Technological Job Destruction and Labor Reallocation on a Job Ladder

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Abstract

This paper examines labor reallocation across industries triggered by a sectoral technology shock. Job destruction in the manufacturing industry during the 2001 and 2008 recessions reflected progress in labor-saving production technology, rather than cyclical fluctuation. The shock directly implied a slow recovery in aggregate employment and provoked massive labor reallocation. By using CPS data, I show that technologically unemployed workers initiated a chain of one-step downward transitions on a submarket ladder sorted by wage. Many unemployed workers from the manufacturing industry moved to construction, construction workers moved to retail trade, and retail trade workers moved to the food service industry. In addition, the unemployment rate from each industry sequentially reached its peak and recovery points like a domino chain. The observed labor reallocation patterns are more consistent with a model with vertical sorting and search friction. I extend Shimer and Smith’s (2000) model to illustrate that a recession can accelerate technology adoption under a capital adjustment cost, which results in lower outside options of jobless workers and pickier reservation levels for low-type recruiting firms. Although technological progress gives benefits to the entire economy in the long run, the model predicts that the sectoral shock ripples through the bottom half of labor market in the short run. Middle unemployed workers should lower their job market standard, and bottom unemployed workers end up experiencing longer unemployment duration, until total employment recovers.

Keywords— Sorting, technological progress, job destruction, reallocation, jobless recovery, job polarization, income inequality, upskilling
1 Introduction

The 2008 Great Recession in the United States was accompanied by a historically lackluster labor market. In just two years, the unemployment rate spiked from 5% to 10%, and the average duration of unemployment increased from 17 to 40 weeks.\(^1\) In addition, the subsequent recovery was abnormally slow, as compared to other expansionary periods after recessions. It took eight (seven) years in total for the unemployment rate (employment level) to obtain the pre-recession value. Hence, many people do not hesitate to say that the 2008 recession was the worst since the Great Depression in the 1930s. Surprisingly, however, other markets (e.g., output, capital and financial markets) recovered more quickly from the negative shock. Corporate profits reattained the pre-recession value within a year, consumption took two years, GDP took three years, and both equity price and gross investment took five years to rebound.\(^2\) Therefore, it is natural to be curious about why the last recession was particularly painful for unemployed workers.

This paper focuses on an atypical phenomenon that occurred during recent recessions in the United States. The durable goods manufacturing industry produces 78% more in total, with 30% fewer employees compared to 20 years ago. The employment dynamics in durable goods sector is noteworthy in four respects. First, the correlation between output and employment is negative. It reflects a progress in labor-saving production technology, rather than a cyclical fluctuation or a composition change. Most of other industries exhibit positive correlation between output and labor input, and even the durable goods manufacturing industry had shown positive correlation in 20th century.\(^3\) Theoretically, can neither total factor productivity nor labor augmented productivity generate higher output with lower labor input. Second, only a subset of industries permanently reduced employment, which contrasts with aggregate temporary shocks. If all of the submarkets reduce and recover the number of employee simultaneously, then unemployed workers have little incentive to alter their optimal submarket choice. However, workers who are technologically unemployed have incentive to avoid the industry-specific negative shock, so they actively move to other industries. Third, the growth in productivity and decline in employment were episodic, as the changes mostly occurred in 4 years of recessions: 2001–2003 and 2008–2010. Because of the coincidence, analyzing employment without considering output dynamics overlook the distinction between technological and cyclical job destruction. Last, the magnitude of changes in the durable goods industry is effectively the same that we eliminate a small two-digits industry (transportation and utilities) in employment axis but add another small industry (food services) in output dimension. Consequently, the technological job destruction is quantitatively not negligible and cannot be understood as a typical cyclical fluctuation, an economic growth, or a composition change.

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\(^1\)Moreover, the proportion of long-term (27 weeks or more) unemployed to total unemployed persons increased from 17% to 45%, while the share of labor compensation in Gross Domestic Production (GDP) dropped from 61.5% to 59.5%.


\(^3\)The information and nondurable goods industries also started to produce more with fewer workers around 2000.
The technological job destruction provokes more researches to understand its impact on the economy. From microeconomic perspective, technological job destruction provides an natural experiment for us to observe labor reallocation. A progress in production technology enables an industry to save labor input, therefore, the decline in jobs are not expected to be recovered even during an expansionary phase of the economy. The jobless workers are forced to change their job market standard and try something new to quickly settle into other jobs. Hence, the technological job destruction induces massive and wide-scope labor transitions between industries. From macroeconomic perspective, the technological job destruction results a permanent change in the input–output ratio. Once an industry produces more with fewer workers, the labor share of income sharply decreases as well.\textsuperscript{4} In addition, a normative approach requires an efficiency study based on a general equilibrium structural analysis. It is challenging to measure the net benefits of technological job destruction. Unemployed workers are damaged obviously, but the general equilibrium effect of higher productivity would increase consumption, output, and employment in other industries. Furthermore, we currently do not know when is the most desirable time for the technological job destruction, instead of in the middle of a recession. Also, we do not know if gradual retooling is better than episodic job destruction.

Leaving aside other issues, this paper investigates the reallocation of unemployed workers on an industrial job ladder, initiated by a technological job destruction. I find that workers from the jobless industry find their next jobs in a lower-paying industry rather than an actively hiring industry. Unemployed workers from the durable goods manufacturing move to construction, construction workers move to retail trade, and retail trade workers move to the food service industry, like a domino chain. Besides the downward worker transitions between industries, some of the highest-wage workers within the jobless industry are also laid off, but they climb up to the higher-paying industry. The reallocation patterns suggest a vertical wage hierarchy, as best workers climb up the ladder while average workers climb down the ladder, step by step. The labor reallocation explains why it is difficult to find jobs for the lowest wage unemployed workers despite an increase in low-wage employment, when middle-wage jobs disappear.

The empirical part of this paper starts from illustrating a technological job destruction. Among 18 two-digits major industries in the United States, durable/nondurable manufacturing and information industries began to produce more with fewer workers.\textsuperscript{5} Employment permanently declined by 25–35\%, whereas real output per employee increased by 45\%–85\%. The change in durable goods manufacturing was concentrated during the 2001 and 2008 recessions, whereas nondurable goods manufacturing and information industries have gradually changed. For all of the three major sectors, we had not observed

\textsuperscript{4}Declining labor share is a broader concept than technological job destruction that this paper focuses on, because faster growth rate of production compared to employment reduces the labor share as well. Nondurable goods manufacturing, Information, Wholesale trade, and Finance sectors are related with the long-term downward trend in the labor share. The durable goods manufacturing industry is related with sudden but permanent drops in the labor share after 2001 and 2008 recessions.

\textsuperscript{5}Construction industry contracted in both output and input from 2006 to 2010. Other major industries has grown both in output and employment.
a negative correlation between output and labor input in 20th century. The result is robust in occupational analysis, because the only two-digit occupation that disappeared during recessions is production occupation (routine manual), which is almost exclusively used in the manufacturing industry.⁶

Data patterns of labor reallocation started from the durable goods sector suggest bumping chains of unemployment on an industrial job ladder. Unemployed workers from durable goods manufacturing sector were more likely to find their next jobs in adjacent lower-paying industries (e.g., construction, retail trade) rather than actively hiring industries (e.g., health services and food services). Also, there were large labor transitions from construction to retail trade, and from retail trade to food services. These industrial transitions are consistent with step-downs on an industry ladder that is ranked by average wage rate. I also document that both the peak of unemployment from the bottom-wage industry (food services) and its recovery timing were the most sluggish compared to the industries accompanied by technological or cyclical job destruction. Besides the downward worker transitions between industries, some of the highest-wage workers within the durable goods manufacturing industry are also laid off, but they climb up to the higher-paying industry (professionals). The observed reallocation patterns imply that a vertical sorting premise in labor market theory is more suitable than a horizontal assumption to analyze the worker reallocation caused by a technological job destruction.

I use a matching and search model to explain how unemployed workers are reallocated due to a technological job destruction. Based on the empirical evidence, this paper suggests a hypothesis of a directional reallocation that I call *trickle-down unemployment*. A drop in a certain class of jobs induces unemployed workers in the jobless class or below to step down a job hierarchy. The key assumptions are that workers were originally sorted by general ability, skill, or learnability, and job positions are ranked by a general labor productivity.⁷ When middle-wage jobs permanently disappear, jobless workers are more likely to win low-wage jobs rather than high-wage jobs, competing with persons who were cyclically unemployed. Because higher type of counter party is expected, firms with a low-type job opening elevate their standard for hiring and target to be matched with workers from jobless sector. Hence, it is difficult for the lowest-wage workers to get a job, even though the low-wage employment was not directly affected by technology. When job positions are hollowed out in the middle, the model predicts that the left half (below the jobless class) of earnings distribution slides into the negative. Also, the model anticipates that the low half of firms become pickier until the congestion caused by technological unemployment is resolved. The bumping jobless workers in this paper bridges from studies working on job polarization, upskilling effect to those on income inequality: middle-wage job positions disappear, low-wage firms

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⁶Admittedly, office occupation (middle-wage routine cognitive) is not easily map to a single industry. However, the decline in office occupation is distinguished from a disappearance of production occupation. The overall decline in office occupation is gradually made in three decades, and there was a large compositional change within occupation. On contrary, 86% of detailed (four-digits) production occupations decreased simultaneously, and most of the drops are concentrated during recessions.

⁷Two-sided heterogeneity with log-supermodular production function generates a positive assortative matching. (See Shimer and Smith (2000)) The type of firm in this paper is the labor augmented productivity rather than firm’s profit or output per worker.
hire better workers, and thus, low-wage unemployed workers are damaged.

Specifically, this paper extends Shimer and Smith (2000)’s model by adding automation that is a labor substitutable technology and time cost of capital adjustment. This model describes several aspects of technological job destruction we observed. First, the model gives a rationale why middle-wage jobs are more likely to adopt automation technology even if all tasks are feasible to be done by machines. Machines should be good enough and cheap enough to replace existing workers: high jobs are matched with workers because of a high quality and low jobs are matched with workers due to an inexpensive cost. Second, it provides a hypothesis why a recession accelerates the substitution of machines for existing employees. A shadow cost of retooling is low during a recession. Third, it explains why over-qualified workers are also laid off despite a high production, and find their next jobs in the upper lung. Because of an increasing outside options to worker’s type, the surplus of a match with an over-qualified (or under-qualified) worker is marginally positive. Lastly, it demonstrates the trickle down of unemployed workers and the pickier reservation level for low-type firms. When middle-wage jobs disappear through massive separations, the unemployed workers due to an industrial shock lower their reservation level and find their next jobs in a lower-paying industry. As an influx of the higher type of the counterparty is expected, the firms below the jobless sector elevate their standards for hiring, which some researchers call an upskilling effect. The bottom unemployed workers, therefore, have lower chances of getting hired until the congestion caused by the trickle down from the upper class is relieved. It results in a persistent low-wage unemployment of which some researchers claim to be a scarring effect.

The model raises a possibility that the many atypical patterns in the labor market after the Great Recession are slices of a single comprehensive phenomenon from different angles. It suggests that technological unemployment and subsequent re-sorting process can be crucial to understand the declining labor share of income, negative skewness in earnings distribution, higher skill requirement for hiring, a shift in the Beveridge curve, and longer duration of bottom unemployment. The remainder of this paper consists of the following content. Chapter 2 introduces related empirical studies and theories in the labor market. The empirical scope of technological job destruction in the durable goods manufacturing industry is located at the intersection between job polarization (microeconomics) and jobless recovery (macroeconomics). Theoretically, I classify the existing labor theories by the underlying sorting premise, to explain why I choose a matching and search model. Chapter 3 illustrates the empirical evidence of technological job destruction. Chapter 4 conveys the empirical evidence of labor reallocation that I call trickle-down unemployment. Chapter 5 uses an extended matching and search model how a lower demand in middle-wage jobs affects other agents. Chapter 6 discusses the contributions of this study and provides recommendations for future studies.


2 Literature Review

The section 2.1 explains why this paper analyzes industrial submarkets instead of aggregate level or occupational level. Analyzing employment details with output data enables us to extract the technological job destruction from cyclical job destruction. The section 2.2 summaries competing hypotheses about what replaced workers. I add comments that why automation machines are more plausible reason for the technological job destruction in durable goods manufacturing, rather than overseas workers. The section 2.3 categorizes existing labor market theory, depending on their premise from vertical sorting to horizontal sorting. The section 2.4 summarizes other empirical papers that are potentially related with technological job destruction and its impact on labor allocation, including wage inequality, upskilling effect, ins and outs of unemployment, and Beveridge curve topics.

2.1 Jobless Recovery and Job Polarization

Macroeconomic papers pay attention to a recent atypical feature in the labor market called jobless recovery, weak recovery, or slow recovery (Groshen & Potter, 2003; Elsby, Hobijn & Şahin, 2010; Stock & Watson, 2012). Initial studies claimed that we now experience a jobless recovery that refers to unrestored employment, despite revived output production. It sounded plausible in the early period of the 21st-century recoveries, however, the drop in total employment did not last forever. For example, the United States aggregate employment achieved the pre-2008-recession level in May of 2014 and has since grown higher. After that, more researchers preferred to use a relaxed concept of jobless recovery called slow recovery or weak recovery. The modified argument is that employment increased at a slow rate during the recent expansionary periods by comparing output growth or old-days recoveries. Even though the wider concept is more consistent with the data, it is difficult to obtain objective criteria to determine how much slow growth in employment is noteworthy.

