for a worker with ability-level $\epsilon$ is subject to the flow value of $b$ and the arrival rate of a vacancy $m(\theta_j)$. All workers discount the future at rate $r$, exit at rate $\delta$ and receive $b$ as unemployment benefits or the value of leisure. If the expected value of employment in $j$ job is equal or greater than the value of unemployment, the worker enters that market to be matched. Since the employment values depend on the worker’s ability and experience, the application choices vary across the worker’s characteristics. This will be discussed further in Section 2.2.4.

Once the unemployed workers are matched with jobs, they are paid a $w^j_i(\epsilon)$ by Nash bargaining. The inexperienced worker who is employed in a routine job would be promoted at a rate $\gamma$ and then get the value of the experienced worker’s employment in a routine job. All employed workers discount the future at rate $r$, exit at rate $\delta$ and are exogenously separated at a rate $\lambda$.

Next, firms can choose to open vacancies for manual tasks ($V_m$) or routine tasks ($V_r$). If that vacancy is filled, the filled manual (routine) job matched with $i$ type worker with $\epsilon$ level of ability provides the value of a filled job as below: $J^0_i(\epsilon)$, $J^1_i(\epsilon)$, $J^0_r(\epsilon)$ and $J^1_r(\epsilon)$.

\[
(r + \delta)E^0_m(\epsilon) = w^0_m(\epsilon) + \lambda(U^0(\epsilon) - E^0_m(\epsilon)) \tag{2.3}
\]
\[
(r + \delta)E^1_m(\epsilon) = w^1_m(\epsilon) + \lambda(U^1(\epsilon) - E^1_m(\epsilon)) \tag{2.4}
\]
\[
(r + \delta)E^0_r(\epsilon) = w^0_r(\epsilon) + \lambda(U^0(\epsilon) - E^0_r(\epsilon)) + \gamma(E^1_r(\epsilon) - E^0_r(\epsilon)) \tag{2.5}
\]
\[
(r + \delta)E^1_r(\epsilon) = w^1_r(\epsilon) + \lambda(U^1(\epsilon) - E^1_r(\epsilon)) \tag{2.6}
\]

When the firm decides to open a vacancy for $j$ task, the vacancy pays a flow cost $c_j$ and is filled with a worker at rate $m(\theta_j)/\theta_j$. Inside the labor market for $j$ task, a firm randomly encounters
either an inexperienced or an experienced worker. The firm meets an inexperienced worker with a probability of $\pi^0_j$ and an experienced worker with a probability of $\pi^1_j$. The probability depends on the number of inexperienced workers and experienced workers in the market $j$, thus $\pi^i_j$ is a fraction of $i$ type worker among all applicants for $j$ task jobs, $u^i_j/(u^0_j + u^1_j)$, where $i \in \{0, 1\}$ and $j \in \{r, m\}$, $u^0_j$ means the number of inexperienced unemployed workers and $u^1_j$ is the number of experienced unemployed workers who apply for the $j$ tasks. When the free entry condition is satisfied, it implies that the values of manual and routine vacancies are driven to zero at any point in time, such that $V_m = V_r = 0$.

The filled job discounts at the rate $r$ and $\delta$ because a match will be terminated when a worker exits. Further, the match is exogenously separated by the catastrophic shock at rate $\lambda$. The matched manual job draws only $p_m$ units of output each period regardless of who was hired. The corresponding value function for the routine jobs, however, relies on a worker’s performance. The vacancy for routine tasks generates productivity $p_r$ basically when matched with a worker, and its output is boosted by the worker’s experience and ability as much as $\alpha \epsilon$ or $\beta \epsilon$. If the job is matched with an inexperienced worker, that job currently adds just $\alpha \epsilon$ but could do $\beta \epsilon$ at a rate of $\gamma$ as the worker gets skilled. A matched job pays the wage $w^i_j(\epsilon)$ determined by Nash bargaining.

### 2.2.3 Wage setting

Once a firm $j$ meets a worker $i$ with $\epsilon$ ability, that match generates the total surplus $S^i_j(\epsilon)$.

$$S^i_j(\epsilon) = [J^i_j(\epsilon) - V^i_j + E^i_j(\epsilon) - U^i(\epsilon)]$$

Nash bargaining splits the total surplus of the match $S^i_j(\epsilon)$ into worker’s share $\eta S^i_j(\epsilon) = [E^i_j(\epsilon) - U^i(\epsilon)]$ and firm’s share $(1 - \eta)S^i_j(\epsilon) = [J^i_j(\epsilon) - V^i_j]$ according to worker’s bargaining weight $\eta$. This leads to the following sharing rule.

$$\eta [J^i_j(\epsilon) - V^i_j] = (1 - \eta) [E^i_j(\epsilon) - U^i(\epsilon)]$$ \hspace{1cm} (2.13)

Combining the value functions above with the sharing rule and the free-entry condition
\( V_j = 0 \), the wage paid to a worker type \( i \) with \( \epsilon \) level of ability by a \( j \) job would be:

\[
w_j^i(\epsilon) = \eta p_j^i(\epsilon) + (1 - \eta) \left[ b + \text{(possible gains from the other job)} \right]
\]

The wage first shares production of the match \( p_j^i(\epsilon) \) by the worker’s bargaining weight \( \eta \). Moreover, the value of unemployment in the Nash bargaining sharing rule includes the value of leisure \( b \) and the achievable value in the opposite labor market. For that reason, even though the productivity of a manual job and the value of leisure are unvarying, the wage for a worker type \( i \) with \( \epsilon \) level of ability in the manual job, \( w_m^i(\epsilon) \), varies in worker’s ability and experience. It is derived from job opportunities available to the worker and the possible gains from matching with a routine job. Likewise, the wage for a worker type \( i \) with \( \epsilon \) level of ability in the routine job, \( w_r^i(\epsilon) \), differs in productivity of the match \( p_j^i(\epsilon) \) as well as the worker’s application option for the manual job.

### 2.2.4 Ability requirements for job application

Nash bargaining fixes the wage of each firm-worker match on the basis of the sharing rule as the equation (2.13). With the free-entry condition, \( V_j = 0 \), the firm and the unemployed worker could figure out whether that match is worth being created by the sign of the value of the filled job \( J_j^i(\epsilon) \). Because all firms within the market \( j \) are homogeneous, the variation of the match surplus is caused by the characteristics of a worker.

The filled manual job produces the constant \( p_m \) units of output, but the wage is escalated as the matched worker’s ability and/or experience increase through the outside option. As the level of ability rises, the filled manual job value drops and becomes negative at some point. If the manual job hires an experienced worker, the job value falls faster than that with an inexperienced worker. Thus, a high level of ability makes the surplus of a manual job be zero. That level, \( \epsilon_i^{**} \), is defined as the maximum ability level to make a non-negative surplus of the manual job. Thus, those who are type \( i \) and have ability \( \epsilon \) between zero and \( \epsilon_i^{**} \) choose to apply for a manual job (The range \( \circ \) and \( \circ \) in Figure 2.1).

\[
J_m^0(\epsilon_0^{**}) = 0, \quad J_m^1(\epsilon_1^{**}) = 0
\]
Figure 2.1: Ability Requirements for Job Application

Similarly, the value of a filled routine job is used as a criteria for determining whether the match is agreeable or not. Far from the constant productivity of manual jobs, a routine job produces more outputs as the matched worker’s ability and experience are developed. Even though the wage also increases as the match productivity rises, the degree of increase in the wage is smaller than the degree of increase in outputs. Therefore, the value of a routine job is growing as the ability level goes to unity and is greater when matched with the experienced than the inexperienced. Some workers who do not have enough high level of ability, for instance, \( \epsilon = 0 \), could not generate a positive surplus, so they cannot form a match for routine tasks. Consequently, to enter the routine labor market, workers have to satisfy the minimum ability level, \( \epsilon^*_i \).

\[
J^0_r(\epsilon^*_0) = 0, \quad J^1_r(\epsilon^*_1) = 0
\]

Workers with ability higher than \( \epsilon^*_i \) could find a job while workers having ability in a range of \([0, \epsilon^*_i]\) would give up searching for a job in the routine task labor market.

It needs to pay close attention to delineate the ability requirement of routine jobs for experienced workers. Although the job value of a routine job matched with an experienced worker \( J^i_r \) asks its own minimum ability level \( \epsilon^*_i \) to the experienced worker, this requirement needs to be compared to \( \epsilon^*_0 \). To be an experienced worker, a worker who satisfies \( \epsilon^*_0 \) should spend years of apprenticeship as an inexperienced worker and must be promoted. Thus, the
first qualification the worker has to satisfy to enter the routine job market is \( \epsilon_0^* \). In case of \( \epsilon_0^* \geq \epsilon_1^* \) as in the Figure 2.1, \( \epsilon_0^* \) determines the ability set of the experienced workers.

Therefore, when workers choose where to apply, their decisions depend on their innate ability and experience. Workers with ability between 0 to \( \epsilon_0^* \), who are in the range of 1 in Figure 2.1, apply for manual jobs only, so they cannot have any chance to be an experienced worker. The worker in the second range in the Figure 2.1, from \( \epsilon_0^* \) up to \( \epsilon_0^{**} \) for the inexperienced and from \( \epsilon_0^* \) to \( \epsilon_1^{**} \) for the experienced, would apply for both a manual and a routine job simultaneously. The remaining workers with ability higher than \( \epsilon_1^{**} \) would not search for a manual job.

2.2.5 Unemployment Dynamics

In the economy, a unit mass of workers is either unemployed or employed in the \( j \) sector. To denote unemployment of \( i \) type worker, I use the notation \( u^i \). Similarly, \( e_j^i \) means the employment of \( i \) worker type in a \( j \) job.

\[
\begin{align*}
u^0 + u^1 + e_m^0 + e_r^0 + e_m^1 + e_r^1 &= 1
\end{align*}
\]

Before understanding the flow of workers between unemployment and employment, I first explain the number of unemployed workers in each labor market. Due to the ability requirements, all unemployed workers do not stay in both labor markets. Among the total unemployed inexperienced workers \( u^0 \), the maximum ability \( \epsilon_0^{**} \) for manual tasks restricts the number of unemployed inexperienced workers in the manual market denoted \( u_m^0 \) as the minimum ability requirement \( \epsilon_0^* \) for routine tasks regulates the number of unemployed inexperienced workers in the routine market, \( u_r^0 \). Likewise, \( \epsilon_1^{**} \) also manages the number of unemployed experienced workers in the routine market, \( u_r^1 \). Among the total unemployed experienced workers, \( u^1 \). The number of the unemployed experienced workers holding a routine job, \( u^1_r \), is exactly the same as the total unemployed experienced workers, \( u^1 \), because all experienced workers satisfy the minimum ability requirement, \( \epsilon_0^* \), which is greater than \( \epsilon_1^* \). Therefore, the number of unemployed workers in the market \( j \), \( u_j \), is the sum of the inexperienced and the experienced unemployed workers in that market, \( (u_j = u_j^0 + u_j^1) \), and the sum of unemployed workers in the manual market and in the routine market is greater
than the aggregate unemployed worker in the economy ($u_m + u_r > u$) because of applicants in both markets.

