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Occupational Networks, Automation, and Social Insurance

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Abstract

This dissertation investigates the labor market consequences of technological change. Chapter I builds an occupational network based on the flows of workers between occupations and shows that the network has a core/periphery structure. Core occupations employ most of the workforce, require fewer skills, and pay lower wages. At the same time, they act as bridges between other occupations and provide insurance value to the workers in other occupations in case they lose their jobs. A key result in this chapter is to show that the core occupations become more likely to be automated thanks to the advances in technologies like machine learning and cloud computing. Consequently, automation is expected to have far more significant consequences than what would be implied by its direct impact. If the occupations with the highest probability of being automated disappear, 7% of the workforce would be displaced from their jobs. Moreover, almost 10% of the edges between occupations would dissolve, further aggravating the impact of automation.

Chapter II develops a structural model of occupational choice that endogenizes worker flows between occupations. It extends the dynamic discrete choice model of occupational choice to include search frictions and transition costs and embeds it into a general equilibrium search environment. Using the Survey of Income and Program Participation and O*NET datasets, search frictions and transition costs are structurally estimated. Results show that transition costs that workers face in automatable jobs are particularly high, and search frictions significantly curtail workers' abilities to transition away from jobs vulnerable to labor substituting technology. Furthermore, low-cost transitions for these workers are towards other highly automatable occupations. Consequently, if such occupations would undergo automation in a similar timeline, the impact of new technologies would be significantly amplified. Finally, a counter-factual is performed where automation decreases revenues of manual firms in "Transportation and material moving" occupations by twenty-five percent. The new steady-state features 150,000 more unemployed workers. Analyzing transition dynamics reveals that unemployment is considerably higher during the transition, and that it takes about seven years for

unemployment rates to reach their steady-state values—a significant portion of a worker's career.

Chapter III uses the framework developed in Chapter II to evaluate two strands of labor market programs that aim to help unemployed workers: a Trade Adjustment Assistance inspired Automation Adjustment Assistance (AAA) program and Unemployment Insurance (UI). The AAA program that provides relief conditional on being unemployed from the automated occupation introduces adverse incentives and induces workers to stay in the automated occupation. UI policies do no carry this risk as workers need not be unemployed from a specific occupation to be eligible for benefits. This chapter considers three alternative UI policies. The first policy is the current implementation of UI in the US economy. The second policy is a UI policy optimized for the pre-automation economy in the absence of automation, which we call SS-Optimal. SS-Optimal policy increases replacement ratio from 30% to 71% and increases the welfare by 0.01%. However, when automation begins, both the current and SS-Optimal UI lead to a massive budget shortfall. The final policy considered is a dynamically-optimal UI policy that takes the transition induced by the automation into account. Dynamically-optimal unemployment insurance provides almost full insurance and increases welfare by 0.01% while keeping a balanced budget. Therefore, UI programs must anticipate and adjust accordingly with technological developments.

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Chapter 1

Occupational Networks

1.1 Introduction

New technologies, such as industrial robots and machine learning, continue to replace tasks traditionally performed by workers (Brynjolfsson and McAfee 2014). As a result, there is a renewed interest in the consequences of automation for the workforce. Frey and Osborne (2017), for example, estimates about 47 percent of total employment is under the risk of computerisation. The McKinsey Global Institute forecasts that by 2030 about 14 percent of the global workforce may need to switch occupations. This Chapter discusses the consequences of automation, with a particular emphasis on the position of these occupations in the occupational network in terms of their connectedness.

The occupational network is a set of nodes representing each occupation and edges between them representing the worker flows. Studying the occupational network to investigate automation is crucial for two reasons. First, occupations does not exist in isolation. A shock to one occupation will have substantial effects on others. Removing a central occupation not only has direct consequences for its workers but also restrains the ability of other workers to relocate themselves within the network. Second, if the automated occupations are connected to other occupations, workers could easily transition away from these occupations. However, if the automated occupations are isolated, then the change would be potentially worrying.

The first contribution of this chapter is to document the structure of the occupational network. The occupational network is sparse—occupations are connected to only a small portion of other occupations. This suggests that workers direct their search accordingly with their preferences, and that transitions across occupations are costly. Furthermore, occupations are very heterogeneous in terms of their positions in the network. Some occupations are more connected than others, while others are isolated. This structure is important because it implies that for some workers, it could be harder to (willingly) move to other occupations than others.

The second contribution is to characterize core and peripheral occupations. The core occupations employ most of the labor force. Their requirements in terms of education, skills, and abilities are significantly lower than peripheral occupations. Furthermore, on average, they pay considerably less than peripheral occupations. There is a monotonic relationship between the centrality of occupations and wages.

The third contribution of this chapter is to show that the core occupations have become more susceptible to automation. This result is based on two different measures of automation. The first is the Routine Task-Intensity (RTI) index developed in Autor and Dorn (2013). This index assumes only the occupations that require performing explicit algorithms without intense social interaction are automatable. RTI suggests that semi-peripheral occupations are prone to automation, while peripheral and core occupations are relatively safe. However, recent technologies have shown the capacity to substitute not only codifiable occupations but also non-codifiable. As such, RTI is a backward-looking index. Building on the premise of these new technologies, Frey and Osborne (2017) create the Computerisability Probability Index. When the measure reflects new capabilities of technology, we find that the core occupations are under the greatest threat of technical change. Therefore, automation's impact is expected to be larger, both in terms of its direct effects on workers employed in core occupations as well as its indirect effects through its implications for the network structure.

As an extension, we analyze two subnetworks: Early Career and Late Career occupational networks. The comparison of the sub-networks reveals that transition patterns in different career stages are entirely different. Both measures suggest that there is a difference in the impact of automation on early and late career networks. RTI measure predicts that semi-peripheral occupations in these networks are prone to technical change. On the other hand, the computerisability index displays a stark contrast in career stages. For early career workers, it predicts that the core occupations will be automatized, whereas for the late career network, it predicts that peripheral occupations are more susceptible to automation.

Finally, using the computerisability index, we project that the occupations with more than 95% probability of automation will disappear. Results suggest that 7% of the workers will be displaced. Moreover, the disappearance of these occupations is expected to result in 9% of the edges in the networks to dissolve. The dissolution of these edges will amplify the effects of automation because workers will be less able to transition to other occupations.

The rest of the chapter develops as follows. Section 2 summarizes the data sets we refer to in our investigations. Section 3 creates the occupational network and analyzes its characteristics in detail. Section 4 turns to literature to identify the possible consequences of technical change with the help of the occupational network. Section 5 concludes.

1.2 Data

In this paper, two data sets are utilized: Survey of Income and Program Participation (SIPP) and the Occupational Information Network (O*Net). SIPP collects detailed information on demographics, labor force, income, and participation in social welfare programs. Administered by the U.S. Census Bureau, SIPP is built in panels where each panel consists of different samples. First, it selects a nationally representative sample of households for a given panel from a resident population of the United States, excluding those living in institutions and military barracks. Once the sample is chosen, SIPP tracks all the individuals and others living with them by interviewing them every four months. These interviews are called waves. This paper uses core wave files from the SIPP 2008 Panel, which consists of 16 waves (64 months).

The demographic information provided in SIPP includes age, sex, race, ethnic origin, marital status, household relationship, education, and veteran status. Core questions cover labor force activity, types and amounts of income, and participation in various cash and non-cash benefit programs for each month of the four-month reference period. Our focus is on the primary occupation held by any participant and their income, age, and gender. Our analysis includes any individual that had a job in any two of the 16 waves.

The other data set used in our analysis is the O*NET data. Being the replacement of the Dictionary of Occupational Titles (DOT), O*NET is a comprehensive data set providing occupational characteristics in a variety of domains. It is developed by O*NET Resource Center under the sponsorship of the U.S. Department of Labor. Information is collected using a two-stage design. Firstly, a random sample of businesses expected to employ workers in the targeted occupations are selected. Then a random sample of workers in those businesses is selected. Data is collected by surveying these job incumbents using standardized questionnaires on what is required to perform the given occupation satisfactorily.

This paper uses the O*Net 19.0 Database, which classifies the occupations accordingly with the SOC 2010 taxonomy of occupations. In total, O*Net contains information on a total of 947 occupations. We crosswalk SOC 2010 occupation titles to Census 2002 Occupation Classification by averaging characteristics of SOC 2010 occupations corresponding to a Census 2002 occupation.

After dropping occupations that we did not observe transitions in 2008 SIPP and matching the remaining with O*NET; final analysis constitutes 327 Census occupations (out of 505).

1.3 Occupational Networks

An occupational network is a set of nodes, representing each occupation, and edges connecting them, which represents how intensely these occupations are connected. We represent this network by a graph (O, p), which consists of a set of occupations $O = \{1, 2, 3...n\}$ and an nxn matrix $p = [p_{ij}]_{i,j \in O}$ where p_{ij} represents the fraction of workers who switched to occupation j from the source occupation i. Thus, p is a Markov-matrix describing transition probabilities between occupations. Two important features of the network is that it is weighted and directed. The edges not only represent if the occupations are connected but also the intensity of the connection. The more workers move between two occupations, the more connected they are. Moreover, the flow of workers need not be the same both ways. It is not necessarily the case that $p_{ij} = p_{ji}$

The network is estimated using the observed transitions in SIPP data.[1] As there are many occupations and links between them, we will rely on two statistical summary statistics of the network. The first such summary statistic is the graph density.

[1]For individuals who undergo unemployment or get out of the labor force during switching occupations, we directly tie their last held occupation to their new occupation.

Graph Density (D) : Let E denote number of edges in the graph and V denote number nodes. Then

$$D = \frac{|E|}{|V|(|V|-1)}$$

Graph density is a means of assessing the connectedness of the network. $D = 1$ if every node is connected and D =0 if all occupations are isolated. It is a measure of how many edges exist out of all edges that could be formed.

The graph density of the occupational network is 0.086. It is a remarkably sparse network. If workers were to move across occupations at random, then most occupations would be connected, culminating in a dense graph. The sparse nature of the network suggests that the workers move between a confined set of occupations and direct their search towards occupations compatible with their preferences and skills. They would like to work at higher salary occupations and ones that offer better work experience. Hence there would be more voluntary transitions towards such occupations. There are also external factors, restricting the ability of workers to migrate across occupations freely. Some occupations involve licensing and specialized skills, barring most employees from finding a job in them.

The second statistic used in characterizing the occupational network is the weighted closeness centrality measure. It is a measure of how well-positioned a node in the network based on its distance to all the other nodes. The edges in the original network reflect how "close" occupations are. As closeness centrality is based on distances, we use the additive inverse of the transition rates as the distance between nodes. Then the distance of occupation i to j is

$$e_{ij} = 1 - p_{ij} \quad if \quad p_{ij} > 0 \tag{1.1}$$

Define a "path" from node i to j as a sequence of edges $\{i_1, i_2\}, \{i_2, i_3\}...\{i_{K-1}, i_K\}$ such that $i_1 = i$ and $i_K = j$, and each node in the sequence is distinct. That is, no node is visited twice when going from i to j. Let $d(i, j)$ be the "shortest path" that has the minimal distance over the edges over all other paths. Then the weighted closeness centrality measure is defined as:

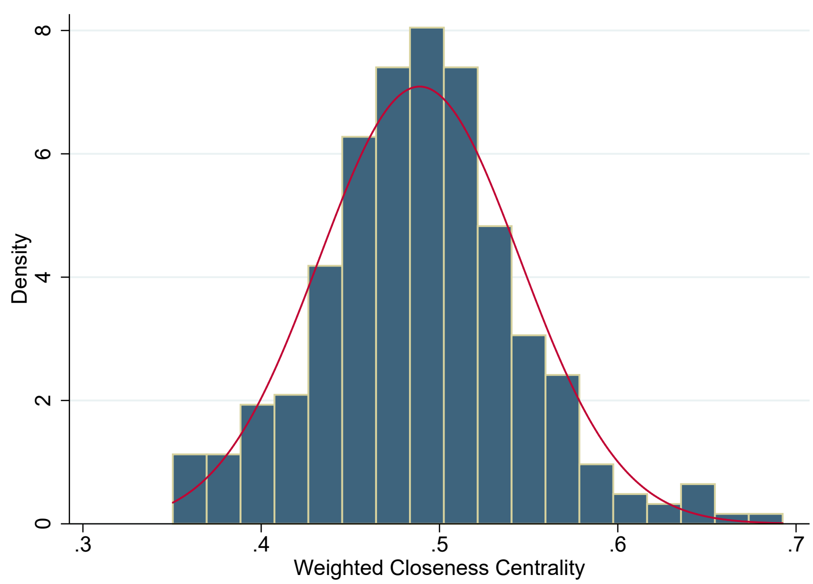
Weighted Closeness Centrality (c): Let $d(i, j)$ denote the shortest path from occupation i to j.

$$c_i = \frac{n}{\sum_{j \neq i}^{n} d(i, j)}$$

The higher the weighted closeness centrality measure is, the more central an occupation is. We will refer to weighted closeness centrality whenever we mention centrality. Figure 1.1 shows the distribution of the occupations in terms of their centrality in the network. Occupations are heterogeneous in terms of their centrality. There is a core/periphery structure. Some are very well connected to other occupations, whereas others are isolated.

The centrality of occupation is essential in assessing the impact of automation. Central occupations are well-connected, and workers can move to other occupations. Therefore, if a central occupation is automated, the workers in that occupation could transition to other jobs with relative ease. However, at the same time, a central occupation ties many other occupations together. Hence, automation of central occupation would hurt workers in other occupations as their ability to change jobs becomes limited. On the other hand, if a peripheral occupation is automated, it might be tough for workers to transition away. However, the disappearance of an isolated occupation would have minimal impact on the occupational network overall.

Figure 1.1: The distribution of occupations in terms of their weighted closeness centrality.



Notes: Occupations are very heterogeneous in terms of their centrality in the network. Higher centrality measure corresponds to more central occupations.

Figure 1.2 provides the graph of the occupational network. When creating this graph, only ten closest occupations are considered to make it more understandable. The relative sizes of the occupation nodes reflect the centrality of occupations. The more central the occupation the bigger the node is. Most central ten occupations are colored differently and labeled. Most of these occupations seems to be Blue-Color and Pink-Color occupations. On the other hand, “Managers, All other” is central as it is possible to become manager following many different career paths. Next sections will analyze the characteristics of the core and peripheral occupations in more detail.

1.3.1 Characteristics of Occupations by Their Centrality

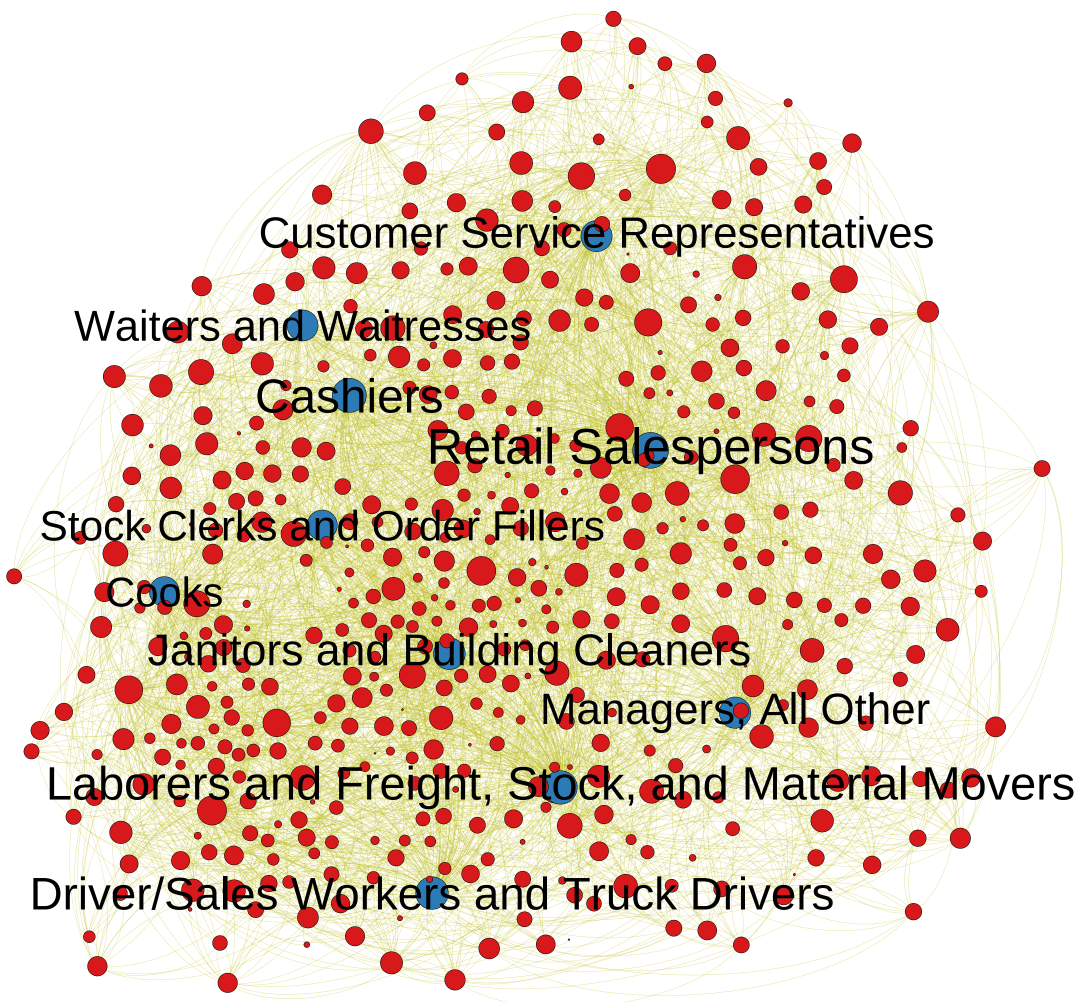
The previous section has documented that occupations are different in terms of their centrality in the occupational network. This section studies the characteristics of these central and peripheral occupations based on centrality quintiles.

The first thing to note is that the central occupations employ most of the working population. Figure 1.3 provides a pie-graph of the distribution of the working population in different quintiles. The figure indicates there is a monotonic relationship between centrality and number of workers. Two factors derive this result. The first is related to how the data is sampled. When an occupation employs many workers, it is more likely for them to be in the sample. As these occupations are represented more, it is also possible to capture smaller transitions. As a result, these occupations look relatively more connected. The second factor has to do with skill requirements. If peripheral occupations require specialized skills, it is natural that fewer people would possess them. Hence they would employ fewer workers.

To see if core and peripheral occupations require different skills, we utilize the O*Net data. For each centrality quintile, the required skills, abilities, knowledge, and job zone requirements are calculated using the number of workers as weights.

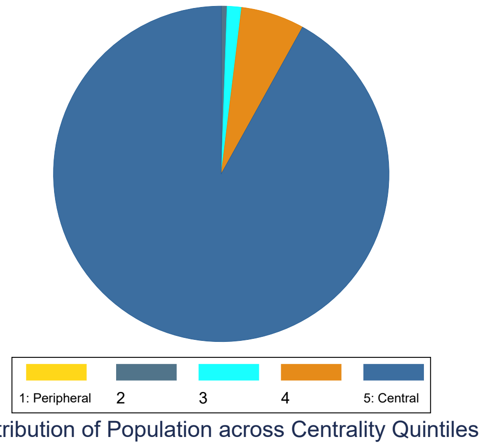
Figure 1.4 summarizes the difference in requirements in core occupations and peripheral occupations. Peripheral occupations demand considerably more skills, abilities, education (Job Zone), and occupation-specific knowledge (Knowledge). On the other hand, core occupations demand more “Physical Abilities”

Figure 1.2: Occupational Network based on employment flows in SIPP



Notes: The occupational network estimated using the SIPP. Each node represents an occupation. The more central an occupation is the bigger node it has. 10 most central occupations are labeled and colored differently for distinction..

Figure 1.3: Distribution of the working population by centrality quintiles.



Notes: 5 represents the most central occupations quintile whereas 1 represents the most peripheral occupations quintile. There is a monotonic relationship between centrality and number of workers. The most central occupations employ most of the working population. On the other hand, number of workers in most peripheral occupation employs a negligible working population in comparison. Thus, a technical change substituting central occupations are expected to impact a high fraction of the workforce.

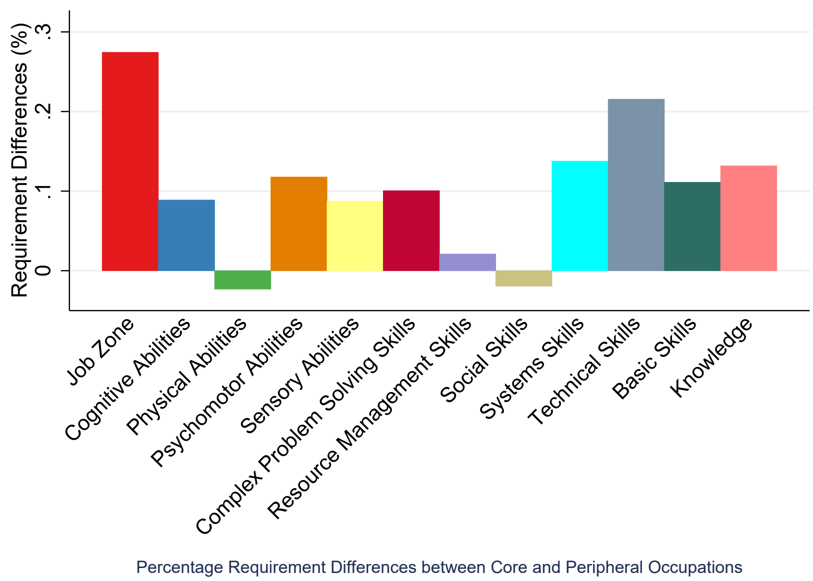
and “Social Skills”. The differences suggest that peripheral occupations require specialized skills and education, whereas core occupations are relatively more generalists.

As the peripheral occupations require more skills, they also pay higher wages to the employees. Figure 1.10 reflects this relationship. Central occupations pay significantly less than peripheral occupations. Therefore, we expect the workers to try and move to peripheral occupations. The fact that they are not doing so in the data is suggestive of hardships in requiring the necessary skills.

1.4 Technical Change and Centrality

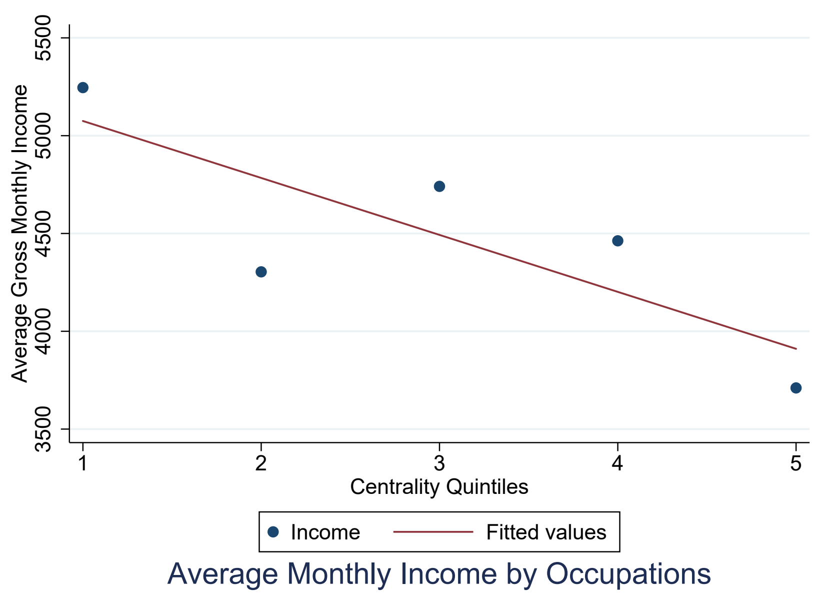
There are two approaches in recent literature to understand which occupations are more prone to technical change. One approach is the Routine Task-Intensity measure as presented in Autor and Dorn (2013). They argue an occupation can only be automatized if it is codifiable; if it can be structured into a set of rules, which then be coded into a program. They relate the codifiability to routineness

Figure 1.4: Requirement Differences between Core and Peripheral Occupations (%).



Notes: Peripheral occupations seems to be demanding more skills, abilities, education (Job Zone), and occupation specific knowledge (Knowledge). On the other hand, core occupations demand more "Physical Abilities" and "Social Skills". Nevertheless, it should be noted this difference in core occupations demand is considerable low compared to peripheral occupations.

Figure 1.5: Average Monthly Income by Occupations.



Notes: 5 represents the most central occupations quintile whereas 1 represents the most peripheral occupations quintile. Central occupations pay significantly less than peripheral occupations.

Table 1.1: Mapping of Tasks to DOT variables.

Tasks	DOT Components
Manual Tasks	“Eye-Hand-Foot Coordination”
Routine Tasks	“Set limits, tolerances, and standards” and “Finger Dexterity”
Abstract Tasks	“Direction control and planning” and “GED Math”

of occupations to get a measure of automatability. However, they underestimate the potential of machine learning based technology which can also automate non-codifiable tasks. Alternatively, Frey and Osborne (2017) use a more general approach. They label a group of occupations whether they will be automatized or not in the near future. They index remaining occupations based on the similarity of their characteristics with the labeled occupations. As modern technologies are reflected in their labels, their measure is more forward-looking compared to Autor and Dorn (2013). Next two subsections detail these approaches and relate their results to the occupational network.

Routine Task-Intensity

Autor and Dorn (2013) classify three types of tasks defining an occupation; routine, manual, and abstract tasks. First, there are routine-intensive occupations that are presumed to be codifiable. These occupations are easiest to automatize. Second group is manual-intensive occupations. Although they are not high ability occupations, they require high-level social interactions like child-care or food service. They are not affected by technical change. Third and final group consists of abstract occupations. They are not codifiable and require high abilities. Technical change usually compliments these occupations allowing them to be more efficient in their time allocations. Autor and Dorn (2013) focus on the Routine Task-Intensity to identify which occupations are susceptible to automation: Let $RTI_{k,t}$ be the routine task-intensity of occupation k at time t. Then

$$RTI_{k,t} = ln(T^R_{k,t}) - ln(T^M_{k,t}) - ln(T^A_{k,t})$$

where T^R is routine tasks, T^M is manual tasks, and T^A is abstract tasks. Higher the RTI measure more prone an occupation to technical change. These tasks are mapped to Dictionary of Occupational Titles (DOT) as in Table 1.1.

We reconstruct RTI index using O*NET, which has been introduced as the replacement of DOT. However, there is a slight variation in the variables between

Table 1.2: Mapping of Tasks to O*NET Variables

Tasks	O*NET Components
Manual Tasks	"Multi-limb Coordination"
Routine Tasks	"Evaluating Information to Determine Compliance with Standards"
	"Finger Dexterity"
Abstract Tasks	"Coordinate or Lead Others" and "Mathematical Reasoning"

the datasets. We choose O*NET variables that is the closest to the variables used in Autor and Dorn (2013), and map the tasks to O*NET as in Table 1.2.