For these reasons, it is important to find a proper measuring scope to convey jobless recovery as a qualitatively different pattern, rather than a matter of degree. This paper finds a long-lasting decline in employment in the manufacturing, information, and construction industries, by observing disaggregated employment. The employment in the three industries is still far below the pre-recession values, even 10 years after the beginning of the Great Recession. The decline in employment in these industries is not short-term fluctuations; instead, it is a permanent change.

On the other hand, microeconomic studies on the labor market investigate a new phenomenon

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8 Besides jobless recovery, numerous papers also studied the decline in the labor share of income, persistent long-term unemployment rate, and outward shift in the Beveridge curve. Many researchers have a conjecture that some (or all) of these are connected, but the linkage is not yet well understood.

9 Groshen and Potter (2003), Bernanke (2003), Schreft and Singh (2003), and Jaimovich and Siu (2014) argue that the lagging start of recovery is a distinctive feature. They find that employment starts to recover within six months after the trough of output in typical business cycles, whereas it took two years to begin growth after the 2001 and 2008 recessions. Some scholars may refer to slow recovery as output growth itself, as compared to the old-days growth trend, but this topic will not be discussed in this paper in detail.
called job polarization (Acemoglu, 1999; Levy & Murnane, 2003; Autor, Katz, & Kearney, 2006; Goos & Manning, 2007; Acemoglu & Autor, 2011; Autor & Dorn, 2012). They argue that the proportion of routine-skill based and middle-wage occupations to total employment has declined since the 1980s. Many empirical studies investigated the occupation, wages, detailed demographics, and the cause of slowly growing middle-wage jobs from a typical microeconomic perspective. However, the canonical approach does not distinguish two qualitatively different patterns of declining jobs. One is a reduction in employment from a fading industry, which is a typical composition change. The other is a downsizing in employment from a growing industry regarding output, as human labor is replaced by non-labor inputs to produce even more.

In this paper, I add a macro flavor to job polarization to distinguish between declining jobs in a fading industry and replaced jobs due to a change in production technology. Among the sectors with permanently reduced employment, construction can be considered a fading industry. The real output for construction substantially decreased and has not fully revived for a decade. It is not surprising that construction did not recover the employment to the pre-recession level. However, the manufacturing and information are ones of the most growing industries in terms of real output. The drop in employment in these two industries should be considered as replaced jobs, rather than canonical declining jobs.

Naturally, this paper is located at the intersection of jobless recovery and job polarization. The technological job destruction in this paper is a narrower concept than jobless recovery or job polarization. The jobless recovery literature usually adopts a wider concept of disappearing jobs, by focusing on a permanent decline in the employment share to gross production (Aaronson, Rissman, & Sullivan, 2004; Bernanke, 2003; Groshen & Potter, 2003; Katz, 2010) or the labor income share to total income (Elsby, Hobijn & Şahin, 2013; Karabarbounis & Neiman, 2014; Rodriguez & Jayadev, 2010). Among others, Groshen and Potter (2003) particularly raised the possibility that structural changes in industrial composition caused the jobless recovery. This conjecture is harmonized with that industrial analysis is important, but I argue that the technological job destruction does not reflect a simple composition change. I say jobs disappeared if there is an actual decline in employment without a significant rebound afterward, rather than a slow growth rate or a drop in proportion.

In the same manner, there are subtle distinctions between job polarization and technological job destruction in this paper. First, the definition of job polarization, as known as disappearing middle-wage jobs, accurately refers to a decline in the employment share: employment in middle-wage occupations grows at a slow speed (or declines), as compared to low-wage or high-wage occupations. However, technological job destruction causes an explicit drop in a particular class of employment. Routine manual middle-wage occupations includes production and construction occupations, but construction is not related with technological job destruction. Second, most job polarization papers analyze long-term changes in employment over decades, whereas I focus on a sudden but long-lasting change in employment around the recessions. Autor (2010) mentioned that job polarization accelerated during a

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10A handbook chapter written by Acemoglu and Autor (2011) summarizes the literature and major findings in job polarization (first noted in Acemoglu, 1999) and the routinization hypothesis (first raised in Autor, Levy & Murnane, 2003).
recession. Moreover, Jaimovich and Siu (2014), Tüzeman and Willis (2014), and Foote and Ryan (2015) argue that job polarization and jobless recovery are actually the same phenomenon. I generally agree with this view, but the most accurate argument is that manufacturing industry is the common area between jobless recovery, job polarization, and technological job destruction. Jobless recovery includes wholesale trade and financial sectors, because of their slow growth in employment with fast growth in output. Job polarization is related with office occupation (routine cognitive) as well, and a decline in the highest wage occupation (chief executive) is also distinctive. The technological job destruction occurred in information industry too.

Because I use a narrow concept, the jobs that disappeared are not found to be related to every atypical phenomena in recent decades. The time framework is important to determine whether recent trends in the United States economy are caused by replaced manufacturing jobs. For example, office occupations and production occupations should be considered separate phenomena. The decline in production occupations was concentrated on just four years around the recessions, whereas the drop in office occupations was gradually made over decades. Even though both changes are permanent negative shocks in labor demand, the source and effect of the shock can be very different, depending on whether the change is suddenly made or gradually occurred. This paper claims that the production occupations that suddenly disappeared were replaced by machines. Also, the destruction of jobs put a large burden on the labor market to reallocate massive number of unemployed workers to scarce job positions during a short period of time. However, it does not eliminate the possibility, for instance, that office occupations gradually diminished because of international trade.

Besides, higher market power and an increase in markup are not particularly related to the jobs that disappeared in durable goods manufacturing industry. Barkai (2016), and De Loecker and Eeckhout (2017) document both the labor share and the capital share declined in the United States. They argue that a large increase in markups and market power within the industry explains the declining input shares. However, the change in markups gradually occurred over 30 years, and the markup even decreased (moved to the opposite direction) during the recessions. They focus on the long-run declining trend in the labor share, while this paper focuses on the sharp drops in the labor share right after the 2001 and 2008 recessions. One of the most important industry to understand a long-run decline in the labor share is the real estate, rental and leasing industry (subgroup in financial industry) that grows in a high speed with an extremely low labor share.

In addition, the declining labor participation rate is not directly caused by jobless workers from the manufacturing industry. The labor force participation rate was 67% before the 2001 recession; it is now 63%. The trend in the labor force participation rate was non-positive during the recent two decades. Also, most of the drop occurred right after the 2001 and 2008 recessions. However, the decreasing labor participation rate is not caused by discouraged or marginally attached workers. Discouraged and marginally attached workers who were not-in-the-labor-force co-moved with the regular unemployment rate. Thus, the rate of discouraged workers became close to the pre-recession level since 2014. On the contrary, the number of young people aged 16 to 24 sharply declined by 16.7% in the recent two
decades, which accounts for 2.8% of the total labor force participation rate.\textsuperscript{11} There is a possibility that a technological job destruction in the manufacturing industry still causes a lower youth participation rate. When a particular skill becomes obsolete, workers who have the skills now become unskilled workers, which leads to an abundant supply of unskilled labor. It alters the education choices for youth so that they choose even higher educations to acquire high-paid skill sets. The relationship between the youth labor market participation decisions and recessions will not be discussed in this paper.\textsuperscript{12}

2.2 Automatic Machines and Overseas Workers

What or who replaces domestic human jobs? Two popular conjectures that have emerged suggest that either overseas workers (international trade) or automation (technological progress) replaces existing workers. In this way, firms can produce more with fewer domestic employees. I explain three reasons why automation is more likely what replaced manufacturing jobs in the 2001 and 2008 recessions, rather than overseas workers.

First of all, jobless recovery is measured as a sharp decline in domestic employment in relation to domestic product. It means that the production from multinational corporations in foreign countries are not accounted, in principle. International workers who acquired visa and worked in the United States are accounted as domestic workers as long as they are enrolled in the payroll system. What we need to understand is that how domestic establishments can produce 5%-10% more with 20%-30% fewer domestic workers. Also, a tax evasion incentive predicts the opposite direction so that multinational companies under-report the United States production to avoid burden of tax.

Secondly, the jobless recovery is a global phenomenon. A Heckscher-Ohlin theory predicts that capital-abundant countries hire fewer workers due to comparative advantages, whereas labor-abundant countries hire more workers and produce more labor-intensive goods. Off-shoring hypothesis results a decline in the labor share for the capital-abundant countries. However, an increase in the labor share is expected for the labor-abundant countries. In data, unskilled-labor-abundant countries including Mexico, China, and India experienced jobless recovery and have a declining labor share (Karabarbounis & Neiman, 2014).

Lastly, cities on the Great Lakes adopted industrial robots (or automatic machines) and decreased employment the most intensively in the United States (Acemoglu & Restrepo, 2017). Acemoglu and Restrepo find that Detroit, the city the hardest hit by the 2008 Great Recession, extremely adopted machines and industrial robots.\textsuperscript{13} For instance, their findings show that the automotive vehicle industry became intensively exposed to robots. In the next chapter, I will show that the automotive industry is


\textsuperscript{12}See Kahn (2010), Bell and Blanchflower (2011), and Oreopoulous, Wachter, and Heisz (2012) for more detail about the youth labor market.

\textsuperscript{13}The city unemployment rate spiked to 28%, and it took six years to attain the pre-recession unemployment rate.
the minor industry that enhanced productivity the most distinctively right after reducing the numbers of workers. Four out of top five three-digit industries that adopted industrial robots are durable goods manufacturing, and the other one is non-durable goods manufacturing.

The speed and timing of a technological job destruction are important, when we analyze the impact and spillover effect of automation technology in the labor market. The manufacturing and information industries reduced 12%–18% of the employment within two years, but there were little rebounds in employment, new hiring, and job openings during subsequent recoveries over more than seven years. In the meanwhile, the most growing industries (health services and food services) increased employment by 2%–4% annually. Because the speed of disappearing jobs exceeds the growth in other job positions, aggregate employment deeply hollows out, the unemployment rate spikes, and the economy appears to slowly recover. When technological job destruction coincides cyclical job destruction, the labor market has an even larger burden of relocating massive numbers of unemployed workers, while dealing with a shortage of labor demand. The replaced jobs may unnecessarily aggravate the labor market, because it add a large negative shock at the worst time of economy. If the replacement is only possible during the recession, then policies would have limited roles. However, if firms replace workers with machines when it is the most cost-efficient time to do it, then policy may provide incentives for firms to reduce employee at the most desirable time.

2.3 Vertical and Horizontal Sorting

Answering the question of what happens in the labor market when technology reduces middle-wage jobs for good is not a trivial task. Suppose that a massive amount of discharges reduced the number of middle-wage employees, and the jobs were not expected to be recovered, even during an expansionary phase of the economy. The now unemployed and jobless workers should change their job market standard and try something new to quickly settle into other jobs. Which industries become their next jobs? Is there a directional labor turnover from a certain industry to another? Do new jobs pay them less, more, or the same wages as compared to jobs that disappeared? Are the people, who changed industries, less or more successful in finding jobs in a new sector, as compared to unemployed workers who originally had worked in the new sector? We can expect qualitatively different reallocation results to the joblessness in a certain wage class, depending on whether workers are allocated vertically or horizontally.

Numerous models generate equilibrium wage dispersion to explain why some workers are paid higher than others. Even if we assume that labor productivity is the sole determinant of wages for simplicity, we have four categories of theories, depending on their fundamental view of labor allocation. Horizontal sorting is based on a belief that workers and jobs are just different and have idiosyncrasies. The most polar case is that workers and jobs are homogeneous a priori. High wage workers are merely the lucky people who have a good idiosyncratic match quality, for now. Mortensen and Pissarides’ (1994) random search model is one of the examples that generates wage dispersion from idiosyncratic productivity shocks. Including Montgomery’s (1991) directed search model, a model with one-sided heterogeneity also results in a strictly horizontal sorting if the other party is identical or randomly matched. In the
polar horizontal sorting models, past wages (or productivity) provides no information about the worker’s future payroll (or performance) in the same or a different job.

A wider concept of horizontal sorting allows workers to be considered differently in terms of productivity and human capital, but the skill is firm–, career–, industry–, or occupation–specific. As long as an employee works in a similar position or does not experience unemployment, his/her wage increases as a specific tenure goes up. In either case of horizontal sorting, industry switchers due to technological job destruction in a particular submarket move to the tightest submarkets. Once they start to work in a new industry, they are more likely to be paid less than incumbent employees, because of a relatively worse fitness for the job or a lower tenure. Similarly, unemployed workers from the jobless sector are less (or at most equally) likely to win jobs in the new sector over unemployed workers who had worked in the sector.