Once the unemployed workers define themselves as qualified for the labor market $j$, the flow of workers into and out of unemployment follows the dynamics below.

$$
\dot{u}^0 = -u^0 \delta - u^0_m m(\theta_m) - u^1_r m(\theta_r) + \lambda(e^0_r + e^0_m) + \delta
$$

$$
\dot{u}^1 = -u^1 \delta - u^1_m m(\theta_m) - u^1_r m(\theta_r) + \lambda(e^1_r + e^1_m)
$$

$\dot{u}^i$ is the changes in the unemployment of $i$ type workers. The first three terms are the flows out of unemployment due to exit of workers ($-u^i \delta$) and the number of workers who find a job at a rate of job finding in the market $j$, ($-u^i_m m(\theta_m) - u^i_r m(\theta_r)$). The next two terms ($\lambda(e^i_r + e^i_m)$) are the flows into unemployment because of the exogenous employment separation shock. In addition, the last term $\delta$ describes new entrants who enter the inexperienced unemployment pool in each period. Similarly, $\dot{e}_j^i$ denotes the change in employment of worker type $i$ in market $j$. The inflow of matched workers from unemployment, $u^i_j m(\theta_j)$, and the outflow of employees to the unemployment pool by a catastrophic shock and retirement. The promotion in the routine job makes inexperienced workers move to the employment pool for the experienced at rate $\gamma$.

$$
\dot{e}_m^0 = u^0_m m(\theta_m) - e_m^0 (\delta + \lambda)
$$

$$
\dot{e}_m^1 = u^1_m m(\theta_m) - e_m^1 (\delta + \lambda)
$$

$$
\dot{e}_r^0 = u^0_r m(\theta_r) - e_r^0 (\delta + \lambda) - e_r^0 \gamma
$$

$$
\dot{e}_r^1 = u^1_r m(\theta_r) - e_r^1 (\delta + \lambda) + e_r^0 \gamma
$$

### 2.2.6 Equilibrium

An equilibrium consists of the value functions for the worker, $\{U^0(\epsilon), U^1(\epsilon), E^0_m(\epsilon), E^1_m(\epsilon), E^0_r(\epsilon), E^1_r(\epsilon)\}$, the value function for the firm $\{V_m, V_r, J^0_m(\epsilon), J^1_m(\epsilon), J^0_r(\epsilon), J^1_r(\epsilon)\}$, the market tightness $\{\theta_m, \theta_r\}$, and ability requirements for qualifying for the routine and the manual jobs $\{\epsilon^*_0, \epsilon^*_1, \epsilon^{**}_0, \epsilon^{**}_1\}$, such that:

1. The value functions $U^0(\epsilon), U^1(\epsilon), E^0_m(\epsilon), E^1_m(\epsilon), E^0_r(\epsilon), E^1_r(\epsilon), J^0_m(\epsilon), J^1_m(\epsilon), J^0_r(\epsilon), J^1_r(\epsilon), V_m, V_r$ satisfy equations (2.1)-(2.12) simultaneously.
2. The ability requirements $\epsilon^*_0$, $\epsilon^*_1$, $\epsilon^{**}_0$, and $\epsilon^{**}_1$ must be optimal decision rules for a job application.

3. The market tightness $\theta_m$ (and $\theta_r$) satisfies the free-entry condition $V_m = 0$ ($V_r = 0$)

4. Nash bargaining: $w^i_j(\epsilon)$ is determined by the Nash bargaining sharing rule (2.13) with a weight $\eta$ given to the workers, where $j \in \{m, r\}$ and $i \in \{0, 1\}$

5. Steady state conditions: The following worker flow equations hold in the steady state.

$$
\begin{align*}
\left. u^0_m(\theta_m) + u^0_r(\theta_r) + u^0\delta & = (e^0_r + e^0_m)\lambda + \delta \\
u^1_m(\theta_m) + u^1_r(\theta_r) + u^1\delta & = (e^1_r + e^1_m)\lambda \\
e^0_r(\delta + \lambda) + e^0_r\gamma & = u^0_r(\theta_r) \\
e^0_m(\delta + \lambda) & = u^0_m(\theta_m) \\
e^1_r(\delta + \lambda) & = u^1_r(\theta_r) + e^0_r\gamma \\
e^1_m(\delta + \lambda) & = u^1_m(\theta_m)
\end{align*}
$$

2.2.7 Characterizing the equilibrium

2.2.7.1 The job value and a wage

Under the Nash bargaining rule (2.13) with free-entry condition ($V_j = 0$), the value functions for the worker, equations (2.1)-(2.6) and the value functions for the firm, equations (2.7)-(2.12) generate the wage $w^i_j(\epsilon)$ for the pair of the $j$ task job and the $i$ type worker with ability $\epsilon$ as below. (See the Appendix B.2 and B.3 for more detail.)

If the worker’s ability level is in the range over $[0, \epsilon^*_0]$, that worker could apply only for a manual job, so they must be inexperienced. The value of a filled manual job would be the equation (2.15) and the worker receives $w^0_m$ as the equation (2.14). Because the worker in the range of $[0, \epsilon^*_0]$ does not have a routine job option and $p_m$ is fixed, the value of a manual job and the wage is constant regardless of a matched worker’s ability. Thus, in Figure 2.2, the value of a manual job on the range between $[0, \epsilon^*_0]$ is flat.

$$
w^0_m = \eta p_m + (1 - \eta)\left\{b + \frac{\eta m(\theta_m)(p_m - b)}{r + \delta + \lambda + \eta m(\theta_m)}\right\} \quad (2.14)
$$
The middle level of ability, from $\epsilon_0^*$ to $\epsilon_0^{**}$ for the inexperienced worker and from $\epsilon_0^*$ to $\epsilon_1^{**}$ for the experienced worker, allows workers to apply for both manual and routine jobs. First of all, the cases for an experienced worker are described below. An experienced worker applies for a routine job and a manual job simultaneously and the worker is matched with a job first arrived. But the wage by Nash bargaining reflects the productivity of unmatched job as an outside option, so the second term of the equation (2.16) and (2.17) are the same. Unlike $w_m^0$ of the equation (2.14), the wage increases as the level of ability of the matched worker increases, therefore the value of a filled job decreases. The wage for routine tasks also increases as the worker’s ability rises. The value of a routine job, however, does not decrease because the units of output grow faster than the wage.

\[ w_m^1(\epsilon) = \eta p_m + (1 - \eta) \left\{ b + \frac{\eta m(\theta_m)(p_m - b) + \eta m(\theta_r)(p_r + \beta \epsilon - b)}{r + \delta + \lambda + \eta m(\theta_m) + \eta m(\theta_r)} \right\} \quad (2.16) \]

\[ w_r^1(\epsilon) = \eta(p_r + \beta \epsilon) + (1 - \eta) \left\{ b + \frac{\eta m(\theta_m)(p_m - b) + \eta m(\theta_r)(p_r + \beta \epsilon - b)}{r + \delta + \lambda + \eta m(\theta_m) + \eta m(\theta_r)} \right\} \quad (2.17) \]
An inexperienced worker whose ability is in the middle range of distribution also applies for both jobs simultaneously, but the range of ability needs to be taken care of. Considering the possibility of being experienced, the job value filled with and the wage paid to an inexperienced worker partially relies upon the experienced ones. Due to the relation \( \epsilon^*_1 < \epsilon^*_0 \), the middle range of ability for inexperienced workers is larger than that for the experienced, workers with ability between \( \epsilon^*_1 \) and \( \epsilon^*_0 \) would stay only in the routine job market after being promoted. Therefore, the workers in the lower part of the middle range \([\epsilon^*_0, \epsilon^*_1]\) are affected by the equations (2.18) and (2.19) and their wages reflects equations (2.16) and (2.17). These values are described in equations (2.20)-(2.23) in terms of the values and the wages of experienced workers in both markets (The value and the wage with respect to parameters are described in the Appendix). Compared to an experienced worker with the same level of ability, an inexperienced worker is paid less regardless of which tasks they perform. The wage gap is derived from the individual productivity gap \((\alpha - \beta)\). It results in the difference in the value of a filled job as shown in Figure 2.2. The constant productivity of a manual task job is not damaged by the worker’s characteristics and hence manual firms would be better to hire inexperienced workers. On the contrary, the productivity of routine task jobs relies on the worker’s ability and experience. At any specific ability level, the value of a routine job that hires an inexperienced worker cannot exceed the one with an experienced worker even though the wage for the inexperienced is lower.

\[
J^1_m(\epsilon) = \frac{1 - \eta}{r + \delta + \lambda} \left\{ p_m - \left[ b + \eta m(\theta_m)(p_m - b) + \eta m(\theta_r)(p_r + \beta \epsilon - b) \right] \right\} \quad (2.18)
\]
\[
J^1_r(\epsilon) = \frac{1 - \eta}{r + \delta + \lambda} \left\{ (p_r + \beta \epsilon) - \left[ b + \eta m(\theta_m)(p_m - b) + \eta m(\theta_r)(p_r + \beta \epsilon - b) \right] \right\} \quad (2.19)
\]

\[
w^0_m(\epsilon) = w^1_m(\epsilon)(2.16) + (r + \delta + \lambda)\eta m(\theta_r)[A] \quad (2.20)
\]
\[
w^0_r(\epsilon) = w^1_r(\epsilon)(2.17) + (\alpha - \beta)\epsilon - (r + \delta + \lambda + \gamma)(r + \delta + \lambda + \eta m(\theta_m))[A] \quad (2.21)
\]
\[
J^0_m(\epsilon) = J^1_m(\epsilon)(2.18) - \eta m(\theta_r)[A] \quad (2.22)
\]
\[
J^0_r(\epsilon) = J^1_r(\epsilon)(2.19) + (r + \delta + \lambda + \eta m(\theta_m))[A] \quad (2.23)
\]

where, \([A] = \frac{(1 - \eta)(r + \delta)(\alpha - \beta)\epsilon}{(r + \delta)(r + \delta + \lambda + \gamma)(r + \delta + \lambda + \eta m(\theta_m)) + \eta m(\theta_r)(r + \delta + \lambda)(r + \delta + \gamma)} \leq 0\)
For the upper part of the middle level of ability, $[\epsilon_1^{**}, \epsilon_0^{**}]$, the job values and wages are suggested in equations (2.24)-(2.27). The difference between the worker holding ability in this range and those who locate the lower section of the ability distribution is the application decision after being experienced. Once they are promoted in the routine task job, the wage paid to them as the experienced is higher than before, and they would stop searching for a manual task job. These changes affect the current wages through outside options. The wage for routine task, in the equation (2.25), grows at a slower speed than (2.21). It seems to be a consequence of the plan, which gives up a manual job opportunity. Thanks to the lower wage, the value of a routine job (2.27) increases rapidly as the matched worker’s ability increases. The manual job which hires the worker responds differently. Even though the firm produces the fixed units of output $p_m$ but knows the worker is treated better in the routine market, so the wage (2.24) is higher than the one (2.20). The value of a manual job (2.26) surely drops quicker than (2.22). Figure 2.2 shows differences in the slope of a job value on the range over $[\epsilon_0^{**}, \epsilon_1^{**}]$ and $[\epsilon_0^{**}, \epsilon_1^{**}]$.\footnote{The term $[B]$ is positive if the ability level is greater than $\epsilon_1^{**}$. The next part explains the minimum/maximum ability requirements to be matched with a routine/manual job, and $\epsilon_1^{**}$ is the maximum ability for the experienced to be matched with a manual job. At $\epsilon = \epsilon_1^{**}$, $[B]$ is zero and increases as the $\epsilon$ goes to the unity.}

$$w^0_m(\epsilon) = w^0_m(\epsilon)(2.20) + (r + \delta + \lambda)\eta m(\theta_r)[B] \quad (2.24)$$
$$w^0_r(\epsilon) = w^0_r(\epsilon)(2.21) - (r + \delta + \lambda)\left\{ \frac{(r + \delta + \lambda + \eta m(\theta_m)) + (r + \delta + \lambda + \eta m(\theta_m) + \eta m(\theta_r))}{\lambda} \right\}[B] \quad (2.25)$$
$$J^0_m(\epsilon) = J^0_m(\epsilon)(2.22) - \eta m(\theta_r)[B] \quad (2.26)$$
$$J^0_r(\epsilon) = J^0_r(\epsilon)(2.23) + (r + \delta + \lambda + \eta m(\theta_m))[B] \quad (2.27)$$

where, $[B] = \frac{(1 - \eta)\gamma \lambda \eta m(\theta_m)}{(r + \delta + \lambda) - \eta m(\theta_r) - \eta m(\theta_m) + \eta m(\theta_r)} \times \left\{ \eta m(\theta_r)(p_r + \beta \epsilon - b_m) - (r + \delta + \lambda)(p_m - b) \right\} \geq 0$