In calculating the RTI, we make a small adjustment. Both in DOT and in O*NET, Manual Tasks intensively have values in $(0, 1)$ interval. This is not true for Routine and Abstract Tasks. Combined with the asymptotic behavior of logarithmic function the RTI measure reflects "the lack of Manual Tasks" rather than how routine intensive they are. We change the functional form so that the measure would not suffer from this bias.

$$RTI_{k,t} = ln(1 + T^R_{k,t}) - ln(1 + T^M_{k,t}) - ln(1 + T^A_{k,t})$$

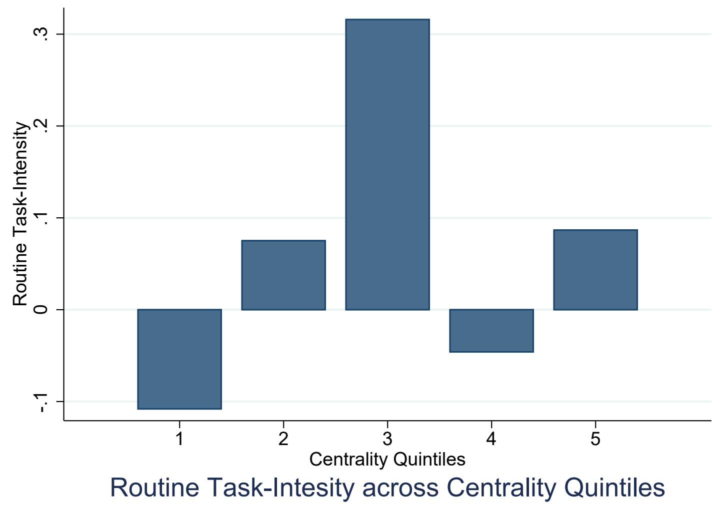
Figure 1.6 shows the relationship between centrality of occupations and their routine task-intensities. 1^{st} and 4^{th} quintiles are not routine intense as the measure for them is below zero. These occupations are protected from technical change. Whereas other quintiles are expected to undergo automation. 3^{rd} quintile consists of the most automatable occupations. The core occupations are also seem to be automatable.

Computerisability

The measure developed in Autor and Dorn (2013) is backward looking. They assume only codifiable occupations will be automatized. This has been largely true throughout history; however, new technologies like "Machine Learning", "Mobile Robotics", and "Cloud Robotics" seem to defy this understanding of technical change.[2] They are able replace tasks that do not have explicit algorithms embedded in them. For example, Frey and Osborne (2017) notes

[2] Pratt (2015) and Frey and Osborne (2017) has an excellent discussion on these new technologies.

Figure 1.6: Routine Task-Intensity index by Centrality Quintiles



Notes: There is a weak positive relationship between RTI and centrality quartiles. 1st and 4th quintiles are not routine intense as the measure for them is below zero. These occupations are protected from technical change. Whereas other quintiles are expected to suffer from technical change. We see that 3rd quintile consists of the most automatable occupations. The core occupations are also seem to be automatable. Given that they employ the most population the effects of automation of these occupations will have enormous consequences in terms of labor displacement.

According to Brynjolfsson and McAfee (2011), the pace of technological innovation is still increasing, with more sophisticated software technologies disrupting labour markets by making workers redundant. What is striking about the examples in their book is that computerisation is no longer confined to routine manufacturing tasks. The autonomous driverless cars, developed by Google, provide one example of how manual tasks in transport and logistics may soon be automated. In the section "In Domain After Domain, Computers Race Ahead", they emphasise how fast moving these developments have been. Less than ten years ago, in the chapter "Why People Still Matter", Levy and Murnane (2012) pointed at the difficulties of replicating human perception, asserting that driving in traffic is insusceptible to automation: "But executing a left turn against oncoming traffic involves so many factors that it is hard to imagine discovering the set of rules that can replicate a driver's behaviour [. . .]". Six years later, in October 2010, Google announced that it had modified several Toyota Priuses to be fully autonomous Brynjolfsson and McAfee (2011).

Building on the new premises suggested by these new technologies; Frey and

Table 1.3: O*NET Variables that Serve as Indicators of Bottlenecks to Computerisation

Computerization Bottleneck	O*NET Variable
Perception and Manipulation	Finger Dexterity
	Manual Dexterity
	Cramped Work Space, Awkward positions
Creative Intelligence	Originality
	Fine Arts
Social Intelligence	Social Perceptiveness
	Negotiation
	Persuasion
	Assisting and Caring for Others

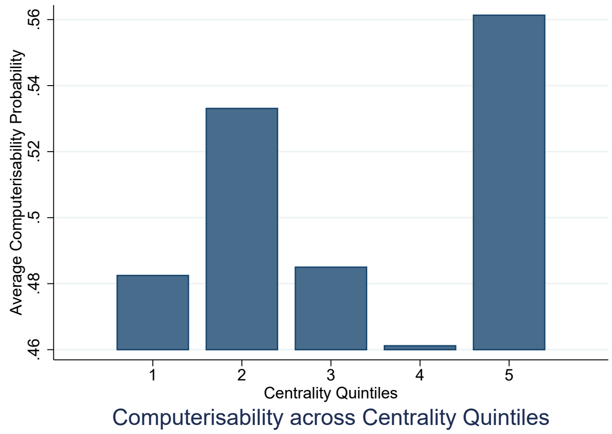
Osborne (2017) constructs an index of computerisability[3] accounting for recent developments. With a group of machine learning experts they identify what they call computerization bottlenecks, biggest problems faced by today's technologies. They categorize these bottlenecks as "Perception and Manipulation", "Creative Intelligence", and "Social Intelligence". They map these categories to O*NET as in Table 1.3.

Then they handpick 70 (Out of 702 O*NET occupations) occupations that they are most confident that they will be automatized or not. They label those "certainly" automatable with 1 and assign 0 to those are "certainly" not automatable. (For example "Economists" is labeled 0 and "Dishwashers" is labeled 1) They use characteristics of these 70 occupations as training data for a machine learning algorithm. And let the algorithm index remaining occupations based on their O*NET characteristics. The algorithm also corrects for possible mistakes in hand labeling using the patterns it found in the data. (For example it assigned .47 probability to "Economists" being computerized.) Also, Frey and Osborne (2017) claim the resulting probabilities are robust to using only subsets of these 70 occupations. We directly use the "Computerisability Probability" measure they provide.

Computerisability index paints a very different picture. As Figure 1.7 represents, computerisability index suggests that core occupations are the most susceptible to computerisation. The difference between the implications of the

[3] The index can be found in the Appendix of the Frey and Osborne (2017)

Figure 1.7: Computerisability Probability by Centrality Quintiles



Notes: Computerisability Probability index suggests core occupations are also the ones which are most susceptible to computerisation. This analysis also shows much of the working populations is susceptible to technical change.

indexes highlights the changing nature of automation. Compared to rule-based automation based on codifiability, newer technologies show the potential for automating core occupations. This change has important consequences. First, core occupations employ the majority of the workers. Consequently, the direct impact of automation will be much more significant than rule-based automation. Second, since workers in core occupations possess fewer skills, it will be harder for them to transition away from automated occupations. Finally, as core occupations play a crucial role in the network, and make it possible for workers to migrate across occupations, the indirect impact of occupations on other workers will also be more substantial.

1.5 Extension: Early Career vs Late Career Networks

This section extends the analysis of occupational networks and automation by focusing on Early Career and Late Career transitions. Studying the subnetworks is essential for two main reasons. First of all, workers in different career stages work at different occupations and transition to different occupations. Therefore, the subnetworks are potentially very different. Second, the ability of the workers to transition to other occupations can be different. Older workers generally possess more skills as they had time to accumulate more human capital. On the other hand, it might be harder for them to adjust to the new environment, whereas young workers could be more adaptable to technical change. We define

Table 1.4: Correlation between career sub-networks

Career Stage	Late Career Transitions
Early Career Transitions	-0.0143

Notes: Early Career: Ages 25-35 Late Career: 40-55. There is a weak negative correlation significant at .14 level.

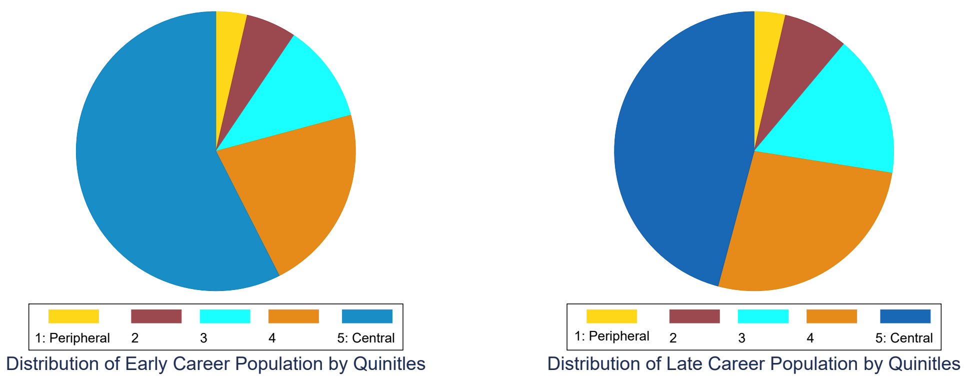
Early Career as occupations held between ages 25-35 and Late Career occupations held in as ages 40-55. We choose these intervals to exclude college students and retirees.

The comparison of early career and late career networks reveals that workers behave differently across career stages. As Table 1.4 shows, the correlation between transitions in different stages is statistically insignificant and negative. If age composition were not to matter for occupational transitions, we would expect a near-perfect positive correlation. The no-correlation means that transitions experienced by early career individuals and late career individuals are vastly different. Therefore, it is crucial to analyze the characteristics of these groups in detail.

The population distribution for these sub-networks has the same characteristics as the main network. Population monotonically declining in the centrality of the occupations. Early Career occupations are a little bit more populated in central occupations than their Late Career counterparts. On the other hand, Late Career Occupations have more mass in the middle.

Furthermore, career stages are also heterogeneous in their skill requirements. Peripheral occupations demand more education (as indicated by Job Zone) than core occupations, as was the case for the main network. However, for the Early Career network, peripheral occupations are demand significantly more education. The differences between “Physical” and “Psychomotor Abilities” also seem to an important indicator in comparing sub-networks. For Early Career occupations, it is the core occupation that demands more “Physical” and “Psychomotor Abilities”. This is reversed in Late Career sub-network. Peripheral occupations require more of these abilities. There are no significant differences in “Resource Management” and “Social Skills” requirements in Early Career occupations. Moreover, Early Career occupations seem to be more differentiated in terms of “Systems Skills”, “Basic Skills”, “Complex Problem Solving Skills” and

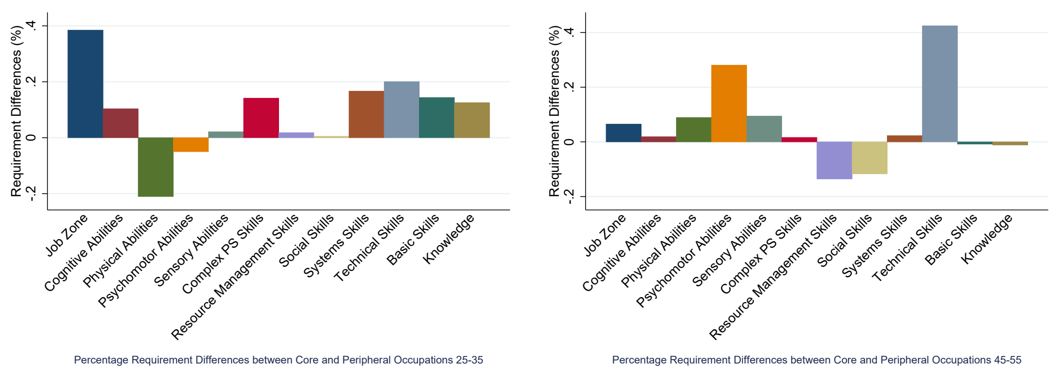
Figure 1.8: Distribution of Population By Centrality Quintiles for Different Career Stages



Notes: 5 represents the most central occupations quintile whereas 1 represents the most peripheral occupations quintile. The population distribution for these sub-networks has the same characteristics the main network. Population monotonically declining in centrality of the occupations. We see that Early Career occupations are little bit more populated in central occupations than their Late Career counterparts. On the other hand, Late Career Occupations have more mass at the middle.

occupations specific knowledge. Whereas peripheral Late Career occupations require more "Technical Skills" compared to its Early Career counterpart.

Figure 1.9: Requirement Differences between Core and Peripheral Occupations for Different Career Stages

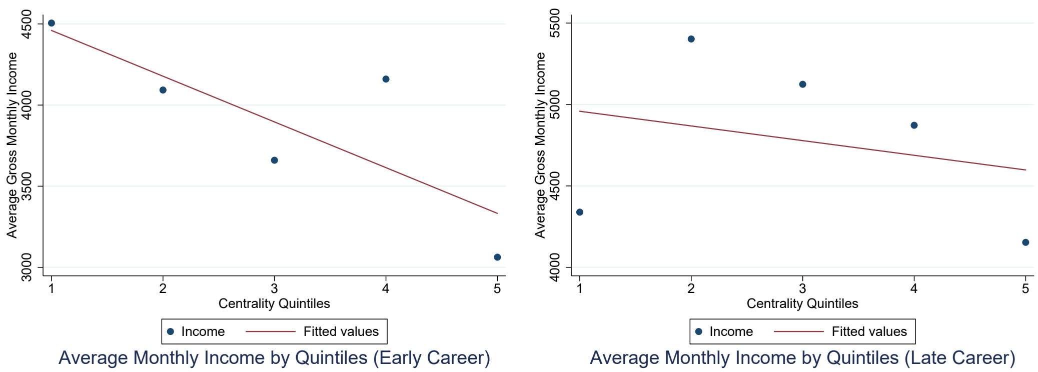


Notes: Core occupations (5th Quintile) Peripheral occupations (1st Quantile). Requirement differences between centrality quantiles are very heterogeneous across career stages. For early career workers peripheral jobs require high levels of education (job zone). Whereas for late career workers technical skills seem to be the main difference.

The differences in Early Career and Late Career Networks do not seem to have opposing implications for income profiles of centrality quintiles, except for peripheral occupations. For Early Career occupations, the average income in the periphery is the highest one, in contrast to Late Career occupations, where peripheral occupations have the second-lowest income average. Otherwise, the average income monotonically decreases, similar to the main network.

The next subsection examines the implications of automation for the subnetworks through the lens of RTI and Computerisability indices.

Figure 1.10: Average Monthly Income by Occupations.



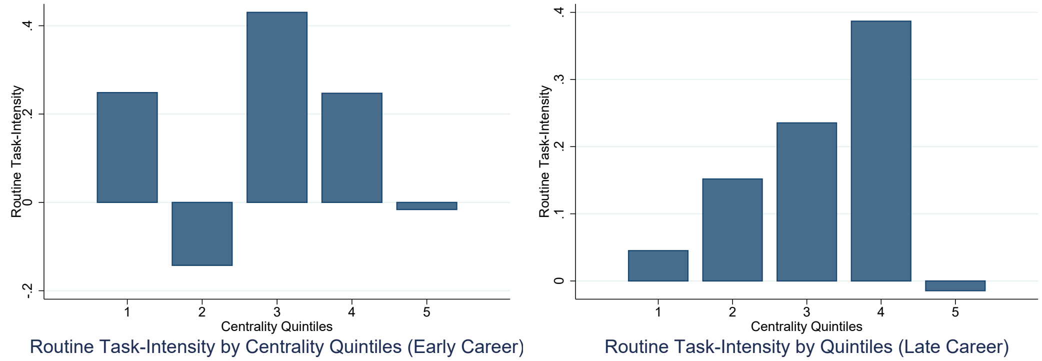
Notes: Except for the peripheral occupations, Early Career and Late Career earning have a similar income profile.

1.5.1 Technical Change for Early Careers and Late Careers

Having documented the differences between the subnetworks, we focus on the implications of automation for the network. We perform the similar analysis we have done in the previous section for "Early Career Transitions" and "Late Career Transitions" to understand if technical change would affect these sub-networks differently.

As shown in Figure 1.11, Early Career employees and Late Career employees will be affected differently from technical change, accordingly with RTI index. Most peripheral occupations for Early Career employees are highly automatable, whereas the same does not apply to Late Career employees. Nonetheless, core occupations are not the high risk area for both of these sub-networks. RTI index predicts it will be the middle occupations will suffer intensely from upcoming technical changes, similar to the main network.

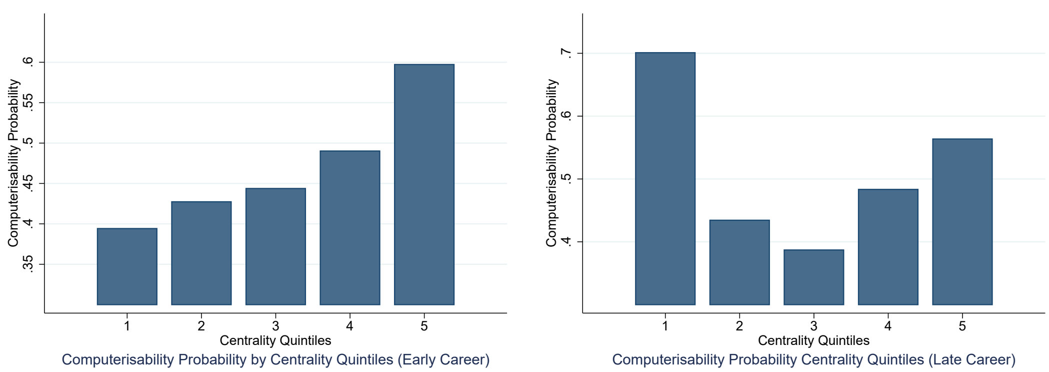
Figure 1.11: Routine Task-Intensity for Different Career Stages



Notes: Early Career employees and Late Career employees will be affected differently from technical change, accordingly with RTI index.

There is a stark difference between the implications of the RTI index and the computerisability index. Figure 1.12 summarizes the results. There is a strong positive correlation between centrality and computerisability for Early Career employees. In contrast with early career, we observe that most peripheral occupations in the Late Career Occupational Network are under the risk of computerisation. The core occupations in this sub-network are also susceptible to technical change.

Figure 1.12: Computerisability Probabilities for Different Career Stages



Notes: With computerisability index we get a stronger relationship in the opposite direction of what RTI suggests.

1.6 A Simple Counterfactual Analysis

This section investigates some possible consequences of automation of occupations by performing a simple counterfactual. Taking Frey and Osborne (2017)'s computerisability probability measure, we ask the following question? "What would happen if occupations that have more than 95% probability of computerization indeed are replaced by robots and computers?"

These occupations employ 7% of the working population. Therefore, the workers will have to be displaced to other occupations or be forced out of the labor force. Moreover, these effects would be amplified by the network effects as the disappearance of these occupations would cause 9% of the links to dissolve in the occupational network. Therefore, the technical change should only be discussed in terms of direct causes of labor displacement but also in terms of the ability to move between occupations.

1.7 Conclusion

This Chapter analyzed the impact of automation on the workforce by focusing on occupational networks. The network structure enabled us to understand how occupations relate to each other. The network is estimated using Survey of Income and Program Participation data on labor flows across occupations. Results showed that there is a core/periphery structure in occupational space and network is sparsely connected. Some occupations are well connected to others whereas some are isolated from other occupations. Core occupations are characterized by high population and lower level of education, skill, ability requirements as documented by O*NET data. Employees in this occupations are also earn considerably less income than employees in peripheral occupations.

The major result of this Chapter was to show that the core occupations have become more susceptible to automation. This result stems from the comparison two different measures of automation. The first is the Routine Task-Intensity (RTI) index. This index assumes only the occupations that require performing explicit algorithms without intense social interaction are automatable. As it disregards the potential of new technologies, this measure is reflects the old technologies. However, recent technologies have shown the capacity to substitute not only codifiable occupations but also non-codifiable. Computerisability Probability Index, on the other hand, aims to capture the new capabilities of technologies like machine learning, and it is more forward-looking. We find that RTI predicts the core occupations are relatively safe from automation. In contrast, Computerisability reveals that the core occupations are under the greatest threat of technical change. Therefore, automation's impact is expected to be larger, both in terms of its direct effects on workers employed in core occupations as well as its indirect effects through its implications for the network structure.

As an extension, we analyzed two subnetworks: Early Career and Late Career occupational networks. The comparison of the sub-networks revealed that transition patterns are significantly different in different career stages. Both measures of automation suggest that there is a difference in the impact of automation on early and late career networks. RTI measure predicts that semi-peripheral occupations in these networks are prone to technical change. On the other hand, the computerisability index displays a stark contrast in career stages. For early career workers, it predicts that the core occupations will be automatized, whereas for the late career network, it predicts that peripheral occupations are more susceptible to automation.

In a simple counter-factual exercise based on Frey and Osborne (2017) index we projected the occupations that have more probability than 95% will be computerized. Results suggested that it is expected that 7% of the workers are expected to be displaced. Moreover, disappearance of these occupations will result in 9% of the links in the networks to dissolve. This would cause further impact as it would be harder for remaining workers to transit between occupations and insure themselves possible unemployment shocks.

The next chapter embeds these results into a structural model of occupational choice to understand how endogenous responses could be formed. This would enable us to do more meaningful counter-factual analysis which are needed for more robust expectations regarding future occupations and better policy advice regarding unemployment insurance and human capital subsidies.

Chapter 2

Technological Advancements and Labor Reallocation

2.1 Introduction

Technology is developing at an unprecedented rate.[1] As computers, robots, and other digital technologies rapidly acquire new skills and abilities, there is increased concern about unintended labor market consequences they may bring. According to a recent McKinsey Global Institute report (Manyika, Lund, Chui, Bughin, Woetzel, Batra, Ko, and Sanghvi 2017), by 2030, as many as 375 million workers—or roughly 14 percent of the global workforce-may need to switch occupational categories as technological advances disrupt the world of work.

Several aspects of labor markets hinder the ability of displaced workers to find new jobs. First, labor markets exhibit search frictions. Even when suitable jobs exist, it takes time and effort for workers to discover them. Therefore, adjustments to technological shocks happen slower than they would in frictionless markets. Moreover, displaced workers may have skill deficiencies that render them under-qualified for surviving jobs. They may require costly retraining to obtain the skills necessary to perform satisfactorily in their new jobs. Finally, technological unemployment not only impacts the workers who lose their jobs to automation but also the workers who keep their jobs due to general equilibrium effects on wages and matching probabilities. Consequently, automation in one occupation may disrupt the labor market as a whole. The impact of automation on labor markets depends on the magnitude of such forces. If small, then au-

[1] See, for example, Pratt (2015), Brynjolfsson and McAfee (2014), and Frey and Osborne (2017).

tomation's effect would be minimal. If large, however, then automation is more likely to generate unintended adverse consequences.

To analyze the labor market impact of new technologies on labor displacement and reallocation, this paper introduces an occupational choice model within an equilibrium search environment of the labor market. The paper makes both theoretical and empirical contributions. On the theoretical side, this paper shows how discrete choice framework with random utilities solve issues related to non-convex bargaining sets in models with on-the-job search. Furthermore, decomposition of transition probabilities into search, and matching probabilities is provided. This decomposition is useful as the primary data sources do not feature workers' search decisions and matching outcomes separately. On the empirical side, we structurally estimate search frictions and transition costs. Results suggest such frictions greatly curtail worker's ability to transition away from jobs vulnerable to automation.

The economic environment in this paper is formulated with search frictions as in Diamond-Mortensen-Pissarides (DMP) model. We treat each occupation as a distinct submarket with a separate matching function dictating job finding and vacancy filling probabilities. Workers are allowed to search on the job; hence, matching functions not only take stock of unemployed workers and vacancies as inputs but also the on-the-job searchers.

Workers in our model resembles those found in structural dynamic discrete choice literature such as Miller (1984) and Keane and Wolpin (1997).[2] Most of literature usually assumed workers have existing offers from all occupations, and they choose which one to accept. Recent work explored cases in which workers randomly get job offers from occupations in continuous time models. In these models workers react passively to the random realizations of offers and cannot direct their search. By contrast, workers in our environment direct their search to their desired occupation.

In each period, they decide whether to stay home, search, or, if already employed, remain in their current job. The utility of each alternative depends on choice-specific random shocks. They are observed by the worker when making their decisions but not by the econometrician. Working with random utilities in an equilibrium search model is desirable as it facilitates tighter connection of model and data and enables estimation of search frictions and transition costs.

[2]For a general review of dynamic discrete choice models, we refer readers to Aguirregabiria and Mira (2010)

Furthermore, they also help reconcile search models with empirical regularities such as job to job transitions that entail wage cuts (Jolivet et al. 2006), and the difference between gross flows and net flows across submarkets (Pilossoph 2014).

The main theoretical contribution of this paper is to establish identification of search and matching probabilities from data on employment transitions. Data on search decisions and matching outcomes are not available separately. Instead, only successful transitions between occupations observed in the data. Therefore, for example, it is not possible to tell apart between a worker who chooses to stay in current job versus a worker who searched for another job but failed to find a job. This issue led most of the occupational labor supply papers to assume job offers always exist, and therefore transitions directly correspond to decisions made by workers. We show that random matching facilitates decomposition transition probabilities into search and match probabilities. As a result, the decomposition permits the identification of search frictions and transition costs separately.

Decoupling transition costs and search frictions is essential for policymaking as they point to different recommendations. For example, if transition costs are relatively more important in determining the impact of automation, then it would make sense to investigate policies that aim to retrain the workforce. A recent example of this policies is the National Retraining Scheme in the United Kingdom that was introduced in response to "the changing nature of jobs and the types of task people do at work". On the other hand, if search frictions are sizable, policies would have aimed at increasing the efficiency of labor markets, such as the Job Search Assistance programs. [3] Furthermore, if general equilibrium responses are extensive, automation would also impact workers whose jobs are not directly threatened by automation. Hence, policymakers might be interested in considering the indirect impact of automation as well and determine the scope of the policies accordingly.

The primary source of data in this paper is the Survey of Income and Program Participation (SIPP). Administered by the U.S. Census Bureau, SIPP consists of series of short panels. Each panel includes earnings information, occupational transitions, as well as workers' characteristics. We rely on 2004 and 2008 panels, and therefore our coverage spans 2004 - 2013. To obtain occupational requirements, we use O*NET. O*NET is a comprehensive data set that provides

[3] For a meta-analysis and comparison of these programs see Card, Kluve, and Weber (2018).

a plethora of information on occupational characteristics. Following Yamaguchi (2010), Principal Component Analysis (PCA) is performed to reduce the dimensionality of O*NET variables. As a result, three principal components emerge: cognitive, physical, and social requirements. For occupational level vacancies, we rely on the estimates by Hobijn and Perkowski (2016). Combining data from the Current Population Survey, Job Openings and Labor Turnover Survey, and state-level Job Vacancy Surveys, they construct annual estimates of the number of job openings by occupations for 2005-2013.

Estimation results indicate that workers face significant transition costs and search frictions. Average job finding probability upon search is below 0.5, meaning that, on average, it takes more than eight months to find a job in the desired occupation. Labor markets also feature substantial transition costs. For an average worker, compensating transition costs require a 10% increase in wages for thirty years. Therefore, frictions in labor markets are sizable and would curtail workers' ability to transition to other jobs in response to automation.

Using an index developed in Frey and Osborne (2017), the paper documents more automatable occupations also face higher transition costs. Furthermore, highly automatable occupations have lower transition costs to each other and high transition costs to other occupations. Therefore, if these occupations were to go through automation together, impact automation would be magnified. Workers would have little option to find another occupation that suits their skills and require high levels of retraining.

To analyze the impact of estimated frictions on labor market transitions, we perform the following counter-factual. We assume increased competition from automation decreases the revenues in "Transportation and material moving" occupations by 25%. As a result, the steady-state economy-wide unemployment rate increases by 5%—leading to 150,000 more unemployed workers. Transition dynamics reveal it takes around seven years for the economy to reach the new steady-state equilibrium, most of which is spent at higher unemployment levels. Considering that firms adjust to the shocks immediately in our model, we consider these results to be a lower bound. Combined, we show that labor markets are characterized by high levels of frictions, and adjustments to automation could take significant time.