In contrast, vertical sorting views some workers as more productive (or more able to learn) than others. Some jobs are also regarded more productive (or higher paying) than other positions. The extreme version of vertical sorting predicts that the worst worker in a high-paying submarket is more productive than the best worker in a low-paying submarket. Positive Assortative Matching (PAM) in Becker’s (1974) sorting model, with a (log-)supermodular production function, is one of the examples. More able workers take better but scarce jobs receiving high wages, whereas less able workers take the remaining low-wage jobs. A relaxed version regards the average worker in a high-paying occupation is better than the average worker in a low-paying occupation. Roy’s (1951) occupational choice model, given a positive correlation across skills, demonstrates a weak concept of vertical sorting. All workers
optimally choose their submarket, but high-wage workers are more productive than low-wage workers in any submarket on average. In either Becker model and Roy model with vertical sorting, career switchers due to a technological job destruction are moving downward on a submarket ladder. New comers from upper lung find a new job faster than unemployed who had experienced the submarket, and they receive higher wage than old-hands workers on average. Comparing to the wage in the previous jobs, industry switchers are expected to earn less in a new job.

This paper uses an extended Shimer and Smith’s (2000) matching and search model in section 5. It generates weakly vertical sorting, but expects different labor reallocation patterns when a particular class of employment declines. Ill-matched workers are laid off from the jobless sector, which includes over-qualified workers who produces more but have even higher outside option. Once over-qualified and under-qualified workers are separated, best (the other) workers find their next jobs in the upper (lower) submarket. Workers who climb up (down) the submarket ladder are more likely to earn less (more) than their previous jobs or incumbent workers in the new submarket.

For a general equilibrium analysis due to a technological job destruction, a careful design in technology or capital is the most important. The distinction between occupation choice model, matching model, and matching and search model is less fundamental. Stokey (2017) presents a general equilibrium occupational choice model to analyze when one of a particular class of jobs (or tasks) disappears. Her model is an extension of Roy’s (1951) model and it shows labor reallocation caused by a submarket specific negative shock, which is the closest alternative model to this paper. However, Stokey’s model simulates when labor productivity, output, and employment in a particular submarket moves to the same direction. The current version of her model analyzes submarket composition change, but cannot measure the general equilibrium effect of technological job destruction. The problem is that technological job destruction requires increasing productivity and output, but decreasing employment. Theory requires a specific technology or capital that substitutes labor, instead of total factor productivity or labor augmented productivity.

It is true that the Becker model, which is one of two origins of a matching and search model, generates extreme vertical sorting, whereas the Roy model generates weak vertical sorting. However, the fundamental difference between two models is not the sorting result. Depending on the specification, both matching and occupational choice models can generate strictly vertical, weakly vertical, or even horizontal sorting as the labor market allocation. More specifically, if the Roy model has a perfect correlation across skills, it results in strict vertical sorting. On the other hand, if the Becker model has positively correlated skills as a vector, instead of a scalar, it induces weak vertical sorting. Furthermore, both models generate horizontal sorting if the correlation between skills is close to zero, or the production function is modular. The crucial difference between the Becker’s matching model and the Roy’s occupational choice model is the role of wages in disequilibrium, which potentially affects dynamic adjustments in future research. Roy’s occupational choice model is based on the Walrasian equilibrium. Therefore, wage primarily guides the extensive margin of employment (allocation of workers to job positions). On the contrary, match surplus based on outside options determines the extensive margin of employment in the Becker’s marriage model. In this case, wages are set secondarily, through
bargaining or non-corporative alternating games, which does not alter the extensive margin.

2.4 Income Inequality and Persistent Unemployment

The trickle-down unemployment hypothesis fills the gap between middle-wage job disappearance and the decline in income for the low-wage unemployed workers. Various data sources consistently illustrated that the bottom unemployed workers have lost the largest percentage of income during the recent recessions in the United States. Guvenen, Ozkan, and Song (2014) found that the lowest percentile of income (in the 5 years before a recession) lost the largest proportion of income during the Great Recession by analyzing a confidential dataset from the U.S. Social Security Administration. Using data from the Current Population Survey (CPS), Bitler and Hoynes (2015) argue that the Great Recession significantly increased non-elderly poverty at the bottom (lowest income-to-poverty) level. The demographic groups were not very relevant. Pfeffer, Danziger, and Schoeni (2013) document that large percentage income losses are concentrated among low-income households by analyzing Panel Study of Income Dynamics (PSID) and the Survey of Consumer Finances (SCF). Gil (2015) finds that disproportional losses in annual earnings among unemployed workers during the 2001 and 2008 recessions by using data from PSID as well. The loss in income for the lowest quintile unemployed workers is more related to the losses in total working hours (mostly due to longer unemployment duration), than the wage rate difference between the past and current job position.

Another distinctive and unusual pattern of the Great Recession is that the long-term unemployment duration rose sharply. The share of 27 weeks or more in duration among the total unemployed persons spiked from 18% to 45% after the 2008 recession. There are two existing hypotheses that explain the persistent unemployment of which some scholars call a scarring effect. The statistical discrimination hypothesis (or stigma effect) explains that firms are reluctant to hire workers who experienced a long unemployment duration under imperfect information, as they believe that the long-term unemployed persons are generally inferior. Alternatively, the human capital deterioration hypothesis argues that a worker’s human capital becomes rusty the longer the unemployment lasts. However, neither alternative can explain the cyclical pattern of long-term unemployment—namely, how bottom unemployed workers start to exit the unemployment pool after experiencing an exceptionally long unemployment period. On contrary, the reallocation hypothesis in this paper predicts a cyclical pattern as a natural consequence. Bottom unemployment is stagnant until the unemployment congestion from the jobless sectors with higher wages is resolved. This trickle-down hypothesis is consistent with Hershbein and Kahn (2017). It analyzes skill requirements in job vacancy postings to conclude that upskilling effect reflects a restructuring of production toward labor-saving technologies during the Great Recession.

The technological job destruction and labor reallocation is consistently related to other aspects of labor market as well, namely, the ins and outs of unemployment, inefficiency in matching, and an outward shift in the Beveridge curve. Ahn and Hamilton (2014) suggest that compositional changes in the inflows of the newly unemployed, and increases in permanent job losses, have caused high and persistent unemployment in the recent recessions. Barnichon and Figura (2010) document that the
inefficiency in matching per vacancy became noticeably severe after the Great Recession, which means it takes longer time to hire given the unemployment and vacancy levels. Barnichon, Elsby, Hobijn, and Şahin (2012) argue that the construction, trade, and Food services industries are significant for the inefficient matching and outward shift in the Beveridge curve.

3 Technological Job Destruction

The technological job destruction or jobs that replaced, which we are going to see in this chapter, is distinguished from traditional senses of declining jobs or business-cycle fluctuations. Declining jobs in composition change mean jobs that both employment and output gradually decrease as the productivity declines from a long-term perspective. Cyclical employment refers that employment, output, and productivity move to the same direction in a short-run, but a drop or rise vanish away over time. Both typical changes in employment predict a positive correlation between output, employment and productivity. However, we currently observe a new pattern of employment that causes a decline in employment, but an increase in real output and real output per worker. Such employees are replaced due to progress in labor-saving technology so that firms can produce more with less labor input. In the United States, a technological job destruction has occurred since 2000 in durable/nondurable goods manufacturing and information industries. Among then, the durable goods manufacturing industry is the most influential, because its size is relatively big and the change coincides recessions episodically.

The main arguments in this chapter is that the jobs that disappeared were the result of progress in production technology. To distinguish the technological change from canonical business cycles or declining jobs in a fading industry, I adopt a mixture of macro– and micro–economic frameworks. Macro empirical papers have an advantage by analyzing employment under the context of a general equilibrium, but they commonly do not focus on the employment details. Microeconomic papers have a strength in scrutinizing the composition of jobs, however, their empirical boundary usually does not reach to the output market. Therefore, the traditional macro– or micro–economic framework have limitations to extract the technological job destruction in a specific class of employment from other cyclical job destruction. Only by overlapping two schemes, can a sudden disappearance of jobs be highlighted as a qualitatively different job destruction rather than a matter of degree. Therefore, this paper analyzes (un)employment and output together at an industry level, instead of an occupational or aggregate level.

3.1 Relationship between Industry and Occupation

Job hierarchy can be sorted by various standards depending on the purpose of a study. The most straightforward sorting criteria for workers and jobs is the hourly wage rate, weekly earnings, or annual earnings. Human capital literature sorts employment by workers’ characteristics, such as education,
Job polarization literature sorts employment by job characteristics such as occupation and skill requirements. Macro papers compare industries over the business cycles and heterogeneous fluctuations in the labor market by industries are usually observed. Among them, Groes, Kircher, and Manovskii (2014) document that a vertical sorting exists along an occupational hierarchy in Danish data.

Occupation captures labor supply side information successfully. It is also directly related to a specific skill that becomes obsolete after a labor-saving technological progress. However, occupation does not provide data such as output, job openings, and hiring, which is related with labor demand and output market. Because the smallest unit of measurement of output is establishment that has various type of occupations, decomposing the contribution to production by each occupation is not easily done. On the other hand, industry captures labor demand side, and aggregate market condition more effectively. This paper uses industrial hierarchy that is also vertically sorted. The downside of the industrial hierarchy is a larger within-group wage dispersion than occupation. However, industrial data include production, corporate profits, unemployment, job openings, quits, and layoffs, which are useful variables to analyze the disappearing job and subsequent worker reallocation. Also, the industrial data covers more than 95% of payroll employment in the United States, and monthly data is available in most cases whereas occupational data is annual.

<table>
<thead>
<tr>
<th>Industry &amp; Occupation</th>
<th>Share in industry</th>
<th>Share in occupation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Information Computer</td>
<td>18.5%</td>
<td>12.5%</td>
</tr>
<tr>
<td>Finance Office</td>
<td>38.8%</td>
<td>13.6%</td>
</tr>
<tr>
<td>Professionals Office</td>
<td>21.8%</td>
<td>27.0%</td>
</tr>
<tr>
<td>Health Healthcare</td>
<td>51.5%</td>
<td>78.7%</td>
</tr>
<tr>
<td>Construction Construction</td>
<td>62.4%</td>
<td>58.9%</td>
</tr>
<tr>
<td>Manufacturing Production</td>
<td>51.6%</td>
<td>68.2%</td>
</tr>
<tr>
<td>Trade Sales</td>
<td>47.4%</td>
<td>65.1%</td>
</tr>
<tr>
<td>Food Food serving</td>
<td>80.4%</td>
<td>81.3%</td>
</tr>
</tbody>
</table>

Conditional proportion of industry and occupation is provided. The first row means that the proportion of computer occupation in information employment is 18.5%, while the share of information industry to the total computer occupation is 12.5%. The computer occupation is not exclusively used in information industry, and vice versa. This table is a summary of national employment matrix form BLS in 2014, which based on OES and CPS.

As the Table 1 shows, the distinction between occupational and industrial analysis in recent recessions is mild. The jobs that disappeared in the United States are characterized as information and manufacturing industries, and office and production occupations. Admittedly, it is hard to map information industry (office occupation) to a single occupation (industry). Office occupation share in
each industry is usually higher than 10%. However, the job suddenly but permanently dropped during a recession—which this paper focuses on—is production occupation in manufacturing industry. The 51.6% of manufacturing employment is production occupation, and 68.2% of production occupation is in manufacturing sector. The industry with the second highest production occupation is the administrative sector (one of three-digit industry in professionals group), and the occupational share is 8.7%. Trade and Food industry have less than four percent of production occupation. Similarly, the most growing job is food preparation and serving occupations in food services industry, which has a roughly exclusive relationship between occupation and industry. Therefore, either industrial or occupational dimension captures disappearing jobs without losing much information.

The data sources for employment is Current Employment Statistics (CES) from the Bureau of Labor Statistics (BLS). The source of unemployment and industrial turnover is Current Population Survey (CPS) from BLS. The source of real GDP is National Income and Product Accounts (NIPA) from Bureau of Economic Analysis (BEA). Also, the source of quits, layoffs, hiring, and job openings by industry is Job Openings and Labor Turnover Survey (JOLTS) from BLS. Occupational employment and wages are from Occupational Employment Statistics (OES). I determine industrial job hierarchy by considering average wage, working hours, median weekly earnings, unemployment risk, health and pension benefits, and illness risk associated with jobs. For details of job quality beyond payroll, Injuries, Illnesses, and Fatalities (IIF), and Quarterly Census of Employment and Wages (QCEW) from BLS are also used.

3.2 Employment and Output Dynamics by Industries

In aggregate level, we trivially expect that both employment and output increases in a long-run (economic growth), and they fluctuate to the same direction around their long term trends (business cycles). Even after the 2008 great recession, the United States economy recovered the pre-recession levels of employment and output, and now achieves the highest levels in the history. However, not all of the major industries exhibit the same pattern that aggregate economy shows.\textsuperscript{14}

We observe five patterns of output and labor input dynamics in major (two-digit) industries level. First, employment oriented growing industry has faster growth rate in employment compared to output. Health, education, and food services are examples of growing industry in employment. They gradually increase the size of worker over a long run under a roughly constant output per worker. Second, output oriented growing industry includes the wholesales trade and real estate (in financial group) sectors. Output grows rapidly, but employment size is roughly constant. Third, a declining industry means a sector of which employment and output decreases in a long-term, which includes the construction industry. Fourth, the professionals industry shows both economic growth with downward fluctuations, and its dynamics is similar with aggregate economy. Lastly, technological job destruction or jobs that

\textsuperscript{14}In this paper, major industry means two-digit (in North American Industry Classification System (NAICS) or Standard Industrial Classification (SIC) code) industries, and minor industry refers three-digit industry. Group industry is supersets of two-digit industries, so it conceptually corresponds to one-digit industry.
Figure 2: Real GDP and Employment by 13 Group Industries (1997–2016)

* Light blue dot of each line represents 1997. The unit of horizontal axis guideline is 0.5 trillion real dollars, and one of the vertical axis is 5 million employees. The aggregate pattern is at the bottom right in a smaller scale. Data source of Employment is the number of employees in payroll system in Current Employment Statistics (CES) survey from Bureau of Labor Statistics (BLS). Employment at May for each year is used to match monthly data to yearly GDP data. Data source of Real GDP is Real Value Added by Industry in National Economic Accounts from Bureau of Economic Analysis (BEA).
Figure 4: Real GDP per Worker and Employment by 13 Group Industries (1997–2016)

Figure 5: Employment and Real GDP per Worker in Manufacturing and Information Sectors
replaced means an increasing output despite a decreasing employment. The nondurable manufacturing and information industries shows the negative correlation between output and employment over two recent decades, and the changes has been gradually made. The durable goods manufacturing industry exhibits an episodic job destruction, that coincides aggregate cyclical downturns.