Workers belong to the highest range of ability, from $\epsilon_1^{**}$ or $\epsilon_0^{**}$ to 1, are now applying for routine tasks only. Since the worker could not be employed by the manual task firm, the
option outside the routine market is just being unemployed thus an increment in wages for 
a routine job per unit of ability decreases. The wage paid to an experienced worker in the 
equation (2.28) and the value of a routine job (2.30) matched with the worker consists of the 
worker productivity, unemployment benefit, and a routine market tightness. Similarly, the 
2.7.2 Ability requirements 
The values of a filled job with Nash bargaining wages in the previous section 2.2.7.1 are 
composed of productivities \( \{p_m, p_r, \alpha, \beta\} \), worker’s ability \( \epsilon \) and the matching rates \( \{\theta_m, \theta_r\} \), 
thus the ability requirements derived from the job values are represented by productivities 
and matching rates. Among nine equations above, (2.18), (2.19), (2.26) and (2.27), bring 
information about qualifications.

Using equations (2.18) and (2.19), \( J^1_r(\epsilon^*_1) = 0 \) and \( J^1_m(\epsilon^{**}_1) = 0 \), derive \( \epsilon^*_1 \) and \( \epsilon^{**}_1 \).

\[
\epsilon^*_1 = \frac{\eta_m(\theta_m)(p_m - p_r) - (r + \delta + \lambda)(p_r - b)}{\beta(r + \delta + \lambda + \eta m(\theta_m))} (2.32)
\]

\[
\epsilon^{**}_1 = \frac{\eta m(\theta_r)(p_m - p_r) + (r + \delta + \lambda)(p_r - b)}{\beta\eta m(\theta_r)} (2.33)
\]

Making Eq.(2.26) and (2.27) equal zero, \( J^0_r(\epsilon^*_0) = 0 \) and \( J^0_m(\epsilon^{**}_0) = 0 \), provide \( \epsilon^*_0 \) and
\(\epsilon_{0}^{**}\text{. For simplicity, I show }\epsilon_{0}^{*}\text{ and }\epsilon_{0}^{**}\text{ by means of }\epsilon_{1}^{*}\text{ and }\epsilon_{1}^{**}\text{.}

\[
\epsilon_{0}^{*} = \frac{(\beta(r + \delta + \lambda) + \beta \gamma)(r + \delta)(r + \delta + \lambda + \eta m(\theta_{r}) + \eta m(\theta_{m})) + \beta \gamma \lambda \eta m(\theta_{r})}{\alpha(r + \delta + \lambda + \beta \gamma)(r + \delta)(r + \delta + \lambda + \eta m(\theta_{m}) + \eta m(\theta_{r})) + \beta \gamma \lambda \eta m(\theta_{r})} [\epsilon_{1}^{*}] \quad (2.34)
\]

\[
\epsilon_{0}^{**} = \frac{\beta(r + \delta + \lambda) + \beta \gamma + \eta m(\theta_{r})(\beta(r + \delta) + \beta \gamma)}{\alpha(r + \delta + \lambda + \beta \gamma) + \eta m(\theta_{r})(\alpha(r + \delta) + \beta \gamma)} [\epsilon_{1}^{**}] \quad (2.35)
\]

As far as \(\beta > \alpha\), the ability requirements of the inexperienced worker are greater than the ones of the experienced worker. However, \(\epsilon_{1}^{**}\text{ relative to }\epsilon_{0}^{*}\text{ is ambiguous.}

\[
\epsilon_{1}^{*} < \epsilon_{1}^{**}, \quad \epsilon_{1}^{*} < \epsilon_{0}^{*}, \quad \epsilon_{0}^{**} < \epsilon_{0}^{**}
\]

2.2.8 Changes in steady state caused by RBTC shock

To describe the impact of the RBTC, I drop the base productivity of a routine job. As computerization and automation have been developed, capital input factors substitute labor force intensely in the section handling routine tasks. ALM(2003) use a decline in the price of computers to explain the substitution of computer inputs for labor inputs in routine tasks. Even though this model does not explicitly contain the role of capital goods, a decrease in productivity of labor inputs in routine tasks could be interpreted as a decline in productivity relative to the performance of the unit dollar value of computer input as ALM(2003) describe. This paper assumes that there are no differences in the complexity or the substitutability across routine task jobs. A decrease in labor productivity relative to the productivity of capital regardless of the worker’s dexterity could be interpreted as a drop in the base productivity. Thus, \(p'_{r}\text{ hereafter indicates new base productivity of a routine job incurred by the one-time RBTC shock, and }p'_{r} < p_{r}\text{ accordingly.}

The drop in productivity of routine tasks brings about several changes in the economy. First, the value of a routine job declines and the value of a manual job increases, holding all other things constant. The value of a routine job is explicitly affected by a change in \(p_{r}\), so a decrease in \(p_{r}\) leads a fall in the value of a routine job. Moreover, Nash bargaining wages are distorted by \(p'_{r}\). Firms performing routine tasks promptly respond to the new match surplus under the new productivity by cutting the wage. While the wage for a manual task also decreases if it is paid to a worker who is qualified for both manual and routine task jobs through an outside option, therefore the value of this manual job increases as the wage
decreases while the productivity of a manual job $p_m$ is constant. On the contrary, the value of a routine job decreases because the impact of $p'_r$ on the wage of a routine job is smaller than the degree of decrease in $p_r$.

Figure 2.3: Comparison of Job Values Before and After the RBTC Shock

![Graph showing changes in job values](image)

**Note:** The initial job values are on the left, whereas right-side graphs describe how the value of a job changes. The graphs on the top show changes in the value of a manual job and the graphs on the bottom show changes in the value of a routine job by a decrease in $p_r$ due to the RBTC shock. A drop in $p_r$ shifts the manual job value upward and the routine job value downward. These changes cause changes in ability requirements, so both $\epsilon_1^*$ and $\epsilon_1^{**}$ increase. All $\epsilon$ shifts to the right, and $\epsilon_0$ moves further than $\epsilon_1$. Solid lines are for the job matched with an inexperienced worker and the dashed line is for the job with an experienced worker.

Second, the ability requirements respond to the changes in the job values. Until the matching rates adapt to new productivity $p'_r$, the minimum level of ability to have a routine
job, $\epsilon_i^*$, follows the change in productivity. From the equations (2.32) and (2.34), $\epsilon_i^*$ are inversely related to $p_r$ so $\epsilon_i^*$ increases as $p_r$ decreases. It means that individual-specific ability is needed to compensate for the commonly low productivity of labor in routine tasks, $\epsilon_0^*$ expands more than $\epsilon_1^*$ because the inexperienced worker cannot fill the gap with their skills. Likewise, the maximum level of ability $\epsilon_i^{**}$ to be qualified for a manual job shifts to the right since the wage paid to an applicant who has an outside option falls, so a worker with a higher ability level would be available for the manual job. Here, $\epsilon'$ indicates new ability requirements. Next, the changes in ability requirements cause changes in unemployment. To begin with, increased ability requirements for routine jobs deprive some employees of a qualification. Thus, existing pairs are broken if matched with a worker whose ability belongs to $\epsilon_0^* \leq \epsilon < \epsilon_1'$, then those workers flow into the unemployment pool. Then, the total unemployment rate jumps. Moreover, new ability requirements occur the changes in the composition of unemployment. All ability requirements shift toward one, thus the total number of applicants for manual jobs increases while that for routine jobs decreases. Furthermore, since ability requirements for inexperienced workers go further than the ones for experienced workers, the possible range of the ability to apply for the routine jobs is much narrower for inexperienced workers than experienced workers, whereas the range of ability for those who are willingly searching for manual jobs is much wider for inexperienced workers than experienced workers. Consequently, the proportion of the inexperienced workers among the total unemployed workers available to routine tasks becomes relatively smaller and the share of inexperienced unemployed workers in the unemployment pool for manual tasks is relatively greater than steady status before the shock arrives.

Finally, the firms respond to $p_r'$ by changing the number of vacancies. The analysis above assumed that the matching rates are constant at the initial level. However, once the job values change and the unemployment rate increases, these affect the value of a vacancy. I rearrange the equation (2.8), the value of a vacancy for a routine job, with free-entry condition $V_r = 0$. The cost of holding a vacancy $c_r$ on the left-hand side is constant but the job value the firm possibly has, terms in the curly braces of the equation (2.8), decreases as soon as the RBTC shock arrives. Even though the probability of meeting an inexperienced worker whose job value $J_r^0(\epsilon)$ is lower than the experienced’s $J_r^1(\epsilon)$, the increase in the probability of hiring a relatively productive experienced worker is far outweighed.

\footnote{For an experienced worker, the match would be separated only if $\epsilon_0^* < \epsilon_1'$.}
by diminished job values. Thus, the expected value of a match declines. The job filling probability should increase to compensate for the shrunken job values. Since the job filling rate, \( m(\theta_r)/\theta_r = M(u_i, v_i)/v_i = M(u_i/v_i, 1) \), is inversely related with the number of the unemployed, which was decreasing by the shock, firms holding vacancies for routine tasks cut the number of vacancies more than the disappeared unemployed workers to raise the job filling rate. A new market tightness of the routine job market \( \theta_r \) is lower than before.

\[
c_r = \frac{m(\theta_r)}{\theta_r} \left\{ \left( \frac{u^0_r}{u^0_r + u^1_r} \right) E \left[ J^0_r(\epsilon) \right] + \left( \frac{u^1_r}{u^0_r + u^1_r} \right) E \left[ J^1_r(\epsilon) \right] \right\} \tag{2.36}
\]

Inversely, manual task firms created more vacancies. The RBTC shock enhances the expected value of a manual job by cutting wages for workers lying on the middle range of ability and expanding the range of ability suitable for manual jobs. It increases the number of the unemployed and a fraction of the inexperienced in the unemployment pool for manual tasks. For the constant cost of job posting \( c_m \) in the equation (2.37), the job filling rate \( m(\theta_m)/\theta_m \) should decrease. Hence, firms create more vacancies than an increment in the unemployed workers. Thus, the new market tightness in the manual job market is higher than the initial \( \theta_m \).

\[
c_m = \frac{m(\theta_m)}{\theta_m} \left\{ \left( \frac{u^0_m}{u^0_m + u^1_m} \right) E \left[ J^0_m(\epsilon) \right] + \left( \frac{u^1_m}{u^0_m + u^1_m} \right) E \left[ J^1_m(\epsilon) \right] \right\} \tag{2.37}
\]

Because the value of a filled job, the ability requirements, and the matching rates are interconnected, the procedures explained above are repeated until reaching a new equilibrium. In the equilibrium with \( p'_r \), ability requirements are larger, new market tightness \( \theta'_m \) is greater and \( \theta'_r \) is lower than ones before the shock arrived. According to qualifications for a job and market tightness in the new equilibrium, workers and firms adjust their behaviors.