Related Literature:— Our paper is similar in methodology to Artuç, Chaudhuri, and McLaren (2010) and Traiberman (2019) in studying labor adjustment and reallocation in response to external shocks. Both of these papers study sectoral shifts due to trade shocks, borrowing techniques from dynamic discrete choice literature. While Artuç et al. (2010) highlights the importance of transition costs workers face, Traiberman (2019) extends their model to emphasize the importance of lost human capital when workers switch between occupations. Our paper follows a similar recipe; however, instead of competitive markets, we employ an equilibrium search model. Studying search models in this context is important as it enables us to study unemployment, an integral part of the discussions surrounding both trade and automation shocks. As in this paper, Pilossoph (2014) also considers a discrete choice framework in the DMP model. She mainly uses random utilities to generate gross inter-sectoral flows above net inter-sectoral flows. In contrast, we use the framework as a basis to estimate the magnitude of labor market frictions and show how it facilitates convex bargaining sets in the presence of on-the-job search.

This paper is also related to the literature that investigates the contraction of routine non-cognitive jobs that started with Autor, Levy, and Murnane (2003). Restrepo (2015) and Cortes, Jaimovich, and Siu (2017) show that automation of routine manual jobs leads to the reallocation of these workers towards non-routine manual jobs and non-employment. Cortes et al. (2017) studies a static environment without search frictions and transition costs. On the other hand, Restrepo (2015) shows that matching frictions substantially amplifies the impact of skill mismatch due to structural changes. Differently from this set of papers, we refrain from categorizing jobs as routine or non-routine and work with occupations directly. As discussed in Frey and Osborne (2017), new technologies do not only replace routine "codifiable" manufacturing work, but even legal and financial services are entering the domain of automation.

Finally, our paper adds to the literature studying the equilibrium impact of technological advancements. This literature predominantly augments growth models with technology adoption such as Alesina, Battisti, and Zeira (2018), Acemoglu and Restrepo (2018), and Acemoglu and Restrepo (2019) highlighting the importance of the interplay between labor costs and technology adoption for employment and wages. Recent papers also explore automation in the context of equilibrium search models. Guimarães and Gil (2019) extends the DMP model by to include automation as an additional alternative of production to entrant firms. Firms observe their productivity after paying an entry cost and then choose how to produce. Therefore, when automation becomes more profitable, more firms pay the entry cost, and the number of firms increases for both technologies. As a result, employment and wages go up after the introduction of technologies that decrease the cost of automation. Cords and Prettner (2018) takes a different approach to introducing automation. They assume that there is a final goods producer that combines aggregate labor output with regular capital and automation capital, where automation capital is a perfect substitute for aggregate manual labor. They then show that a decrease in the costs of automation capital decreases employment and wages. In this paper, automation impacts the output prices of firms through being a substitute for manual labor, but that substitution happens at a disaggregated level. Therefore, in our model, increased automation in a subset of occupations does not necessarily mean higher unemployment and lower wages for the total economy.

The paper is organized as follows. Section 2 introduces the model. Section 3 discusses identification and estimation, while section 4 introduces the data. Section 5 presents the estimation results. Section 6 investigates the impact of automation. Section 6 concludes.

2.2 Model

The environment is stationary and features N occupations denoted by the set $O = \{o_1, o_2, o_3, ..., o_N\}$. Workers can be in three employment statuses: Working (W), not-working with unemployment benefits (U), and not-working without unemployment benefits (H). There is a continuum of workers distributed across occupations and employment statuses denoted by L. Workers search for a job in the occupational segments and a continuum of firms post vacancies to recruit them. The labor market is frictional due to search frictions and occupational transition costs.

2.2.1 Matching Technology

Labor markets are characterized by search frictions. Even when a suitable jobs exists, it takes time and effort for these jobs to turn in to successful matches. For each occupation there exists a matching technology that captures these frictions. Number of matches $m_i L$ is given by a $M_i(s_i L, v_i L)$ where s_i is the fraction of workers (employed and unemployed) searching jobs in occupation i and v_i is total number vacancies post in occupation i as a fraction of the labor force. The matching function has a Cobb-Douglas form

$$m_i = \mu_i s_i^{\alpha} v_i^{1-\alpha} \tag{2.1}$$

where submarkets are heterogenous in efficiency μ_i. Let $\theta_i = \frac{v_i}{s_i}$ denote labor market tightness in occupation i. The probability of a vacant jobs becoming filled is

$$Q_i = Q(\theta_i) = \mu_i \theta_i^{-\alpha} \tag{2.2}$$

Similarly, workers searching for a job in occupation i get matched with a job with probability

$$P_i = \theta_i Q(\theta_i) = \mu_i \theta_i^{1-\alpha} \tag{2.3}$$

These probabilities play a crucial role in determining the impact of automation shocks. Even in the absence of skill deficiency across workers and jobs, if the search frictions are large, it would take a long time for markets to transition into the new steady state.

2.2.2 Workers' Problem

Workers maximize lifetime utility by choosing whether to stay in their current occupation, search for a different one, or stay at home. Therefore, their choice set consists of occupations O and staying home H: $O \cup H$.

When making their choices, workers take choice specific idiosyncratic shocks $\boldsymbol{\epsilon} = \{\epsilon_1, \epsilon_2, \epsilon_3, ..., \epsilon_N, \epsilon_H\}$ into account, where the first N terms are for occupations (including their own) and ϵ_H is for staying home. They are observed to agents when they are making choices but unobserved to econometricians. Throughout this paper, shocks are assumed to be distributed independently and identically with "*Type-1 Extreme Value*" across choices, individuals, and time with pdf $g(\boldsymbol{\epsilon})$. This assumption facilitates analytical derivations and ease computation as conditional choice probabilities (*CCP's*) and expectations with respect to shocks have closed-form solutions (Rust 1994).

Workers employed in occupation i enjoy wages ω_i and non-pecuniary benefits ξ_i. If a worker chooses to stay in their current occupation, they get to keep their job with probability $(1 - t_i)$, where t_i denotes exogenous separation rate. On the other hand, searching is time-consuming and costs ϕ. Workers seeking for a job in occupation j get matched to an employer with probability P_j in accordance with the matching function. If they fail to find a job, they go back to their current occupation. As firms and workers are atomistic, they take the values of wages and job finding probabilities as given. If matched, workers update their skills by paying transition costs C_{ij}, and bargain with firms over the surplus created by their alignment.

Transition costs C_{ij} capture the degree of skill compatibility across occupations. In the case that workers are able to move across jobs costlessly we have $C_{ij} = 0$. When costs are low, other occupations provide insurance against automation. If one of the occupations is hit by an automation shock, workers can move to other occupations easily. As C_{ij} gets larger, the flows between occupations converge to zero and occupations become isolated. As occupations become isolated, the impact of automation increases as the workers in those occupations cannot find employment in other jobs.

The problem of an individual worker employed in occupation i with taste shocks ϵ can be represented as

$$W(i,\epsilon) = \max \Bigg[u(\omega_i) + \xi_i + \epsilon_i + \beta\big((1-t_i)EW(i) + t_iEU(i)\big), \tag{2.4}$$

$$\Big(\max_{j \in O \setminus \{i\}} u(\omega_i) + \phi + \xi_i + \epsilon_j + \beta\big(P_j(C_{ij} + EW(j)) + (1-P_j)(1-t_i)EW(i) + (1-P_j)t_iEU(i)\big)\big] \Big),$$

$$u(\omega_i) + \xi_i + \epsilon_H + \beta EH(i) \Bigg]$$

where β is the discount factor and $EW(i)$, $EU(i)$, $EH(i)$ denote ex-ante value of being in occupation i with respective employment statuses. As the uncertainty regarding shocks in the next period are not revealed yet expectations are taken over ϵ and we have $EX(i) = \int X(i,\epsilon)g(\epsilon)d\epsilon$. The first line gives the value of staying in the current occupation. The second line gives the value of searching for another occupation being the maximal value that can be attained by optimally choosing which occupation to search for. If workers become unemployed due to exogenous reasons they qualify for unemployment benefits and receive the continuation value $EU(i)$. The third line describes the value of stay home next period. Since such transition is voluntary, workers choosing to stay home do not qualify for benefits and get the continuation value $EH(i)$.

As customary in the dynamic discrete choice literature, it is easier to works with conditional value functions. Define the conditional value functions as value function net of the idiosyncratic shock as

$$w_i(i) = u(\omega_i) + \xi_i + \beta\big((1-t_i)EW(i) + t_i EU(i)\big), \tag{2.5}$$
$$w_j(i) = u(\omega_i) + \xi_i + \phi + \beta\big(P_j(C_{ij} + EW(j)) + (1-P_j)(1-t_i)EW(i) + (1-P_j)t_i EU(i)\big),$$
$$w_H(i) = u(\omega_i) + \xi_i + \beta EH(i)$$

Each of these denotes the value of choosing $k \in O \cup H$ in the current period without taking ϵ_i into account and behaving optimally starting the next period. These are key values in forming conditional choice probabilities. Using conditional value functions workers problem can be represented as:

$$W(i,\epsilon) = \max_{j \in O \cup H} w_j(i) + \epsilon_j \tag{2.6}$$

As is standard in discrete choice problems, for each choice j, *Type-1 Extreme Value* assumption results in following conditional choice probabilities[4]

$$\pi_j^e(i) = \frac{e^{w_j(i)}}{\sum_{k \in O \cup H} e^{w_k(i)}} \tag{2.7}$$

Expected values also have an analytical form

$$EW(i) = \ln \sum_{k \in O \cup H} \exp w_k(i) + \gamma \tag{2.8}$$

where γ is the Euler-Mascheroni constant.

Next, we focus on the problem of an unemployed worker enjoying unemployment benefits who last worked at occupation i. Conditional value functions and choice probabilities for unemployed workers are defined similarly:

$$u_j(i) = u(b_i) + \lambda + \phi + \beta\big(P_j(C_{ij} + EW(j)) + (1-P_j)\rho EU(i) + (1-P_j)(1-\rho)EH(i)\big) \tag{2.9}$$
$$u_H(i) = u(b_i) + \lambda + \beta EH(i)$$

where λ captures the value of leisure and ρ represents the probability that the worker will continue receiving unemployment benefits in the subsequent period. This is a computationally attractive way of capturing the fact that unemployment benefits are given for a finite amount of time without having to track each

[4]See Train (2009) for derivations.

individual's unemployment duration. Bellman equation is

$$U(i, \boldsymbol{\epsilon}) = \max_{j \in O \cup H} u_j(i) + \epsilon_j \tag{2.10}$$

Conditional choice probabilities for non-employed workers qualified for unemployment insurance has the form

$$\pi_j^u(i) = \frac{e^{u_j(i)}}{\sum_{k \in O \cup H} e^{u_k(i)}} \tag{2.11}$$

Value of having last work at occupation i while consuming benefits is

$$EU(i) = \ln \sum_{k \in O \cup H} \exp u_k(i) + \gamma \tag{2.12}$$

When workers choose to stay home or exhaust their benefits they earn z reflecting home production and other social insurance programs. Conditional value functions for non-employed workers without unemployment benefits is given by

$$\begin{aligned} h_j(i) &= u(z) + \lambda + \phi + \beta\big(P_j(C_{ij} + EW(j)) + (1 - P_j)EH(i)\big) \\ h_H(i) &= u(z) + \lambda + \beta EH(i) \end{aligned} \tag{2.13}$$

When such workers cannot find a job, they get the continuation value $EH(i)$. This is because the eligibility of unemployment insurance requires working at least one period prior to involuntary separation. Associated Bellman equation is

$$H(i, \boldsymbol{\epsilon}) = \max_{j \in O \cup H} h_j(i) + \epsilon_j \tag{2.14}$$

Conditional choice probabilities are

$$\pi_j^h(i) = \frac{e^{h_j(i)}}{\sum_{k \in O \cup H} e^{h_k(i)}} \tag{2.15}$$

And the expected value function is given by

$$EH(i) = \ln \sum_k \exp h_{k \in O \cup H}(i) + \gamma \tag{2.16}$$

2.2.3 Firms' Problem

Firms' problem closely follows DMP formulation. There is a continuum of firms in each occupation. Firms search for workers by posting a vacancy which costs κ_i. With probability Q_i they are matched with a worker start producing. If not the position stays vacant. The value of posting vacancy in occupation i is

$$V(i) = -\kappa_i + \beta[Q_i J(i) + (1 - Q_i)V(i)] \tag{2.17}$$

Next we define the value of a filled vacancy. If the match is fruitful firms start producing an occupational good and sell it for p_i and pay wages ω_i. We assume that p_i is exogenously determined in the goods market where manual and automated firms compete against each other. Jobs get exogenously terminated with probability t_i. Until then the match persists unless worker leaves either by successfully finding another job or quitting. The value of a filled position

$$\begin{aligned} J(i) = p_i - \omega_i + \beta \Big[&\pi^e_H(i)V(i) + \pi^e_i(i)t_iV(i) + \pi^e_i(i)(1-t_i)J(i) \\ &+ \sum_{k \neq i,H} \pi^e_k(i)P_kV(i) + \sum_{k \neq i,H} \pi^e_k(i)(1-P_k)t_iV(i) + \sum_{k \neq i,H} \pi^e_k(i)(1-P_k)(1-t_i)J(i) \Big] \end{aligned} \tag{2.18}$$

where $\pi^e_j(i)$ denotes the conditional choice probabilities for employed workers as derived in Equation 2.7. As opposed to cannonical DMP framework without on-the-job search, the value of a job takes the searching behavior of workers into account. The first term in brackets is the probability that the worker will quit their job. The second and third term captures the value of a worker who wanted to stay in the current job. In this case, jobs can either exist in the next period or exogenously terminate. The fourth term captures the probability of workers successfully finding a job in another occupation. The last two terms deal with searchers who failed to find a job and come back to their original job. Their match survives or terminates again with respect to separation rate t_i.

There is free entry, and firms enter until all profit opportunities are exhausted: $V(i) = 0$. Therefore, in equilibrium value of a filled position reduces to

$$J(i) = \frac{\kappa_i}{\beta Q_i} \tag{2.19}$$

This equation asserts that in equilibrium, market tightness is such that value of a job in occupation i is equal to the expected cost of hiring a worker. Let

$\pi_s^e(i) = \left(\pi_i^e(i) + \sum_{k\neq i,H} \pi_k^e(i)(1-P_k)\right)$ denote the probability that the worker will show up to work either by choosing to stay or searching for another occupation but failing to find a job. Substituting $J(i)$ back into associated value function we get

$$\omega_i = p_i + \left[\beta(1-t_i)\pi_s^e(i) - 1\right]\frac{\kappa_i}{\beta Q_i} \tag{2.20}$$

is the job creation condition which is analogous to classical labor demand function. As market tightness θ_i increase probability of filling a vacancy Q_i decreases. Since term in brackets is less than zero this leads to a decrease in the wage rate.

2.2.4 Wage Determination

So far, wages ω_i are assumed to be given. This subsection introduces them as an outcome to bargaining process. We assume that firms and workers only bargain over the wage.

The value of a match to a worker is the expected value of match given by $EW(i)$ as at the time of the match, the uncertainty has not revealed to the worker. We assume the worker's threat point is $EH(i)$. Although it is natural for unemployed and non-employed workers, there is a merit for such an assumption for employed workers too, as discussed in Flinn and Mabli (2009) Firstly, it might reflect the inability of workers credibly convey their current employment conditions to a new potential employer. On top of that, if offers must be rejected or accepted at the instant when they arrived, then a worker loses his or her outside option the moment after it is received. When the option is lost, the only relevant one becomes quitting. If firms are unable to commit to the wages negotiated at the time of the match and renegotiate once the job starts, non-employment becomes the threat point of the worker. Furthermore, when non-employment from occupation i becomes the threat point of workers from all possible employment states and occupations, wages become uniform, simplifying the analysis greatly. This simplification is also used in Pissarides (1994), Shimer (2006), and Mercan and Schoefer (2019) among many others.

Equipped with the value functions and threat points, Nash Bargaining solution to the wages are given by

$$\omega_i = argmax\left(EW(i) - EH(i)\right)^{\eta} J(i)^{1-\eta} \tag{2.21}$$

As Shimer (2006) and Bonilla and Burdett (2010) pointed out when there are on the job searchers, Nash bargaining might not be appropriate as a mechanism. They identified two distinct reasons as to why the bargaining set might become non-convex. Shimer (2006) assumed that workers always search on the job but only interested in moving to higher wages. As a result, even when worker searches, firms could affect turnover as higher wages implied it is harder for the worker to find an even higher wage offer. Hence, a marginal increase in wages comes with the benefit of decreasing turnover, making firms value function potentially non-convex. The critical assumption here is that the workers move to higher-paying wages. However, Jolivet, Postel-Vinay, and Robin (2006) shows that %25 to %40 percent job to job transitions across Europe and the US entails a wage loss. In contrast, in this model, once workers choose to search, current wages have no impact on whether the worker will change jobs or not. As a result, some workers will optimally accept wage cuts paralleling the empirical findings of Jolivet et al. (2006).

Bonilla and Burdett (2010) focused on a different channel of non-convexity. In their model, workers make a binary search decision. As a result, workers employ a cut-off strategy they do not search when wages are high $\omega > \omega^*$ and search when wages are low $\omega < \omega^*$. A marginal increase of wages around ω^* causes the firm's value to jump discontinuously as it induces the worker not to search. As can be seen in Figure 2.1, this leads to a non-convex bargaining set. Correspondingly maximizing the Nash product may lead to Pareto dominated wages where both the worker and the firm would benefit from higher wages. Such discontinuities do not arise in the random utility framework employed here. Although the choice set is discrete, choice probabilities themselves are smooth functions of wages. Therefore, marginal changes in wages do not result in discontinuous behavioral changes.

Even though our approach is immune to both concerns, a different dynamic comes into play. Although in our model wages do not have any impact of job finding probabilities upon search, they impact the probability of searching itself. As a result, bargained wages impact turnover through a different channel and leave scope for bargaining set to be non-convex. However, our numerical analysis shows non-convexities happen in an *"irrelevant"* subset of the bargaining set and has no impact on Nash Bargaining due to the independence of irrelevant alternatives.

Figure 2.1: Example: On-the-job Search with Cut-off Rules

Notes: Consider the case when workers make a binary decision to whether to search or not without preference shocks. Then there exists a cut-off point ω^* such that the worker does not search when wages are high $\omega > \omega^*$ and search when wages are low $\omega < \omega^*$. A marginal increase around ω^* causes firms value to jump discontinuously as it induces worker not search. This leads to a non-convex bargaining set. As a result maximizing the Nash product may lead to Pareto dominated wages where both worker and firm would benefit from higher wages.

The surplus splitting rule has the following form:

Proposition 1. *Nash bargaining results in the following surplus sharing rule*

$$EW(i) - EH(i) = \frac{\eta\left[\Big(J(i)\Big) + \Big(EW(i) - EH(i)\Big)\right]}{1 - \frac{\eta((u'(\omega)+\beta t_i \pi_s^e(i) EU'(i)|_{\omega_i})-1)J(i)}{EW(i)-EH(i)} - (1-\eta)\beta J(i)\frac{\partial \pi_s^e(i)}{\partial \omega_i}} \tag{2.22}$$

The details of the derivation are deferred to the Theoretical Appendix. Inspecting the surplus division highlights the importance of searching behavior, risk aversion, and unemployment benefits. If searching behavior were not impacted by offered wage ($\frac{\partial \pi_i(i)}{\partial \omega_i} = 0$), the utility function was linear in wage $u' = 1$, and unemployment benefits did not depend on wages then we go back to the usual bargaining setting where surplus is divided accordingly with the bargaining power.

On-the-job search increases the share of surplus that goes to workers. When workers are more likely to stay in their current job when offered higher wages ($\frac{\partial \pi_i(i)}{\partial \omega_i} > 0$), the firm offers a higher wage than non-search case to incentivize the worker to stay on the job. Effectively, the ability to search acts as if the worker has higher bargaining power as in Gottfries (2019). On the other hand, risk aversion and unemployment benefits do not have a clear impact on wages. Depending on whether $u'(\omega) + \beta t_i \pi_s^e(i) EU'(i)|_{\omega_i} < 1$ they can increase or decrease the share of worker.

2.2.5 Equilibrium

Stationary rational expectations equilibrium is given by tuple of wages, proportion of searchers in a given submarket, and market tightness $\{\omega_i^*, s_i^*, \theta_i^*\}_i^J$ and distribution of workers across occupations (indexed by i) and employment statuses (indexed by k) D_i^k such that for all i

1. Workers behave optimally given wages and expectations about number of searchers and market tightness in each occupation accordingly with value functions derived above

2. Job creation condition is satisfied

$$\omega_i^* = p_i + \left[\beta(1 - t_i)\pi_s^e(i) - 1\right] \frac{\kappa_i}{\beta Q_i} \tag{2.23}$$

3. Bargaining condition is satisfied

$$EW(i) - EH(i) = \frac{\eta\left[\Big(J(i)\Big) + \Big(EW(i) - EH(i)\Big)\right]}{1 - \frac{\eta((u'(\omega) + \beta t_i \pi_s^e(i) EU'(i)|_{\omega_i}) - 1) J(i)}{EW(i) - EH(i)} - (1 - \eta)\beta J(i) \frac{\partial \pi_s^e(i)}{\partial \omega_i}} \tag{2.24}$$

4. Expectation about number of searchers are realized

$$s_i^* = \sum_{j \neq i} D_j^e \pi_i^e(j) + \sum_j D_j^u \pi_i^u(j) + \sum_j D_j^h \pi_i^h(j) \tag{2.25}$$

5. Inflow of workers to each occupation-employment state equals to the outflow of workers

6. Entry condition is satisfied

$$V(i) = 0 \tag{2.26}$$

The definition of the equilibrium finishes the model. Next section introduces the data sources used in estimation.

2.3 Data

Our primary source on individual-level data is Survey of Income and Program Participation (SIPP)[5]. SIPP is designed to collect detailed information on demographics, labor force, income, and participation in social welfare programs. Administered by the U.S. Census Bureau, SIPP is built in panels where each panel consists of different samples. It selects a nationally representative sample of households for a given panel from the resident population of the United States, excluding those living in institutions and military barracks and interviews them every four months. These interviews are called waves. There are two different surveys held in each wave. This paper uses wave files between 2004-2013 from SIPP 2004 and SIPP 2008 panels.

Core questions cover labor force activity, types, and amounts of income, and participation in various cash and non-cash benefit programs for each month of the four-month reference period. Our focus is on the primary occupation held by any participant and their income. Data also includes information on when workers left their jobs if they left voluntarily or involuntarily. Moreover, we are also able to see if a non-employed worker searched for a job or not. A key observation about the data is that, although SIPP provides a lot of information on the employment dynamics of workers, unfortunately, as in other available data sets, it is not possible to observe searching behavior by occupations.

Since occupations are reported quarterly in SIPP, this paper uses only the last interview to minimize recall bias. It focuses on workers in ages between 25

[5]SIPP has a couple of advantages compared to other widely used data sets, such as the Current Population Survey (CPS), The Panel Study of Income Dynamics (PSID), and the National Longitudinal Survey of Youth (NLSY). Compared to CPS, SIPP has the obvious advantage of having a true panel data nature. CPS tracks its sample in two waves, a total of four months separated by eight months in between. On the other hand, although PSID has much longer panel information, it only has five thousand households (it also excludes immigrants), thus it has a very limited sample size. Moreover, it has only annual information on occupational changes. Such limitation makes it impossible to identify a higher frequency of changes. Aside from these, the major short-coming of PSID is that the occupation code has not been updated from its beginning from 1968 to 2001. Therefore, the emergence and disappearance of occupations are not reflected in these files, and it makes it impossible to have a clear understanding of recent transitions. Lastly, NLSY targets children or young adults and tracks their life cycle behavior. Therefore it is not also as representative of the U.S. labor market as SIPP.

to 55. To identify transitions, we need information on the previous occupation the worker has worked. Therefore, we drop observations where the worker has never worked in the entire panel or just worked in the last period. Because in such cases, workers' origin occupation is not available. We also drop workers who have multiple jobs. In the interview, workers only provide the total earned income. When they are working in multiple jobs, it is not possible to attribute which portion of income is from the main job. Finally, we drop workers who have preventing disabilities and injuries as the nature their continued unemployment is beyond the scope of this paper. The selected sample features 520,309 transitions between occupations and employment statuses.

For occupational level skill requirements, we turn to the O*NET data set. Being the replacement of the Dictionary of Occupational Titles (DOT), the O*NET is a comprehensive data set providing occupational characteristics in a variety of domains. It is developed by the O*NET Resource Center under the sponsorship of the U.S. Department of Labor. Information is collected using a two-stage design. Firstly, a random sample of businesses expected to employ workers in the targeted occupations are selected. Then a random sample of workers in those businesses is selected. Data is collected by surveying these job incumbents using standardized questionnaires on what is required to perform the given occupation satisfactorily. To reduce the dimensionality of the O*Net data, we perform principal component analysis (PCA). PCA is a statistical technique that represents the high dimensional variable space with a few orthogonal variables that capture most of its variation. The results of this procedure are valid when the original variables are highly correlated, as is the case in O*Net. In our analysis, three central components emerge loading on cognitive, physical, and social requirements that explain more than 65% of the variation in the original 144 variables. Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy is 0.9834, indicating variables have a lot in common, and data is perfectly suited for PCA. Loadings of different requirements on components are available in the Data Appendix.

For occupational level vacancies, we rely on the estimates by Hobijn and Perkowski (2016). Combining data from the Current Population Survey, Job Openings and Labor Turnover Survey, and state-level Job Vacancy Surveys, they construct annual estimates of the number of job openings by occupations for 2005-2013.

2.4 Identification and Estimation

In this subsection, we will discuss the identification of parameters in the model and our estimation strategy.

Assumption 1. *Utility function $u(\cdot)$, transition cost function $C(\cdot)$, and the density function $g(\cdot)$ are known. Idiosyncratic shocks ϵ are iid across time and individuals, and additively separable from utilities.*

We have already assumed $g(\cdot)$ is a Type-1 Extreme Value distribution and that they are additive. We further impose functional forms on utility and transition costs. Utilities are given by log earnings:

$$u(\cdot) = \ln(\cdot) \tag{2.27}$$

Next we parameterize the transition costs similarly to Traiberman (2019) and Yamaguchi (2010) using skill differentials. Firstly define skill deficiency and skill abundance between source occupation i and destination occupation j in terms of skill s

$$d^s_{i,j} = \begin{cases} s_j - s_i & \text{if } s_j - s_i > 0 \\ 0 & \text{otherwise} \end{cases} \tag{2.28}$$

$$a^s_{i,j} = \begin{cases} s_i - s_j & \text{if } s_i - s_j > 0 \\ 0 & \text{otherwise} \end{cases} \tag{2.29}$$

then occupational transition costs are given by

$$C_{ij} = \beta_0 * 1(i \neq j) + \sum_s d^s_{i,j}\beta^s_u + \sum_s {d^s_{i,j}}^2 \beta^{s,sq}_u + \sum_s a^s_{i,j}\beta^s_d + \sum_s {a^s_{i,j}}^2 \beta^{s,sq}_d \tag{2.30}$$

β_0 is the fixed cost of transitioning uniform across all occupations. $1(i \neq j)$ is the index function that takes the value one whenever source and destination occupations are different. Therefore, cost of staying in the current occupation is normalized to zero: $C_{ii} = 0, \ \forall i \in O$. β^s_u and $\beta^{s,sq}_u$ determines how costly it is to overcome skill deficiencies across different skills. The former is measures how costs change linearly and the latter adjusts for possible non-linearities. For example it could be the case that moving further in skill space could be increasingly harder in which case we would have $\beta^{s,sq}_u > 0$. Last two terms deal with the

Table 2.1: Calibrated Parameters

Discount Factor	β	0.99
Bargaining Power	η	0.5
Elasticity of Vacancies	α	0.5
Benefits Duration	ρ	0
Replacement Rate	b	0.3
Social Assistance	z	$0.5 \min_{i \in O} b\omega_i$

Notes: Given one period in our model is 4 months we calibrate the discount rate to 0.99. Elasticity of matching function is calibrated to 0.5 following Şahin et al. (2014). We assume Hosios condition and assume bargaining is symmetric: implying $\eta = 0.5$. Average unemployment benefits is four months (one period) therefore we choose $\rho = 0$. Finally replacement rates is calibrated to $b = 0.3$ to match the generosity of the US unemployment benefits.

cases when workers already posses more skills than required in the destination occupation.