I combined adjacent major industries that show the same output-input dynamics as a single group. Figure 2 shows a trajectory by 13 group industry from 1997 to 2016 in Real GDP (x axis) and employment (y axis) space. Professional and business services sector (yellow line) shows both economic growth and business cycle in a conventional sense with procyclical employment. Education and health care service industry (skyblue line) keep grows in both employment and output without a particular declines even during a recession. Construction sector (dark blue line) is the sector moved toward origin the most intensively, as it decreased (and then increase) both employment and output. Real estate industry (grey line) grows in output without hiring substantially more workers. In summary, education and health services is a typical growing industry, real estate is a growing industry with roughly constant employment, and construction is a conventional declining industry.

Meanwhile, manufacturing and information industries show unique trajectories that employment declines while production increases. Information (dark yellow line) grows in output by 93% while it decreased employment by 25% from 2001 to 2016. Durable goods manufacturing (dark orange line) cut employment size by 26%, even though its production increased by 47%. Nondurable goods manufacturing (dark grey line) reduced employment by 25% where the real output is almost the same. To highlight the improvement of productivity, figure 4 shows the same information of previous figure but having x-axis as real output per worker instead of aggregate real output. Information industry doubled real output per worker in last 16 years. Durable and nondurable goods manufacturing increased output per employee by 58% and 19%, respectively. We cannot easily characterize these jobless growing sectors as business cycle or economic growth effect, as labor input and output move to the opposite directions.

Only manufacturing and information industries reduced employees and also enhanced real output per worker. Except housing finance industry, the other industries have relatively constant real output per worker: see appendix A for the other graphs. As figure 5 shows, drops in employment is occurred during a recession despite a growing output per employee. Jobs in durable goods manufacturing and information industries disappeared, leading a higher real output per worker.

I analyze details of industry and occupational compositions for a robustness, see Appendix A for details. In summary, among 22 major (two-digits) occupations, production occupation permanently decreased during recent two recessions, which is heavily used in manufacturing industry. Among over 700 detailed (four-digits) occupations, the most 13 growing jobs are mostly food services, health services, retail salespersons, and customer service representatives. The most 12 declining jobs includes executives, typists, sewing machine operators, packers, delivery services, and order clerks. The 85% of detailed production occupations decreased, and most of them shows a waning w pattern: the number of employees heavily dropped during recessions with little declines during expansionary periods. W pattern dynamics is appeared in team assemblers, first-line supervisors of production, and machinists.
3.3 A New Phenomenon

A sharp decline in employment despite a higher output per worker is a new trend rather than ordinary industrial idiosyncrasy. To show the replaced jobs had never observed in the past, I analyze a longer time period for the jobless sectors. Figure 6 shows employment and output per employee from 1947 to 2016 in the durable goods, nondurable goods manufacturing and information industries. In early 50 years (1947–1996), all of the industries moved to north-east (or east). It means that they hired more workers (or maintained the same level of employment), while real output per worker increased in a long-run. Since 2000, all of three industries have moved south-east, in other words, they reduce employment even though the real output per worker is keep increasing. Especially the durable goods manufacturing reduced 3 million of workers and average real output per worker increased by $33,000 in just four years of recessions: from 2001 to 2003 and from 2008 to 2010. For reference, employment size in transportation and warehousing is about 5 million, and real output per employee in food industry is about $40,000 in 2017. The changes in the durable goods industry from 2001 to 2010 is quantitatively the same with that a small industry is added in productivity but another small industry is eliminated in employment.

Figure 6: A New Trend of Replaced Jobs (1947–2016)
Given the same amount of job destruction, the timing, speed, and way of job destruction matters when we analyze unemployment dynamics. First, technological job destruction results in a permanent decline in employment, unlike to the cyclical job destruction. The job openings and net hiring during expansionary periods were low in the durable/nondurable goods manufacturing and information industries, while employment in professionals and trade sectors revived and then grow higher. Second, the job destruction in the durable goods sector was episodic contrast to the gradual declines in the nondurable or information sector. Unemployment spikes if there is an influx of labor supply as one time shock, compared to a mildly higher inflows over a long-period. Third, durable goods firms reduced employment by massive layoffs during the 2008 recession, whereas they hired less in net during the 2001 recession. Less net hiring is a passive and soft way of downsizing employment, because it causes slow outs from unemployment without high ins to unemployment. On the other hand, massive layoffs is an active and direct way of downsizing, because we have both high ins to and outs from unemployment. Therefore, the technological job destruction in the durable goods sector during the 2008 recession was the most influential to unemployment rate, \textit{ceteris paribus}.

Business cycles are generally designed as a aggregate shock in total factor productivity. When an aggregate labor market consist with several submarkets (like industry, occupation, or education attainment), a recession generates cyclical job destruction for every submarkets. If submarket is optimally chosen, cyclically unemployed workers have little incentive to change their submarkets, because all of the submarkets become tight and loose simultaneously. However, technological job destruction occurred in a particular submarket. Workers now have incentive to alter their optimal submarket choice to avoid the industry-specific negative shock. In the next chapter, we observe industrial transitions initiated by the technological job destruction from the durable goods manufacturing industry.

4 Labor Reallocation

This chapter analyzes the empirical patterns of labor reallocation triggered by a sectional technological job destruction. A labor-saving technology replaced workers in a middle-wage industry, and thus, the particular labor demand (or job positions) disappeared permanently. It is evident that the unemployed workers from the jobless industry are directly suffering for the technological job destruction. However, once jobless workers start to move to other submarkets, it is not a simple question how other unemployed workers are affected by the joblessness in the middle.

Suppose that there is no spill-over effect to other submarkets, then we can expect following three patterns as a consequence of technological job destruction in a particular submarket. First, the technologically unemployed workers should wait longer than the cyclically unemployed workers until finding new jobs on average. For example, a middle-wage employment (the durable goods manufacturing industry) declined, whereas the lowest-wage employment (the food services industry) expands after the
recession. If unemployed workers stick to their original submarkets, we unambiguously predict that the
unemployment rate from the middle industry have both higher ins (to unemployment) and lower outs
(from unemployment). Second, the middle unemployed workers must be losing a substantial amount of
long-term labor income than unemployed workers from other industries. We expect a hollowing-out in
the middle of the annual earnings distribution, which is exactly the same pattern of initial shock in the
distribution of labor demand. Third, recruiting firms from the jobless industry would be pickier, but
not the firms in other industries.

On the contrary, the empirical patterns are quite different with the no-spill-over predictions above.
First, unemployment from the lowest-wage industry was more persistent and lagged, compared to the
unemployment from the jobless industry. The increase in unemployment of the bottom industry caused
by the slow outs in spite of no ins. The increase in unemployment from the jobless industry was
fast due to high ins, but its decline was also faster due to high outs. Second, existing studies based
on various data sources consistently show that the lower a worker earned before the recession, the
larger percentage losses the worker get after the Great recession: see section 2.4 for the summary of
literature. The change in earnings distribution is a severe negative skewness, rather than hollowing out
in the middle of distribution. Third, existing literature about upskilling effect an outward shift in the
Beveridge curve point out lower-wage industries, not the jobless industry.\(^\text{15}\)

In this chapter, I focus on the Great Recession and show the unemployment recovery that is mostly
determined by the speed of outs from unemployment. A rapid and preceding increase in unemployment
is mostly due to high ins to unemployment, however, other industries also followed by an increasing
unemployment rate despite no ins. A recovery speed is contradictory with the net employment, but it
is consistently related with the wage hierarchy. For a direct evidence of trickle-down unemployment, I
analyze industries and earnings of a lost job in last three years to their current industries and earnings in
the CPS. I find a domino chain of industrial transitions: the durable goods workers move to construction,
construction workers move to retail trade, and retail trade workers move to the food services. Even
though the construction and retail trade industries largely reduced their employment size, but upper
class unemployed workers successfully settle down in the one-step-lower-paying industry. I emphasize
that the direct transition from jobless sector to actively hiring sector is lower than other transitions or
the same transitions in non-recession periods.

4.1 Trickle-Down Unemployment

\(^{15}\)See section 2.4 for a summary of literature.
## Table 2: Change in Employment and Unemployment during the Great Recession

<table>
<thead>
<tr>
<th>Industry</th>
<th>Average Wage $/hour</th>
<th>Change in Employment thousands (percentage)</th>
<th>Range of Unemployment thousands (percentage)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Information</td>
<td>$28.12</td>
<td>-349 (−11%)</td>
<td>+296 (2% → 12%)</td>
</tr>
<tr>
<td>Finance</td>
<td>$25.54</td>
<td>-706 (−8%)</td>
<td>+486 (2% → 8%)</td>
</tr>
<tr>
<td>Professionals</td>
<td>$24.61</td>
<td>-316 (−2%)</td>
<td>+1,130 (5% → 12%)</td>
</tr>
<tr>
<td>Health (and Education)</td>
<td>$20.67</td>
<td>+1,719 (+9%)</td>
<td>+941 (3% → 7%)</td>
</tr>
<tr>
<td>Construction</td>
<td>$22.98</td>
<td>-1,926 (−26%)</td>
<td>+1,882 (5% → 27%)</td>
</tr>
<tr>
<td>Durable Manufacturing</td>
<td>$22.43</td>
<td>-1,694 (−19%)</td>
<td>+1,038 (3% → 14%)</td>
</tr>
<tr>
<td>Nondurable Manufacturing</td>
<td>$19.64</td>
<td>-600 (−12%)</td>
<td>+482 (3% → 12%)</td>
</tr>
<tr>
<td>Trade (and Transportation)</td>
<td>$18.50</td>
<td>-903 (−3%)</td>
<td>+1,800 (4% → 11%)</td>
</tr>
<tr>
<td>Food (and Leisure)</td>
<td>$12.34</td>
<td>-181 (−1%)</td>
<td>+982 (7% → 14%)</td>
</tr>
</tbody>
</table>

The industry for unemployment refers the industry of previous job in which an unemployed worker had worked. The change in employment is the difference between employment level in 2007 and 2010 \((E_{10} - E_{07})\). The range of unemployment is the maximum unemployment level minus the minimum unemployment level in 2007 to 2010. The average earnings rate represents the nominal value of May 2007, and all the wages have increased holding the same order in recent two decades.

Auto correlation of \(u\) (total, 2008–2010, 2010–2016): persistence of unemployment is high in increasing phase and decreasing phase. When more workers are laid off so that inflow to unemployment is high, persistency in unemployment is low. Also, if more workers find their next jobs quickly, then outflow from unemployment is high. Again, persistency in unemployment is low.