While the economy converges toward the new steady-state, a higher job-finding rate

---

8The changes in the ability thresholds with respect to market tightness are suggested below.

\[
\frac{\partial \epsilon^*_1}{\partial \theta_m} > 0, \quad \frac{\partial \epsilon^*_1}{\partial \theta_r} = 0, \quad \frac{\partial \epsilon^*_1}{\partial \theta_m} > 0, \quad \frac{\partial \epsilon^*_1}{\partial \theta_r} < 0 \\
\frac{\partial \epsilon^*_0}{\partial \theta_m} > 0, \quad \frac{\partial \epsilon^*_0}{\partial \theta_m} > 0, \quad \frac{\partial \epsilon^*_0}{\partial \theta_r} < 0, \quad \frac{\partial \epsilon^*_0}{\partial \theta_r} < 0
\]

As \( \theta_m \) increases and \( \theta_r \) decreases, these changes shift ability thresholds to the right further. These higher \( \epsilon \)s in the process for the value of vacancies raise \( \theta_m \) and lower \( \theta_r \). The adjustment procedures caused by interdependence between ability requirements and market tightness iterate.
$m(\theta_m')$ leads to rapid transitions from unemployment to employment in the manual task sector. A lower rate of routine job-finding rate $m(\theta_r')$, meanwhile, slows down flows from unemployment into employment in a routine task sector. As more workers are matched with a manual task job, the share of employment in routine tasks decreases. Besides, the total employment rate falls. Even though $\theta_m$ increases, the degree of an increment of $\theta_m$ cannot exceed the degree of a decrease in $\theta_r$ because the impact of the RBTC is delivered to a manual job only through workers while it hits the routine market directly. For that reason, an increase in manual task employment is lesser than a decrease in routine task employment, so the unemployment rate increases. Furthermore, a low $\theta_r$ eventually decreases the proportion of experienced workers. New entrants filling the vacancies for the experienced workers who left are inexperienced, but they cannot get the opportunity of being experienced as much as the old workers had because the RBTC shock lowers the probability of finding a routine job and makes ability requirements stricter. Note that the prerequisite of being experienced is getting a routine job, it generates a decrease in the number of experienced workers and a fall in the number of unemployed experienced workers in the economy as well.

Consequently, when the RBTC shock decreases the productivity of workers hired to do routine tasks, that impact lowers the surplus of a routine task match, the wage paid to a qualified worker, and the employment in the routine job market. It also reallocates existing workers between employment and unemployment or across the labor markets. Furthermore, the new entrants have inferior opportunities to old workers because young entrants are hard to achieve a qualification for a routine job, less likely to be matched with a routine job, and more likely to remain unemployed. To further understand this analysis numerically, I examine how the RBTC shock affects experienced and inexperienced workers in the next section.

### 2.3 MODEL SIMULATION

#### 2.3.1 Parameters

This part investigates how the change in routine task productivity affects the labor markets in terms of the unemployment rate and changes in the number of routine jobs or manual jobs in the economy. The model operates at a monthly frequency. The parameters are chosen to match key features of the labor market in the United States in 1980, the
period that was not affected by the RBTC yet to understand the impact of changes in base productivity of labor in routine tasks. Since it is considered that the disappearance of occupations focused on “routine” tasks is vastly accelerated in the 1980s, the first year of the 1980s is suitable (Acemoglu & Autor, 2011; Autor & Dorn, 2013; Autor, Katz, & Kearney, 2008; Cortes, 2016; Cortes, Jaimovich, & Siu, 2017; Jaimovich & Siu, 2012).9

A summary of the parameter values chosen is presented in Table 2.1.

Table 2.1: Parameter Values

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>r</td>
<td>0.003</td>
<td>annual 4% interest rate.</td>
</tr>
<tr>
<td>δ</td>
<td>1/480</td>
<td>worker’s exit rate. the average 40 years of work.</td>
</tr>
<tr>
<td>λ</td>
<td>1/30</td>
<td>job separation rate. One job last around 30 months</td>
</tr>
<tr>
<td>γ</td>
<td>0.009</td>
<td>probability of promotion rate in routine job</td>
</tr>
<tr>
<td>η</td>
<td>0.5</td>
<td>workers bargaining power</td>
</tr>
<tr>
<td>b</td>
<td>0.4</td>
<td>Utility value of unemployment</td>
</tr>
<tr>
<td>p_m</td>
<td>1</td>
<td>productivity of manual jobs (normalized)</td>
</tr>
<tr>
<td>p_r</td>
<td>0.7</td>
<td>base productivity of routine jobs</td>
</tr>
<tr>
<td>α</td>
<td>1.033</td>
<td>productivity per unit of ability for an inexperienced worker</td>
</tr>
<tr>
<td>β</td>
<td>2.411</td>
<td>productivity per unit of ability for an experienced worker</td>
</tr>
<tr>
<td>c_r</td>
<td>6.243</td>
<td>the flow cost of a vacancy for a routine job</td>
</tr>
<tr>
<td>c_m</td>
<td>2.409</td>
<td>the flow cost of a vacancy for a manual job</td>
</tr>
</tbody>
</table>

The discount rate $r$ is set 0.003 to match an annual interest rate 4%. The rate of labor force exit $δ$ was set to 1/480 based on the assumption that workers stay an average of 40 years. Thus, at each time, 1/480 fraction of the labor is new and inexperienced entrants who replace retirees.10 Even if the worker stays in the labor force, the worker’s current employment could be separated because of the aggregate shock that hits the economy according to a Poisson process with arrival rate $λ$. The separation results in unemployment, so I used some clues about $λ$ from previous research. Shimer (2005) provides a quarterly separation

9However, some research explains that the impact of the RBTC was started earlier than the 1980s. For example, the fundamental research by ALM (2003) examine the changes in the composition of job tasks and find that shifts in the labor demand were commenced in the 1970s according to progress in technologies and rapid computerization.

10I assume that workers enter the labor market at the age of 20. Rutledge et al. (2018) reveal that the average retirement age for men with only a high school diploma is around 62.1 to 62.6 between 1980 and 2009 based on CPS. For simplicity, I cut the average retirement age at 59 to make the average expected remaining length of participation of workers be 40.
rate of 0.1 from the process of calibration to match the time-series behavior of the U.S. unemployment rate, Hall (2005) sets 0.034 for a monthly separation rate and Shimer (2012) suggests the average employment exit probability of 3.4% per month. These studies suggest approximately 30 months duration of the job. It is similar to the job tenure reported by the Bureau of Labor Statistics (BLS). Thus, I set the separation rate to 1/30 which means one matching last for 2.5 years.

The rate at which inexperienced workers become experienced is not frequently discussed in the previous literature, but Rutledge and Guan (2015) give a hint about skill level transitions based on Survey of Income and Program Participation (SIPP). Authors fundamentally follow the conventional ALM(2003) occupation classification, but they rearrange the workers by skill levels. So, we can use information about middles-skilled workers or low-skilled workers in the same occupation group. For example, administration occupation is classified as a routine job by ALM(2003) regardless of worker’s proficiency, but Rutledge and Guan (2015) divide those who hold administrative occupation into Low-skilled administration and Skilled administration. I define low-skilled workers as inexperienced and skilled workers as experienced if they are hired in the routine job for this model. In Rutledge and Guan (2015), the fraction of skilled workers is 75.1% and low-skilled workers 24.9% within the routine task category. Based on this, I set a monthly promotion rate as 0.009; an annual promotion rate is around 11%. It is almost consistent with the skill level transition rate within the same employer for workers aged 35-49, 11.2% in Rutledge and Guan (2015). This probability of promotion, $\gamma = 0.009$ is expected to make the proportion of experienced

---

11 Hall (2005) examines the impact of wage stickiness on unemployment with the Job Openings and Labor Turnover Survey (JOLTS). While he calculates the fixed-wage model to match observed data regarding unemployment, the separation rate is set to 0.034 per month. Shimer (2012) measures transition rates between employment and unemployment by using the Current Population Survey (CPS) from 1948 to 2010. During this period, the average employment exit probability considers only transitions between employment and unemployment, not in and out of the labor force. Thus, this measurement corresponds to the assumption of the model that takes only the labor force into account.

12 Horvath (1982) reports job tenure trend in 1981. Although job tenure in the report includes termination of employment by voluntarily quitting, being laid off for 30 days or more, or transferring to a job in a different company, that explains the length of time a worker has worked continuously for the same employer to calculate job separation rate. The median years of tenure with current employer for men in 1981 were 4.0 years. However, this duration is affected by age, occupation, industry. If professional jobs, which have longer job tenure in general, are excluded, the job tenure of occupations available to the less-educated workers in this model is much shorter: sales 3.4, clerical 3.4, craft 4.4, operative 3.5, transportation 3.7, non-farm labor 1.8, service 2.1 years. When wage and salary workers are included, the median years on the current job becomes 3.7. The trend could be followed each year, and the trend seems not to be volatile. The recent reports for 2018: https://www.bls.gov/news.release/pdf/tenure.pdf.
The matching function takes the standard Cobb-Douglas form, \( m(u_j, v_j) = u_j^{\eta_j}v_j^{1-\eta_j} \), where \( \eta \) is set to 0.5. This value is at the lower end of the range of estimates found in Petrongolo and Pissarides (2001). The choice of the elasticity of the matching function with respect to unemployment which is set equal to \( \eta \) ensures that the Hosios condition applies (Hosios, 1990).