Assumption 2. *β, b, z, η, λ, and ρ are known parameters of the model.*

Next, we calibrate a subset of parameters. The discount factor is calibrated to 0.99 as a period in the model is four months. Elasticity of the matching function is calibrated to 0.5 following Şahin, Song, Topa, and Violante (2014). Bargaining is assumed to be symmetric, implying $\eta = 0.5$. Therefore Hosios condition holds and matching markets are constrained efficient (Hosios 1990). The average benefits duration in the US is around four months. In the model, this implies that the workers are eligible for benefits for only one period giving the value $\rho = 0$. Finally, we set replacement ratio (benefits to wages ratio) to $b = 0.3$. Since it is hard to quantify the amount of other social assistance programs and home production in benchmark we set $z = 0.5 \min_{i \in O} b\omega_i$.

Assumption 3. *Agents have rational expectations about job finding probabilities P.*

Workers in the model choose their actions based on their subjective beliefs about job finding probabilities. Assuming rational expectation guarantees their subjective beliefs correspond to actual job finding probabilities in equilibrium.

To highlight the importance of the assumptions regarding the job finding probabilities assume they depend on the current occupation and employment of the worker. Hence job finding probability of a worker in occupation i with employment status k searching for jobs in occupation j is given by $P(i, j, k)$. The transition probability to employment in occupation j for a worker in occupation i and employment status k is observed in the data and given by probability that the worker searched for a job in occupation j conditional on current status, $\pi_j^k(i)$, and job finding probability $P(i,j,k)$

$$Tr(i,j,k,e) = \pi_j^k(i)P(i,j,k) \tag{2.31}$$

$$\tag{2.32}$$

with the exception when worker stays working in her current occupation: $k = e$ and $i = j$

$$Tr(i,i,e,e) = \pi_i^e(i)(1-t_i) + \sum_{j \neq i} \pi_j^e(i)(1-P(i,j,e))(1-t_i) \tag{2.33}$$

reflecting that when we observe a worker stay employed in her current occupation it could be because they wanted to stay in their current occupation or they searched for another occupation but failed to match with a job and returned to their original occupation, adjusted for exogenous job separation rates.

Transitions to unemployment with benefits is only possible for currently employed workers and worker who are receiving unemployment benefits. For employed workers we have

$$Tr(i,i,e,u) = \pi_i^e(i)t_i + \sum_{j \neq i} \pi_j^e(i)(1-P(i,j,e))t_i \tag{2.34}$$

Workers can get involuntarily separated from their occupations either when they wanted to stay in their job or searched for another one, failed to find one, and get involuntarily separated. For unemployed workers eligible to receive unemployment benefits the transition rates are

$$Tr(i,i,u,u) = \rho \sum_{j \in O} \pi_j^u(i)(1-P(i,j,e)) \tag{2.35}$$

as continued eligibility for unemployment insurance depend on search behavior and probability that eligibility carries to next period given by probability ρ which relates to institutional details of unemployment benefits.

Finally workers can always choose to voluntarily stay home. in which case they are not eligible for unemployment benefits

$$Tr(i,i,k,h) = \pi_H^k(i) \tag{2.36}$$

The first step to identification is to establish under what conditions we can tell apart searching behavior π from matching probabilities $P(i, j, k)$ using only transition rates. Next proposition shows that observing only transition probabilities is not enough to separate searching probabilities from matching probabilities:

Proposition 2. *Conditional choice probabilities π and job finding probabilities P are not identified—from transition rates. For any search probabilities π there exist a set of job finding probabilities P that justifies observed transitions.*

Unidentification result is not surprising as for each observed transition rate there are two parameters. Hence the system of equations are under-identified. To be able to distinguish between how workers choose where to search and how they match with a possible employer, we need to impose structure on either search process or matching process. Here we introduce "*Random Match*" assumption:

Assumption 4. *Matching is random, and job finding probabilities are the same for any worker searching in a given segment regardless of their previous occupation and employment status:*

$$P(i, j, k) = P_j \tag{2.37}$$

Equipped with "*Random Match*", we get the following result.

Theorem 1. *Under random match, conditional choice probabilities π and job finding probabilities P are over-identified. Identification of conditional choice probabilities together with Assumptions 1, 2, and 3, facilitates the identification of the remaining parameters in workers' problem.*

The identification argument above is a generalization of arguments in Şahin et al. (2014). In estimating occupational matching functions they assume random search to be able to back out number of unemployed searchers in a given occupational segment. Differently from their work, their results are extended to also allow for on-the-job searchers.

Once conditional choice probabilities and matching probabilities are separated, expected value functions and parameters of the occupational transition costs are identified using arguments in Hotz and Miller (1993) and Magnac and Thesmar (2002).

Given identification arguments, the model can be estimated. The parameters to be estimated are job finding probabilities P_i, exogenous separations rates t_i, non-pecuniary benefits ξ_i for each occupation i, value of leisure λ, search cost ϕ and the parameters of transition costs β_0, β_u^s, $\beta_u^{s,sq}$, β_d^s and $\beta_d^{s,sq}$ for all skills s.

To estimate these parameters, we use the Nested Fixed Point Algorithm introduced in Rust (1994). For an initial guess of parameters, value functions are calculated using the contraction mapping in expected value functions. Given value functions, we can calculate conditional choice probabilities. Using them together with job separation and job finding probabilities, transition probabilities are calculated and used as a basis for maximum likelihood estimation.

Next we use the estimation results from workers side to identify rest of the model. Given job finding probabilities and elasticity of matching function α heterogeneous matching efficiencies are identified as

$$\mu_i = \exp(\log(P_i) - \alpha \log(\theta_i)) \tag{2.38}$$

Given the fact that equilibrium return on posting a vacancy is zero; Nash Bargaining solution pins down the value of having a worker for a firm at a given occupation $J(i)$ (for a known value of bargaining power η)

$$J(i) = \frac{(1-\eta)\Big(EW(i) - EH(i)\Big)}{\eta\left(u'(\omega_i) + \beta t_i \pi_s^e(i) EU'(i)\right) + (1-\eta)\beta \frac{\partial \pi_s^e(i)}{\omega_i}\Big(EW(i) - EH(i)\Big)} \tag{2.39}$$

where all the variables on the right hand-side are known from previous steps. Than the expression for $J(i)$ can be used together with "*Job-Creation Condition*" to back out output prices.

$$p_i = \omega_i + [1 - \beta(1-t_i)\pi_i^e(i)]J(i) \tag{2.40}$$

Finally, we can calculate market tightness using model predicted searchers rate and data from occupational vacancy rates. Having the parameters of the matching functions we can calculate vacancy filling probability Q_i and use steady state firms value to get occupation specific vacancy costs as

$$\kappa_i = \beta J(i) Q_i \tag{2.41}$$

finishing identification and estimation of all parameters in the model.

2.5 Results

In this section, the estimation results are presented.

2.5.1 Occupational Level Estimates

Table 2.2 presents the occupational level estimates of job finding probabilities, exogenous separation probabilities, and non-pecuniary benefits. Occupations are significantly different in terms of job finding probabilities. For example, a worker searching for a “Legal” occupations is twice as likely to find a job compared to another worker searching in “Management” occupations. Average job finding probability across occupations is 0.41, and it takes around two periods on average for workers to find a job in their target occupation.

Job separation probabilities indicate workers in service occupations like “Food preparation and serving related”, “Building and grounds cleaning maintenance” and workers in “Farming, fishing, and forestry” are more than twice as likely to leave their job involuntarily compared to other occupations. However, overall, job separation probabilities are quite small, and the average duration of jobs would be around fifty years if workers decided to stay in their occupation all the time.

In estimating non-pecuniary benefits, we normalize the non-monetary benefit of working in “Management” to zero. Estimation suggests that manufacturing and service jobs offer higher non-wage benefits to workers. Although we find this result counterintuitive, they have similar ordering of non-pecuniary benefits as Traiberman (2019). Finally, non-pecuniary benefits are an order less critical in determining the value of working in an occupation compared to wages. Therefore, differences in non-pecuniary benefits are secondary to differences in wages when workers make their decisions to which occupation to search.

Table 2.2: Occupational Level Estimates

	Job Finding Probabilities	Job Separation Probabilities	Non-Pecuniary Benefits
Management	0.283	0.005	0.000
	(0.007)	(0.000)	(0.000)
Business and financial operations	0.375	0.005	0.062
	(0.006)	(0.000)	(0.006)
Computer and mathematical	0.436	0.003	-0.128
	(0.007)	(0.000)	(0.008)
Architecture and engineering	0.453	0.002	-0.102
	(0.008)	(0.000)	(0.008)
Life, physical, and social science	0.504	0.004	-0.085
	(0.008)	(0.000)	(0.008)
Community and social service	0.432	0.005	0.466
	(0.008)	(0.000)	(0.008)
Legal	0.547	0.004	-0.215
	(0.008)	(0.000)	(0.006)
Education, training, and library	0.421	0.006	0.419
	(0.005)	(0.000)	(0.008)
Arts, design, entertainment, sports, and media	0.518	0.005	0.107
	(0.008)	(0.000)	(0.009)
Healthcare practitioners and technical	0.437	0.003	0.082
	(0.006)	(0.000)	(0.007)
Healthcare support	0.449	0.011	0.729
	(0.007)	(0.000)	(0.015)
Protective service	0.452	0.002	0.318
	(0.007)	(0.000)	(0.014)
Food preparation and serving related	0.403	0.015	0.875
	(0.006)	(0.000)	(0.026)
Building and grounds cleaning and maintenance	0.374	0.011	0.786
	(0.006)	(0.000)	(0.030)
Personal care and service	0.431	0.014	0.782
	(0.006)	(0.000)	(0.021)
Sales and related	0.369	0.009	0.349
	(0.006)	(0.000)	(0.016)
Office and administrative support	0.332	0.008	0.581
	(0.006)	(0.000)	(0.016)
Farming, fishing, and forestry	0.476	0.018	0.794
	(0.009)	(0.000)	(0.031)
Construction and extraction	0.407	0.005	0.399
	(0.007)	(0.000)	(0.022)
Installation, maintenance, and repair	0.357	0.004	0.312
	(0.006)	(0.000)	(0.021)
Production	0.318	0.007	0.530
	(0.005)	(0.000)	(0.023)
Transportation and material moving	0.344	0.008	0.526
	(0.007)	(0.000)	(0.026)

Notes: There is considerable heterogeneity occupational level estimates. Workers searching in “Legal” occupations are twice as likely to find a job compared to searching in “Management” occupations. Given that workers choose to stay in their current job, the average duration in “Architecture and engineering” is nine times longer than in “Farming, fishing, and forestry”. Non-pecuniary benefits for “Management” is normalized to zero.

Bootstrapped Standard Errors in Parenthesis: N=120

Table 2.3: Naive Estimates of Job Finding Probabilities by Occupation

	Baseline Model	Search in Own Occupation
Management	0.283	0.312
Business and financial operations	0.375	0.365
Computer and mathematical	0.436	0.397
Architecture and engineering	0.453	0.460
Life, physical, and social science	0.504	0.347
Community and social service	0.432	0.272
Legal	0.547	0.352
Education, training, and library	0.421	0.270
Arts, design, entertainment, sports, and media	0.518	0.287
Healthcare practitioners and technical	0.437	0.311
Healthcare support	0.449	0.366
Protective service	0.452	0.472
Food preparation and serving related	0.403	0.359
Building and grounds cleaning and maintenance	0.374	0.379
Personal care and service	0.431	0.346
Sales and related	0.369	0.376
Office and administrative support	0.332	0.349
Farming, fishing, and forestry	0.476	0.558
Construction and extraction	0.407	0.543
Installation, maintenance, and repair	0.357	0.504
Production	0.318	0.467
Transportation and material moving	0.344	0.543

Notes: The baseline model indicates current estimates. "Search in Own Occupation" probabilities *'naive'* estimates calculated as the ratio of occupational hires to unemployed workers who last worked at that occupation. The correlation between probabilities is -0.155 and not statistically significant. Therefore such estimates that do not account for on-the-job searchers and the ability of workers to move across occupations can be misleading.

To highlight the importance of accounting for on-the-job searchers and workers' ability to change their occupations, we compare our estimates to a naive estimate where only unemployed workers participate in search, and they are restricted to search in their occupation as assumed in the main text of Şahin et al. (2014) [6]. Table 2.3 indicates that such estimates differ significantly. The correlation of job finding probabilities has a negative sign with a correlation coefficient of -0.155, and it is not significantly different from no correlation. Therefore, such direct calculations of occupational job finding probabilities can be misleading.

2.5.2 Transition Costs

Table 2.4 presents estimated cost parameters. We observe the high cost of upskilling, especially for cognitive and social skills. Costs are convex; as a result, it is increasingly harder to move further in a given skill. Results suggest negative downskilling costs. This is similar to Traiberman (2019), and it stems from the fact that the model is not able to justify workers transitioning into lower-paying jobs and lose accumulated human capital. As a result, those transitions are

[6] They report that their results are robust to letting unemployed workers to search indifferent occupations.

Table 2.4: Cost Parameters

	Upskilling Costs	Downskilling Costs	Other Parameters
Cognitive	8.036	-7.103	
	(1.218)	(1.210)	
Physical	1.587	1.939	
	(0.968)	(0.968)	
Social	12.811	-7.205	
	(0.662)	(0.634)	
Cognitive^2	0.079	-0.030	
	(0.027)	(0.027)	
Physical^2	0.384	0.218	
	(0.027)	(0.027)	
Social^2	0.047	0.186	
	(0.027)	(0.027)	
Entry Cost			6.547
			(0.127)
Search Cost			1.729
			(0.028)
Leisure			1.823
			(0.017)

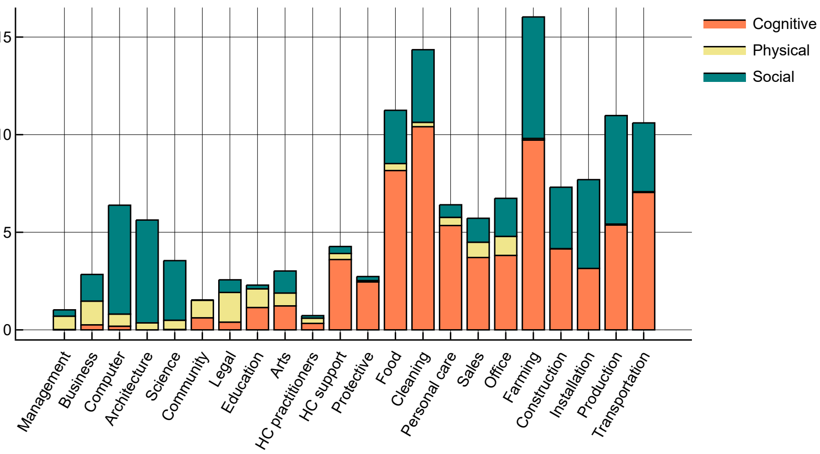
Notes: Coefficients for costs are not normalized. Therefore direct comparisons of costs of moving in different skill spaces are not possible. See figures for such comparisons.
Bootstrapped Standard Errors in Parenthesis: N=120

justified with a one-time payment depending on the skill differential. As occupations that are susceptible to automation require lower levels of skills, for this paper, downskilling-costs do not play an integral role in determining the impact of new technologies.

Although Table 2.4 is informative in terms of statistical significance, the interpretation of the number is complicated due to the fact that skills are possibly scaled differently. To facilitate interpretation, Figure 2.2 and Figure 2.3 plots average upskilling costs faced by workers depending on their occupation. Figure 2.2 presents the unconditional mean of upskilling costs. They are calculated under the assumption that workers will leave their occupation and are equally likely to end up in all other occupations. We observe that skills that curtail worker ability to change occupations are mainly cognitive and social.

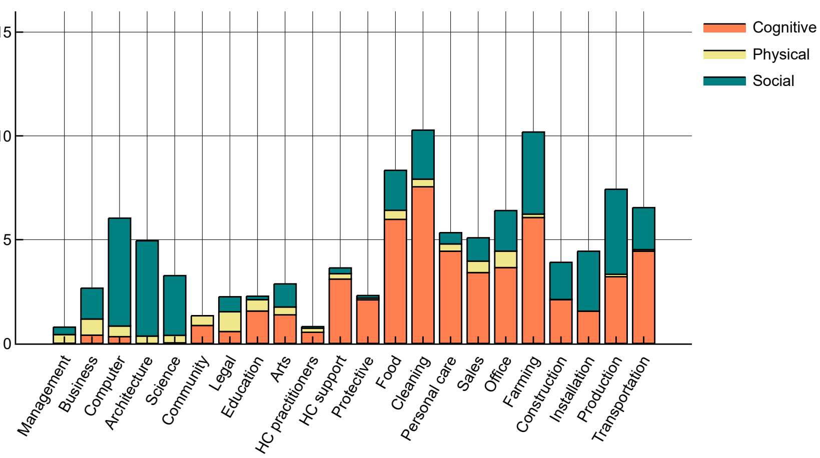
Results stay similar when costs are weighted with respect to searching probabilities. All else equal workers are more likely to search in occupations where they do not face high transition costs. As such weighted costs are lower than

Figure 2.2: Unconditional Average Costs by Occupations and Skills



Notes: Average skill costs faced by workers in a given occupation. The left panel indicates skill costs when workers need to increase a given skill. The right panel indicates going to another occupation that requires lower skill. Occupations like "Management", "Architecture and engineering", and "Life, physical, and social science" have minimal cognitive skill deficiency, and their transitions do not require them to pay cognitive skill upskilling cost.

Figure 2.3: Conditional Average Costs by Occupations and Skills

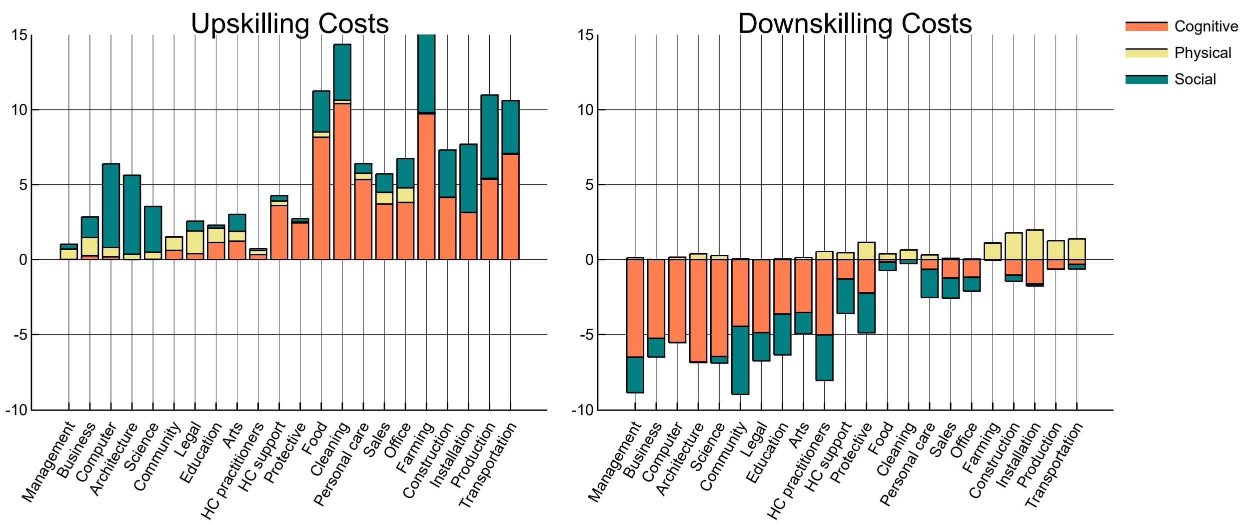


Notes: Average upskilling costs faced by workers who want to change their jobs, weighted by the probability of their destination occupation. The left panel indicates skill costs when workers need to increase a given skill. The right panel indicates going to another occupation that requires lower skill. Occupations like "Management", "Architecture and engineering", and "Life, physical, and social science" have minimal cognitive skill deficiency, and their transitions do not require them to pay cognitive skill upskilling cost.

their unconditional counterparts. However, the main message stays the same; it is harder for workers to upgrade their cognitive and social skills compared to physical skills.

Figure 2.4 pictures unconditional upskilling costs and unconditional down-skilling costs side by side. Workers enjoy moving to occupations with lower social and cognitive requirements. However, moving down the physical scale is still costly for workers, albeit being small. This might suggest that higher cognitive and social skills imply workers' ability to perform in jobs with lower requirements of such skills. However, for physical jobs, it might be the case that activities in highly physical work are different from the ones having low physical requirements. Therefore, even though the workers move down in the skill space, they might need to learn how to perform their new tasks.

Figure 2.4: Downskilling Costs Compared to Upskilling by Occupations and Skills



Notes: Average skill costs faced by workers in a given occupation. The left panel indicates skill costs when workers need to increase a given skill. The right panel indicates going to another occupation that requires lower skill. Occupations like "Management", "Architecture and engineering", and "Life, physical, and social science" have minimal cognitive skill deficiency, and their transitions do not require them to pay cognitive skill upskilling cost.

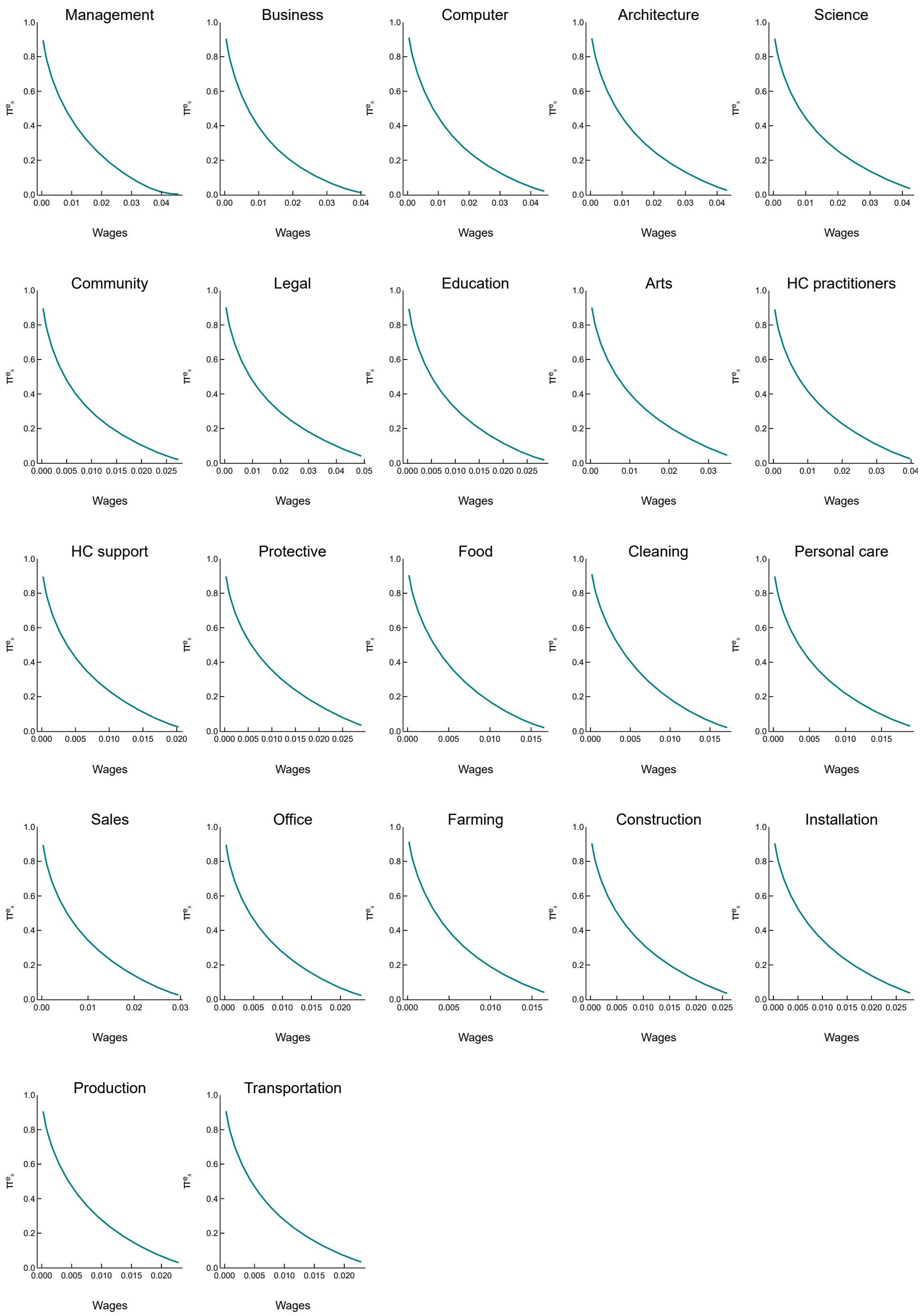
2.5.3 Search Behavior and Bargaining Sets

Using our estimation results, we plot the workers' search behavior and the resulting bargaining sets. Figure 2.5 depicts searching behavior by occupations over all possible arrangements of feasible wages. The impact of wages on search is non-linear; a marginal increase in wages when the wage is low decreases the propensity of the worker to leave them substantially. However, as wages grow, additional wage increase is not as impactful.

As shown in Figure 2.6, the continuity in searching behavior also leads to continuous Pareto frontier for bargaining sets. At low levels of wage, both firms and workers benefit from increasing wages. In this region, the increased discounted value from higher wages dominates the mechanical cost of the additional wage bill. As wages get high, gain of firms from higher wages vanish as behavioral responses to higher wage is smaller. Eventually, they become decreasing in wages similar to bargaining sets in the regular DMP model.