High R square. Ergodic and unit root. Prediction is not interesting. Nonstationary is bad for robustness in simulation. Add ladded unemployment in other industries. Stationary

Regression

\[
U_{k,t} = \beta_{k,0} + \beta_{k,1}E_t + \beta_{k,2}V_{k,t} + \beta_{k,3}L_{k,t} + \beta_{k,4}Q_{k,t} + \sum_{i=1}^{K} \beta_{k,i+4}U_{i,t-1} + \epsilon_{k,t}
\]
Figure 7: High Unemployment from Industries with Employment Growth: Health Services and Food Services

Unemployment level from the Financial and the Health Services

Unemployment level from the Durable Goods and the Food Services
Figure 8: Trickle-Down Unemployment: Reversed Recovery in Unemployment by Industry
Table 3: Regression of Unemployment to Other Industrial Unemployment (1/2)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Dependent</th>
<th>Information</th>
<th>Professional</th>
<th>Finance</th>
<th>Construction</th>
<th>Manufacturing</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$E_t$</td>
<td>$-0.0030$</td>
<td>$-0.0014$</td>
<td>$-0.0009$</td>
<td>$-0.0002$</td>
<td>$-0.0040$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(.0008)</td>
<td>(.0027)</td>
<td>(.0012)</td>
<td>(.0032)</td>
<td>(.0023)</td>
</tr>
<tr>
<td>Job Openings</td>
<td>$V_{k,t}$</td>
<td>$-2.405$</td>
<td>$-0.0232$</td>
<td>$-0.0867$</td>
<td>$0.0749$</td>
<td>$-2.403$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(.0677)</td>
<td>(.0563)</td>
<td>(.0608)</td>
<td>(.2438)</td>
<td>(.1419)</td>
</tr>
<tr>
<td>Layoffs</td>
<td>$L_{k,t}$</td>
<td>$0.4030$</td>
<td>$0.2227$</td>
<td>$0.3243$</td>
<td>$1.3448$</td>
<td>$0.9798$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(.1857)</td>
<td>(.0846)</td>
<td>(.1232)</td>
<td>(.1535)</td>
<td>(.1297)</td>
</tr>
<tr>
<td>Quits</td>
<td>$Q_{k,t}$</td>
<td>$0.0881$</td>
<td>$0.0617$</td>
<td>$0.0266$</td>
<td>$-0.4127$</td>
<td>$-0.2155$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(.1540)</td>
<td>(.0766)</td>
<td>(.1020)</td>
<td>(.2411)</td>
<td>(.1628)</td>
</tr>
<tr>
<td>Information</td>
<td>$U_{1,t-1}$</td>
<td>$0.4343$</td>
<td>$0.4728$</td>
<td>$0.0166$</td>
<td>$0.0203$</td>
<td>$0.2620$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(.0668)</td>
<td>(.2179)</td>
<td>(.1014)</td>
<td>(.2679)</td>
<td>(.1792)</td>
</tr>
<tr>
<td>Professional</td>
<td>$U_{2,t-1}$</td>
<td>$0.0150$</td>
<td>$0.4733$</td>
<td>$-0.0122$</td>
<td>$-1.069$</td>
<td>$-0.565$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(.0236)</td>
<td>(.0769)</td>
<td>(.0360)</td>
<td>(.0979)</td>
<td>(.0641)</td>
</tr>
<tr>
<td>Finance</td>
<td>$U_{3,t-1}$</td>
<td>$0.0051$</td>
<td>$0.0528$</td>
<td>$0.5728$</td>
<td>$-1.404$</td>
<td>$0.2023$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(.0385)</td>
<td>(.1373)</td>
<td>(.0607)</td>
<td>(.1607)</td>
<td>(.1068)</td>
</tr>
<tr>
<td>Construction</td>
<td>$U_{4,t-1}$</td>
<td>$0.0088$</td>
<td>$0.0565$</td>
<td>$0.0253$</td>
<td>$0.8462$</td>
<td>$0.0814$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(.0121)</td>
<td>(.0390)</td>
<td>(.0178)</td>
<td>(.0474)</td>
<td>(.0327)</td>
</tr>
<tr>
<td>Manufacturing</td>
<td>$U_{5,t-1}$</td>
<td>$0.0564$</td>
<td>$0.0199$</td>
<td>$-0.0026$</td>
<td>$-0.0596$</td>
<td>$0.6470$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(.0177)</td>
<td>(.0567)</td>
<td>(.0270)</td>
<td>(.0699)</td>
<td>(.0525)</td>
</tr>
<tr>
<td>Edu &amp; Health</td>
<td>$U_{6,t-1}$</td>
<td>$0.0493$</td>
<td>$0.0766$</td>
<td>$0.0013$</td>
<td>$-0.0803$</td>
<td>$0.0809$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(.0203)</td>
<td>(.0650)</td>
<td>(.0308)</td>
<td>(.0802)</td>
<td>(.0327)</td>
</tr>
<tr>
<td>Transport</td>
<td>$U_{7,t-1}$</td>
<td>$0.0187$</td>
<td>$0.2746$</td>
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<tr>
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<td>$.9480$</td>
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$N = 198$. Parenthesis reports the standard deviation of each coefficient. Data source is JOLTS and CES from BLS from Dec 2000 to Jun 2017.
<table>
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<th>Transport</th>
<th>Other</th>
<th>Trade</th>
<th>Leis &amp; Hospit</th>
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<td>.9415</td>
<td>.8966</td>
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$N = 198$. Parenthesis reports the standard deviation of each coefficient. Data source is JOLTS and CES from BLS from Dec 2000 to Jun 2017.
### 4.2 Industrial Transitions

Table 5: Weakly Earnings at the Lost Job and the Current Job

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<td>Previous</td>
<td>Current</td>
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<tr>
<td>Professional →</td>
<td>Retail</td>
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<td>$987</td>
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<tr>
<td>Durable →</td>
<td>Professional</td>
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<td>Administrative</td>
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<tr>
<td></td>
<td>Retail</td>
<td>44</td>
<td>$700</td>
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<tr>
<td></td>
<td>Food</td>
<td>28</td>
<td>$596</td>
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<td>Administrative</td>
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<td>$723</td>
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<td>Food</td>
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<td>Administrative →</td>
<td>Retail</td>
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<td>$520</td>
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<tr>
<td>Retail →</td>
<td>Food</td>
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<td>$429</td>
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<tr>
<td></td>
<td>Total</td>
<td>2595</td>
<td>1491</td>
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</table>

The industry for unemployment refers the industry of previous job in which an unemployed worker had worked. The change in employment is the difference between employment level in 2007 and 2010 ($E_{10} - E_{07}$). The range of unemployment is the maximum unemployment level minus the minimum unemployment level in 2007 to 2010. The average earnings rate represents the nominal value of May 2007, and all the wages have increased holding the same order in recent two decades.
Figure 9: Worker Transitions after Job Loss: The 2001 Recession and Recovery

Transitions between 2001 and 2004

Transitions between 2005-2008

Average Hourly Wage

Employment Growth
Figure 10: Worker Transitions after Job Loss: The 2008 Recession and Recovery

Transitions between 2007-2010

Transitions between 2011 to 2014

- Employment Growth +
5 A Matching and Search Model

In this section, I use a matching and search model to analyze labor reallocation initiated by technological job destruction. This paper uses an extension of Shimer and Smith (2000) model with automation technology and time cost for capital adjustment. Firstly, the model gives a rationale why middle-wage jobs are more likely to adopt automation even if all tasks are feasible to be done by machines. Industrial robots are good enough and cheap enough to replace the middle-wage workers. High wage workers are better than the machines, whereas low wage workers are less costly than the machines. Secondly, this model provides a hypothesis why a recession accelerates the substitution of machines for existing employees. When there is time cost for capital adjustment, firms cannot produce in old way while substituting machines for workers. Because the recession is the time the shadow cost of retooling is low, more existing employee-employer matches are destructed. Thirdly, the model explains why over-qualified workers are also laid off despite a high production. The higher wage of over-qualified workers is not worth for the job position, and the lower productivity of under-qualified workers is not attractive for the firm. The worst-matched workers are laid off and replaced by machines. Lastly, the model demonstrates the trickle down of unemployed workers and the pickier reservation level for low-type firms.

I show that disappearing middle jobs causes trickle-down unemployment, which is a bumping chain in allocation of workers to jobs by stepping down a vertical occupation ladder. When middle jobs disappear abruptly but permanently, middle unemployed workers find their next jobs in the one-step lower paying occupation. They crowd out worst workers in the one-step lower lung so that bumped workers move to two-step lower paying occupation. The bumping chain is repeated from the jobless class to the bottom class. Even though middle jobs are disappearing, it is the bottom workers who lose their jobs and labor income. The wage distribution become more skewed negatively rather than hollowing out the middle.

I need to mention that the quality of labor demand side is ranked by the labor productivity of a job position rather than a firm’s productivity or profitability itself. In real world, not every industry has the same labor share, therefore, the rank of productivity is not monotone to one of the labor productivity. For example, real estate and leasing industry has particularly low employment level comparing to the output production, and the rank of wages are middle despite the highest rank of production per worker.

For simplicity, the contribution of labor to production is assumed to be identical across industry, but the result is identical with a particular order of jobs. In this model, labor productivity of a firm’s job opening is positively monotone to the firm’s productivity. However, what fundamentally determines the quality of job is its labor productivity. If learning process or on-the-job search is added, then the wage is not solely determined by labor productivity. However, the efficient wage to prevent worker’s quitting does not alter the extensive margin—job creation or destruction. The current version of model results the polar case of vertical sorting. If we allow worker’s skill set is a vector instead of a scalar, then even weak vertical sorting can be generated. In such extension, Becker’s sorting model and Roy’s occupation choice model will share a larger intersection.
The theory part of this paper claims that a sudden and enduring decline in a particular class of employment causes a chain of reallocation in the labor market that induces unemployed workers in the jobless class or below to step down a job hierarchy, which I refer to as *trickle-down unemployment*. I use Pissarides’ (1985) search model by adding two-sided heterogeneity to analyze acceptance sets in the search equilibrium addressed by Shimer and Smith (2000). This approach enables me to analyze how disappearing jobs in a certain class relocate unemployed workers over time. Mortensen and Pissarides’ (1994) model has an idiosyncratic shock with identical productivity for new job openings. Productivity shock makes bottom matches dissolve rather than middle matches in a recession, and only the quantity of vacancy matters instead of the quality of vacancy in the subsequent recovery. Lise and Robin’s (2017) model is the closest to the current model as it has two-sided heterogeneity for workers and firms; it also has on-the-job search and a free entry condition. If there is an influx of middle workers in the job market in their model, the free entry condition makes firms open bottom vacancies as a jump variable. What we see in data is that the number of bottom vacancies does not jump upward, but the bottom vacancies become pickier so that it causes an outward shift in the Beveridge curve. Shimer and Smith (2000) focus on the core sorting allocation in a search equilibrium with the constant job finding rate. This model has an endogenous job finding rate, and the purpose of this study is to analyze reallocation patterns to disappearing jobs over time. Comparative statics can be done using Shimer and Smith’s algorithm, but dynamic adjustments may occur some new issues, such as algorithm path dependence (non-uniqueness) and irrational beliefs of agents.

I add two-sided heterogeneity to Pissarides’ (1985) indirect search model to show why firms adopt automation to replace *middle*-wage workers during a *recession*. Two assumptions are the most essential. Firstly, an exogenous technology growth and price processes make automatic machines get better—regarding a quality of task that it can replace the human labor—and cheaper. Secondly, firms need to spend a time to adjust capital (or production technology) instead of paying monetary costs. To replace some workers with machines, a firm needs to stop current production line, install new machines, do test runs, and educate workers who will operate the new machines. While retooling production facilities and retraining workers, the firm should give up producing goods in an original way for a certain time. The cost of adapting automation includes not only the cost of purchasing it but also a shadow cost that fluctuates over business cycles.

Under the two assumptions I made above, firms have a bang-bang equilibrium. The best time of adapting automation during an expansionary period is the farthest point of time due to the continuous advent of better and cheaper machines. Whereas, the best time of retooling facilities during a recession is the closest point of time because the opportunity cost of capital adjustment is low enough. This is the reason why jobs replaced during a recession rather than other time.

Employees will be laid off if and only if a machine is good enough and cheap enough to replace them.

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16Log supermodularity is the necessary condition for positive assortative matching, which is perfect one-to-one matching with the same percentile of the counter-party without a single exception. However, this model does not strictly require a positive assortative matching as the core, so the log supermodularity assumption can be relaxed to supurmmodularity.
Replaced worker’s ability (or skills) should be lower than the productivity of machine, and the worker’s reservation wage must be higher than the cost of automation. Even though all tasks can be programmed ex-ante, it is natural that ex-post replaced workers are mostly middle-wage workers. High-wage workers are not replaced by machine, because the technology is not good enough to substitute them. On the other hand, low-wage workers have no incentive to be substituted by advanced technology, as hiring human labor is cheaper than using machines.

5.1 Setup

Time is continuous with discount rate \( \rho \) and agents live forever. Workers are heterogeneous in general ability of \( x \) with density \( H(x) \). Job positions (or tasks) are also heterogeneous in general productivity of \( y \) with density \( I(y) \). Productivity is not an optimal choice. Once a firm creates a job position, the labor augmented productivity is drawn randomly from distribution \( I_0(y) \). Firms pay fixed costs \( B \) to create a job position, otherwise firms repeatedly draw and discard the productivity until they get the maximum realization. The number of workers \( n_w \) is exogenous, whereas the number of job positions \( n_j \) is endogenously determined by a free entry condition. Matched jobs are separated by Poisson rate of \( \delta \). A worker’s non-working benefit is \( b(x) \). A flow cost for a vacant job position is \( c \).

The total factor productivity process \( z \) is ergodic, thus, agents cannot predict business cycles. The recession is the time when total factor productivity is lower than one. Production flow is denoted as \( zp(x,y) \) for a match with a worker of type \( x \) and a job position of type \( y \) in current state of \( z \). Unemployment level is \( n_u \) with distribution of unemployed workers \( F_u \). In the same manner, vacancy level is \( n_v \) with density of vacant job positions \( F_v \). Acceptance sets are denoted as \( A(x,y) \) that indicate if searching agents are willing to form a match bilaterally when a worker \( x \) meets a firm with job position \( y \).

Only can unmatched agents search and successfully locate a random counter party with a matching function of \( M(n_v,n_u) \). A feasibility condition for matching function is \( M(n_u,n_v) \leq \min\{n_u,n_v\} \). From a vacant firm’s perspective, the worker arrival rate is \( \lambda^F(n_u,n_v) = M(n_u,n_v)/n_v \). From an unemployed worker’s perspective, the job arrival rate is \( \lambda^W(n_u,n_v) = M(n_u,n_v)/n_u \).