Next, parameters for productivity and the unemployment benefit need to be chosen. I normalize the productivity of a manual job parameter to \( p_m \) to unity. Relative to normalized \( p_m \), I set the value of leisure to \( b = 0.4 \) as in Shimer (2005). However, parameters for the productivity of a routine job, \( p_r \), \( \alpha \), and \( \beta \), are hard to measure directly, so they are rarely discussed in previous papers. Instead, the seminal research concerning the impact of RBTC uses the wages for those who hold the job to compare productivity (Acemoglu & Autor, 2011; Autor & Dorn, 2009, 2013; Autor et al., 2003). These studies show the changes in the productivity of routine jobs by decreases in wages for routine tasks relative to wages for abstract and manual tasks or the price of computers. However, productivity is still not stated. Thus, I estimate the productivity of routine jobs and other remaining parameters, the cost of posting a vacancy, \( c_m \) and \( c_r \), jointly to target features of labor market condition in 1980. To find the parameters \( p_r \), \( \alpha \), and \( \beta \), I begin with the unemployment rate, the fraction of employment in routine jobs and in manual jobs. The unemployment rate among male adults was 6.9% in 1980. The employed workers in this model are hired either in routine jobs or in manual jobs, so I calculated the fraction of routine employment based on Autor and Dorn (2013).\(^{13}\) Because authors measure employment shares by occupation groups among workers without a college education, it fits well for the assumption of this paper regarding education attainments of workers.\(^{14}\) Conditional on employment, a share

\(^{13}\)In Autor and Dorn (2013), Table 1 in Appendix shows that levels and changes in employment share and mean real log hourly wages by major occupation groups among workers without a college education during 1950-2005. The authors state that occupation categories follow Census classification. I add ALM(2003) occupation classification: Managers/prof/tech/finance/public safety (Abstract, 14.5%); Production/craft (Routine, 6.0%); Transportation/construct/mech/mining/farm (Routine, 29.5%); Machine operator/assembly workers (Routine, 14.7%); Clerical/retail sales (Routine, 22.4%); Service occupations (Manual, 12.9%)

\(^{14}\)Autor and Dorn (2013) includes both male and female workers to measure employment shares. Compared to the male and female employment share in Acemoglu and Autor (2011), however, the employment shares of this measurement is much closer to the employment share of male workers; the employment share of male workers in routine jobs is 85.8% and manual employment share is 14.2% conditional on employment in either routine or manual jobs. The same one for female workers are 75.3% and 24.7% respectively (in 1979, Census IPUMS 5 percent samples by Acemoglu and Autor (2011)).
of routine tasks is 84.9% and a manual portion is 15.1%. Therefore, the productivity of routine jobs targets the unemployment rate 6.9%, the employment share of routine jobs 79.1%, and the employment share of manual jobs 14.0%. Moreover, I add the relative wages for inexperienced and experienced workers as Gorry (2013) does. To keep the consistency with other data, I used the median earnings of male workers in 1980. Young workers aged 20-24 earned $223 while 45-54 years old workers made $366 per week. Even though this wage ratio does not sort the influence of education attainments or occupations, the relative ratio of 1.64 could reflect the difference in productivity due to experience because it is stable that the trend of changes in median wages among age groups over time. Since the wages for routine tasks depend on the level of ability $\epsilon$ as well as experience, the average wages over the level of ability available to routine jobs are used to match the target.

The estimation generates $p_r = 0.7$, $\alpha = 1.03$ and $\beta = 2.41$. The estimate $p_r$ satisfies the condition that $p_r < p_m$ to prevent those who do not have high ability from applying for a routine job. When parameters of routine tasks productivity follow the estimated values, the share of experienced workers among routine job holders $e_r^1/(e_r^1 + e_r^0)$ is 79.84% which is almost the same as the probability 80% expected by $\gamma = 0.009$. While the productivity of routine jobs were estimated, the job finding rates $m(\theta_r)$ and $m(\theta_m)$ are also set to match targets. The results show that $m(\theta_r) = 0.47$ and $m(\theta_m) = 0.43$, these belongs to the range of an average job finding rate between 0.4 by Shimer (2005) and 0.48 by Hall (2005).

Given the productivity and matching rates, the ability requirements are determined: $\epsilon^*_1 = 0.0863$, $\epsilon^*_0 = 0.1217$, $\epsilon^{**}_1 = 0.1645$ and $\epsilon^{**}_0 = 0.2121$. These ability requirements divide the entire range of ability over [0,1] into three sections, and it determines the number of unemployed workers in each section. Additionally, the job values are generated. Based on the values, the flow cost of a vacancy $c_r$ and $c_m$ are chosen to make the value of a vacancy be zero. This implies $c_r = 6.243$ and $c_m = 2.409$

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15Gorry (2013) estimates the productivity of experienced workers that targets to match the mean wage for the experienced relative to the mean wage for the inexperienced in 2006. The $7.88 mean wage for 18-year-old is taken for inexperienced workers while $15.31 mean wage of 45–54-year-old is taken for experienced workers.


17The job-finding probability calculated by Shimer (2005) is very volatile during 1980 and 2004 along the business cycle. However, the possible range for the job-finding rates is between 0.3 to 0.5
2.3.2 Model prediction

2.3.2.1 Changes in ability requirements by the RBTC

Before the shock arrived, the economy was in a steady state. The steady-state implies the fraction of unemployed workers and employed workers by worker’s experience and job type in Table 2.2. Previously, the ability requirements for holding routine occupations were not too high, so most workers could apply for routine jobs. 79% of workers are employed in routine task jobs and 68.8% of workers are experienced.

Table 2.2: The Share of Population in Each Status in the Initial Steady State

<table>
<thead>
<tr>
<th>Status</th>
<th>Fraction</th>
</tr>
</thead>
<tbody>
<tr>
<td>$u^0$</td>
<td>0.0244</td>
</tr>
<tr>
<td>$u^1$</td>
<td>0.0446</td>
</tr>
<tr>
<td>$e_r^0$</td>
<td>0.1593</td>
</tr>
<tr>
<td>$e_r^1$</td>
<td>0.6313</td>
</tr>
<tr>
<td>$e_m^0$</td>
<td>0.1283</td>
</tr>
<tr>
<td>$e_m^1$</td>
<td>0.0122</td>
</tr>
<tr>
<td>sum</td>
<td>1</td>
</tr>
</tbody>
</table>

As soon as $p_r$ drops, the ability thresholds shift immediately. Figure 2.4 shows how ability requirements expand as $p_r$ falls. Due to the difference in experience-induced productivity, $\alpha < \beta$, the inexperienced workers are requested to fill the decrease in base productivity with higher ability, so ability requirements of inexperienced workers increase faster than that of experienced workers. Thus, although the maximum ability level that makes experienced workers willing to accept manual task jobs, $\epsilon_r^*_1$ is initially greater than the minimum ability requirement for routine task occupations for inexperienced workers, $\epsilon_m^0$, these two ability thresholds are reversed around $p_r = 0.4585$. It means that all experienced workers only search for routine task occupations if $p_r$ drops more than 37 percent.

2.3.2.2 Response of the routine and the manual job market to the RBTC

While the ability thresholds are adjusted, the market tightness, the number of unemployed workers, and the number of vacancies also respond to the new value $p'_r$. Figure 2.5 describes changes in the market tightness, $\theta_r$, the number of unemployed workers in the routine job market, $u_r$, and the number of vacancies for routine tasks, $v_r$, before and after $p_r$ declines. It also includes the impact of a change in $p_r$ on the job market for manual tasks, $\theta_m$, $u_m$ and $v_m$.

Table 2.3 summarizes the ability requirements before and after $p_r$ falls by 21 percent.
Figure 2.4: Ability Requirements across the Base Productivity

Note: The graph shows that increase in ability requirements to apply for routine task jobs ($\epsilon^*$) and expanded range of ability to stay in the manual task job($\epsilon^{**}$) as the base productivity of workers in performing routine task. The bold lines represent ability requirements for inexperienced workers and the dashed lines represent one for experienced workers.

All thresholds shift up that cause unemployment. Under the new circumstance, higher ability is needed to compete with the high capability of technology, so inexperienced workers are asked to have $\epsilon_0'' = 0.2103$ and experienced workers should have at least $\epsilon_1'' = 0.1483$. I do not consider $\epsilon_1^*$, the requirement for experienced workers in the initial steady-state without the RBTC shock because $\epsilon_0^*$ is always greater than $\epsilon_1^*$ regardless of $p_r$ and all workers should hurdle $\epsilon_0^*$ first to become experienced. Moreover, a worker who has already acquired experiences needs not to pass $\epsilon_0''$, even in the case $p_r$ changes. Instead, $\epsilon_1''$ is a criterion to judge the validity of a current match. Consequently, any inexperienced worker who has ability between $\epsilon_0^* = 0.1217$ and $\epsilon_0'' = 0.2103$ or any experienced worker whose ability is below $\epsilon_1'' = 0.1483$ is dismissed if matched with a routine task occupation and then goes to the unemployment pool only for manual task occupations.

In Figure 2.5, the middle column shows the changes in unemployed workers. The bold lines express unemployed workers who want to apply for the manual job and the dot-dashed
Table 2.3: Changes in Ability Requirements by the RBTC Shock

<table>
<thead>
<tr>
<th>$p_r$</th>
<th>$\epsilon_1^*$</th>
<th>$\epsilon_0^*$</th>
<th>$\epsilon_1^{**}$</th>
<th>$\epsilon_0^{**}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.700</td>
<td>0.0863</td>
<td>0.1217</td>
<td>0.1645</td>
<td>0.2121</td>
</tr>
<tr>
<td>0.553</td>
<td>0.1483</td>
<td>0.2103</td>
<td>0.2270</td>
<td>0.2930</td>
</tr>
</tbody>
</table>

line is for those searching for routine task jobs. The bold line jumps when the productivity shock hits the economy due to an inflow of workers from routine jobs. At the same time, unemployed workers with ability between an old and a new ability threshold lose their qualification for routine tasks, so they leave the unemployment pool for routine jobs. It is shown on the dot-dashed line that goes down slightly at the moment of shock arrival.

Figure 2.5: The Impact of the RBTC on Job Markets

Note: The graph shows the impact of a decline in $p_r$ by 21 percent ($p_r$ from 0.7 to 0.553) on the labor market. The graph shows the change in market tightness (left), the change in unemployment rate (middle) and the change in the number of vacancies (right) for routine task (dash-dot lines) and manual task (bold lines) occupations around the time the RBTC shock arrives.

Meanwhile, the firm which opens vacancies for routine tasks also responds to the new value of $p_r$. On the firm’s side, some existing matches are separated due to disqualification of workers with a low level of ability, the value of a filled routine task jobs plummets and the number of unemployed workers diminishes, but the cost of posting vacancies is still constant. For the free entry condition to be satisfied, firms holding routine task vacancies need a higher vacancy filling rate. Thus, vacancies are closed more than workers were displaced, and therefore routine task job market tightness drops. The right graph in Figure 2.5 illustrates how the firms adjust the number of vacancies and the left graph, a decline in the market tightness of routine task jobs, represents the consequence of both workers’ and
firms’ responses. On the contrary, the firms that create vacancies for manual tasks react in exactly the opposite way. Thus, the number of unemployed workers increases, the vacancies are opened to a lesser extent, and the market tightness for manual task occupations jumps.

2.3.2.3 Changes in the composition of type of workers

The case illustrated in Section 2.3.2.2 is the economy with the level of $p_r$ equal to 0.553. This value causes the reallocation of workers from routine tasks to manual tasks, therefore, conditional on employment, the share of employment in the routine jobs falls to 76.7%. This is approximately close to the employment share in 2005 suggested by Autor and Dorn (2013). The same employment share in routine task occupations in 1980 (84.9%), 1990 (81.4%), 2000 (79.2%) and 2014 (69.1%) are also denoted in the Table 2.4 on the column (R %).