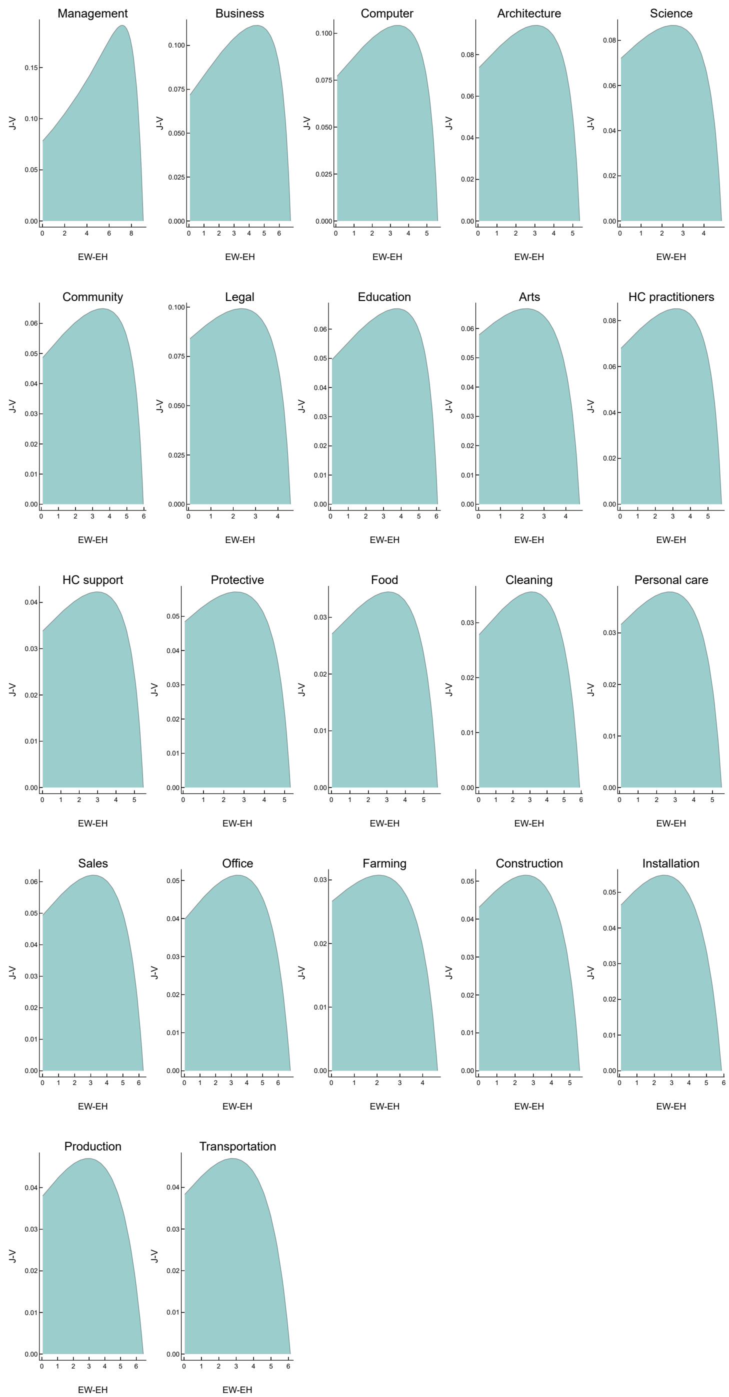
Figure 2.6 also show an interesting case for "Management" occupations. The value of firm is increases fast for lower wages. This leads to a non-convexity of the bargaining set in the area that firms value is increasing in wages. However, that part of the bargaining set is *"irrelevant"* to bargaining as indifference curves comes from the right side of the graph. Given the IIA assumption in Nash Bargaining, the non-convexity does not have any bearing on the bargaining result.

Figure 2.5: Propensity to Leave Current Job by Occupations



Notes: Impact of wages on search behavior. Y-axis is the probability that the worker will leave current job either through quitting to unemployment or successfully finding a job in another occupation. Search behavior is nonlinear in wages. As bargained wage increases the impact it has on searching behavior decreases.

Figure 2.6: Bargaining Sets by Occupations



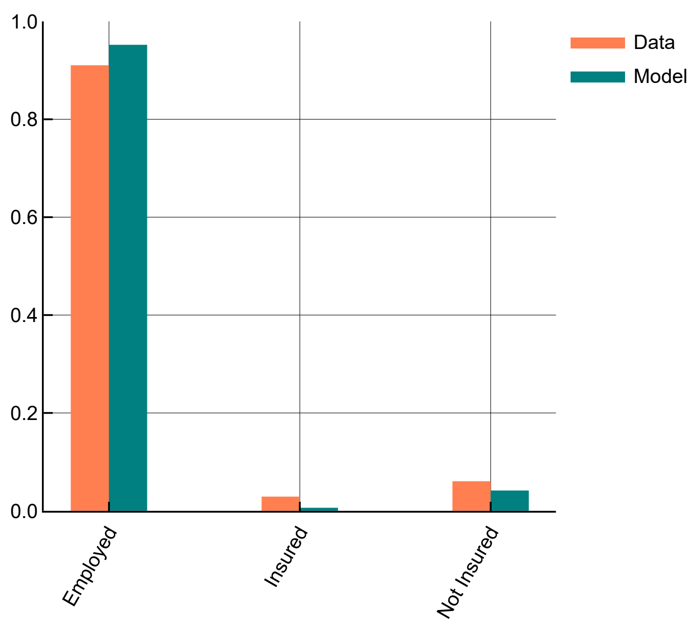
Notes: Bargaining set for each occupation at equilibrium. With discrete choice framework wages have a continuous impact on the search behavior of the worker- resulting in a well defined bargaining sets. When the bargained wage is low marginal increase in wages increases the probability that the worker will not search. This increases both firms value and workers value. However, as wages get higher behavioral responses diminish causing a trade of between firms value and workers value.

2.5.4 Stationarity and Model Fit

The estimation strategy employed here only takes mean wages and transitions of individuals workers across occupations and employment states. In particular, estimation does not utilize any information on the given distribution of workers across states. When the environment is stationary, and data begins from a steady state, transition probabilities fully describe the distribution of workers. However, the same is not correct when the data generating process is not stationary, in which case, the estimated steady-state distribution can be widely different from the actual distribution observed in the data.

Assuming stationarity can be especially improper as our data set covers *"Great Recession"* in its entirety. To address this problem and provide a test of model fitness, we compare the steady-state distribution of our model to the distribution observed in the data.

Figure 2.7: Steady State Model Fit



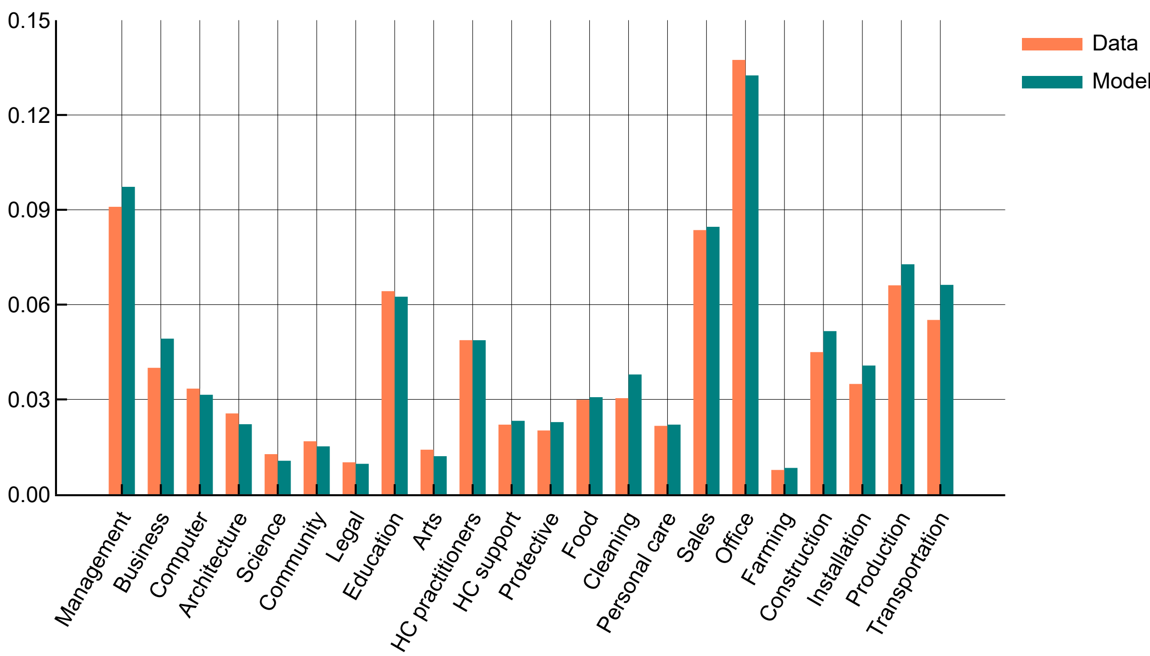
Notes: The distribution of workers in the data calculated using by averaging panel weighted employment for 2004 and 2008 panels. For unemployed workers, occupation is given by the last occupation they have worked. Model can reproduce the distribution of workers across employment statuses although they were not targeted in the estimation.

Figure 2.7 compares the distribution of workers across employment states. The model provides a good fit for employment distribution even though it over-estimates the percentage of employed workers.

Matching employment is only part of the story as the model also needs to match where workers work. Figure 2.8 compares the distribution of employed workers in the model to the weighted average of employment distribution across sample years. The model does a particularly good job of matching the occupational content of employment.

In conclusion, the model provides an excellent fit to data by matching both levels of employment and the distribution of workers across occupations. This result also indicates that, although it could potentially be significant, assuming stationary in estimation does not lead to an essential loss of information.

Figure 2.8: Steady State Model Fit



Notes: Steady-state distribution of employed workers across occupations in the model versus data. Even though employment levels across occupations are not targeted in the estimation strategy, the model does a good job replicating the distribution of workers. The fact that the stationary distribution calculated in the model using only transition rates matches the observed distribution mitigates concerns about the stationarity of the data generating process.

2.6 Automation

2.6.1 Transition Costs and Automation

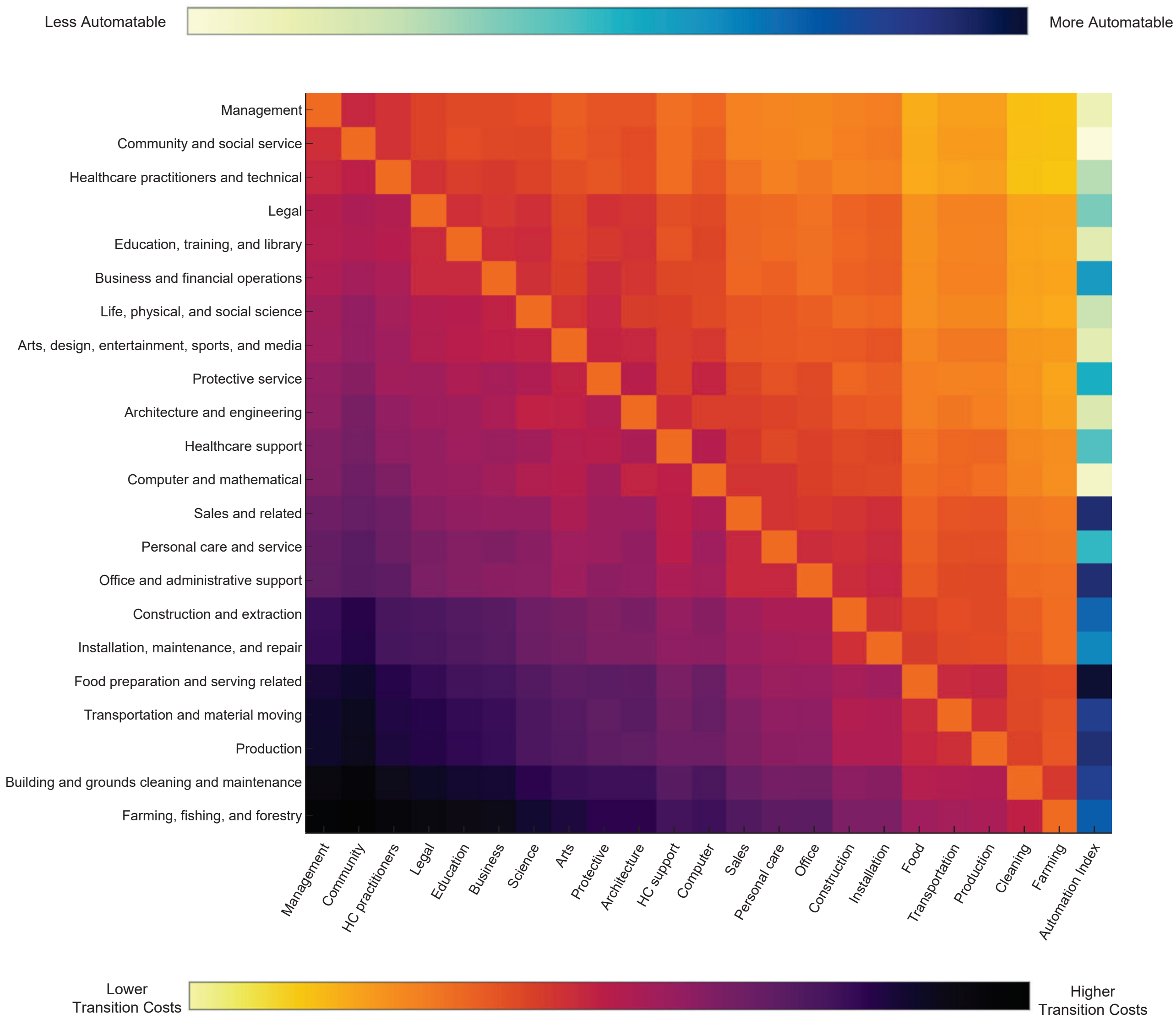
This subsection focuses on the transition costs faced by occupations and how it relates to their risk of automation. Using expert opinions and O*NET variables, Frey and Osborne (2017) estimated the probability automation for each occupation at six digits. We map their results into two-digit occupational codes using employment levels in each detailed occupation as weights.

Figure 2.9 plots occupational transition costs together with automation policy. On the y-axis, source occupations are depicted. Each row correspondi to source occupations represents the transition cost to a target occupation in the x-axis. Rows are sorted with respect to average transition costs. Occupations that face higher costs are at the bottom rows. The last column shows how automatable the source occupation is, according to Frey and Osborne (2017).

Figure 2.9 reveals two key results. First, transition costs are significantly higher for occupations that are more likely to be automatized. Thus, the impact of automation pronounced as it is harder for these workers to move to other occupations. For example, automation targeting "Management" would be less problematic compared to automation of "Farming, fishing, and forestry" as those workers are already equipped with skills suitable to other occupations.

The second key result from Figure 2.9 reveals that for workers in highly automatable occupations, the occupations that would be easier for them to transition to are also under high risk of automation. Consider the following occupations at bottom raws: *"Food preparation and serving related"*, *"Transportation and material moving"*, *"Production"*, *"Building and grounds cleaning and maintenance"*, and *"Farming, fishing, and forestry"*. All these occupations face high transition costs. However, they are easier to move across each other. Therefore, in the case that only one of these occupations undergoes automation, other occupations would serve as insurance. Unfortunately, the automation index shows that all of these occupations are facing high risks. As a result, if these occupations were to undergo automation at the same time, the labor market consequences would be magnified.

Figure 2.9: Occupational Transition Costs and Automation



Notes: Source occupation is on the y-axis, and destination occupation is on the x-axis. The last column indicates the probability of automation based on Frey and Osborne (2017). Occupations that are more likely to be automatized are also the ones that face higher transition costs. Furthermore, such occupations are their "easy exists". As a result, if they were to be automatized together, labor market consequences would be magnified.

2.6.2 Automation and Transitional Dynamics

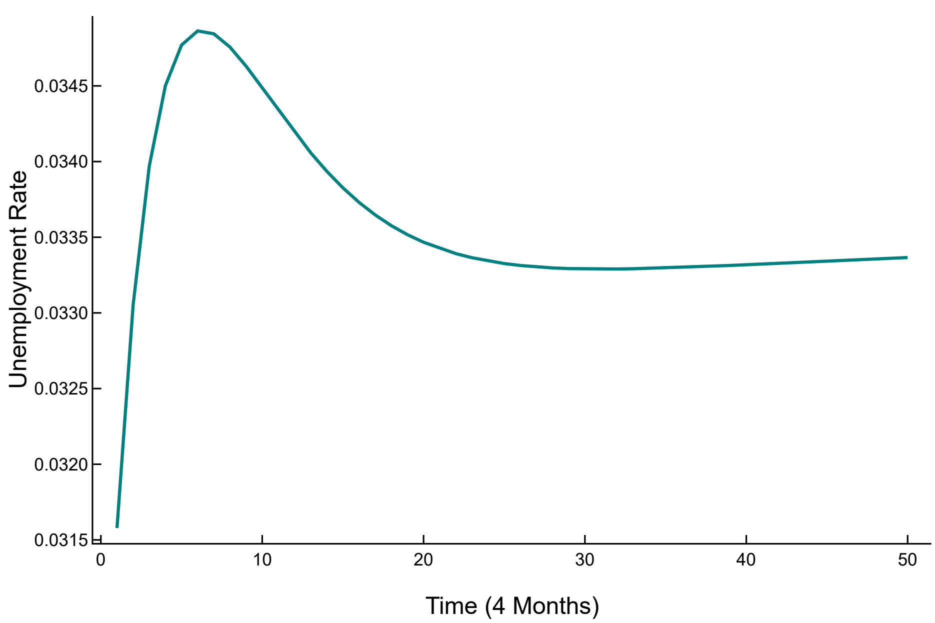
To demonstrate the importance of search frictions and transition costs, this subsection performs the following counter-factual. We assume that manual firms and automated firms are producing perfectly substitutable and as a result, compete in the output markets. When automation becomes cheaper, more automated firms enter the output market and depress the price faced by manual firms. We assume this results in a 25% decrease in prices (hence revenues) of manual "Transportation and material moving" firms.

As a result of the automation shock, the steady-state economy-wide unemployment rate increase by 5%. Consequently, the equilibrium features 150,000 more unemployed workers.

Although significant, focusing on the steady-state differences can miss essential aspects of the consequences of automation. Next, we focus on the transitional dynamics between the two steady states. To solve for transition, we will assume entry condition is satisfied at each point of time, and the value of posting vacancies is zero throughout the transition: $V_t = 0$.

Figure 2.10 considers the case where after the output shock, wages are renegotiated, and as a result, transition starts from initial distribution. The figure shows that unemployment rates overshoot their steady-state values. It takes around seven years for unemployment to reach its steady-state value. Therefore such a shock would entail workers to spend a significant portion of their careers in adverse labor market conditions.

Figure 2.10: Transition Dynamics

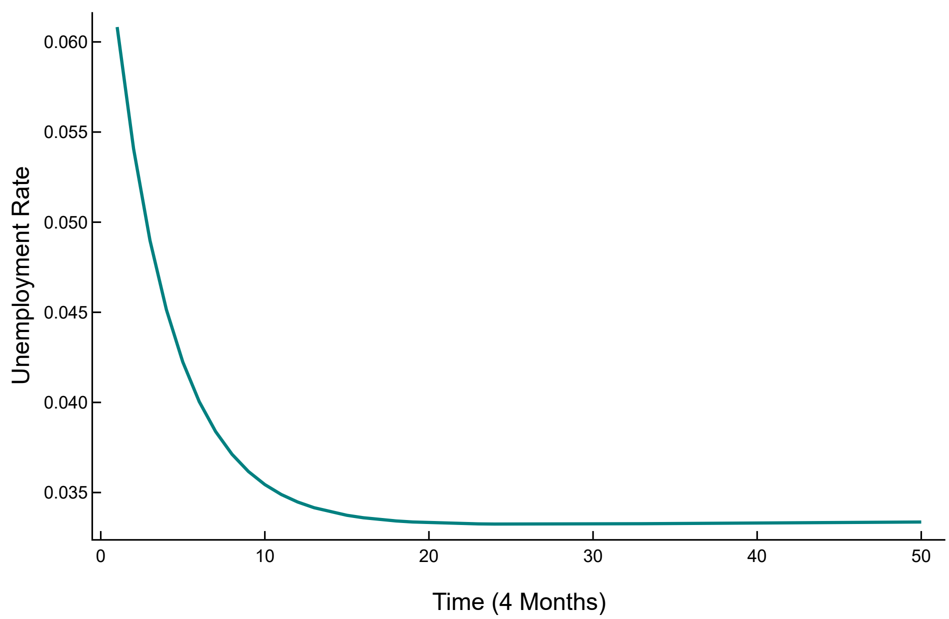


Notes: Unemployment rates along the transition when renegotiate wages after the shock is realized.

In a second counter-factual, we assume that the "Transportation and material moving" workers are displaced to unemployment after the realization of shock. As a result unemployment rate almost doubles. Figure 2.11 shows the transition path under this scenario. After the initial spike in unemployment, workforce slowly transitions to its new steady state. It takes a significant part of a worker's career for unemployment rates to fall. However, the situation is worsened here as the economy spends a significantly longer time above the steady-state value of the unemployment rate.

Together these exercise suggests it is vital to recognize short term ramifications of technological shocks as well as the long-run consequences. Even when new technologies can be beneficial in longer horizons, short term impacts can be overwhelming.

Figure 2.11: Transition Dynamics



Notes: Unemployment rates along the transition when workers are fired upon the realization of automation shock.

2.7 Conclusion

This paper investigates the labor market consequences of technological advancements. To that end, it develops a dynamic discrete occupational choice model within a general equilibrium search environment. The model features two crucial characteristics of labor markets—search frictions and transition costs emerging from skill incompatibilities.

One of the main contributions of this paper is to show that the discrete choice framework leads to well-defined bargaining sets. In contrast to cut-off strategies employed in the literature, random utility models result in continuous choice probabilities. Consequently, the concerns about non-convexities related to discontinuous firms' values vanish. Although the bargaining set still can be non-convex due to endogenous turnover, using structurally estimated parameters, this paper shows that such non-convexities happen at an irrelevant subset of the bargaining set and does not impact the Nash Bargaining outcome.

The second contribution of this paper was to establish the identification of search and matching probabilities using only using data on transition probabilities. This is useful as current data does not have search decisions of workers and their matching outcomes separately. Using the identification result, this paper structurally estimated search frictions and transition costs faced by workers.

Our results revealed that high levels of frictions characterize labor markets. On average, it takes around eight months for workers to find a job in their desired occupation. Transition costs also significantly curtail workers' ability to move into other occupations. Such costs are significantly higher in occupations that are more susceptible to automation. Furthermore, automation threatens groups of occupations that are each other's easy-exits. Subsequently, if automation would happen in a similar time-line across these occupations, labor market consequences would be amplified as workers would have to go through high levels retraining.

As an example, a counter-factual is performed where revenues of "Transportation and material moving" firms are depressed by 25%. The new steady-state unemployment rate is 5% higher, and the number of unemployed workers increase by 150,000. Transition dynamics reveal that adjustments happen slowly, and the unemployment rate is consistently above its steady-state value. It takes around seven years for labor markets to reach the new steady state. As such, it is vital to recognize short term ramifications of technological shocks as well as the long-run consequences.

Chapter 3

Policy Implications of Automation

3.1 Introduction

The previous chapter developed a detailed model of labor markets. It showed that the labor market is characterized by high levels of search frictions and skill incompatibilities. Consequently, workers can potentially undergo prolonged durations of unemployment if they were to be displaced due to automation. In this chapter, we investigate the policy implications of technological developments in this environment by focusing on two prominent labor market programs.

The first of these programs is the unemployment insurance (UI) program. UI is a general policy that insures against unemployment regardless of the reason behind it, so long as it is involuntary. The second program is the adaptation of the Trade Adjustment Assistance (TAA) policies to automation, which we call Automation Adjustment Assistance (AAA). TAA provides a cash benefit to workers *conditional* on being unemployed due to their employer downsizing because of the foreign competition. In this sense, TAA is a targeted unemployment insurance that differentiates among the reasons for unemployment.[1]

We model automation as a shrinking occupation. Workers are barred from finding employment in the automated occupation. The speed of automation is determined by the rate of firms firing workers. As workers are displaced from the occupation and no new workers are hired, employment starts to decrease. The automation process continues until all the jobs are automated. The economy begins at the pre-automated steady-state. Automation starts in the first period,

[1] In reality, both of these programs also entail retraining opportunities. However, following Jaimovich, Saporta-Eksten, Siu, and Yedid-Levi (2020), this paper abstracts from such considerations as literature provides little guidance on cost structure and effectiveness of retraining.

and the economy continues to the infinite horizon where the new steady-state is reached. Therefore, our focus is on the economy's transition as well as the steady-state comparisons.

The first result shows that the current implementation of the UI program in the US is not optimal, even when there is no automation. The replacement ratio (the ratio of benefits to wages) does not provide enough insurance and consumption smoothing. The replacement ratio is significantly higher in the optimal policy based on the pre-automation economy, what we call an SS-Optimal policy. Increasing the current replacement rate from 30% to 71.5% and providing unemployment benefits indefinitely, increases the total welfare by 0.1%

Second, although SS-Optimal policy improves welfare in the absence of automation, it leads to a massive budget shortfall if automation takes place. Being a conservative policy, the current UI policy is budget proof during the transition. Finally, the dynamically-optimal policy that takes into account the full transition increases welfare by 0.01%, while sustaining a balanced budget. Therefore, it is crucial to take structural changes into account when designing the unemployment insurance program.

Finally, this Chapter shows that AAA is an attractive program due to its lower budget requirement. It requires lower levels of distortionary taxes to be financed. However, it induces workers to stay in the automated occupation instead of voluntarily moving to other occupations. Nevertheless, AAA provides a high replacement ratio meaning the insurance motive overrides the negative behavioral responses.

The structure of this Chapter is as follows: The next section introduces automation to the environment in Chapter II. Section 3 derives optimal unemployment insurance programs and compares their performance is transition induced by automation. Section 4 discusses optimal AAA policy, and Section 5 concludes.

3.2 Automation

This section builds on the model developed in Chapter II. Differently, wages (ω) and job finding probabilities (P) are assumed to be exogenous and do not change as a result of automation and government policies. The automation scenario considered is as follows. The occupation undergoing automation is "Transportation and Material Moving". As autonomous vehicles become available, firms start to replace their drivers. The automation induces firms to fire workers at an increased rate.

Assumption 5. *Workers in automated occupations get separated (fired) with probability $t_A = 0.1$.*

Each time a worker leaves the job becomes automated. This could be either because the firm with a worker chooses to automate, in which case the worker is fired, or it could be because the worker voluntarily left the job. As workers can also voluntarily leave the job, the speed of automation is given by the

$$v = \sum_{j \neq A} P_j \pi_j^W(A) + \sum_{j \neq A} t_A (1 - P_j) \pi_j^W(A) + t_A \pi_A^W(A) \tag{3.1}$$

where $\pi^W(\cdot)$ represents post-automation choice probabilities. We assume when workers leave the occupation (either voluntarily or involuntarily) the job is automated and is not available to another worker.

Assumption 6. *New workers cannot be hired at the automated occupation. This is ensured by making it infinitely costly for possible hires $C_{i,A} = -\infty$.*

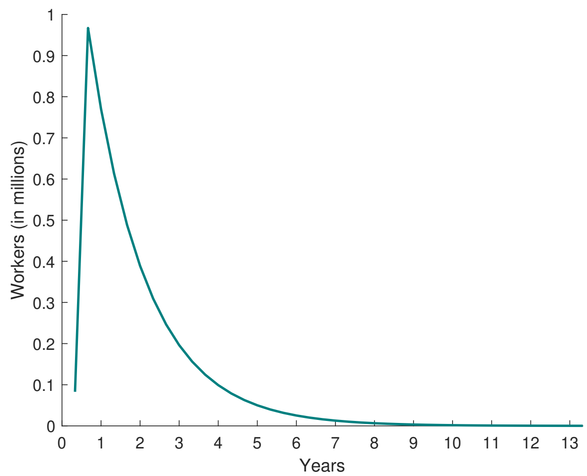
Before going into the detailed implications of automation in this environment, a few caveats are in order. Combined together, Assumption 5 and Assumption 6 guarantee that the occupation will disappear at the rate v. In the new steady-state, no workers will be employed in occupation A. Although most automating technologies have not eradicated an occupation entirely, we believe this is an appropriate approximation as autonomous vehicles have the potential to replace almost all drivers employed at "Transportation and Material Moving" occupations.