5.2 Values and Surplus

The values of a matched job position, a vacant job position, an employed worker, and an unemployed worker are \( J(x,y), V(y), W(x,y) \) and \( U(x) \), respectively.

\[
\begin{align*}
\rho J(x,y) &= zp(x,y) - w(x,y) + \delta (V(y) - J(x,y)) \\
\rho V(y) &= -c + \lambda^F (E_{x|y}[J(x,y)] - V(y)) \\
\rho W(x,y) &= w(x,y) + \delta (U(y) - W(x,y)) \\
\rho U(x) &= b(x) + \lambda^W (E_{y|x}[W(x,y)] - U(x))
\end{align*}
\]
\( J(x, y) \) is the value of a job with productivity \( y \) that matched with worker whose ability is \( x \). \( V(y) \) is the value of an unmatched job of type \( y \). \( W(x, y) \) is the value of an employee whose type is \( x \) working at a firm with productivity \( y \). \( U(x) \) is the value of an unemployed worker of type \( x \). Only unemployed workers and firms with vacant job positions search in the job market. The flow cost of maintaining vacancy is constant for any job positions, which implies that the value of vacant job is increasing in productivity \( V'(y) > 0 \).

The total surplus of a match between worker of type \( x \) and firm of type \( y \) is defined as following.

\[
S(x, y) = J(x, y) - V(y) + W(x, y) - U(y)
\]  

(2)

Because this paper analyzes comparative statics, the generalized Nash bargaining wage is the most simple without loss of generality when we only consider equilibrium wages.\(^{17}\)

\[
w^N(x, y) = \arg \max_w [W(x, y) - U(x)]^\beta [J(x, y) - V(y)]^{1-\beta}
\]  

(3)

The generalized Nash bargaining satisfies two conditions.\(^{18}\)

\[
W(x, y) - U(x) = \beta S(x, y)
\]

\[
J(x, y) - V(x) = (1 - \beta) S(x, y)
\]

After some algebra, the convenient expression for the generalized Nash bargaining wage is derived as following.\(^{19}\)

\[
w^N(x, y) = \beta ( z p(x, y) - \rho V(y) ) + (1 - \beta) \rho U(x)
\]  

(4)

\(^{17}\)Hall’s (2005) acyclical equilibrium wage is an alternative wage, but it gives the same results unless we analyze dynamics. A rigid equilibrium wage is denoted as \( w^R \), which stays constant unless Pareto improvement by wage renegotiation is possible. Whenever employer-employee match negotiate the wage including the first wage, the wage is determined by generalized Nash Bargaining.

\[
\dot{w}^R_t(x, y) = \mathbb{I}\{[J_t(x, y) - V_t(y)][W_t(x, y) - U_t(x)] \leq 0\} \left( w^N_t(x, y) - w^R_t(x, y) \right)
\]  

\[
\dot{w}^M_t(x, y) = \mathbb{I}\{J_t(x, y) \leq V_t(y)\} \left( z p(x, y) - \rho V_t(y) - w^M_t(x, y) \right) + \mathbb{I}\{W_t(x, y) \leq U_t(x)\} \left( \rho U_t(x) - w^M_t(x, y) \right)
\]  

\[
(3.a)
\]

\[
(3.b)
\]

\(^{18}\)Plug in the generalized Nash bargaining wage into the equations (1). Multiply time discount rate \( \rho \) to the equation (2) and substitutes four values.

\[
pS(x, y) = z p(x, y) + c - b(x) - \lambda^F (1 - \beta) E_{x|y} [S(x, y)] - \lambda^W \beta E_{y|x} [S(x, y)]
\]

The surplus is a function of parameters and matching rate and expected gains when agents find an alternative counterparty after separation. A stationary acceptance set is used to calculate the conditional expectation terms.

\(^{19}\)To derive a wage as a function of outside options, we need two expression for a fraction of surplus. Firstly,
The formula for value of an unfilled vacancy, and an unemployed worker are derived as following.

\[(\rho + \delta) J(x, y) = (1 - \beta) (zp(x, y) - \rho U(x)) + (\beta \rho + \delta)V(y)\]

\[(\rho + \lambda^F) V(y) = -c + \lambda^F E_{x|y}[J(x, y)]\]

\[(\rho + \delta) W(x, y) = \beta (zp(x, y) - \rho V(y)) + ((1 - \beta) \rho + \delta)U(x)\]

\[(\rho + \lambda^W) U(x) = b(x) + \lambda^W E_{y|x}[W(x, y)]\]

The value of a filled job, and an employed worker are easily calculated as we know the outside values. The formula for value of an unfilled vacancy, and an unemployed worker are derived as following.

\[\rho V(y) = \frac{(\rho + \delta) (-c) + \lambda^F (1 - \beta) E_{x|y}[zp(x, y) - \rho U(x)]}{\rho + \delta + \lambda^F (1 - \beta)}\]

\[\rho U(x) = \frac{(\rho + \delta) b(x) + \lambda^W \beta E_{y|x}[zp(x, y) - \rho V(y)]}{\rho + \delta + \lambda^W \beta}\]

The value of a searching agent is the weighted average between net benefit when they do not form a match and expected net production when they form a match given the counter party’s outside option.

5.3 Stationary Equilibrium

I use Shimer and Smith’s (2000) definition of steady-state search equilibrium with two-sided heterogeneity. As the algorithm for finding the equilibrium is the same, I simply explain the notations in this paper. \(V(y)\) and \(U(x)\) are the unmatched values, \(F_u(x)\) and \(F_v(y)\) are the density for searching agents, and \(A(x, y)\) is a match indicator function that represents acceptance sets that is binary decision who is willing to be matched with whom bilaterally.

Firstly, unmatched values solve the following equations given acceptance sets and distribution of vacancies and unemployed workers.

\[V(y) = \frac{-(\rho + \delta) c + (1 - \beta) \lambda^F \int A(x, y) [zp(x, y) - \rho U(x)] dF_u(x)}{\rho (\rho + \delta + (1 - \beta) \lambda^F)}\]

\[U(x) = \frac{(\rho + \delta) b(x) + \beta \lambda^W \int A(x, y) [zp(x, y) - \rho V(y)] dF_v(y)}{\rho (\rho + \delta + \beta \lambda^W)}\]

we subtract \(\rho V\) from the first line in equations (1) and replace \(J - V\) as a bargaining share of surplus.

\[\rho (1 - \beta) S(x, y) = p(x, y, z) - c^f(x, y) - w^N(x, y) - \delta (1 - \beta) S(x, y) - \rho V(y)\]

(5.a)

Secondly, we plug two values of matched agents \(J\) and \(W\) from equations (1) into the surplus equation (2), then multiply \(\rho (1 - \beta)\) for both hand sides.

\[\rho (1 - \beta) S(x, y) = (1 - \beta) \left(p(x, y, z) - c^f(x, y) - \delta S(x, y) - \rho V(y) - \rho U(x)\right)\]

(5.b)

Equating the right hand sides of (5.a) and (5.b), the generalized Nash bargaining wage is solved as equation (4).
Secondly, the acceptance set satisfies the optimality condition as following.

\[ A(x, y) = \mathbb{I}\{ (\rho + \delta) S(x, y) \geq 0 \} = \mathbb{I}\{ z p(x, y) - \rho V(y) - \rho U(x) \geq 0 \} \]  

(8)

Thirdly, density functions satisfy the steady-state condition for distribution of searching agent given acceptance sets.

\[ \delta(h(x) - f_u(x)) = \lambda^W f_u(x) \int A(x, y) f_v(y) dy \]  

(9)

The stationary equilibrium is a set of \{ V(y), U(x), F_u(x), F_v(y), A(x, y) \} for any \( x \) and \( y \) that satisfies equations (7)–(9).

5.4 Free entry condition

Free entry condition in this model does not imply zero value of vacant job position. Instead, the value of empty job position is non-negative and increasing in its productivity: \( V(y) \geq 0 \) and \( V'(y) > 0 \).

There are two reasons why I do not impose the condition in this paper. When firms can freely choose the level of productivity, the reason why a firm ever choose low productivity is the lower vacancy maintaining cost. A specification of recruiting cost maps to the distribution of the job openings, under the free entry condition, \( c^V(p) \mapsto F_v(p) \). Even using the free entry condition, the initial distribution of job positions is still arbitrary. Secondly, if the free entry condition holds, then the firm’s pickiness (or reservation threshold) gets very simple. What matters for the vacant firm is whether the worker who it encounters can jointly produce more than the worker’s unemployment benefit. The firm’s reservation decision is about viability whether the joint net product is positive or not. On the other hand, if the productivity of job position is a random draw instead of what a firm can choose, then the firm strategically rejects to hire a mediocre worker who can marginally produce more than his unemployment benefit. Since a higher-productive job opening is more valuable asset to the firm, \( V(y) \geq 0 \) and \( \frac{dV(y)}{dy} > 0 \), the firm that intends to fill up the high productive position prefers to search longer instead of hiring a marginally qualified but not excellent worker. The firm’s reservation decision in this paper is whether the surplus is positive or not with positive outside options.

When firms can choose any productivity type of \( y \), then free entry condition implies zero value of vacancy, \( V_t(p) = 0 \) for any \( y \). There are two reasons why I do not impose the condition in this paper. When firms can freely choose the level of productivity, the reason why a firm ever choose low productivity is the lower vacancy maintaining cost. A specification of recruiting cost maps to the distribution of the job openings, under the free entry condition, \( c^V(y) \mapsto F_v(y) \). Even using the free entry condition, the initial distribution of job positions is still arbitrary. Secondly, if the free entry condition holds, then the firm’s pickiness (or reservation threshold) gets very simple. What matters for the vacant firm is whether the worker who it encounters can jointly produce more than the worker’s unemployment benefit. The firm’s reservation decision is about viability whether the joint net product is positive or not. On the other hand, if the productivity of job position is a random draw instead of what a firm can choose, then the firm strategically rejects to hire a mediocre worker who can marginally produce more than his
unemployment benefit when he works in the position. Since a higher-productive job opening is more valuable asset to the firm, $V(y) \geq 0$ and $\frac{dV(y)}{dy} > 0$, the firm that intends to fill up the high productive position prefers to search longer instead of hiring a marginally qualified but not excellent worker. The firm’s reservation decision in this paper is whether the surplus is positive or not with positive outside options.

5.5 Automation Technology

I extend the baseline search model to have automation technology. Firms now choose to use either a human labor or an automatic machine to perform a task. As firm’s productive job position is a scarce asset, the automation technology substitutes human labor.

If the job is currently done by a worker of type $x$, then the firm’s share of surplus is the same with the previous chapter.

$$J(x, y) = \frac{p(x, y, z) - c^J(x, y) - w^N(x, y) + \delta V(y)}{\rho + \delta}$$

$$J(r, y) = \frac{\sum_{z} e^{-\rho \tau} E_{z} \left( p(r, y, z) - c^J(r, y) - g(r) + \kappa V(y) \right)}{\rho + \kappa}$$

The firm optimally choose whether it replaces an existing worker by a robot or not. The value of an occupied job position by a worker of type $x$ is denoted as $K(x, y)$.

$$K(x, y) = \max_{\{labor, robot\}} \{ J(x, y), J(g, y) \}$$

Firms replace existing worker of type $x$ with an equilibrium wage of $w(x, y)$ by a robot of ability $r$ with a flow cost of $g(r)$ if it is optimal to do so.

$$J(x, y) < J(r, y) \iff \frac{\rho + \kappa}{\rho + \delta} \left( p(x, y, z) - c^J(x, y) - w(x, y) + \delta V(y) \right) < e^{-\rho \tau} E_{z} \left( p(r, y, z) - c^J(r, y) - g(r) + \kappa V(y) \right)$$

In the special case of $\kappa = \delta$, $p(x, y, z) = zp(x, y)$, and $z$ is constant for any time, the automation adopted if following inequality holds.
\[ zp(x,y) - c^J(x,y) - w(x,y) < e^{-\rho \tau} \left( zp(r,y) - c^J(r,y) - g(r) \right) \]  

(14)

If a job position of type \( y \) is currently not occupied, then the firm choose if it is going to search a worker or purchase a robot to fill up the position. The value of a vacancy of type \( y \) if the firm installs automatic machine is \( V(g,y) \).

\[
V(r,y) = \frac{e^{-\rho \tau} E_z \left( p(r,y,z) - c^J(r,y) - g(r) + \kappa V(y) \right)}{\rho + \kappa}
\]  

(15)

The value of empty job position is denoted as \( K(y) \).

\[
K(x,y) = \max_{\{\text{labor, robot}\}} \{V(y), V(g,y)\}
\]  

(16)
6 Conclusion

In the post-war period, a negative correlation between output and labor input in a major industry level is firstly sighted. We now observe technological progress that is associated with job destruction in the manufacturing and information industries. To analyze the general equilibrium effect of the new trend, a new type of shock is required, instead of total factor productivity or labor augmented productivity. Even for the employment dynamics, we need to consider the capital-labor substitution (or technology-labor substitution) more seriously.

This paper documents that a technological job destruction provoked labor reallocation on a vertically sorted industry ladder. The previous wage in the lost job was helpful to predict the worker’s future success in the labor market. It means that the two-sided heterogeneity in the labor theory becomes more essential to understand the recent dynamics in the United States economy. A vertical reallocation explains that disappearing middle-wage jobs do not necessarily imply the most suffered middle-wage workers. If middle-wage unemployed workers take low-wage jobs successfully, then the bottom class of unemployed workers may lose their earnings the most until the aggregate employment recovers. Despite the limitation in scope of the initial shock, its impact spreads out to the half of economy through the labor reallocation from the jobless industry to the lowest-wage industry.
References


Appendices

A Detailed Industries and Occupations

A.1 Occupational Employment and Wage

Figure 11: Average Nominal Wage and Employment by 12 Group Occupations (2000–2016)

* The aggregate employment and average wage pattern is in the right top corner. Both employment and nominal average wage are annual Occupational Employment Statistics (OES) data from BLS.