From 1980 to 2014, the employment share in routine task occupation among non-college workers drops 15.8 percentage points (from 84.9% to 69.1%) and the model explains that it is the result of a decrease in $p_r$ by 40 percent (from 0.7 to 0.42). In Table 2.4, other consequences caused by the RBTC productivity shock are estimated. As $p_r$ is decreasing, unemployment for both the inexperienced and the experienced is rising, employment in manual task jobs is growing while employment in routine task jobs is declining.

The change in the productivity of routine tasks leads not only changes in the share of employment in manual and routine task occupations along with the growing unemployment rate but also changes in the share of experienced workers and inexperienced workers. To scrutinize the impact of the RBTC on workers with respect to their type, I separate workers into inexperienced and experienced workers first. Before the base productivity declines, the proportion of experienced workers was 68.83%, and most of them worked in routine task occupations. However, if the RBTC shock raises the hurdles for routine task jobs and lowers

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18 The literature reports employment share by occupational groups among workers without a college education. I eliminate the share of employment in professional/managerial (abstract) occupations from the sample and calculate the share of employment in routine tasks among employed workers, either routine or manual jobs. Employment in abstract jobs has been very constant over the past 50 years (from 14.5 % in 1950 to 15.0% in 2005), whereas employment in service has been consistently increasing (from 12.2 % in 1950 to 19.8% in 2005). Cortes et al. (2017) includes similar employment share, and the fraction working in routine occupations in 2014 was 69.1%.
the routine job market tightness, a smaller number of workers could be experienced. For instance, in the case of \( p_r \) equal to 0.553, the share of experienced workers falls to 61.58% in a new steady state. In each period, the \( \delta \) portion of workers are replaced by new workers who are inexperienced. However, after the economy adapts to the new productivity, entrants could not become experienced as easy as existing workers did before the shock arrival because being hired in a routine task job itself becomes less likely to happen. Even inexperienced workers who entered the labor market at the beginning also struggle to be experienced because both new young entrants and existing inexperienced workers are asked to satisfy new strict qualifications and are less likely to be matched with routine task jobs. During the transition periods to a new steady-state, existing experienced workers who achieved that position before the era of RBTC exit the economy at a rate of \( \delta \) and new entrants fill the gap at a lesser extent, thus the share of experienced workers converges to a lower level.

One example for a change in the composition of the worker types is illustrated in Figure 2.6. This case is the consequence of a decrease in \( p_r \) by 21 percent. When the base productivity of routine tasks suddenly drops, it makes the unemployment rate soar by 2.52 percentage points immediately. It was caused by shifts in ability thresholds to keep the routine task match profitable. The degree of an increase in unemployed workers at that time was much higher for the inexperienced workers (from 2.44% to 3.92%) than for experienced workers (from 4.46% to 5.55%), we could understand how the new ability requirements are harsh to inexperienced workers. At the moment the productivity shock arrived, it seemed the inexperienced workers were vulnerable to the shock. However, as the economy converges to

<table>
<thead>
<tr>
<th>( p_r )</th>
<th>( u^0 )</th>
<th>( u^1 )</th>
<th>( u )</th>
<th>( e_m^0 )</th>
<th>( e_m^1 )</th>
<th>( e_m )</th>
<th>( m(\theta_m) )</th>
<th>( e_r^0 )</th>
<th>( e_r^1 )</th>
<th>( e_r )</th>
<th>( m(\theta_r) )</th>
<th>( \text{(R %)} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.700</td>
<td>2.44</td>
<td>4.46</td>
<td>6.90</td>
<td>12.83</td>
<td>1.22</td>
<td>14.05</td>
<td>0.430</td>
<td>15.93</td>
<td>63.13</td>
<td>79.05</td>
<td>0.469</td>
<td>(84.9)</td>
</tr>
<tr>
<td>0.637</td>
<td>2.67</td>
<td>4.36</td>
<td>7.03</td>
<td>16.34</td>
<td>0.92</td>
<td>17.25</td>
<td>0.437</td>
<td>15.22</td>
<td>60.49</td>
<td>75.72</td>
<td>0.460</td>
<td>(81.5)</td>
</tr>
<tr>
<td>0.595</td>
<td>2.82</td>
<td>4.30</td>
<td>7.12</td>
<td>18.71</td>
<td>0.71</td>
<td>19.42</td>
<td>0.443</td>
<td>14.75</td>
<td>58.71</td>
<td>73.46</td>
<td>0.452</td>
<td>(79.1)</td>
</tr>
<tr>
<td>0.553</td>
<td>2.96</td>
<td>4.21</td>
<td>7.17</td>
<td>21.04</td>
<td>0.49</td>
<td>21.53</td>
<td>0.447</td>
<td>14.29</td>
<td>57.02</td>
<td>71.31</td>
<td>0.449</td>
<td>(76.8)</td>
</tr>
<tr>
<td>0.420</td>
<td>3.42</td>
<td>3.96</td>
<td>7.39</td>
<td>28.43</td>
<td>-</td>
<td>28.43</td>
<td>0.454</td>
<td>12.81</td>
<td>51.38</td>
<td>64.19</td>
<td>0.430</td>
<td>(69.3)</td>
</tr>
</tbody>
</table>
Figure 2.6: Changes in Unemployment by Types of Workers

Note: The graphs show the impact of a decline in $p_r$ by 21 percent ($p_r$ from 0.7 to 0.553) on the unemployment rate (top), employment in routine task jobs (middle) and employment in manual task jobs (bottom). The left graphs describe changes in total numbers and the right graphs show the changes in experienced/inexperienced workers. A vertical fine black dashed line indicates the time of productivity shock and horizontal lines are new steady states.
the new steady-state, unemployed experienced workers are disappearing and the unemployed inexperienced workers are growing due to worker replacement. In the new steady-state, compared to the initial state, the unemployed experienced workers decrease by 0.52 percentage points while the unemployed inexperienced workers rise by 0.25 percentage points. The total unemployment rate in the left top graph corresponding to these changes increases by 0.27 percentage points as well. The increased unemployment rate in the economy is partly explained by the decreasing job fining rate of routine tasks which could not be covered by the change in the manual job market, but it could be interpreted as diluted importance of the experienced workers in number. Since the proportion of experienced workers has fallen, the trace of total unemployment follows the inexperienced one. Changes in the composition of the worker types are observable in the job markets, too. The graphs in the middle of Figure 2.6 describe the employment in routine task jobs. Routine task occupations take the largest portion of employment for high-school graduates, so its employment share in this model is the highest before and after the RBTC shock hits the economy. However, the decline in employment of experienced workers in a routine task in the new steady-state depicts the falling number of experienced workers as a result of a strict qualification. Seeing that the share of employment of experienced workers in manual task jobs in the new steady-state is almost same as the one in the initial state, the decreased share of employment in routine task is not occurred by the migration of experienced workers from a routine task to a manual task but caused by a decline in the number of experienced workers in the economy.

In short, workers are less likely to hold a routine task occupation and thus hard to be experienced, more likely to be unemployed after the RBTC transforms the labor market. The further workers’ productivity in routine tasks declines, the more significant the impact of productivity shock by the RBTC on the labor force becomes.

2.3.2.4 The difference in the wage growth by occupational choices

I check whether the model prediction conforms to the observed pattern of wage changes as previous research studies report the trend of wages under the influence of the RBTC from the data (Acemoglu & Autor, 2011; Autor & Dorn, 2013; Autor, Katz, & Kearney, 2008; Cortes, Jaimovich, & Siu, 2017). The model sets wages by Nash bargaining, so the wages are directly linked to productivity. Therefore, when the base productivity of routine tasks
decreases, the model predicts that it decreases wages paid to routine task jobs directly and alters wages for the manual task occupations implicitly.

Figure 2.7: The Gap of Log-Wage on the Distribution of the Worker’s Ability

Note: The graph shows the gap between log wage paid in the initial status with $p_r = 0.7$ and log wage paid after $p_r$ drops by 21% ($p_r = 0.553$) on the distribution of worker’s ability. The blue dots describe changes in log wage paid to inexperienced workers in manual task occupation. The yellow and the red dots indicate changes in log wage for inexperienced workers and experienced workers holding routine jobs respectively. These lines are for those who did not switch their job type. The green dots with a star show changes in log wage paid to the inexperienced who transit from a routine job to a manual job. The magenta dots with a star is the same one for experienced workers. Two vertical lines are the ability requirements $\epsilon^{**}_1$ and $\epsilon^{**}_0$ under the circumstances with the low productivity.

Figure 2.7 shows the wage differentials caused by the RBTC productivity shock over the ability distribution. It shows a narrowing wage inequality between the lowest-skilled and middle-skilled workers when wage reductions by a drop in the base productivity vary by the types of tasks and workers’ experience and ability. I use wages under the initial status with $p_r$ equal to 0.7 that corresponds to 1980 and compare it with new wages paid after the productivity falls to 0.553, which implies the circumstance in 2005. Changes in the log wage between 1980 and 2005 on the figure represent the productivity shock on the wage. Blue dots in the figure describe the changes in log wage for those who have been qualified only for manual jobs. The flat part between 0 to 0.11 on the ability distribution shows no
difference for workers who are never qualified for routine jobs. On the contrary, for those who are on the right side of the vertical lines $\epsilon^{*}_{i}$, workers who have stayed only in the routine job market, changes of log wages are negative. It is connected to the adverse influence of the RBTC on wages of routine task jobs. Even though the routine wages paid to workers in the upper tail on ability distribution are still much higher than the one for workers in the lower tail on the distribution, the disadvantage from the productivity loss is concentrated in routine job workers, so the wage gap between those who with the highest ability and those who with the lowest ability is tapered. The parallel gap between the yellow line and red lines is involved in the disparity in workers’ type-specific productivity ($\alpha$ and $\beta$). Since the inexperienced workers cannot cope with the loss of base productivity with their relatively low individual productivity, they are worse off than experienced workers. Next, grey dots with a star between 0.15 and 0.32 on the ability distribution are for those who are inexperienced and willing to switch their jobs. By reason of the low ability of these workers, routine task jobs did not compensate as much as a manual job did. After the new ability requirements are adopted, some workers who lose qualification for routine task occupations (the level of ability between 0.12 and 0.21, old and new $\epsilon^{*}_{0}$, the least ability required to perform routine tasks) are forced to remain a manual job market. However, by considering wage gains from positive wage growth, it seems to be advantageous for them to discard their eligibility for routine jobs. This reminds me of the analysis by Cortes (2016) that the short-term wage loss for switchers from routine jobs to manual jobs is reversed in the long run.

### 2.4 CONCLUSION

I explore the impact of the RBTC on less-educated male workers with their inherent ability and work experience in the search model. I analyze workers qualified for routine and non-routine manual occupations under the influence of the RBTC. They could be displaced or reallocated to less-paying manual jobs when labor productivity in routine task occupations decreases. However, the degree of influence widely varies with worker characteristics because job experience and worker-specific ability mitigate the impact of the RBTC.