Furthermore, the type of automation considered here happens in a vacuum. In reality, technological developments have multi-facet implications for employment and production. Technology not only displaces some workers but also compliments others, as documented in the vast literature studying skill-biased technical change. Moreover, as in Chapter II, the displacement of a large number of workers would lead to changes in equilibrium wages and job finding probabilities. In addition, the productivity improvements due to automation may even expand employment in the affected occupation (Acemoglu and Restrepo 2019). However, adequately capturing these intricacies requires detailed information on the nature of the technical change, characteristics of the production network, and the relevant elasticities of output, labor demand, and matching functions.

As such, we abstract from these concerns and focus only on the automation of "Transportation and Material Moving" occupations and the resulting displacement of workers and their transition to other occupations.

The following figures depict the impact of automation on labor markets. Figure 3.1 show the number of workers who lose their jobs due to automation. Automation leads to a sharp increase in the number of unemployed workers. Starting in period 2, the number of workers who find employment exceeds the rate of automation and unemployment begins to decline. In the limit, unemployment is driven down to zero as no workers are employed at "Transportation and Material Moving" occupations.

Figure 3.1: Unemployed Workers Last Worked at Transportation

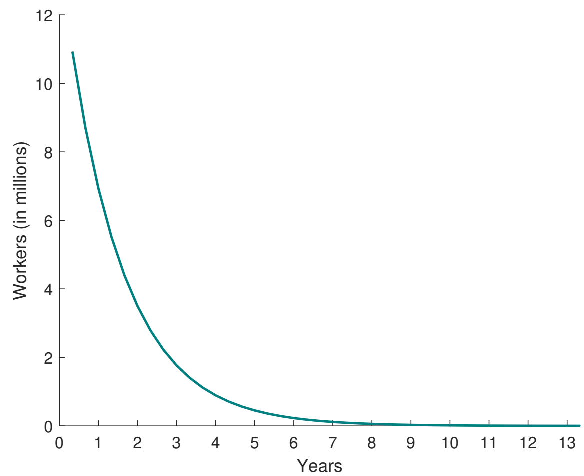


Notes: The number of unemployed workers who had last worked at "Transportation and Material Moving" occupations. These number reflect workers who left their job involuntarily and does not include worker who voluntarily left.

Figure 3.2 show the number of workers employed at the automated occupation. Employment rapidly declines at the rate v. When $t_A = 0.1$, it takes around 10 years for occupation to be vacated.

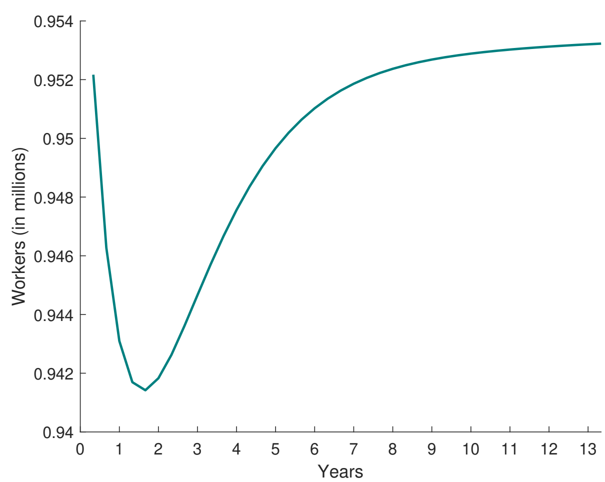
Figure 3.3 shows the evolution of the employment rate after the automation. After the initial rapid decline, the employment rate recovers in around 9 to 10 years. Even though Chapter II has established that these workers face a high

Figure 3.2: Workers employed at Transportation



Notes: The number of workers in the "Transportation and Material Moving" occupations. Employment decreases due to both voluntary and involuntary separations.

Figure 3.3: Total Employment Rate



Notes: Total employment rate. Note that the employment rate is very high because the universe of workers only include employed, unemployed, and marginally attached (who stay home but was employed recently) workers.

transition cost, in time, they acquire the necessary skills to perform in other occupations and find suitable matches. Interestingly, when the transition is complete, new steady-state features more employed workers. This is due to a combination of job finding probabilities and separation rates in the non-automated occupations.

3.3 Optimal Unemployment Insurance with Automation

This section develops and compares different unemployment insurance programs with respect to their budget feasibility and welfare improvement. We define an UI program as the tuple $\{\theta, \tau, \rho\}$. θ is the replacement ratio provided to the unemployed workers. As the programs are required to self-sustain, they are financed using distortionary income taxes τ. Finally ρ represents how long the UI eligibility lasts. When $\rho = 0$, workers obtain benefits for only one period. In the case that $\rho = 1$ workers remain eligible for benefits indefinitely, conditional on searching for jobs.

We consider three different UI programs. The first program is the current implementation of the program in the US. It provides $\theta = .3$ replacement ratio. Workers are, on average, eligible for one period (four months) which corresponds to $\rho = 0$. To calculate the income taxes, we assume the current system is budget-neutral in pre-automation world and find the tax rate that balances the budget. This result in the income taxes of $\tau = .0017$. The second program is the SS-Optimal policy in which the unemployment insurance is optimized for the pre-automation economy. Finally we consider the Dynamically-Optimal policy, which accounts for the automation process.

The main focus of the UI literature is the insurance/incentives trade-off due to moral hazard. The planner would like to smooth consumption for unemployed workers; however, higher benefits make workers less likely to search. If the planner is not able to costlessly monitor searching behavior, then workers can reduce searching effort and free-ride on the unemployment insurance program. There is an extensive literature studying the impact of moral hazard on search effort, starting with the seminal works of Shavell and Weiss (1979), Hopenhayn and Nicolini (1997), and Hansen and Imrohoroğlu (1992). In our model, workers are not able to hide if they are searching for jobs or not. Therefore, the classical moral hazard problem does not occur in this environment. This assumption is consistent with Chetty (2008), who estimates low levels of moral hazard in the US.

Instead, the model considered here has a novel variant of moral hazard. Even though whether or not the worker searches is observable, the planner cannot observe the preference shocks of workers and which occupation they are searching for. As a result, workers are free to change where they search (not whether to search) in response to UI policy. In this case, the behavioral responses are reminiscent of Acemoglu and Shimer (1999), albeit through different mechanisms. UI makes workers search in high-wage and/or high-risk occupations. In Acemoglu and Shimer (1999), equilibrium wages and job finding probabilities are determined in competitive search equilibrium. Unemployment insurance makes workers search in high wage occupations, which are associated with higher unemployment risk.

In our paper, the occupation ex-ante heterogeneous with respect to wages, job finding probabilities, and separation rates. [2] As the UI benefits are a proportion of the last earned wages, it becomes even more valuable to find jobs in high paying occupations. Not only workers in those occupations earn higher wages, but they also enjoy higher benefits when they are hit with an unemployment shock. Moreover, as wages and skills are highly correlated, workers also acquire more skills to be employable in high wage jobs. This further increases their welfare because when they are unemployed, they no longer face high transition costs.

Furthermore, also like Acemoglu and Shimer (1999), the workers would like to search for jobs that have a higher risk of unemployment. When the replacement ratio is high enough, it becomes more valuable to be unemployed than working as unemployed workers also enjoy leisure. As a result, workers become more likely to search for jobs with low job finding probabilities (if they are unemployed) and high exogenous separation rates.

3.3.1 SS-Optimal Unemployment Insurance

First, we consider the SS-optimal insurance, which is designed to be optimal for the pre-automation economy. In designing the program, the social planner does not anticipate the automation and assumes the economy will continue to be in the steady state. This is the unemployment reform considered in the majority of the literature. It provides a useful benchmark and enables the comparison of the current and the dynamically optimal UI policies. As such, it abstracts away from transitions induced by the change in the policy and only considers the steady state.

The goal of the planner is to maximize the sum of the welfare of workers subject to the budget constraint. With Type-1 Extreme Value specification, the

[2] For example, in our model, an occupation can be low paying with high unemployment risk

welfare is expressed as the log-sum of exponentiated conditional value functions as derived in Chapter II. Given that workers are distributed across different occupations and employment statutes, the welfare functions is the weighted sum of expected value functions, where the weights are population shares. The Stationary-UI program is financed by an income tax τ that balances the budget. Taken together the planners problem is expressed as

$$\max_{\theta,\tau,\rho} \sum_{i \in O} D_i^H EH(i) + D_i^U EU(i) + D_i^W EW(i) \tag{3.2}$$

$$s.t.$$

$$\sum_{i \in O} D_i^H \tau \omega_i - \sum_{i \in O} D_i^U \theta \omega_i = 0$$

$$D = T(D, \pi, P, t, \rho)$$

where D_i^K represents the measure of workers in employment status K occupation i. T is a mapping from the current distribution D, choice probabilities π, job finding and separation probabilities t, and UI benefit eligibility parameter ρ to the next periods distribution. We impose that, at the solution the economy is at its steady state and todays D is equal to the tomorrows D. We drop time subscripts for convenience.

3.3.2 Dynamically-Optimal Unemployment Insurance

Dynamically-Optimal UI starts with initial stationary equilibrium distribution. Automation begins in the first period and "Transportation and Material Moving" begins the shrink. When designing the UI program, the planner takes the transition into account. Since the environment is non-stationary we use t subscript, not to be confused with job separation rate t. The planners problem is very similar by now includes the law of motion for the workers.

$$\max_{\theta,\tau,\rho} \sum_{i \in O} D^H_{i,1} EH_1(i) + D^U_{i,1} EU_1(i) + D^W_{i,1} EW_1(i) \tag{3.3}$$

$s.t.$

$$\sum_{t}^{\infty} \frac{1}{(1+r)^{t-1}} \Big(\sum_{i \in O} D^H_{i,t} \tau \omega_i - \sum_{i \in O} D^U_{i,t} \theta \omega_i \Big)$$

$$D_{t+1} = T(D_t, \pi_t, P, t, \rho)$$

$$D_1 = D^c$$

where D^c is the distribution of workers induced by the current-UI program at the pre-automation economy. As discussed in Chapter II, the model does a great job fitting the actual distribution observed in the data. Therefore, D^c corresponds to the distribution of workers during the time-period covering 2004 to 2013. We assume the government has access to borrowing and lending at the interest rate r.

3.3.3 Comparison of UI Programs

In this subsection, we compare the current implementation of the UI program, with SS-Optimal, and the Dynamically-Optimal programs when the Transportation and Material Moving occupations become automated.

Table 3.1 shows the optimum levels of policy parameters. The current UI provides lower benefits for shorter amount of time. This could be attributed to the fact that the model considered in this model does not feature moral hazard, whereas it is possible workers to hide their searching behavior from the authorities. As there is no moral hazard problem, both optimally designed policies provide insurance indefinitely. Dynamically-Optimal policy features higher replacement ratio, and as a result, a higher tax rate than the SS-Optimal policy.

Table 3.1: Comparison of UI programs

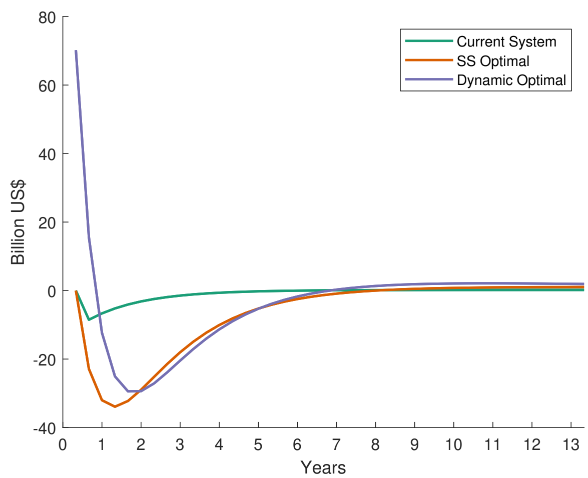
Program	θ	τ	ρ
Current	.300	.0017	0
SS-Optimal	.715	.0114	1
Dynamically-Optimal	.993	.0164	1

The SS-Optimal replacement ratio of 71.5% is similar in magnitude to Chetty

(2008) and to the no moral hazard case of Hansen and Imrohoroğlu (1992), who find the optimum rate to be 50% and 65% respectively. To compare the welfare impact of the SS-Optimal policy, we ask the following hypothetical: "How much the income of workers in the current-UI environment should be increased to reach the welfare provided by the SS-Optimal?" We find that the wages should increase .01% in the Current-UI environment for workers to be as well off as in the SS-Optimal economy. The welfare gains are also comparable to Chetty (2008) and Hansen and Imrohoroğlu (1992), who find .03% wage gains.

Figures 3.4 and 3.5 analyze feasibility of these policies when an occupation undergoes unemployment. Figure 3.4 depicts the change is the governments budget. The current system and SS-Optimal UI starts with zero deficit as they were optimized to satisfy balanced budget in the pre-automation steady-state. As worker find jobs and discount rate factors in, all programs starts to self finance as the time progresses.

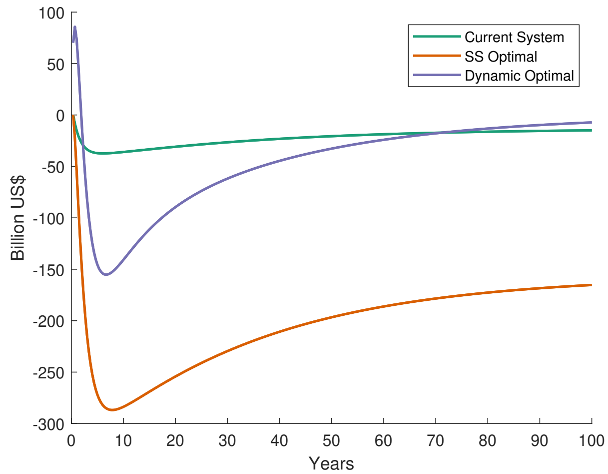
Figure 3.4: Period-by-Period Budget Deficit with different UI Programs



Notes: This graph depicts the changes in the Budget Deficit period-by-period. The current system and SS-Optimal UI starts with zero deficit as they were optimized to satisfy balanced budget in the pre-automation steady-state. As worker find jobs and discount rate factors in, all programs starts to self finance in the future.

Figure 3.5 represents the evolution of the budget constraint over time. As the current system is a conservative policy, its budgetary impact is minimal. It does not provide adequate levels of insurance, but it also does not hurt the budget as

Figure 3.5: Evolution of Budget Deficit with different UI Programs



Notes: This graph depicts the evolution of the Budget Deficit. As the current system is a conservative policy, its budgetary impact is minimal. However, if the unemployment insurance is optimized for pre-automation steady-state the budget deficit becomes very large. The dynamic-optimal policy features higher replacement ratios and higher taxes and it is designed to be budget neutral.

much. However, if the unemployment insurance is optimized for pre-automation steady-state the budget deficit becomes very large. The dynamic-optimal policy features higher replacement ratios and higher taxes and it is designed to be budget neutral. Therefore, anticipating automation shocks are very important for the feasibility of the unemployment insurance programs.

To get a comparison of welfare gains throughout the transition, we ask the following question" "How much the income of workers in the current-UI environment should be increased to reach the welfare provided by the SS-Optimal and Dynamically Optimal insurance programs?" We find that for current-UI economy to as well of as the SS-Optimal economy the wages needs a permanent increase by 0.0085% for every worker in the economy. However, note that some of this extra gain is due to the higher budget deficit. For the Current-UI economy to be as well of as the Dynamically-Optimal economy wages need a 0.0115% permanent increase. Given that dynamically-optimal policy is already budget neutral, this increase totally reflect the welfare gains from the policy.

3.4 Automation Adjustment Assistance

This subsection introduces the Automation Adjustment Assistance program as an automation analogue of Trade Adjustment Assistance. Under this program, government provides relief to workers who have become unemployed from the automated occupations. We will assume that all the workers who become unemployed from "Transportation and Material Moving" are eligible for the relief and there are no other reasons for separation.[3]

The planner solves a similar problem like in the unemployment insurance. The welfare criterion is unchanged from the dynamically-optimal UI. Even though this program only helps workers whose jobs are automated, the program is financed through a distortionary income tax from workers in all occupations. Therefore, the planner not only takes the welfare gains by unemployed workers into account but also the welfare loss associated with the additional tax burden. The planner provides the relief only for four months and chooses only the AAA benefit ratio χ and the taxes τ that finance the benefits. The problem is formally given as

$$
\begin{aligned}
&\max_{\chi,\tau} \sum_{i \in O} D^H_{i,1} EH_1(i) + D^U_{i,1} EU_1(i) + D^W_{i,1} EW_1(i) \qquad (3.4)\\
s.t.&\\
&\sum_{t}^{\infty} \frac{1}{(1+r)^{t-1}} \Big(\sum_{i \in O} D^H_{i,t} \tau \omega_i - D^U_{A,t} \chi \omega_A \Big) = 0\\
&D_{t+1} = T(D_t, \pi_t, P, t, \rho)\\
&D_1 = D^c
\end{aligned}
$$

As mentioned above, unemployment insurance nudges workers to search for high wage and/or high risk occupations. The AAA, on the other hand, induces workers to stay in the automated occupation. When the insurance is provided conditional on having last worked at the automated occupation, changing occupations becomes less valuable.

Proposition 3. *Automation Adjustment Assistance induces workers to stay in the automated occupation:* $\frac{\partial \pi(i)}{\partial \chi} > 0$

[3] In reality, we expect testing for the reason of unemployment as in TAA which requires proof that the employer is downsizing due to foreign competition. In the case of automation, testing might require using receipts of recently purchased industrial robots or softwares.

Proof.

$$\frac{\partial w_A(A)}{\partial \chi} = \beta t_A \frac{\partial EU(A)}{\partial \chi}$$
$$\frac{\partial w_j(A)}{\partial \chi} = \beta(1-P_j)t_A \frac{\partial EU(i)}{\partial \chi}, \forall j \neq A$$
$$\frac{\partial w_H(A)}{\partial \chi} = 0$$

As the value of staying in the current occupation increases more than other options (provided that $P_j < 1$, which is empirically relevant case) we get $\frac{\partial \pi_A(A)}{\partial \chi} > 0$ Rather than moving to other occupations, workers are more likely wait in the automatable occupation. □

Moreover, increases in the benefits makes workers want like to stay unemployed as long as possible. Since they cannot hide their search behavior, instead they search in occupations where job finding probabilities are lower.

Proposition 4. *Automation Adjustment Assistance induces unemployed workers from automated occupation to delay employment by searching in occupations where job finding probabilities are lower:* $\frac{\partial \pi_j(A)}{\partial \chi} > \frac{\partial \pi_k(A)}{\partial \chi}$ *when* $P_j < P_k$.

Proof.

$$\frac{\partial u_j(A)}{\partial \chi} = \beta(1-P_j)t_A \frac{\partial EU(A)}{\partial \chi}$$

Therefore, the value of searching in occupations with lower job finding probabilities is higher. □

3.4.1 Optimal Automation Adjustment Assistance

Having formulated the planners problem and the adverse behavioral impacts, this subsection provides the numerical analysis of the optimal AAA policy.

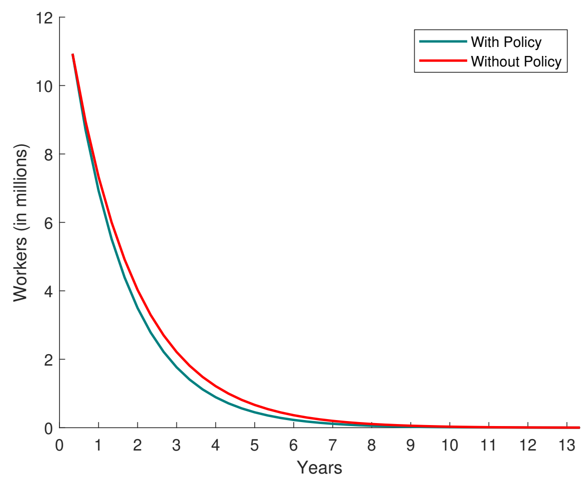
Table 3.2: Optimal-AAA Program

	χ	τ
Optimal-AAA	0.949260	0.0009

As can be seen in Table 3.2 the replacement ratio is close to .95%. Therefore, consumption smoothing motivation dominates the adverse impacts derived in the previous section. Moreover, as the income tax required to finance this policy is significantly lower, the policy introduces lower distortions through the income tax.

These results, however, does not mean that the behavioral effects are not significant. Figure 3.6 shows the evolution of the employment in Transportation and Material Moving occupations after the automation. The AAA policy shift the curve to the right, which means workers are not leaving the automated occupation as quickly as they would without the insurance. As workers do not have control over the exogenous separation rate, this shift is due to changes in their searching behavior. Workers who would voluntarily switch to other occupations without the policy stop searching and try to get unemployment benefits.

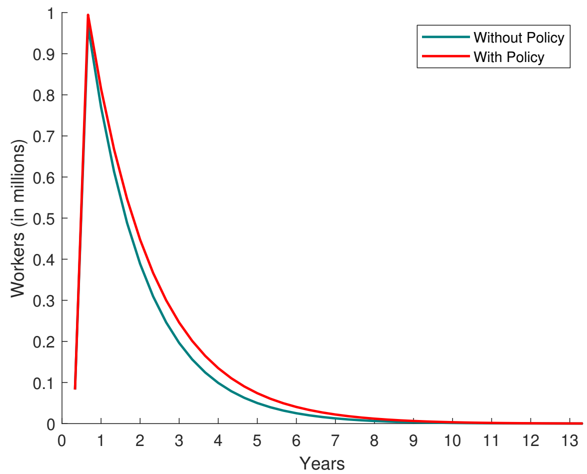
Figure 3.6: Evolution of employment in the automated occupation with and without AAA



Notes: AAA nudges workers to stay in the automated occupation longer to be eligible for the benefits and discourages them from finding employment elsewhere.

Similar pattern is also observed by the evolution of unemployment as described in Figure 3.7. Again the transition is shifted to the right. This is the combination of workers staying in the automated occupation and also the unemployed workers searching in occupations with lower probability of finding a job.

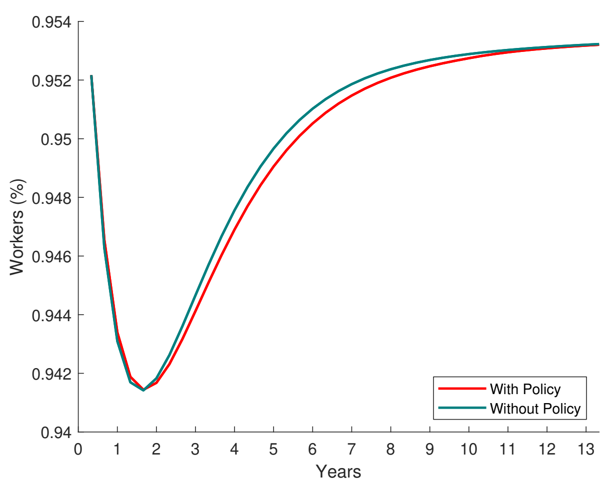
Figure 3.7: Evolution of unemployment in the automated occupation with and without AAA



Notes: AAA policy leads to prolonged unemployment as workers search in occupations with lower chance of employment and they do not switch to other occupations.

Finally, Figure 3.8 shows the aggregate employment rate among employed, unemployed, and marginally attached workers. Even though the long term employment level is identical, with the policy, the transition is slower in reaching the new steady-state.

Figure 3.8: Evolution of the economy-wide employment rate with and without AAA



Notes: AAA leads to slower recovery as workers delay leaving the automated occupation.

3.5 Conclusion

The previous chapter highlighted the importance of labor market frictions and skill incompatibilities in determining how hard it for workers to move across occupations. The estimation results showed that automatable occupations are particularly ill-positioned as labor markets are characterized by significant search frictions, and they particularly face high transition costs. One of the questions of interest was then to ask what can policy-makers do to provide relief to whose jobs are being replaced by machines.

This chapter analyzed two strands of labor market institutions that aim to help unemployed workers. The first of which is the unemployment insurance (UI), providing insurance against the unemployment risk without discriminating across reasons for unemployment. Other policy in consideration was the Automation Adjustment Assistance program, which is inspired by the Trade Adjustment Assistance program. In contrast to the UI program, AAA provided cash benefits to workers who got unemployed due to automation.

Qualitative results highlighted the behavioral responses of workers to the policies mentioned above. In our environment, the optimal UI program induces similar incentives as in Acemoglu and Shimer (1999) and nudged workers to search in higher-wage and/or higher-risk occupations. On the other hand, AAA programs induce workers to stay in the automated occupation to stay eligible for the benefits. It caused workers who would normally find employment in other occupations to stop searching.

Numerical analysis building on the results from Chapter II showed the importance of taking automation into account when designing the UI policy. The current UI policy proved to be too conservative; however, as a result, it does not lead to massive deficits. On the other hand, an optimal UI program based on the pre-automation economy led to very high levels of budget deficits. The dynamically-optimal UI policy provides higher welfare for workers while sustaining a balanced budget. On the other hand, the AAA policy requires significantly less budget to provide high levels of benefits. However, the AAA policy nudges workers to stay in the disadvantaged, automated occupation for more extended periods as predicted by the qualitative analysis.

The analysis in this chapter contributes to the policy discussions when a massive wave of automation is expected. Our analysis cautions policy-makers to consider the possibility of the automation to make sure the relief is provided to the unemployed workers while sustaining a budget a balance and minimizing the adverse impacts of policies on the workers' decisions.

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Appendix A

Appendix: Chapter I

The Routine Task-Intensity index constructed using O*NET and based on Autor and Dorn (2013) is provided in the preceding tables. High RTI implies the occupation is more likely to be automatized.