Even though this paper analyzes employment by industry, we can find a link between industry and occupation. This chapter characterizes the disappeared job by occupation to contrast typical growing job and declining job from disappeared job. Output production data is collected by establishment that uses various types of occupations, hence, it is hard to decompose the contribution to production by occupation within a firm. I use nominal average wage instead of real GDP in occupational analysis. Figure 11 shows how employment and average wage of each group occupations evolved from 2000 to 2016.20 First two dots of each line mark the beginning and ending of 2001 Dot-com bust and third and forth dots represents the start and finish of 2008 financial crisis. Most occupations moves to the

20Similar to the industry, major occupation means two-digit (in Standard Occupational Classification (SOC) code) occupations, and detailed occupation refers four-digit occupation. Group occupation is supersets of two-
north-east as both average wage and employment grows over time. The growth are more distinctive in non-recession periods. Meanwhile, there are five unique trajectories that are worth to mention among 22 major occupations. The highest paid occupation is managers (dark green line), and the employment have declined in early 2000 despite the fast growing average wage. Employment in sales and transportation (grey line) occupations are highly sensitive to the business cycles. The number of employees declines during a recession and increases in an expansionary phase of economy. Construction (dark blue line) and office (line with yellow triangle) occupation does not recover the employment after the 2008 Great Recession, even though it had rebounded after 2001 recession. Both occupations have a downward trend in employment despite the increasing nominal average wage. Production occupation (red line) is the most declined occupation regarding employment, and most of drops happened during recessions. Therefore, the disappeared job can be characterized as production occupation unambiguously while office occupation is hard to be defined.

I scrutinize the minor occupations to see whether production occupation consist with the same unique patterns of minor occupations. Also as a control group, I sort 711 detailed occupation by the difference in employment level between 2000 and 2016 to determine most declining and growing detailed occupations. Figure 12 shows 13 most growing occupations, 12 most declining occupations, and 16 disappearing production occupations. Both growing and declining occupations have a long-term trend and such a change gradually made over time. It is even common that both growing and declining occupation coexist within a given major occupation. For example, data entry keyers (OCC 43-9021) and word processors and typists (43-9022) are top 2% most declining jobs, whereas customer service representatives (43-4051), interviewers, and medical secretaries (43-6013) are top 5% most growing jobs. All of them are in the same major occupation that is office and administrative support (43).

However, many production occupations suddenly disappeared and they are not replaced by another production occupations. 68 out of 79 detailed occupations related with factory production reduced employment. The only two continuously growing production occupations are food batch-makers (51-3092) and water waste system operators (51-8031). Most production occupations shows waning w-shape or continuously declining pattern. Among them, team assemblers (51-2092) and first line supervisors (53-1021) workers were reduced the most. The employment adjustments are focused on two years of recessions rather than five to seven years of recovery. These disappeared production occupations are distinguished from sewing machine operators (51-6031) that decrease employment continuously over time. It means that sewing machine operators are likely to be a declining job whereas team assemblers and first line supervisors are replaced jobs.

A.2 Detailed Industries and Replaced Jobs

Once we point out production occupation as the disappearing jobs, industry and occupation are interchangeable without losing much information. The disappeared jobs are production occupations in digit occupations that are adjacent with a similar pattern in employment and wage space, so it conceptually corresponds to one-digit occupation.
Figure 12: Most Growing and Declining Occupations among over 700 detailed Occupations
manufacturing industry. Waning w-shape occupations are including team assemblers and first line supervisors. We investigate which minor industry is related with a sudden but permanent employment loss.

As Figure 13 shows, there are three patterns in real output per worker: jump, business cycle and growth. Output per employee in Motor vehicles, Machinery, and Wood products industries jumped up a year later reducing employment size during the Great recession. Computer and electronic, Electrical equipment, Primary metals, and Miscellaneous manufacturing industries have a negative trend in employment whereas a positive trend in output per worker. Fabricated metal, Nonmetallic mineral, and Furniture products have a distinctive business cycle in output per worker, despite the permanently downsized employment. Appendix A has a combined scatter plots to compare each durable goods manufacturing industries. Acemoglu and Restrepo (2017) shows that industries adopted robots the most intensive are automotive, plastic and chemicals, metal products, electronics, and wood industries, in descending order. Among them, automotive and wood industries shows a jump in their output per worker after the Great Recession. Chemicals and electronics exhibits constant and rapid growth in output per worker while reducing employment. It is fair to mention that automotive industry also imported from Mexico the most intensively, and the electronics industry is the second. However, other industries that also show a higher production per labor are not related with Mexican imports.

B Employment and Output by Industry
Figure 13: 3-digit Minor Industries in (Durable Goods) Manufacturing

Manufacturing > Durable Goods > Motor vehicles, bodies and trailers, and transportation equipment

Manufacturing > Durable Goods > Machinery

Manufacturing > Durable Goods > Wood products

Manufacturing > Durable Goods > Primary metals

Manufacturing > Durable Goods > Computer and electronic products

Manufacturing > Durable Goods > Electrical equipment, appliances, and components

Manufacturing > Durable Goods > Miscellaneous manufacturing

Manufacturing > Durable Goods > Primary metals

Manufacturing > Durable Goods > Computer and electronic products

Manufacturing > Durable Goods > Wood products

Manufacturing > Durable Goods > Machinery

Manufacturing > Durable Goods > Motor vehicles, bodies and trailers, and transportation equipment

Manufacturing > Durable Goods > Electrical equipment, appliances, and components

Manufacturing > Durable Goods > Primary metals

Manufacturing > Durable Goods > Computer and electronic products

Manufacturing > Durable Goods > Wood products

Manufacturing > Durable Goods > Machinery

Manufacturing > Durable Goods > Motor vehicles, bodies and trailers, and transportation equipment

Manufacturing > Durable Goods > Electrical equipment, appliances, and components

Manufacturing > Durable Goods > Primary metals

Manufacturing > Durable Goods > Computer and electronic products

Manufacturing > Durable Goods > Wood products

Manufacturing > Durable Goods > Machinery

Manufacturing > Durable Goods > Motor vehicles, bodies and trailers, and transportation equipment

Manufacturing > Durable Goods > Electrical equipment, appliances, and components

Manufacturing > Durable Goods > Primary metals

Manufacturing > Durable Goods > Computer and electronic products

Manufacturing > Durable Goods > Wood products

Manufacturing > Durable Goods > Machinery
C Occupation

C.1 Wage hierarchy?

Figure (??) shows the wage distribution by 22 major (2-digit) occupations in 2000 and 2016. The ranking in average wage is robust over time, but dispersion within occupation is not negligible. The lowest wage worker in an occupation usually earn less than the highest wage worker in one-step lower occupation in terms of average wage. Data is favorable to the weak version of vertical sorting rather than the strict vertical sorting.

As the speed of decline and growth is asymmetric, a sudden job disappearance deeply hollows out aggregate employment, drops the labor share, and accelerates unemployment rate. Both in 2001 and 2008 recessions, manufacturing and information industries reduced 12%–18% of employment, whereas health and food services sectors increased 2%–4% of employment. After a recession, the labor market has a large burden to relocate massive unemployed workers while dealing with a long-lasting shortage of job openings.

D Industrial Wage Hierarchy

- Average wage for all employees (2017 March) | Average wage for non-supervisory workers (2017 March) | Median weekly earnings for full time employees (2016) | Average weekly hours for all
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<td>7,782,680</td>
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<td>6,116,380</td>
<td>7,090,790</td>
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<td>Computer and Mathematical</td>
<td>15</td>
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<td>2,932,810</td>
<td>2,772,620</td>
<td>3,191,360</td>
<td>3,303,690</td>
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<td>4,505,200</td>
<td>4,424,740</td>
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<td>4,720,130</td>
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<td>Healthcare Practitioners</td>
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<td>Education, Library, Entertainment</td>
<td>25, 27</td>
<td></td>
<td>8,964,280</td>
<td>9,276,150</td>
<td>10,077,630</td>
<td>10,234,410</td>
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<td>47</td>
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<td>6,187,360</td>
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<td>21, 33, 49</td>
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<td>51</td>
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<td>12,400,080</td>
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<td>Office and Administrative Support</td>
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<td>10,518,710</td>
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<td>9,955,060</td>
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<td>11,273,850</td>
<td>11,218,260</td>
<td>12,981,720</td>
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</table>
1. Tier 1 (30 mil workers, 22% of total employment)

   - Information $37.56 | $30.47 | $1,143 | 36.3 hours

   ▶ Information: NAICS 51


   13% of decline in employment during the Great Recession has recovered
Figure 15: Employment and Real GDP per Worker in Other Group Industries
○ Publishing Industries (except Internet): NAICS 511
  $42.94 | $33.64 | $1,094 | 37.0 hours

○ Data Processing, Hosting, and Related Services: NAICS 518
  $41.02 | $32.77 | — | 37.8 hours

○ Other Information Services: NAICS 519
  $40.76 | $33.78 | — | 33.6 hours

○ Broadcasting (except Internet): NAICS 515
  $35.41 | $28.26 | $1,017 | 34.5 hours

○ Telecommunications: NAICS 517
  $32.90 | $28.41 | $1,182 | 38.3 hours

○ Motion Picture and Sound Recording Industries: NAICS 512
  $31.91 | $23.52 | $1,085 | 30.4 hours

● Financial Activities  $32.74 | $26.36 | $977 | 37.3 hours
  ○ Finance and Insurance: NAICS 52  — | — | $1,039 | —
      ○ Securities, Commodity Contracts, and Other Financial Investments and Related Activities: NAICS 523
Figure 16: Employment and Real GDP per Worker in Manufacturing and Information 3-digit Minor Industries
Figure 17: Robust Occupation Hierarchy in Average Wage by 22 Major Occupations

- **Food Preparation and Serving Related Occupations**: NAICS 524
  - $49.95 | $40.24 | — | 37.4 hours
- **Insurance Carriers and Related Activities**: NAICS 524
  - $49.95 | $40.24 | — | 37.4 hours
- **Credit Intermediation and Related Activities**: NAICS 522
  - $34.30 | $29.11 | $977 | 38.2 hours
- **Monetary Authorities - Central Bank**: NAICS 521
  - $34.30 | $29.11 | $977 | 38.2 hours
- **Funds, Trusts, and Other Financial Vehicles**: NAICS 525
  - $30.18 | $22.77 | — | 38.1 hours
- **Real Estate and Rental and Leasing**: NAICS 53
  - $30.18 | $22.77 | — | 38.1 hours
- **Real Estate**: NAICS 531
  - $25.83 | $21.12 | — | 33.9 hours
- **Rental and Leasing Services**: NAICS 532
  - $24.30 | $19.89 | — | 35.2 hours
- **Lessor of Nonfinancial Intangible Assets (except Copyrighted Works)**: NAICS 533
  - — | — | — | —
Figure 18: Wage Distribution by Major Occupations

- Professional and Business Services  $31.57 | $25.92 | $992 | 36.0 hours
Professional, Scientific, and Technical Services: NAICS 54
  ◦ Professional, Scientific, and Technical Services: NAICS 541
    $40.04 | $33.91 | $1,273 | 36.8 hours
Management of Companies and Enterprises: NAICS 55
Employment: −0.05 mil (2008–10) +0.40 mil (2010–17)
  ◦ Management of Companies and Enterprises: NAICS 551
    $39.11 | $27.76 | — | 38.6 hours
Administrative and Support and Waste Management and Remediation Services: NAICS 56
Employment: −1.50 mil (2008–09) +2.00 mil (2009–17)
  ◦ Waste Management and Remediation Services: NAICS 562
    $25.67 | $22.37 | — | 40.7 hours
  ◦ Administrative and Support Services: NAICS 561
    $19.85 | $17.60 | — | 33.5 hours

2. Tier 2a (40 mil workers, 29% of total employment)
   • Federal, State, and Local Government: NAICS 99 $28.26 | — | — | —
   • Education and Health Services= Educational Services: NAICS 61 + Health Care and Social Assistance: NAICS 62 $26.08 | $22.88 | $817 | 32.9 hours

3. Tier 2b (19 mil workers, 14% of total employment)
   • Construction $28.55 | $26.37 | $822 | 38.7 hours
     ◦ Construction: NAICS 23
       63% of decline in employment during the Great Recession has recovered
       ○ Construction of Buildings: NAICS 236
         $30.65 | $25.80 | — | 37.4 hours
       ○ Heavy and Civil Engineering Construction: NAICS 237
         $30.22 | $28.14 | — | 42.0 hours
       ○ Specialty Trade Contractors: NAICS 238
         $27.57 | $26.06 | — | 37.7 hours
   • Manufacturing: NAICS 31-33 $26.39 | $20.70 | $857 | 40.7 hours
     Employment: −2.70 mil workers (2007–10) +0.93 mil (2010–17)
     35% of decline in employment during the Great Recession has recovered
4. Tier 3 (49 mil workers, 35% of total employment, average wage below $20)

- Trade, Transportation, and Utilities: Wholesale Trade: NAICS 42 + Retail Trade: NAICS 44-45 + Transportation and Warehousing: NAICS 48-49 + Utilities: NAICS 22 $22.64 | $19.22 | — | 34.3 hours

- Other Services (except Public Administration): NAICS 81 $23.50 | $19.73 | $686 | 31.9 hours

- Leisure and Hospitality: Arts, Entertainment, and Recreation: NAICS 71 + Accommodation and Food Services: NAICS 72 $15.32 | $13.24 | $528 | 26.0 hours

E Trickle Down details

Manufacturing and Leisure and Hospitality industries are a good contrast. Employment size in manufacturing has declined in the most two recessions, while leisure and hospitality industry is growing overall. Figure 2 shows that the net hiring in manufacturing was negative while leisure and hospitality industry shows little changes.