Workers in the routine job market cannot avoid the influence of the RBTC since all

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19Magenta dots with stars over the range between 0.12 and 0.15 are for experienced workers who are not dismissed from the routine job market.
workers become less competitive than the computer capital. Even for a worker who has the experience and the highest level of ability, the wage and the likelihood of being employed in a routine job decrease. The severity of these adverse impacts is growing as the level of ability and experience is falling. In addition, workers with a moderate level of ability are forced to switch an occupation from a routine to a manual task job. Manual task occupations are generally thought lousy so switching a job from routine to manual makes workers worse off except some who are not sufficiently able to do routine task work. Ironically, the least able workers in the model do not have severe disadvantages caused by the RBTC. Their job opportunities were consistently restricted to a non-routine manual task solely whether the productivity shock arrived in the routine task sector. Rather than being displaced or reallocated across occupations, since their only job choice has a higher market tightness as a result of labor market adjustment to the RBTC, they could be partly benefited from the RBTC. Ability requirements control different occupational choices in accordance with individual-specific ability and experience. Depending on market tightness and base productivity, ability requirements are endogenously determined in the model. The drop in productivity of routine tasks incurred by the RBTC and corresponding changes in market tightness shift the ability thresholds immediately. After the RBTC adjusts the ability thresholds required to keep routine jobs, more workers are excluded from routine job opportunities.

Even though there is a significantly large number of studies focusing on the impact of RBTC, this paper contributes to the understanding of why the RBTC works differently by workers’ characteristics. The link between workers’ ability and experience and the changes in occupational structure this paper tries to reveal can add more explanation about an increasing mean age in the routine tasks and reallocation of workers across occupations under the RBTC shock. Since I do not include people who are not in the labor force and the non-routine cognitive sector, this paper has limitations to explain those who give up searching for a job or choose another option to climb the career ladder. I leave this question for future work, but I expect the development of this model provides useful guidance for further research.
APPENDIX B
This Is An Appendix

B.1 The share of employment by task

From the CPS from 1970 to 2016, I calculated the employment share of male workers by tasks (non-routine/routine and cognitive/manual). I follow Acemoglu and Autor (2011) for occupational classification. Workers are full-time, full-year wage/salary paid workers.

In 1973, approximately 40% of male workers were employed in routine manual tasks, but its share has been decreasing since then. The second-largest employment was occupied by non-routine cognitive occupations, and it has been growing. Besides, the importance of non-routine tasks, non-routine manual occupations, has been increasing as well. As Autor and Dorn (2013) pointed out, the service sector has been growing, so it is shown on the line of non-routine manual tasks. However, the increase in non-routine manual occupations cannot offset the decrease in routine manual occupations, so the unemployment rate of less-educated workers is expected to grow. More details are discussed in Appendix B.1.1.

Figure B.1: The share of employment by job tasks
B.1.1 The share of employment by educational attainments

The level of education is measured by years of schooling: 12 years of schooling is classified as high school graduates and 16 years of schooling is classified as college graduates in the CPS.

By the educational attainment, the share of employment in each task is clearly different. Most college graduates are hired in cognitive jobs. During the past four decades, the share of employment in non-cognitive tasks has been fairly consistent but slightly decreasing. It is due to the rising education level. Cognitive occupations hire workers with a bachelor’s degree or a higher education degree in general and the share of workers who achieved a master’s degree or higher has been increasing, so the employment of college graduates in cognitive tasks could not rise as the previous section showed. However, considering that the supply of workers with a degree has continuously increased, the steadily constant fraction of employment of them in cognitive jobs means the growing cognitive occupations absorb these workers.

![Figure B.2: The share of employment by education attainment](image)

While occupations high school graduates are most likely to hold are routine manual tasks, the share of employment in routine manual tasks has significantly decreased over 40 years. It was around 50% in 1980 and less than 40% after 2010. The routine manual employment plummeted after recessions (Jaimovich & Siu, 2012), it is prominent that a drop in 2010. As the share of employment of high school graduates in routine manual tasks decreases, the share in non-routine manual jobs rises. Since the qualification, opportunities to hold a cognitive job are restricted to those who do not have a degree. Thus they are more
likely to find new chances in the non-routine manual task sector, but its increment is not enough to cover disappeared routine task jobs.

B.2 Nash Bargaining wage

Given productivity \( \{p_m, p_r, \alpha, \beta\} \), matching rates \( \{\theta_m, \theta_r\} \) and ability requirements \( \{\epsilon_0^*, \epsilon_1^*, \epsilon_0^{**}, \epsilon_1^{**}\} \), the Nash bargaining rules implies the wages as below.

B.2.1 Wages for those who apply for the manual jobs only: \( \epsilon \in [0, \epsilon_0^*] \)

These workers apply only for the manual jobs because the surplus from the matching with a routine job will be negative, thus the value of unemployment (2.1) would be the equation (B.1).

\[
(r + \delta)U^0(\epsilon) = b + m(\theta_m)(E_m^0(\epsilon) - U^0(\epsilon))
\] (B.1)

With the value of employment in a manual job (2.3), the value of filled manual job (2.9), and free-entry condition \( V_m = 0 \), the Nash bargaining rule with worker’s weight \( \eta \), \( \eta J_m^0(\epsilon) = (1 - \eta)(E_m^0(\epsilon) - U^0(\epsilon)) \), gives the equation (2.14).

\[
w_m^0(\epsilon) = \eta p_m + (1 - \eta) \left[ b + \frac{\eta m(\theta_m)(p_m - b)}{r + \delta + \lambda + \eta m(\theta_m)} \right]
\] (2.14)

These workers remain only in the manual job market, so workers could be either unemployed or employed in the manual job. Therefore, the wage of the manual job is composed of worker’s productivity \( p_m \) and the value of leisure \( b \). In addition, workers who never have an opportunity of being promoted are always inexperienced.

B.2.2 Wages for those who apply both manual and routine jobs: \( \epsilon \in [\epsilon_0^*, \epsilon_1^{**}] \)

B.2.2.1 The experienced workers: \( \epsilon_1 \in [\epsilon_0^*, \epsilon_1^{**}] \)

Workers with the middle range of the ability could have a positive surplus from both manual and routine jobs. Therefore, unlike the equation (B.1), the value function of unem-
Employment will be the equation (B.2).

\[
(r + \delta)U^1(\epsilon) = b + m(\theta_m)(E^1_m(\epsilon) - U^1(\epsilon)) + m(\theta_r)(E^1_r(\epsilon) - U^1(\epsilon)) \tag{B.2}
\]

Therefore, the Nash bargaining rule using the equation (2.4), (2.6), (2.10), and (2.12) yields the wage for an experienced workers in manual jobs (2.16) or routine jobs (2.17) as below.

\[
w^1_m(\epsilon) = \eta p_m + (1 - \eta) \left[ b + \frac{\eta m(\theta_m)(p_m - b) + \eta m(\theta_r)(p_r + \beta \epsilon - b)}{r + \delta + \lambda + \eta m(\theta_m) + \eta m(\theta_r)} \right] \tag{2.16}
\]

\[
w^1_r(\epsilon) = \eta (p_r + \beta \epsilon) + (1 - \eta) \left[ b + \frac{\eta m(\theta_m)(p_m - b) + \eta m(\theta_r)(p_r + \beta \epsilon - b)}{r + \delta + \lambda + \eta m(\theta_m) + \eta m(\theta_r)} \right] \tag{2.17}
\]

An experienced worker with the ability \(\epsilon^*_0 \leq \epsilon \leq \epsilon^{**}_{1}\) could be employed in a manual job or a routine job, or unemployed. Thus, the wage includes workers’ productivity of a matched job with a worker’s weights (\(\eta\)) and the values of two outside options, unemployed and employed in the opposite job, with the firm’s share (\(1 - \eta\)). Since the productivity of a routine job depends on the matched worker’s ability, the wage from Nash bargaining reflects variations of the productivity by the worker’s ability. It changes the wage of a manual job and the value of the filled manual job eventually.

**B.2.2.2 The inexperienced workers**

The process of wage determination of inexperienced workers with the middle level of ability, \(\epsilon^*_0 \leq \epsilon \leq \epsilon^{**}_{0}\), and the results are very similar to that of the experienced. However, since the inexperienced worker has one more outside option, a promotion, that is connected to the job value and the wage of the experienced, the entire middle range of ability should be separated into \(\epsilon^*_0 \leq \epsilon \leq \epsilon^{**}_{1}\) and \(\epsilon^{**}_{1} \leq \epsilon \leq \epsilon^{**}_{0}\).

**(1) The case for** \(\epsilon \in [\epsilon^*_0, \epsilon^{**}_{1}]\)

The first range \(\epsilon^*_0 \leq \epsilon \leq \epsilon^{**}_{1}\) is almost the same as the experienced one but wages of the inexperienced workers include the probability of being the experienced \(\gamma\). The equation (B.3) shows two choices of the inexperienced unemployed worker who is in the middle range.
of the ability requirement.

\[(r + \delta)U^0(\epsilon) = b + m(\theta_m)(E^0_m(\epsilon) - U^0(\epsilon)) + m(\theta_r)(E^0_r(\epsilon) - U^0(\epsilon)) \quad (B.3)\]

In addition to equations (2.3) and (2.9), the value of employment in a manual job and the value of a filled manual job, and equations (2.5) and (2.11), the value of employment in a routine job and the value of a filled routine job, describe the possibility of climbing a career ladder of an inexperienced worker by term with $\gamma$.

With wages of the experienced worker, wages of the inexperienced workers are given as in eq (2.20) and (2.21). As shown in equation (B.4) and (B.5), the wage for the inexperienced workers with middle range ability is complex. It is because that those workers have more options than any other types of workers. Like experienced workers who apply for both manual and routine job, inexperienced workers holding the middle level of ability have an option of being unemployed and another option of being employed in an opposite job. Moreover, they also have an opportunity of becoming the experienced worker if hired in a routine job. Although a worker is currently matched with a manual job, that worker still has a chance to be hired in a routine job through the period of unemployment. Therefore both $w^0_m$ and $w^0_r$ include influence of the wage for the experienced worker in routine jobs.

\[w^0_m(\epsilon) = \eta p_m \quad (B.4)\]
\[
+ (1 - \eta) \left[ b + \frac{(r + \delta + \lambda)\eta}{r + \delta + \lambda + \eta m(\theta_m)} \left\{ m(\theta_m)(p_m - b) + m(\theta_r)(p_r + \alpha \epsilon - b) \right\} - \frac{r + \delta + \lambda + \gamma}{(r + \delta)(r + \delta + \lambda + \gamma)^2} \right] + \frac{\eta}{r + \delta + \lambda + \eta m(\theta_m) + \eta m(\theta_r)} \left\{ \frac{m(\theta_m)(p_m - b) + m(\theta_r)(p_r + \beta \epsilon - b)}{r + \delta + \lambda + \gamma} \right\}
\]

\[w^0_r(\epsilon) = \eta(p_r + \alpha \epsilon) \quad (B.5)\]
\[
+ (1 - \eta) \left[ b + \frac{\eta}{r + \delta + \lambda + \eta m(\theta_m) + \eta m(\theta_r)} \left\{ m(\theta_r)(p_r + \alpha \epsilon - b) + m(\theta_m)(p_m - b) \right\} + \frac{(r + \delta + \lambda + \eta m(\theta_m))\gamma \eta m(\theta_r)(\alpha - \beta) \epsilon}{(r + \delta)(r + \delta + \lambda + \gamma)(r + \delta + \lambda + \eta m(\theta_m) + \eta m(\theta_r)) + \gamma \lambda \eta m(\theta_r)} \right\}
\]
(2) The case for $\epsilon \in [\epsilon_1^{**}, \epsilon_0^{**}]$