Table A.1: RTI Index for Census Occupations

1	Telephone Operators	2.641308
2	Technical Writers	2.597183
3	Miscellaneous Legal Support Workers	2.571783
4	Insurance Underwriters	2.481014
5	Billing and Posting Clerks and Machine Operators	2.432077
6	Tax Preparers	2.43084
7	Computer Hardware Engineers	2.428564
8	New Accounts Clerks	2.384709
9	Eligibility Interviewers, Government Programs	2.379751
10	Paralegals and Legal Assistants	2.36072
11	Brokerage Clerks	2.340627
12	Nuclear Engineers	2.339262
13	Tax Examiners, Collectors, and Revenue Agents	2.320807
14	Accountants and Auditors	2.319619
15	Personal Financial Advisors	2.295427
16	Loan Interviewers and Clerks	2.288378
17	Administrative Services Managers	2.284443
18	Bill and Account Collectors	2.283411
19	Financial Analysts	2.277813
20	First-Line Supervisors/Managers of Office and Administrative Support Worker	2.261533
21	Correspondence Clerks	2.255339
22	Proofreaders and Copy Markers	2.25287
23	Telemarketers	2.246284
24	Credit Authorizers, Checkers, and Clerks	2.243826
25	Human Resources Assistants, Except Payroll and Timekeeping	2.243825
26	Financial Examiners	2.239437
27	Actuaries	2.22827
28	Dietitians and Nutritionists	2.212477
29	Credit Analysts	2.208752
30	Postmasters and Mail Superintendents	2.183473
31	Management Analysts	2.178364

32	Human Resources, Training, and Labor Relations Specialists	2.173938
33	Computer Programmers	2.170202
34	Medical and Health Services Managers	2.159967
35	Purchasing Managers	2.156412
36	Statistical Assistants	2.153769
37	Logisticians	2.1182
38	Bookkeeping, Accounting, and Auditing Clerks	2.113322
39	Securities, Commodities, and Financial Services Sales Agents	2.106968
40	Database Administrators	2.103067
41	Public Relations Managers	2.0812
42	Market and Survey Researchers	2.067545
43	Financial Managers	2.055202
44	Data Entry Keyers	2.035605
45	Interviewers, Except Eligibility and Loan	2.030826
46	Budget Analysts	2.029979
47	First-Line Supervisors/Managers of Non-Retail Sales Workers	2.023562
48	Procurement Clerks	2.013721
49	Purchasing Agents, Except Wholesale, Retail, and Farm Products	2.002631
50	Payroll and Timekeeping Clerks	1.962995
51	Human Resources Managers	1.949403
52	Court, Municipal, and License Clerks	1.947276
53	Sales Representatives, Services, All Other	1.939025
54	Cost Estimators	1.857194
55	Economists	1.836667
56	Insurance Claims and Policy Processing Clerks	1.825142
57	Operations Research Analysts	1.778332
58	Mathematicians	1.755711
59	Sociologists	1.74262
60	Computer Scientists and Systems Analysts	1.698429
61	Statisticians	1.623748
62	Cargo and Freight Agents	1.597551
63	Atmospheric and Space Scientists	1.507265
64	Physical Scientists, All Other	1.285929
65	Editors	1.277093
66	Customer Service Representatives	1.268402
67	Aerospace Engineers	1.190339
68	Lawyers	1.175649
69	Public Relations Specialists	1.152073
70	Writers and Authors	1.104535
71	Word Processors and Typists	1.021473
72	Counter Attendants, Cafeteria, Food Concession, and Coffee Shop	.9387717
73	Travel Agents	.9365653
74	Financial Specialists, All Other	.9238197
75	Other Life, Physical, and Social Science Technicians	.8908237
76	Managers, All Other	.856968
77	Door-To-Door Sales Workers, News and Street Vendors, and Related Workers	.849211
78	Natural Sciences Managers	.8111079
79	Switchboard Operators, Including Answering Service	.7874323
80	Speech-Language Pathologists	.7543579
81	Hotel, Motel, and Resort Desk Clerks	.714941
82	Emergency Management Specialists	.6940684
83	Network Systems and Data Communications Analysts	.5166609
84	Chemical Engineers	.3890964
85	Transportation, Storage, and Distribution Managers	.3540243
86	Gaming Managers	.3505145

87	Compliance Officers, Except Agriculture, Construction, HealSafety, a	.2747584
88	Order Clerks	.2361932
89	Advertising and Promotions Managers	.2281747
90	Barbers	.1714515
91	Medical Records and Health Information Technicians	.0436018
92	Producers and Directors	.0076773
93	Insurance Sales Agents	-.0307781
94	Ushers, Lobby Attendants, and Ticket Takers	-.048647
95	Environmental Engineers	-.0494828
96	Chief Executives	-.0613076
97	Librarians	-.0704205
98	Health Diagnosing and Treating Practitioners, All Other	-.0778521
99	Civil Engineers	-.0782219
100	Urban and Regional Planners	-.0799838
101	Medical Assistants and Other Healthcare Support Occupations	-.0962726
102	Teacher Assistants	-.1308444
103	Property, Real Estate, and Community Association Managers	-.1605916
104	Graders and Sorters, Agricultural Products	-.1770967
105	Agents and Business Managers of Artists, Performers, and Athletes	-.1823939
106	Gaming Cage Workers	-.1877491
107	Detectives and Criminal Investigators	-.1934113
108	Mining and Geological Engineers, Including Mining Safety Engineers	-.212888
109	Massage Therapists	-.2344888
110	Production, Planning, and Expediting Clerks	-.2347317
111	Sales and Related Workers, All Other	-.2395089
112	Computer and Information Systems Managers	-.2429635
113	Receptionists and Information Clerks	-.2447218
114	Private Detectives and Investigators	-.2523492
115	Materials Engineers	-.2746539
116	Hunters and Trappers	-.2782538
117	Miscellaneous Community and Social Service Specialists	-.2887749
118	Laundry and Dry-Cleaning Workers	-.3607859
119	Prepress Technicians and Workers	-.3630108
120	Mechanical Engineers	-.366323
121	Maids and Housekeeping Cleaners	-.3683814
122	File Clerks	-.3743792
123	Registered Nurses	-.3992836
124	Directors, Religious Activities and Education	-.4005807
125	Biomedical Engineers	-.4096724
126	Residential Advisors	-.4144454
127	Locksmiths and Safe Repairers	-.4232187
128	Appraisers and Assessors of Real Estate	-.4280041
129	Electronic Home Entertainment Equipment Installers and Repairers	-.4382278
130	Reservation and Transportation Ticket Agents and Travel Clerks	-.4392309
131	Motion Picture Projectionists	-.440137
132	Pressers, Textile, Garment, and Related Materials	-.4415121
133	Agricultural Engineers	-.4599577
134	Cleaning, Washing, and Metal Pickling Equipment Operators and Tenders	-.4675667
135	Petroleum Engineers	-.4733445
136	Bakers	-.473528
137	Audiologists	-.4840391
138	First-Line Supervisors/Managers of Personal Service Workers	-.4893075
139	Network and Computer Systems Administrators	-.4915964
140	Recreational Therapists	-.4930482
141	Crossing Guards	-.4930903

142	Purchasing Agents and Buyers, Farm Products	-.500803
143	Computer Operators	-.5033789
144	Textile Knitting and Weaving Machine Setters, Operators, and Tenders	-.5116043
145	Tire Builders	-.5325935
146	Library Assistants, Clerical	-.537179
147	Library Technicians	-.5453513
148	Shoe Machine Operators and Tenders	-.5468143
149	Coin, Vending, and Amusement Machine Servicers and Repairers	-.5479341
150	Postal Service Mail Carriers	-.5484647
151	Social and Community Service Managers	-.5561613
152	Dental Hygienists	-.565559
153	Advertising Sales Agents	-.5737619
154	Engineering Managers	-.5739722
155	Textile Winding, Twisting, and Drawing Out Machine Setters, Operators, and	-.58306
156	Automotive Body and Related Repairers	-.5853565
157	Mail Clerks and Mail Machine Operators, Except Postal Service	-.5881664
158	Desktop Publishers	-.5894873
159	Engineers, All Other	-.5902982
160	Textile Bleaching and Dyeing Machine Operators and Tenders	-.5977645
161	Paper Goods Machine Setters, Operators, and Tenders	-.6009202
162	Pharmacists	-.6020827
163	Construction and Building Inspectors	-.6044351
164	Hairdressers, Hairstylists, and Cosmetologists	-.6141037
165	Parking Enforcement Workers	-.6141171
166	Optometrists	-.6226729
167	Surveying and Mapping Technicians	-.6236307
168	Parts Salespersons	-.6302956
169	Forging Machine Setters, Operators, and Tenders, Metal and Plastic	-.6351355
170	Shoe and Leather Workers and Repairers	-.6354551
171	Security Guards and Gaming Surveillance Officers	-.6367071
172	Lifeguards and Other Protective Service Workers	-.6367071
173	Postal Service Clerks	-.6399947
174	Food Service Managers	-.6414431
175	Sales Engineers	-.6562114
176	Electronic Equipment Installers and Repairers, Motor Vehicles	-.6618166
177	Jewelers and Precious Stone and Metal Workers	-.6632633
178	Food and Tobacco Roasting, Baking, and Drying Machine Operators and Tenders	-.6730444
179	Animal Control Workers	-.6759326
180	First-Line Supervisors/Managers of Correctional Officers	-.6759537
181	Tellers	-.6822097
182	Pest Control Workers	-.685334
183	Retail Salespersons	-.6857283
184	Packers and Packagers, Hand	-.6869635
185	Automotive Glass Installers and Repairers	-.6902033
186	Meter Readers, Utilities	-.701473
187	Food Servers, Nonrestaurant	-.7032533
188	Office Clerks, General	-.7088321
189	Extruding and Drawing Machine Setters, Operators, and Tenders, Metal and Pl	-.7153611
190	Nonfarm Animal Caretakers	-.715458
191	Transportation Inspectors	-.7159389
192	Agricultural Inspectors	-.7187369
193	Bartenders	-.7190586
194	Dental Assistants	-.7257392
195	Inspectors, Testers, Sorters, Samplers, and Weighers	-.7271298
196	Semiconductor Processors	-.7312119

197	Chemical Technicians	-.7380072
198	Biological Scientists	-.7392697
199	Industrial Production Managers	-.7454784
200	Construction Managers	-.7482036
201	Opticians, Dispensing	-.7524421
202	Manufactured Building and Mobile Home Installers	-.7566745
203	Actors	-.7573972
204	Food Preparation Workers	-.7581321
205	Electric Motor, Power Tool, and Related Repairers	-.7632272
206	Textile Cutting Machine Setters, Operators, and Tenders	-.7634242
207	Postal Service Mail Sorters, Processors, and Processing Machine Operators	-.7650968
208	Food Batchmakers	-.7669943
209	Geological and Petroleum Technicians	-.7673411
210	Personal and Home Care Aides	-.7754217
211	Machine Feeders and Offbearers	-.7767515
212	Home Appliance Repairers	-.7780363
213	Nuclear Technicians	-.7809284
214	Office Machine Operators, Except Computer	-.7902374
215	Helpers–Production Workers	-.7921634
216	Railroad Brake, Signal, and Switch Operators	-.796461
217	Avionics Technicians	-.8009611
218	Water and Liquid Waste Treatment Plant and System Operators	-.801715
219	Stationary Engineers and Boiler Operators	-.8092182
220	Paperhangers	-.811317
221	Tool Grinders, Filers, and Sharpeners	-.8138973
222	Combined Food Preparation and Serving Workers, Including Fast Food	-.8141677
223	Sewing Machine Operators	-.8184931
224	Agricultural and Food Science Technicians	-.8218282
225	Explosives Workers, Ordnance Handling Experts, and Blasters	-.8231269
226	Fabric and Apparel Patternmakers	-.8300183
227	Upholsterers	-.8318976
228	Dishwashers	-.8335758
229	Podiatrists	-.8336657
230	Service Station Attendants	-.8384321
231	Bus and Truck Mechanics and Diesel Engine Specialists	-.8388912
232	Maintenance Workers, Machinery	-.8463088
233	Marine Engineers and Naval Architects	-.8482929
234	Licensed Practical and Licensed Vocational Nurses	-.850432
235	Extruding and Forming Machine Setters, Operators, and Tenders, Synthetic	-.8504381
236	Packaging and Filling Machine Operators and Tenders	-.8541082
237	Transit and Railroad Police	-.8546664
238	Drilling and Boring Machine Tool Setters, Operators, and Tenders, Metal...	-.8584959
239	Physician Assistants	-.8591421
240	Boilermakers	-.861943
241	Lathe and Turning Machine Tool Setters, Operators, and Tenders, Metal...	-.8674486
242	Tool and Die Makers	-.8696382
243	Pile-Driver Operators	-.8705153
244	General and Operations Managers	-.8716699
245	Molders, Shapers, and Casters, Except Metal and Plastic	-.8737146
246	Occupational Therapists	-.8739799
247	Ambulance Drivers and Attendants, Except Emergency Medical Technicians	-.874409
248	Electrical Power-Line Installers and Repairers	-.8757548
249	Aircraft Structure, Surfaces, Rigging, and Systems Assemblers	-.8784642
250	Food Cooking Machine Operators and Tenders	-.879961
251	Dining Room and Cafeteria Attendants and Bartender Helpers	-.8803573

252	Transportation Attendants	-.8815582
253	Fish and Game Wardens	-.8840399
254	Computer, Automated Teller, and Office Machine Repairers	-.890426
255	Security and Fire Alarm Systems Installers	-.8910509
256	Chiropractors	-.9004881
257	First-Line Supervisors/Managers of Housekeeping and Janitorial Workers	-.901102
258	Helpers–Installation, Maintenance, and Repair Workers	-.9029213
259	Heating, Air Conditioning, and Refrigeration Mechanics and Installers	-.9031399
260	Clergy	-.9147999
261	Roofers	-.917323
262	Aircraft Mechanics and Service Technicians	-.9183977
263	Roof Bolters, Mining	-.9196938
264	Miscellaneous Construction and Related Workers	-.9240081
265	Glaziers	-.9258907
266	Cooling and Freezing Equipment Operators and Tenders	-.9266855
267	Taxi Drivers and Chauffeurs	-.9272304
268	Police and Sheriff's Patrol Officers	-.9280015
269	Shuttle Car Operators	-.928925
270	Respiratory Therapists	-.9289472
271	Multiple Machine Tool Setters, Operators, and Tenders, Metal and Plastic	-.9311058
272	Milling and Planing Machine Setters, Operators, and Tenders, Metal...	-.935317
273	Extruding, Forming, Pressing, and Compacting Machine Setters, Operators...	-.936696
274	Photographers	-.9426689
275	Chefs and Head Cooks	-.9439878
276	Radiation Therapists	-.9469597
277	Hosts and Hostesses, Restaurant, Lounge, and Coffee Shop	-.9497916
278	Shipping, Receiving, and Traffic Clerks	-.9515399
279	Stock Clerks and Order Fillers	-.952974
280	Signal and Track Switch Repairers	-.954421
281	Painters, Construction and Maintenance	-.9565026
282	Biological Technicians	-.960218
283	Weighers, Measurers, Checkers, and Samplers, Recordkeeping	-.9654402
284	Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal	-.9655498
285	Refuse and Recyclable Material Collectors	-.9675552
286	Plasterers and Stucco Masons	-.9694912
287	Etchers and Engravers	-.9759542
288	Cabinetmakers and Bench Carpenters	-.9800901
289	Therapists, All Other	-.9828883
290	Laborers and Freight, Stock, and Material Movers, Hand	-.9866416
291	First-Line Supervisors/Managers of Police and Detectives	-.989264
292	Grinding, Lapping, Polishing, and Buffing Machine Tool Setters, Operators,	-.989429
293	Lodging Managers	-.9899825
294	Ship Engineers	-.9946973
295	Conveyor Operators and Tenders	-.9975365
296	Bridge and Lock Tenders	-1.002735
297	Elevator Installers and Repairers	-1.009797
298	Construction Laborers	-1.010686
299	Structural Metal Fabricators and Fitters	-1.011688
300	Waiters and Waitresses	-1.012
301	Commercial Divers	-1.012578
302	Other Installation, Maintenance, and Repair Workers	-1.013878
303	Printing Machine Operators	-1.016378
304	Job Printers	-1.016378
305	Woodworking Machine Setters, Operators, and Tenders, Except Sawing	-1.019802
306	Helpers–Extraction Workers	-1.020079

307	Forest and Conservation Workers	-1.026156
308	Animal Trainers	-1.026795
309	Heat Treating Equipment Setters, Operators, and Tenders, Metal and Plastic	-1.02884
310	Engine and Other Machine Assemblers	-1.030703
311	Plating and Coating Machine Setters, Operators, and Tenders, Metal and Plas	-1.037436
312	Parking Lot Attendants	-1.038459
313	Roustabouts, Oil and Gas	-1.04112
314	Child Care Workers	-1.043975
315	Counter and Rental Clerks	-1.04697
316	Automotive Service Technicians and Mechanics	-1.049306
317	Electrical and Electronics Installers and Repairers, Transportation Equipme	-1.05027
318	Animal Breeders	-1.0523
319	Veterinarians	-1.053036
320	Railroad Conductors and Yardmasters	-1.053979
321	Cleaners of Vehicles and Equipment	-1.056563
322	First-Line Supervisors/Managers of Construction Trades and Extraction Workers	-1.058532
323	Couriers and Messengers	-1.066361
324	Structural Iron and Steel Workers	-1.066795
325	Electricians	-1.066979
326	Fence Erectors	-1.083349
327	Industrial Truck and Tractor Operators	-1.086625
328	Machinists	-1.090666
329	Fishers and Related Fishing Workers	-1.091292
330	Funeral Directors	-1.094121
331	Sheet Metal Workers	-1.09467
332	Hazardous Materials Removal Workers	-1.10106
333	Lay-Out Workers, Metal and Plastic	-1.102394
334	First-Line Supervisors/Managers of Farming, Fishing, and Forestry Workers	-1.112614
335	Wholesale and Retail Buyers, Except Farm Products	-1.114698
336	Reinforcing Iron and Rebar Workers	-1.116836
337	Septic Tank Servicers and Sewer Pipe Cleaners	-1.118366
338	First-Line Supervisors/Managers of Landscaping, Lawn Service, and Groundske	-1.122517
339	Riggers	-1.122882
340	Telecommunications Line Installers and Repairers	-1.126733
341	Cementing and Gluing Machine Operators and Tenders	-1.12704
342	Maintenance and Repair Workers, General	-1.128154
343	Farmers and Ranchers	-1.132413
344	Farm, Ranch, and Other Agricultural Managers	-1.132413
345	Sawing Machine Setters, Operators, and Tenders, Wood	-1.137118
346	First-Line Supervisors/Managers of Production and Operating Workers	-1.148378
347	Furniture Finishers	-1.155912
348	Production Workers, All Other	-1.161129
349	Rail-Track Laying and Maintenance Equipment Operators	-1.162478
350	Sailors and Marine Oilers	-1.175661
351	Operating Engineers and Other Construction Equipment Operators	-1.185336
352	Millwrights	-1.185585
353	Physical Therapists	-1.188192
354	Rolling Machine Setters, Operators, and Tenders, Metal and Plastic	-1.206973
355	Fire Fighters	-1.207739
356	Emergency Medical Technicians and Paramedics	-1.221729
357	Furnace, Kiln, Oven, Drier, and Kettle Operators and Tenders	-1.222028
358	First-Line Supervisors/Managers of Food Preparation and Serving Workers	-1.222587
359	First-Line Supervisors/Managers of Mechanics, Installers, and Repairers	-1.223801
360	Tank Car, Truck, and Ship Loaders	-1.257557
361	Hoist and Winch Operators	-1.261587

362	First-Line Supervisors/Managers of Fire Fighting and Prevention Workers	-1.285222
363	Carpenters	-1.286485
364	First-Line Supervisors/Managers of Retail Sales Workers	-1.293756
365	Paving, Surfacing, and Tamping Equipment Operators	-1.333255
366	Earth Drillers, Except Oil and Gas	-1.349429
367	Highway Maintenance Workers	-1.376281
368	Crane and Tower Operators	-1.399173
369	Meeting and Convention Planners	-1.500331

Notes: This table reproduces the Routine-Task Intensity index using O*NET data, adjusted for scale effects as described in the main text.

Appendix B

Appendix: Chapter II

B.1 Data Appendix

SIPP

As our model assumes a stationary environment we restrict our sample to post Great Recession, 2011-2015. To be able to back out wages we drop workers with multiple jobs and/or moonlighting. We also drop workers with preventing disabilities and injuries as the reason for their immobility is not by choice. As opposed to other variables in SIPP occupations of workers are provided for the entirety of four months. As such we only use the final month (srefmon=4) as it is subjected to less recall bias.

SIPP provides researchers with plethora of information about reasons for labor market developments. RMESR provides information on employment status for the interview month. ERSEND1 enables us to understand if the reason for leaving job was voluntary or not. Finally ERSNOWRK gives us information on if the worker is not working because could not find a job or did not searched for one. We also utilize ER05 to see if the worker received unemployment compensation.

Since continuous decisions are coded in discrete times some observations might have contradictory or time inconsistent information. For example, a worker might be observed as employed but also provide reason for leaving work. This happens when worker has worked for most of the month but left job right before the interview. In these instances we simply correct for timing of events. It is also possible for worker to find a job but also report no search behavior. For these cases we assume if a worker has find a job she must have searched.

As we are mapping continuous transitions to discrete outcomes we use fourth week employment status for current employment status.

Table B.1: Mapping of Employment Status from Data to Model

RWKESR4: Employment status	
-1. Not applicable	Not in Universe
1. With job - working	Employed
2. With job - not on layoff, absent without pay	Not in Universe
3. With job - on layoff, absent without pay	Not in Universe
4. No job - looking for work or on layoff	Unemployed
5. No job - not looking for work and not on layoff	Home

Table B.2: Mapping of Reason Stopped Working from Data to Model

ERSEND1: Main reason stopped working for employer	
-1. Not in Universe	Not in Universe
1. On Layoff	Not in Universe
2. Retirement or old age	Not in Universe
3. Childcare problems	Involuntary
4. Other family/personal obligations	Involuntary
5. Own illness	Involuntary
6. Own injury	Involuntary
7. School/Training	Not in Universe
8. Discharged/fired	Involuntary
9. Employer Bankrupt	Involuntary
10. Employer sold business	Involuntary
11. Job was temporary and ended	Involuntary
12. Quit to take another job	Voluntary
13. Slack work or business conditions	Not in Universe
14. Unsatisfactory work arrangements	Voluntary
15. Quit for some other reason	Voluntary

O*NET Principle Component Analysis

For our analysis of O*NET we use "level" information from "Skills", "Abilities", "Work Context", and "Work Activities". Since some data is scaled differently we use minmax normalization following O*NET's suggestions.[1] Principle component analysis was performed and the results were rotated using "promax" rotation. Cognitive requirements load onto the first component whereas physical requirements and equipment handling load onto the second one. Finally third component loads on social skills.

Table B.4: Principle Component Analysis—Loadings

			rho = 0.657	**KMO = 0.9834**
	Component 1	**Component 2**	**Component 3**	**Unexplained**
Information Ordering	**.1349565**	.0170221	-.0564862	.2085585
Complex Problem Solving	**.1329465**	-.0010965	-.0271518	.1334151
Systems Evaluation	**.1311614**	.0075261	-.010572	.1509176
Systems Analysis	**.1311561**	.0009924	-.0271558	.1648007
Mathematical Reasoning	**.127899**	-.0167416	-.1072212	.2309596
Category Flexibility	**.1276602**	-.0045968	-.0748513	.2578217
Deductive Reasoning	**.1275493**	-.0150729	-.021331	.1357181
Mathematics	**.1249461**	-.0003647	-.1176064	.3090684
Analyzing Data or Information	**.1245555**	-.0189466	-.0550444	.2210302
Judgment and Decision Making	**.124034**	-.0115599	.0011083	.1417106
Active Learning	**.1223384**	-.0212798	-.0023638	.1280982
Inductive Reasoning	**.1212597**	-.007229	-.0042467	.2106971
Updating and Using Relevant Knowledge	**.120887**	.0007481	-.015456	.2709192
Number Facility	**.1206269**	-.010862	-.0972029	.3306388
Making Decisions and Solving Problems	**.1204265**	.0311389	.025938	.2589618
Fluency of Ideas	**.1200602**	-.0173565	-.0074137	.1903882
Process Information	**.1188457**	-.0188316	-.0547242	.2907849
Flexibility of Closure	**.1181245**	.0745447	-.0445446	.3987876
Critical Thinking	**.1177862**	-.026732	.0054696	.1385588

[1] More details on scaling of variables are available at https://www.onetonline.org/help/online/scale

Table B.4 – *Continued from previous page*

	Component 1	Component 2	Component 3	Unexplained
Originality	**.1173888**	-.0154278	-.0079604	.2346256
Analytical Thinking	**.1170749**	-.0105301	-.0335183	.3116119
Estimating the Quantifiable Characteristics	**.1167045**	.062313	-.0704087	.431345
Provide Consultation and Advice to Others	**.1165448**	-.0000816	.0107888	.258894
Problem Sensitivity	**.1157336**	.0251934	.0354178	.2759676
Monitoring	**.1153793**	.015034	.0443552	.2241421
Reading Comprehension	**.1153398**	-.0421276	-.0114966	.1320735
Written Comprehension	**.114938**	-.0488344	-.0269921	.1358234
Science	**.1137308**	.0273492	-.063119	.4663381
Speed of Closure	**.1126214**	.0538677	.0151006	.3994253
Oral Comprehension	**.1110161**	-.0339604	.0013685	.1994252
Thinking Creatively	**.1103375**	-.0069837	-.0298982	.3959188
Interpreting the Meaning of Information for Others	**.1097337**	-.024942	-.011516	.2942304
Developing Objectives and Strategies	**.1086129**	.0012163	.0307672	.3036444
Operations Analysis	**.1082362**	-.006672	-.0736986	.4650362
Documenting/Recording Information	**.107479**	.0068861	.0046091	.4041298
Written Expression	**.1072421**	-.0548005	-.0020482	.1313947
Instructing	**.1070943**	.0105625	.0549286	.2759459
Scheduling Work and Activities	**.1064257**	.0167	.0372825	.3586464
Time Management	**.1060522**	.0039103	.0450004	.2991267
Interacting with Computers	**.1059714**	-.0402597	-.0806678	.3701905
Writing	**.1058988**	-.053304	.0039248	.1407765
Organizing, Planning, and Prioritizing Work	**.1049874**	-.0131398	.0309297	.289209
Communicating with Supervisors, Peers, or Subordinates	**.1048574**	.0054985	.0363888	.3458382
Management of Personnel Resources	**.1047809**	.0309686	.0618436	.3345228
Getting Information	**.1044689**	-.0349155	.0073552	.2588481
Learning Strategies	**.1039653**	.0011862	.060869	.2588028
Identifying Object, Actions, and Events	**.1026294**	.027063	.0318075	.438983
Oral Expression	**.1014302**	-.046534	.0210791	.1867082
Memorization	**.1013681**	.005159	.0291799	.4052371
Evaluating Information	.0985401	.03862	.0233436	.5160247
Judging the Qualities of Things, Services, or People	.0983198	.0328147	.0441277	.4610926
Management of Material Resources	.0981184	.0415416	-.0101344	.5772653
Monitoring and Controlling Resources	.0979467	.0379976	.0146854	.5384995
Near Vision	.0966383	-.0100026	-.067073	.5639352
Developing and Building Teams	.0964211	.0358263	.0719162	.4015362
Coordinating the Work and Activities of Others	.0959465	.0433698	.0635148	.4433152
Guiding, Directing, and Motivating Subordinates	.0956821	.0445918	.0752916	.4102391
Active Listening	.0939482	-.0524698	.0448151	.1574339
Speaking	.0934535	-.0551649	.0476161	.1344686
Management of Financial Resources	.0898092	.0060357	-.019856	.6220556
Staffing Organizational Units	.0893746	.0144212	.0596668	.4688429
Training and Teaching Others	.0891601	.0252379	.0709323	.4598808
Persuasion	.0852677	-.0277688	.0796273	.2715539
Persistence	.0815225	-.008232	.0592516	.4773231
Performing Administrative Activities	.0810631	-.0289985	.0604124	.386223
Communicating with Persons Outside Organization	.080845	-.0393022	.0583472	.3407399
Achievement/Effort	.0786991	-.0238474	.0438897	.4901791
Innovation	.0735578	-.0024748	.0172955	.6794246
Attention to Detail	.0585017	-.0040415	-.0106265	.8246977
Selling or Influencing Others	.0555944	-.0241691	.0507042	.6712913
Depth Perception	.0230676	**.1671982**	-.0202396	.1765752
Response Orientation	-.013234	**.1635331**	.0383911	.1699971