Manufacturing industry laid off more than 400 thousands workers in the 2008 recession, while leisure and hospitality industry does not particularly lays off workers in the Great recession. Job openings declined during a recession as quits declined. Manufacturing sector do not open much vacancies during a recovery, so the decline in employment is associated with shortage in labor demand.

Figure 5 compares the persistency in unemployment for all industries by normalizing the unemployment rate at March 2009 into zero. For all of the industries, we can see the lower average wage the sector unemployed workers worked before, the more persistent unemployment during a recovery, even though the employment fluctuations and layoffs were different by sectors.
Figure 19: Manufacturing (Tier 3) and Leisure and Hospitality (Tier 4): JOLTS
Jobless Recovery v.s. Recovery with Jobs

Employees in Manufacturing Industry

Employees in Leisure and Hospitality Industry

Net Hiring in Manufacturing Industry

Net Hiring in Leisure and Hospitality Industry

58
When we compare the unemployment level or rate, unemployed workers from the jobless sector (manufacturing) exits faster than the unemployed from lower-paying but actively hiring industry (leisure and hospitality).
Figure 21: Manufacturing (Tier 3) and Leisure and Hospitality (Tier 4): JOLTS
Fast Exit from Unemployment v.s. Persistent Unemployment
Figure 22: Manufacturing (Tier 3) and Leisure and Hospitality (Tier 4): JOLTS
Fast Exit from Unemployment v.s. Persistent Unemployment
# Great Recession by Sectors

![Figure 23: Great Recession by Sectors](image)

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</thead>
<tbody>
<tr>
<td></td>
<td>Year</td>
<td>Loss in Profits // Contribution to BC</td>
<td>Additional Layoffs</td>
</tr>
<tr>
<td><strong>Tier 1</strong> 21%</td>
<td>Information Services</td>
<td>2007-09</td>
<td>17% loss (- $13 bil) - 1% of GDP</td>
</tr>
<tr>
<td>1 Injury</td>
<td>Financial Activities</td>
<td>2006-08</td>
<td>177% loss (- $243 bil) - 2.3% of GDP</td>
</tr>
<tr>
<td>Professional and Business Services</td>
<td></td>
<td></td>
<td>30% more (+120 k)</td>
</tr>
<tr>
<td><strong>Tier 2</strong> 29%</td>
<td>Government</td>
<td></td>
<td></td>
</tr>
<tr>
<td>26-28 2 Injuries</td>
<td>Education and Health Services</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Tier 3</strong> 14%</td>
<td>Construction</td>
<td>2007-11</td>
<td>54% loss (- $30 bil) - 1.9% of GDP</td>
</tr>
<tr>
<td>21-27 8 Injuries</td>
<td>Manufacturing</td>
<td>2007-09</td>
<td>60% loss (- $127 bil) - 1.9% of GDP</td>
</tr>
<tr>
<td><strong>Tier 4</strong> 35%</td>
<td>Trade, Transportation and Utilities</td>
<td>2007-08</td>
<td>25% loss (- $55 bil) - 3.6% of GDP</td>
</tr>
<tr>
<td>15-23 13 Injuries</td>
<td>Leisure and Hospitality</td>
<td>2007-08</td>
<td></td>
</tr>
</tbody>
</table>

![Injury: Average number of sickness caused by work, injuries or fatality per year for an employee](image)

![Loss in profit: percentage loss in profit per previous year profit (dollar amount of loss)](image)

![Contribution to BC: sectoral output loss as percentage of contribution to aggregate output](image)

![Additional layoffs: Spike in layoffs and discharges at 2008 comparing to 2003–2007, percentage of additional layoffs to previous layoffs (number of people)](image)

![Fewer hiring: Decline in hiring at 2009–2010 comparing to 2004–2008, percentage of declined hiring to previous level (number of people)](image)

![Jobless means that the employment level declined permanently after recession. Partially jobless means that the employment level have recovered but it takes 5–7 years, so we cannot tell whether the employment is recovered or economic growth has increased the employment.](image)
Figure 24: Contributions to Percent Change in Real GDP by Private Industries (2005–2017) from U.S. Bureau of Economic Analysis, Industry Economic Accounts
Figure 25: Corporate Profits after Tax (1998–2017) from U.S. Bureau of Economic Analysis, National Economic Accounts
Outward shift in Beveridge Curve

Figure 26: Outward Shift in Beveridge Curve (2000–2017): JOLTS

United States Beveridge Curve

Vacancy Rate vs. Unemployment Rate over different time periods:
- Dec 2000 - Jun 2003
- Dec 2007 - Apr 2010
- May 2010 - Nov 2016
H Regression

H.1 Regression

The unemployment level from a industry $k$ in time $t$ evolves from the unemployment level in previous period by subtracting the outflow from unemployment and adding the inflow to unemployment.

$$U_{k,t} = U_{k,t-1} - O_{k,t} + I_{k,t}$$

$U$ is the unemployment level, $O$ is the outflow from unemployment, $I$ is the inflow to unemployment, $k$ denotes the industry and $t$ refers a year. The outflow from unemployment for workers who had worked in industry $k$ is deduced in following equation.

$$O_{k,t} = U_{k,t-1} - U_{k,t} + I_{k,t}$$

Unemployment level is observable in data, however, inflow to unemployment is not perfectly measurable. I use separation variables such as discharges and layoffs, quits, and other separation for regressions instead of inflow.

I add control variables including aggregate unemployment level, aggregate job openings level, net hiring level by industry, to capture aggregate and industrial labor market tightness. Unemployment trickle down hypothesis predicts that the outflow rate after controlling tightness is decreasing in average wage in the industry.

$$O_{k,t} = \beta_0 + \beta_1 W_k + \beta_2 H_{k,t} + \beta_3 \sum_{j=1}^{k-1} H_{k,t} + \beta_4 \sum_{j=k+1}^{K} H_{k,t} + \beta_5 \sum_k U_{k,t} + \beta_6 \sum_k V_{k,t} + \beta_7 D_t + \epsilon_{k,t}$$

(17)

$W$ is industrial average wage rate, $H$ is net hiring, $D$ is discouraged and marginally attached workers in the not-in-the-labor-force and $\epsilon$ is a regression error. If $\beta_1$ is significantly negative, then unemployment exit is negatively associated with average wage in industry.

$\beta_2$ captures how hiring in the same industry helps the unemployment exits (home advantage), $\beta_3$ measures how hiring in higher-paying industries enhance the unemployment exits, and $\beta_4$ refers how hiring in lower-paying industries increases job findings.

Alternatively, I regress unemployment exit level to hiring in the most adjacent industries.

$$O_{k,t} = \beta_0 + \beta_1 W_k + \beta_2 H_{k,t} + \beta_3 H_{k+1,t} + \beta_4 H_{k-1,t} + \beta_5 \sum_k U_{k,t} + \beta_6 \sum_k V_{k,t} + \beta_7 D_t + \epsilon_{k,t}$$

(18)

H.2 Worker Transitions

Where Do Workers from Jobless Sector Find Their Next Jobs?
H.3 Unemployment exit rate

\[ U_k(t + 1) = U_k(t) + E_k U_k - U_k E_k - U_k E_{-k} + NU_k - U_k N \]

\[ U_k E_k + U_k E_{-k} = U_k(t) - U_k(t + 1) + E_k U_k + NU_k - U_k N \]

Job finding transition for unemployed workers whose previous job is in industry \( k \) is the change in unemployment from industry \( k \) plus newly unemployed from \( k \) and net inflow from not-in-the-labor force. I assume that the net inflow from not-in-the-labor-force to unemployment is zero. Newly unemployed worker is not precisely measured, but I use proxy variable of discharges and layoffs.

\[ JF_k(\equiv U_k E_k + U_k E_{-k}) \approx U_k(t) + D_k - U_k(t + 1) \]

H.4 Installation cost

Installation shadow cost of automation when the job position is occupied by a worker of type \( x \) is following.

\[ O^{I}(x, y, z) = \left[ (1 - \beta) \left( p(x, y, z) - c^{I}(x, y) - \rho U(x) \right) + (\beta \rho + \delta) V(y) \right] \left( 1 - e^{-\rho \tau} \right) \frac{1}{\rho + \delta} \]  \hspace{1cm} (19)

Installation shadow cost of automation when the job position is empty is following.

\[ O^{V}(y, z) = \] \hspace{1cm} (20)

\[ J(g, y) = \frac{e^{-\rho \tau} \left( p(g, y, z) - c^{I}(g, y) - r + \kappa V(y) \right)}{\rho + \kappa} - O^{I}(x, y, z) \]  \hspace{1cm} (21)

where \( O^{I}(x, y, z) = \left[ (1 - \beta) \left( p(x, y, z) - c^{I}(x, y) - \rho U(x) \right) + (\beta \rho + \delta) V(y) \right] \left( 1 - e^{-\rho \tau} \right) \frac{1}{\rho + \delta} \)

\[ V(g, y) = \frac{e^{-\rho \tau} \left( p(g, y, z) - c^{I}(g, y) - r + \kappa V(y) \right)}{\rho + \kappa} - O^{V}(y, z) \]  \hspace{1cm} (22)

where \( O^{V}(y, z) = \left[ (1 - \beta) \left( p(x, y, z) - c^{I}(x, y) - \rho U(x) \right) + (\beta \rho + \delta) V(y) \right] \left( 1 - e^{-\rho \tau} \right) \frac{1}{\rho + \delta} \)

Opportunity cost of automation is followings.
I A Sorting Model

I.1 Setup

Time is discrete with a discount rate $\rho$. The population is given by $N$. Workers are different in general ability $x$ that follows an exogenous density function of $H(x)$. Jobs are heterogeneous in productivity $y$.

There are $K$ occupations indexed by $k \in \{0, 1, \cdots, K\}$. For simplicity, jobs are assumed to be identical within an occupation but heterogeneous across occupations. The productivity in occupation $k$ is denoted as $y_k$, and the index of occupation are assigned by an ascending order of its productivity, $y_0 < y_1 < \cdots < y_K$. Occupation 0 implies the not-in-the-labor force or home production preferably. Anyone can be out-of-the marker (or work at home) of which productivity is zero, $y_0 = 0$. Productive jobs are scarce so that the total number of jobs with positive productivity is smaller than the population, $\sum_{k=1}^{K} \gamma_k < N$. The number of jobs for each occupations are exogenously given as a vector of $\gamma = (N, \gamma_1, \gamma_2, \cdots, \gamma_K)$.

Production function is $p(x, y)$ that depends on both the worker’s ability and the job’s productivity. The specification can be any super-modular function so that the core equilibrium allocation is a Positive Assortative Matching (PAM). Production is distributed between a worker and a firm in terms of wages and profits, respectively. Wage is the over production after giving the firm a fixed profit that depends on occupation, therefore, it is increasing in worker’s ability, $\frac{\partial w_k(x)}{\partial x} > 0$.

$$w_k(x) = p(x, y_k) - \Pi_k$$

(23)

As Groes, Kircher, and Manovskii (2015) explained, stationary competitive equilibrium makes entrepreneurs’ profits and worker cutoffs as constant over time. All employees who select occupation $k$ prefer to work in occupation $k$ instead of $k-1$, which gives incentive compatibility condition for occupation $k$.

$$w_{k-1}(x) \leq w_k(x) \iff p(x, y_{k-1}) - \Pi_{k-1} \leq p(x, y_k) - \Pi_k$$

(24)

The equality in equation (24) holds for a worker with the lowest ability in occupation $k$, and it is denoted as $B_k$.

$$B_k = \arg_{x} p(x, y_{k-1}) - \Pi_{k-1} = p(x, y_k) - \Pi_k$$

(25)

Workers whose ability in $[B_k, B_{k+1})$ would prefer to work in occupation $k$. The occupational labor market clears if the number of workers who select occupation $k$ and the number of jobs in the occupation are the same.

$$H(B_{k+1}) - H(B_k) = \gamma_k \quad \text{for} \quad k \in \{1, 2, \cdots, K\}$$

(26)

As we aggregate the market clearing conditions across occupations, the worker cutoffs can be calculated by ascending order, for $k \in \{1, 2, \cdots, K\}$.

$$\sum_{i=k}^{K} \gamma_k = N - H(B_k)$$

Given workers occupational choices as a vector $B = (B_1, \cdots, B_k)$, a vector of firms profits $\Pi = (\Pi_1, \cdots, \Pi_K)$ is derived by applying equation (25).