If the inexperienced worker’s ability is greater than $\epsilon_1^{**}$, all processes to reach the Nash bargaining wage is the same as the case (1), but the job value $J_1^1(\epsilon)$ in the equation (2.11) and $E_r^1(\epsilon)$ in the equation (2.5) are different because the worker would choose to stay only in the routine job market when he becomes experienced. Thus, the worker receives (2.21) instead of (2.17). Because outside options of workers in this range of ability are different from workers in the previous section in (1), the wage for manual tasks (B.6) has a higher slope than (B.4), the wage for routine task (B.7) has a lower slope than (B.5).

\[
w_m^0(\epsilon) = \eta p_m \\
+ (1 - \eta) \left[b + \frac{(r + \delta)(r + \delta + \lambda + \gamma)\eta[m(\theta_r)(p_r + \alpha \epsilon - b) + m(\theta_m)(p_m - b)]}{(r + \delta)(r + \delta + \lambda + \gamma)(r + \delta + \lambda + \eta m(\theta_r) + \eta m(\theta_m)) + \gamma \lambda \eta m(\theta_r)} + \right. \\
\left. \gamma \eta \frac{m(\theta_r)(r + \delta + \lambda)(r + \delta + \eta m(\theta_r))(\beta - \alpha)\epsilon + m(\theta_r)\lambda(p_r + \alpha \epsilon - b)}{(r + \delta)(r + \delta + \lambda + \gamma)(r + \delta + \lambda + \eta m(\theta_r) + \eta m(\theta_m)) + \gamma \lambda \eta m(\theta_r)} \right] \\
\]

\[
w_r^0(\epsilon) = \eta(p_r + \alpha \epsilon) \\
+ (1 - \eta) \left[b + \frac{(r + \delta)(r + \delta + \lambda + \gamma)\eta[m(\theta_r)(p_r + \alpha \epsilon - b) + m(\theta_m)(p_m - b)]}{(r + \delta)(r + \delta + \lambda + \gamma)(r + \delta + \lambda + \eta m(\theta_r) + \eta m(\theta_m)) + \gamma \lambda \eta m(\theta_r)} + \right. \\
\left. \gamma \eta \frac{\lambda m(\theta_r)(r + \delta + \lambda)(\alpha - \beta)\epsilon + \eta m(\theta_r)(p_r + \alpha \epsilon - b)}{(r + \delta)(r + \delta + \lambda + \gamma)(r + \delta + \lambda + \eta m(\theta_r) + \eta m(\theta_m)) + \gamma \lambda \eta m(\theta_r)} + \right] \\
\left. \frac{m(\theta_m)(r + \delta + \lambda + \gamma)(r + \delta + \lambda + \eta m(\theta_r))(p_m - b) - \eta m(\theta_r)(p_r + \beta \epsilon - b)}{(r + \delta)(r + \delta + \lambda + \gamma)(r + \delta + \lambda + \eta m(\theta_r) + \eta m(\theta_m)) + \gamma \lambda \eta m(\theta_r)} \right] \\
\]

**B.2.3 Wages for those who apply for routine jobs only: $\epsilon_1^{**} \leq \epsilon \leq 1$**

Workers with enough high ability choose to stay only in the routine task market because high wages for these workers make manual jobs decline to hire. Hence, workers with ability level over the maximum ability requirement of the manual job $\epsilon_1^{**}$ have only the value of leisure $b$ and gains from employment in routine jobs as below.

\[
(r + \delta)U_1^1(\epsilon) = b + m(\theta_r)(E_r^1(\epsilon) - U_1^1(\epsilon)) \tag{B.8}
\]

\[
(r + \delta)U_0^0(\epsilon) = b + m(\theta_r)(E_r^0(\epsilon) - U_0^0(\epsilon)) \tag{B.9}
\]

The first equation (B.8) is the value of employment of the experienced worker and the
second one (B.9) is for the inexperienced worker. Along with equations (2.6), (2.12), (2.5), and (2.11), the Nash bargaining rule gives wages for workers in the routine labor market.

\[
w^1_r(\epsilon) = \eta(p_r + \beta \epsilon) + (1 - \eta) \left[ b + \frac{\eta m(\theta_r)(p_r + \beta \epsilon - b)}{r + \delta + \lambda + \eta m(\theta_r)} \right]
\]

(B.10)

\[
w^0_r(\epsilon) = \eta(p_r + \alpha \epsilon) + (1 - \eta) \left[ b + \frac{\eta m(\theta_r)(r + \delta + \gamma)(p_r + \alpha \epsilon - b)}{(r + \delta)(r + \delta + \lambda + \gamma) + \eta m(\theta_r)(r + \delta + \gamma)} \right]
\]

\[+ \left\{ \frac{\gamma \lambda}{r + \delta + \lambda + \eta m(\theta_r)} \left[ \frac{\eta(p_r + \alpha \epsilon - b) - (1 - \eta)(p_r + \beta \epsilon - b)}{(r + \delta)(r + \delta + \lambda + \gamma) + \eta m(\theta_r)(r + \delta + \gamma)} \right] \right\}
\]

(B.11)

Figure B.3 shows one example of wages with the initial base productivity \( p_r = 0.7 \). Dot-dashed lines represent wages paid to experienced workers and bold lines do for inexperienced workers by tasks they perform. It shows that wages are kinked at the ability thresholds and are differently sloped by the ability level as explained above.

Figure B.3: Changes in wage for each task
B.3 Job value with Nash bargaining wages.

The value of a filled job is represented by productivity \( \{p_m, p_r, \alpha, \beta\} \), ability of a matched worker \( \epsilon \) and matching rates \( \{\theta_r, \theta_m\} \) base on the Nash bargaining wages calculated in Appendix B.2.

First, inexperienced workers are uniformly distributed with respect to their ability over zero to one as shown in Figure B.4. A worker with ability lying on the first section (1) is paid \( w_m^0(\epsilon) \) in equation (2.14), and those who has middle level of ability (2) or (3) receives \( w_m^0(\epsilon) \) as (2.20) or (2.24) when they apply for the manual job. Thus, the value of a filled job matched with a worker in (1) becomes (2.15) and that with a worker applying for both jobs would be (B.12) or (B.13) which correspond (2.22) and (2.26), respectively.

Figure B.4: The ability requirement for inexperienced workers

\[
J_m^0(\epsilon) = (1 - \eta) \frac{p_m - b}{r + \delta + \lambda + \eta m(\theta_m)} \quad \text{(2.15)}
\]

\[
J_m^0(\epsilon) = \frac{(1 - \eta)}{(r + \delta + \lambda)} \left\{ (p_m - b) - \frac{(r + \delta)(r + \delta + \lambda + \gamma)[m(\theta_m)(p_m - b) + m(\theta_r)(p_r + \alpha \epsilon - b)] - (r + \delta)\gamma(\alpha - \beta)\epsilon}{(r + \delta)(r + \delta + \lambda + \gamma)(r + \delta + \lambda + \eta m(\theta_m) + \eta m(\theta_r)) + \gamma \lambda \eta m(\theta_r)} \right\} \quad \text{(B.12)}
\]

\[
J_m^0(\epsilon) = \frac{(pm - b)[(r + \delta)(r + \delta + \lambda + \gamma)(r + \delta + \lambda + \eta m(\theta_r)) + \eta m(\theta_r)\gamma \lambda]}{(r + \delta + \lambda + \eta m(\theta_r))[(r + \delta)(r + \delta + \lambda + \gamma)(r + \delta + \lambda + \eta m(\theta_r) + \eta m(\theta_m)) + \eta m(\theta_r)\gamma \lambda]} + \eta m(\theta_r)\gamma \lambda \left\{ (r + \delta)(r + \delta + \lambda + \eta m(\theta_r))(pm - pr - \alpha \epsilon) + \gamma (r + \delta + \eta m(\theta_r))(pm - pr - \beta \epsilon) \right\} \quad \text{(B.13)}
\]
When the worker who is in the middle range of ability requirements (2) applies for the routine job, \( w_r^0(\epsilon) \) (2.21) is paid to the worker and the value of a routine job matched with this worker will be eq.(2.23). The highly productive worker in the range 3 applies only for a routine job. If a routine job hires this highly able worker, the firm pays a wage as much as \( w_r^0(\epsilon) \) in ep.(2.29) and the job value becomes eq.(2.31).

\[
J_r^0(\epsilon) = \frac{1 - \eta}{r + \delta + \lambda + \gamma} \left\{ (p_r + \alpha \epsilon - b) - \frac{(r + \delta)(r + \delta + \lambda + \gamma)[\eta m(\theta_m)(p_m - b) + \eta m(\theta_r)(p_r + \alpha \epsilon - b)] + \gamma \lambda \eta m(\theta_r)(\alpha - \beta)\epsilon}{(r + \delta)(r + \delta + \lambda + \gamma)(r + \delta + \lambda + \eta m(\theta_m) + \eta m(\theta_r)) + \gamma \lambda \eta m(\theta_r)} \right\} + \gamma \frac{(p_r + \beta \epsilon - b) - \frac{\eta m(\theta_m)(p_m - b) + \eta m(\theta_r)(p_r + \beta \epsilon - b)}{r + \delta + \lambda + \eta m(\theta_m) + \eta m(\theta_r)}}{r + \delta + \lambda + \eta m(\theta_r)} \right\} \]

Next, the experienced workers have narrower range of ability requirement set because only workers who were qualified for routine jobs when they were inexperienced could be experienced.

Any worker who becomes experienced seeks a routine job. Meanwhile, a worker in the middle range (2) of ability requirements searches for a manual job simultaneously. This worker would receive \( w_m^1(\epsilon) \) as in eq.(2.16) or \( w_r^1(\epsilon) \) by eq. (2.17) depending on the job.
matched, then that filled job value is eq. (2.18) or eq. (2.19).

\[
J_1^m(\epsilon) = \frac{1 - \eta}{r + \delta + \lambda} \left\{ (p_m - b) - \left[ \frac{\eta m(\theta_m)(p_m - b) + \eta m(\theta_r)(p_r + \beta \epsilon - b)}{r + \delta + \lambda + \eta m(\theta_m) + \eta m(\theta_r)} \right] \right\}
\tag{2.18}
\]

\[
J_1^r(\epsilon) = \frac{1 - \eta}{r + \delta + \lambda} \left\{ (p_r + \beta \epsilon - b) - \left[ \frac{\eta m(\theta_m)(p_m - b) + \eta m(\theta_r)(p_r + \beta \epsilon - b)}{r + \delta + \lambda + \eta m(\theta_m) + \eta m(\theta_r)} \right] \right\}
\tag{2.19}
\]

The worker crossed $\epsilon_1^{**}$, the maximum level of ability qualifying for manual jobs as an experienced worker, applies for a routine job only to be paid $w_1^r(\epsilon)$ such as eq. (2.28), and this wage make the value of job become eq. (2.30).

\[
J_1^r(\epsilon) = (1 - \eta) \frac{p_r + \beta \epsilon - b}{r + \delta + \lambda + \eta m(\theta_r)}
\tag{2.30}
\]
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