Table B.4 – *Continued from previous page*

	Component 1	**Component 2**	**Component 3**	**Unexplained**
Reaction Time	-.0152166	**.1603081**	.0136593	.1458513
Operation and Control	.0173365	**.1595154**	-.0439846	.1714868
Multilimb Coordination	-.0286153	**.1590745**	.042059	.1252648
Performing General Physical Activities	-.0264177	**.1570457**	.0818602	.2048069
Inspecting Equipment, Structures, or Material	.0481714	**.1558528**	-.0229734	.3159758
Operating Vehicles, Mechanized Devices, or Equipment	-.0003239	**.1554091**	.034982	.3050399
Operation Monitoring	.0500516	**.1547332**	-.0754575	.2043244
Rate Control	-.0165879	**.1520999**	-.0078813	.1694404
Repairing and Maintaining Mechanical Equipment	.0181823	**.1499808**	-.0605569	.217652
Controlling Machines and Processes	.0116938	**.1487722**	-.0483856	.2405675
Control Precision	-.0058096	**.148548**	-.0282936	.2145935
Auditory Attention	.013781	**.1476961**	.0206095	.4022792
Trouble Shooting	.0420286	**.1470323**	-.096027	.19579
Static Strength	-.0509356	**.1455146**	.0838697	.1461525
Gross Body Equilibrium	-.0388835	**.1454026**	.0973679	.2424469
Hearing Sensitivity	.0310151	**.1446403**	.0006183	.4342262
handling and Moving Objects	-.0356816	**.1432539**	.0370328	.222129
Sound Localization	-.0089673	**.1427984**	.038246	.3850012
Glare Sensitivity	-.01238	**.1420467**	.0398418	.3776528
Spatial Orientation	-.0049716	**.1420333**	.0363645	.4064203
Extent Flexibility	-.0506768	**.1400717**	.0604156	.1723733
Peripheral Vision	-.0158955	**.1396191**	.0523288	.3946149
Dynamic Strength	-.0512211	**.139251**	.0801632	.198703
Gross Body Coordination	-.0542438	**.139051**	**.1090348**	.1938989
Speed of Limb Movement	-.0468498	**.138394**	.0782562	.2383781
Night Vision	-.008951	**.1378977**	.0436545	.4321932
Quality Control Analysis	.0680358	**.1370092**	**-.1048691**	.2672767
Stamina	-.0582376	**.1358978**	**.1100826**	.1907519
Manual Dexterity	-.0263396	**.1358199**	-.0049919	.2691214
Arm Hand Steadiness	-.0164925	**.1327923**	-.0085392	.3514337
Equipment Maintenance	.0151724	**.1324004**	-.0804178	.3015775
Visual Color Discrimination	.0604704	**.1309626**	-.0622524	.4311634
Repairing	.0173968	**.1301258**	-.0831268	.3208257
Equipment Selection	.0417751	**.1301204**	**-.1094166**	.295044
Trunk Strength	-.0567467	**.1296467**	.0941083	.2499158
Wrist-Finger Speed	-.0125723	**.1252138**	-.0414866	.3529633
Visualization	.0931842	**.1199485**	-.0940043	.3498896
Finger Dexterity	.0163181	**.1177667**	-.0575765	.4976331
Perceptual Speed	.0891151	**.1177204**	-.0481624	.4505871
Repairing and Maintaining Electronic Equipment	.0545169	**.1157262**	**-.1010796**	.4433305
Far Vision	.0780345	**.1083829**	.0209803	.5608563
Monitor Processes, Materials, or Surroundings	.093712	**.1069715**	.0446351	.4376226
Selective Attention	.0784256	.0992079	-.00883	.6067078
Dynamic Flexibility	-.0445238	.0602216	.0513282	.7581252
Social Orientation	-.0311039	-.0054835	**.2482857**	.3139382
Concern for Others	-.0283698	.0117523	**.2461368**	.359764
Self Control	-.0209699	.0107011	**.2439633**	.353889
Assisting and Caring for Others	.0025214	.0541951	**.2188606**	.4548232
Performing for or Working Directly with the Public	-.0078405	-.0038157	**.1983236**	.5207562
Stress Tolerance	.016651	.005322	**.1911905**	.4717292
Cooperation	.0026953	-.0100766	**.1855905**	.5233676
Dependability	.015749	.0066259	**.1717242**	.5743563
Leadership	.0601776	.0333665	**.1635884**	.3663741

Table B.4 – *Continued from previous page*

	Component 1	**Component 2**	**Component 3**	**Unexplained**
Programming	**.1064813**	-.0249415	**-.1600028**	.3884246
Adaptability/Flexibility	.0438778	.0021585	**.1554453**	.4584086
Service Orientation	.0446797	-.0295491	**.1513584**	.3368148
Social Perceptiveness	.063286	-.0272261	**.1429568**	.2150964
Resolving Conflicts and Negotiating with Others	.0651041	.0040382	**.1418797**	.34584
Technology Design	**.1085364**	.0387187	**-.1352277**	.4632207
Drafting. Laying out, and Specifying Equipment	.0826036	.0928487	**-.1255028**	.4619386
Establishing and Maintaining Interpersonal Relationships	.0675813	-.0299956	**.1181902**	.2801401
Integrity	.0471244	-.0400272	**.1161942**	.4287833
Time Sharing	.0523704	**.1045354**	**.1153051**	.5506241
Coordination	.0895645	.0340738	**.1050427**	.3481567
Explosive Strength	-.0305453	.0856982	**.1037227**	.6934556
Coaching and Developing Others	.08975	.0182872	**.1002699**	.3268256
Negotiation	.0750085	-.027504	.0898939	.3429116
Independence	.0243905	-.0277628	.0884465	.7471164
Installation	.0309892	.0804665	-.0848645	.6938034
Speech Recognition	.0662216	-.0508258	.0846678	.3222057
Speech Clarity	.0671737	-.0515935	.084086	.309983
Initiative	.0799883	-.0100274	.0800442	.4117603

Notes: Principle component analysis on O*NET data on skills, abilities, work activities, and work styles. Cognitive requirements load onto the first component and physical requirements and equipment handling load onto the second component. Finally social skill requirements load onto third component. "*Unexplained*" measures the variation in a given variable that is not captured by principle components. Loadings greater than 0.1 is presented in bold. $rho = 0.657$ means three components were able to capture 0.657 percent of the overall variation in the data. Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy is 0.9834 indicating variables have a lot in common and data is perfectly suited for PCA. Note that Stata normalizes sum of squared loading scores to unity rather than to associated eigenvalues as in most other softwares.

Table B.3: Mapping of Reason for Not Having a Job from Data to Model

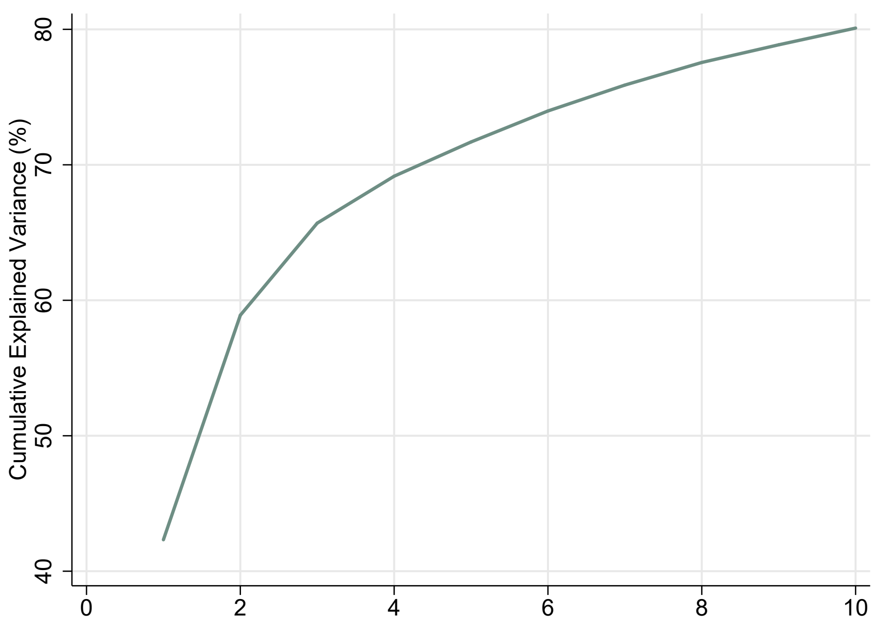
	ERSNOWRK: Main reason for not having a job during the reference period	
-1.	Not in Universe	Not in Universe
1.	Temporarily unable to work because of an injury	Not in Universe
2.	Temporarily unable to work because of an illness	Not in Universe
3.	Unable to work because of chronic health condition or disability	Not in Universe
4.	Retired	Not in Universe
5.	Pregnancy/childbirth	Not in Universe
6.	Taking care of children/other persons	Not in Universe
7.	Going to school	Not in Universe
8.	Unable to find work	Searching
9.	On layoff (temporary or indefinite	Not in Universe
10.	Not interested in working at a job	Not Searching
11.	Other	Not in Universe

Table B.5: Correlation Matrix of Rotated Principle Components

	Cognitive	Physical	Social
Cognitive	1		
Physical	-0.373***	1	
Social	0.402***	-0.342***	1

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure B.1: Cumulative percentage of explained variance



Notes: The first three components increase explained variance substantially. Additional components have marginal effects.

B.2 Technical Appendix

Proposition 5. *Nash bargaining has the following closed-form solution*

$$EW(i) - EU(i) = \frac{\eta\left[\Big(J(i)\Big) + \Big(EW(i) - EU(i)\Big)\right]}{1 - \frac{\eta((u'(\omega)+\beta t_i \pi^e_s(i) EU'|_{\omega_i})-1)J(i)}{EW(i)-EU(i)} - (1-\eta)\beta J(i)\frac{\partial \pi^e_s(i)}{\partial \omega_i}} \tag{B.1}$$

Proof. Firstly note that, assuming type-1 extreme value distribution expected value of working at occupation i at wage rate ω_i is $EW(i) = \ln \sum_k \exp w_k(i) + \gamma$ where γ is the Euler-Mascheroni constant. Then we have

$$\frac{\partial EW(i)}{\partial \omega_i} = \sum_k \frac{\partial w_k(i)}{\partial \omega_i} \pi_k(i) \tag{B.2}$$

We assume that changing current offer for particular offer for a match has no impact on the value of being in another job that is $\frac{\partial EW(k)}{\partial \omega_i} = 0$. This implies we have

$$\frac{\partial w_k(i)}{\partial \omega_i} = \begin{cases} u'(\omega) & k = H \\ u'(\omega) + \beta(1-t_i)\frac{\partial EW(i)}{\partial \omega_i} + \beta t_i \frac{\partial EU(i)}{\partial \omega_i} & k = i \\ u'(\omega) + \beta(1-t_i)(1-P_k)\frac{\partial EW(i)}{\partial \omega_i} + \beta t_i (1-P_k)\frac{\partial EU(i)}{\partial \omega_i} & \text{otherwise} \end{cases} \tag{B.3}$$

substituting back gives us

$$\frac{\partial EW(i)}{\partial \omega_i} = u'(\omega)\pi^e_H(i) + \left[u'(\omega) + \beta(1-t_i)\frac{\partial EW(i)}{\partial \omega_i} + \beta t_i \frac{\partial EU(i)}{\partial \omega_i}\right]\pi^e_i(i) \tag{B.4}$$

$$+ \sum_{k \neq i,H} \left[u'(\omega) + \beta(1-t_i)(1-P_k)\frac{\partial EW(i)}{\partial \omega_i} + \beta t_i(1-P_k)\frac{\partial EU(i)}{\partial \omega_i}\right]\pi^e_k(i) \tag{B.5}$$

$$= u'(\omega) + \beta(1-t_i)\frac{\partial EW(i)}{\partial \omega_i}\left[\pi^e_i(i) + \sum_{k \neq i,H}(1-P_k)\pi^e_k(i)\right] \tag{B.6}$$

$$+ \beta t_i \frac{\partial EU(i)}{\partial \omega_i}\left[\pi^e_i(i) + \sum_{k \neq i,H}(1-P_k)\pi^e_k(i)\right] \tag{B.7}$$

Letting $\pi_s^e = \left[\pi_i^e(i) + \sum_{k \neq i,H}(1-P_k)\pi_k^e(i)\right]$ and solving for $\frac{\partial EW(i)}{\partial \omega_i}$ gives

$$\frac{\partial EW(i)}{\partial \omega_i} = \frac{u'(\omega) + \beta t_i \pi_s^e \frac{\partial EU(i)}{\partial \omega_i}}{1 - \beta(1-t_i)\pi_s^e} \tag{B.8}$$

This equation shows that as the offered wage ω_i increases the expected value from being in occupation i increases smoothly. The probability of not searching increases in ω_i therefore denominator becomes smaller as ω_i increases. Repeating the same procedure for $\frac{\partial EU(i)}{\partial \omega_i}$ (Not to be confused with the derivative in the bargaining problem) we get

$$\frac{\partial EU(i)}{\partial \omega_i} = \sum_k \frac{\partial u_k(i)}{\partial \omega_i}\pi_k^u(i) \tag{B.9}$$

$$\frac{\partial u_k(i)}{\partial \omega_i} = \begin{cases} ru'(r\omega) & k = H \\ ru'(r\omega) + \rho\beta(1-P_k)\frac{\partial EU(i)}{\partial \omega_i} & \text{otherwise} \end{cases} \tag{B.10}$$

Solving these together implies

$$\frac{\partial EU(i)}{\partial \omega_i} = \frac{ru'(r\omega)}{1 - \rho\beta\pi_s^u} \tag{B.11}$$

where $\pi_s^u = \sum_{k \neq H}(1-P_k)\pi_k^u(i)$. Plugging this back into $\frac{\partial EW(i)}{\partial \omega_i}$ we have

$$\frac{\partial EW(i)}{\partial \omega_i} = \frac{u'(\omega) + \beta t_i \pi_s^e \frac{ru'(r\omega)}{1-\rho\beta\pi_s^u}}{1 - \beta(1-t_i)\pi_s^e} \tag{B.12}$$

where r is the replacement ratio for unemployment benefits. The second term in the numerator captures the value workers get through higher wages due to the increase in their unemployment benefits. equation

Next we focus on how the value for firm changes. Taking derivative and rearranging yields

$$\frac{\partial J(i)}{\partial \omega_i} = -1 + \beta\Bigg[\frac{\partial \pi_H^e(i)}{\partial \omega_i}V(i) + \frac{\partial \pi_i^e(i)}{\partial \omega_i}t_i V(i) + \frac{\partial \pi_i^e(i)}{\partial \omega_i}(1-t_i)J(i) + pi_i^e(i)(1-t_i)\frac{\partial J(i)}{\partial \omega_i} \tag{B.13}$$

$$+ \sum_{k\neq i,H}\frac{\partial \pi_k^e(i)}{\partial \omega_i}P_k V(i) + \sum_{k\neq i,H}\frac{\partial \pi_k^e(i)}{\partial \omega_i}(1-P_k)t_i V(i)$$

$$+ \sum_{k\neq i,H}\frac{\partial \pi_k^e(i)}{\partial \omega_i}(1-P_k)(1-t_i)J(i) + + \sum_{k\neq i,H}\pi_k^e(i)(1-P_k)(1-t_i)\frac{\partial J(i)}{\partial \omega_i}\Bigg]$$

which implies

$$\frac{\partial J(i)}{\partial \omega_i} = \frac{-1 + \beta V(i)\big(\frac{\partial \pi_H^e(i)}{\partial \omega_i} + \frac{\partial \pi_i^e(i)}{\partial \omega_i}t_i + \sum_{k\neq i,H}\frac{\partial \pi_k^e(i)}{\partial \omega_i}P_k + \sum_{k\neq i,H}\frac{\partial \pi_k^e(i)}{\partial \omega_i}(1-P_k)ti\big)}{1-\beta(1-t_i)\big(\pi_i^e(i) + \sum_{k\neq i,H}\pi_k^e(i)(1-P_k)\big)} \tag{B.14}$$

$$+ \frac{\beta J(i)\big(\frac{\partial \pi_i^e(i)}{\partial \omega_i}(1-t_i) + \sum_{k\neq i,H}\frac{\partial \pi_k^e(i)}{\partial \omega_i}(1-P_k)(1-t_i)\big)}{1-\beta(1-t_i)\big(\pi_i^e(i) + \sum_{k\neq i,H}\pi_k^e(i)(1-P_k)\big)} \tag{B.15}$$

Letting $\pi_l^e \equiv \pi_H^e + \sum_{k\neq i,H}\pi_k^e P_k$ we get

$$\frac{\partial J(i)}{\partial \omega_i} = \frac{-1 + \beta V(i)\left(\frac{\partial \pi_l^e}{\partial \omega_i} + t_i\frac{\partial \pi_s^e}{\partial \omega_i}\right) + \beta J(i)(1-t_i)\frac{\partial \pi_s^e}{\partial \omega_i}}{1-\beta(1-t_i)\pi_s^e} \tag{B.16}$$

This equation shows that the firm takes the impact the wage offer on search behavior. If the wages did not impact searching behavior then we would get

$$\frac{\partial J(i)}{\partial \omega_i} = \frac{-1}{1-\beta(1-t_i)\pi_s^e} \tag{B.17}$$

which is clearly negative. The firms value is a decreasing function of wages. However, when wage offers generate behavioral responses it is not certain if this equation is positive or not. Firms value can be increasing in wages as the marginal cost of increasing wages can be less than marginal value of increasing the probability the worker would stay in the job. Firms value being decreasing in wages is crucial for Nash Bargaining to function as the other way around it is possible to get Pareto improvement by increasing wages compared to bargaining outcome. Now let's investigate how the wages impact the search behavior of the worker:

$$\frac{\partial \pi_j^e(i)}{\partial \omega_i} = \frac{\frac{\partial w_j(i)}{\partial \omega_i} e^{w_j(i)} \sum_k e^{w_k(i)} - e^{w_j(i)} \sum_k \frac{\partial w_k(i)}{\partial \omega_i} e^{w_k(i)}}{\left(\sum_k e^{w_k(i)} \right)^2} \tag{B.18}$$

$$\frac{\partial \pi_j^e(i)}{\partial \omega_i} = \frac{\partial w_j(i)}{\omega_i} \pi_j^e(i) - \pi_j^e(i) \sum_k \frac{\partial w_k(i)}{\partial \omega_i} \pi_k^e(i) \tag{B.19}$$

We will go over all three cases: Staying home, staying in current occupation, and searching for other occupations. Staying home propensity is impacted as follows

$$\begin{aligned} \frac{\partial \pi_H^e(i)}{\partial \omega_i} &= u'(\omega_i)\pi_H^e(i) - \frac{\partial EW(i)}{\partial \omega_i} \pi_H^e(i) \\ &= \pi_H^e(i) \Big[u'(\omega_i) - \frac{u'(\omega_i) + \beta t_i \pi_s^e EU'|_{\omega_i}}{1 - \beta(1-t_i)\pi_s^e} \Big] \\ &= -\pi_H^e(i)\beta\pi_s^e(i) \frac{(1-t_i)u'(\omega_i) + t_i EU'|_{\omega_i}}{1 - \beta(1-t_i)\pi_s^e} \\ &< 0 \end{aligned} \tag{B.20}$$

Increasing wages makes staying home through two channels: First, being able to get these increases directly decreases probability of staying home through the discounted sum of future wages. Moreover, the fact that unemployment benefits are tied to employment means unemployment insurance further decreases the propensity to stay home.

Now we focus on how increased wages incentivize the worker to stay in current job

$$\begin{aligned} \frac{\partial \pi_i^e(i)}{\partial \omega_i} &= \Big(u'(\omega_i) + \beta(1-t_i) \frac{\partial EW(i)}{\partial \omega_i} + \beta t_i \frac{\partial EU(i)}{\partial \omega_i} \Big) \pi_i^e(i) - \frac{\partial EW(i)}{\partial \omega_i} \pi_i^e(i) \\ &= \pi_i^e(i) \Big[u'(\omega_i) - (1 - \beta(1-t_i)) \frac{\partial EW(i)}{\partial \omega_i} + \beta t_i \frac{\partial EU(i)}{\partial \omega_i} \Big] \\ &= \pi_i^e(i) \Big[u'(\omega_i) - (1 - \beta(1-t_i)) \frac{u'(\omega_i) + \beta t_i \pi_s^e EU'|_{\omega_i}}{1 - \beta(1-t_i)\pi_i^e} + \beta t_i EU'|_{\omega_i} \\ &= \pi_i^e(i)\beta(1-\pi_s^e) \frac{(1-t_i)u'(\omega_i) + t_i EU'|_{\omega_i}}{1-\beta(1-t_i)\pi_s^e} \\ &> 0 \end{aligned} \tag{B.21}$$

Finally for $k \neq i, H$ we have

$$\frac{\partial \pi_k^e(i)}{\partial \omega_i} = \Big(u'(\omega_i) + \beta(1-t_i)(1-P_k)\frac{\partial EW(i)}{\partial \omega_i} + \beta t_i(1-P_k)\frac{\partial EU(i)}{\partial \omega_i}\Big)\pi_k^e(i) - \frac{\partial EW(i)}{\partial \omega_i}\pi_k^e(i) \tag{B.22}$$

$$\begin{aligned}
&= \pi_k^e(i)\Big[u'(\omega_i) - (1-\beta(1-t_i)(1-P_k))\frac{\partial EW(i)}{\partial \omega_i} + \beta t_i(1-P_k)\frac{\partial EU(i)}{\partial \omega_i}\Big] \\
&= \pi_k^e(i)\Big[u'(\omega_i) - (1-\beta(1-t_i)(1-P_k))\frac{u'(\omega_i) + \beta t_i \pi_s^e EU'|_{\omega_i}}{1-\beta(1-t_i)\pi_i^e} + \beta t_i(1-P_k)EU'|_{\omega_i} \\
&= \pi_k^e(i)\beta(1-\pi_s^e - P_k)\frac{(1-t_i)u'(\omega_i) + t_i EU'|_{\omega_i}}{1-\beta(1-t_i)\pi_s^e}
\end{aligned} \tag{B.23}$$

whether this value is positive or negative depends on the respective values of π_s^e and P_k. If $\pi_s^e + P_k = 1$ then change in the wage does not impact the searching intensity toward occupation k. If $\pi_s^e + P_k > 1$ then workers search less in occupation k and they search more if $\pi_s^e + P_k < 1$.

Impact of wages on the longevity of the match is given by the impact of a marginal increase in wage on $\pi_s^e(i) = \pi_i^e(i) + \sum_{k\neq i,H} \pi_k^e(i)(1-P_k)$. We have

$$\begin{aligned}
\frac{\partial \pi_s^e(i)}{\partial \omega_i} &= \frac{\partial \pi_i^e(i)}{\partial \omega_i} + \sum_{k\neq i,H} \frac{\partial \pi_k^e(i)}{\partial \omega_i}(1-P_k) \qquad \text{(B.24)} \\
&= \beta\Big[\pi_i^e(i)(1-\pi_s^e(i)) + \sum_{k\neq i,H} \pi_k^e(i)(1-\pi_s^e(i) - P_k)\Big]\frac{(1-t_i)u'(\omega_i) + t_i EU'|_{\omega_i}}{1-\beta(1-t_i)\pi_s^e}
\end{aligned}$$

It is easy to see this term is positive when $P_k = 0$ for all k. Therefore we inspect what happens when $P_k = 1$, at the minimum. Then $\pi_s^e(i) = \pi_i^e(i)$. Replacing these terms back in we get

$$= \pi_i^e(i)\big(1-\pi_i^e(i)\big) - \pi_i^e(i)\sum_{k\neq i,H}\pi_k^e(i)\frac{(1-t_i)u'(\omega_i)+t_iEU'|_{\omega_i}}{1-\beta(1-t_i)\pi_s^e} \tag{B.25}$$

$$= \pi_i^e(i) - \pi_i^e(i)\big(\pi_i^e(i) + \sum_{k\neq i,H}\pi_k^e(i)\big)\frac{(1-t_i)u'(\omega_i)+t_iEU'|_{\omega_i}}{1-\beta(1-t_i)\pi_s^e} \tag{B.26}$$

$$= \pi_i^e(i)\big(1-\pi_i^e(i) - \sum_{k\neq i,H}\pi_k^e(i)\big)\frac{(1-t_i)u'(\omega_i)+t_iEU'|_{\omega_i}}{1-\beta(1-t_i)\pi_s^e} \tag{B.27}$$

$$= \pi_i^e(i)\pi_H^e(i)\frac{(1-t_i)u'(\omega_i)+t_iEU'|_{\omega_i}}{1-\beta(1-t_i)\pi_s^e} > 0 \tag{B.28}$$

Therefore, even though it is possible increased wages to induce search into some other occupations, the total effect is to induce staying in the job.

Assuming free entry, partial derivative of $J(i)$ in equilibrium becomes

$$\frac{\partial J(i)}{\partial \omega_i} = \frac{-1+\beta J(i)\Big(\frac{\partial \pi_i^e(i)}{\partial \omega_i}(1-t_i) + \sum_{k\neq i,H}\frac{\partial \pi_k^e(i)}{\partial \omega_i}(1-P_k)(1-t_i)\Big)}{1-\beta(1-t_i)\big(\pi_i^e(i)+\sum_{k\neq i,H}\pi_k^e(i)(1-P_k)\big)} \tag{B.29}$$

Now we go back to the first order condition of the bargaining problem and plug derivatives of the value functions back

$$\eta\frac{\partial EW(i)}{\partial \omega_i}J(i) = -(1-\eta)(EW(i)-EU(i))\frac{\partial J(i)}{\partial \omega_i} \tag{B.30}$$

$$\eta\frac{\Big(u'(\omega)+\beta t_i\pi_s^e EU|_{\omega_i}\Big)J(i)}{1-\beta(1-t_i)\pi_s^e} = (1-\eta)\Big(EW(i)-EU(i)\Big)\frac{1-\beta J(i)\frac{\partial \pi_s^e}{\partial \omega_i}}{1-\beta(1-t_i)\pi_s^e} \tag{B.31}$$

Adding and substracting $\eta J(i)$, multiplying and diving $\eta J(i)(1-(u'(\omega)+\beta t_i\pi_s^e EU|_{\omega_i})$ by $(EW(i)-EU(i))$, and with little algebra we get

$$EW(i)-EU(i) = \frac{\eta\Big[\Big(J(i)\Big)+\Big(EW(i)-EU(i)\Big)\Big]}{1-\frac{\eta((u'(\omega)+\beta t_i\pi_s^e(i)EU|_{\omega_i})-1)J(i)}{EW(i)-EU(i)} - (1-\eta)\beta J(i)\frac{\partial \pi_s^e(i)}{\partial \omega_i}} \tag{B.32}$$

□

Proposition 6. *Even with assumptions 1, 2, and 3, conditional choice probabilities π and job finding probabilities P are not identified. For any search probabilities π there exist a set of job finding probabilities P that justifies observed transitions. The degree of under-identification is $3N^2 - 2N$.*

Proof. The reason for non-identification is that there are $6N^2 - 2N$ number of unknowns consisting of $3N^2 - 3N$ unknowns in conditional choice probabilities π, $3N^2$ unknowns in job finding probabilities P, and N unknowns in t. However, observed transition probabilities impose only $3N^2$ restrictions given that some transitions are not possible. For example a worker in occupation i cannot become unemployed in occupation j and an unemployed worker without benefits cannot become eligible for benefits without first finding a job. □

Theorem 2. *With assumptions 1, 2, 3, and 4 conditional choice probabilities π and job finding probabilities P are over-identified. Identification of conditional choice probabilities facilitate the identification of remainder of parameters in workers problem.*

Proof. Equipped with "*Random Match*" assumption the number of unknowns decrease to $3N^2 - N$ and we $3N^2$ equations. Once conditional choice probabilities π are identified, the rest of the parameters are identified using arguments in Hotz and Miller (1993) and Magnac and Thesmar (2002). □