THE UNIVERSITY OF CHICAGO

SECTOR-SPECIFIC HUMAN CAPITAL AND THE EFFECTS OF JOB DISPLACEMENT

A DISSERTATION SUBMITTED TO
THE FACULTY OF THE DIVISION OF THE SOCIAL SCIENCES
IN CANDIDACY FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY

DEPARTMENT OF ECONOMICS

BY
HOSEIN JOSHAGHANI

CHICAGO, ILLINOIS
JUNE 2017

To Marzieh, Zainab and Hassan

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ABSTRACT

Job loss has a permanent negative effect on life-time earnings and, in general, on labor market outcomes of workers. This negative effect is larger if job loss happens in recession than the case of job loss during expansion. In this paper, using linked employer–employee data of Germany from 1975 to 2014, I show that about 55% of the variation in earning loss is accounted for by negative sectoral performance. Intuitively, earning losses associated with job loss are greater during recessions, because the average displaced worker in a recession comes from an industry with poor performance relative to the average industry which makes sector-specific skills less valuable. In other words, recessions are not only periods of more job loss but also periods with more sectors of very poor performance. Hence, workers displaced in recessions are, on average, more likely to struggle with lack of demand for their skills.

By building a model of sector-specific human capital, it is shown how loss of sector-specific human capital can explain huge and persistent earning and wage loss of displaced workers. In addition, it is shown that concentration of displaced workers in severely declining sectors during recessions is a potential explanation for larger earning loss in recessions than job-losses in expansions.

JEL classification: J24, J38, J64, J65

CHAPTER 1
INTRODUCTION

Why is job loss in a recession much more painful than job loss in an expansion? This paper reconsiders two prominent features of displaced workers.[1] First, workers' earnings largely declines after displacement and starts recovering shortly, but never completely recovers to the counterfactual of non-displacement even after 20 years. Topel (1990) and more recently Davis and Von Wachter (2011) well document this fact. Second, and more puzzling, is that the magnitude of earning loss associated with job loss is counter-cyclical. That is if displacement happens during a recession, earning loss is persistently larger rather than the case when displacement happens during an expansion. Davis and Von Wachter (2011) well document these two facts using United States micro data. I add to this literature the fact that earning loss is much larger for workers displaced from relatively declining sectors, even after controlling for aggregate economic conditions at the time of job loss. In this paper, using German administrative matched employer–employee data, I show to what extent the loss of sector-specific human capital is crucial in explaining these three facts. Then I develop a theoretical model of sector-specific human capital that exhibits earning loss upon job loss similar to what has been documented in the empirical literature on displaced workers.

The main idea is that if displacement happens from a declining sector, then the displaced worker may have a hard time finding a new job in their previous sector. The worker will either accept a lower wage offer in their original sector or prefer to switch to a new sector. In either case, the worker's sector-specific human capital is less valuable, which can result in permanent wage losses. This can explain the observed large and persistent earning loss upon job displacement from declining sectors (fact 3). Moreover, if recessions are periods in which more sectors are shrinking their employment relative to the average sector, then more displaced workers would find their skills less valuable. Therefore, at least in theory, loss of sector-specific human capital can explain all these three facts: 1) The permanent loss

1. Displacement is defined as involuntary and permanent separation of high tenured workers during mass layoff events. Identified as at least 30% decline in employment of large establishments, mass layoff events are used to filter separations to make sure that lay off is demand side driven and not confounded with supply side characteristics of workers. More details are provided in chapter 2.

of earnings upon displacement; 2) Larger earning losses for displacements during a recession; and 3) Larger earning losses for displacements from a relatively declining sector.

To empirically test this hypothesis, I use administrative data for German workers from 1975 to 2014 which records all jobs of individual workers, their wages, their occupations as well as the industry of the main economic activity of their employer. First I replicate the findings of Davis and Von Wachter (2011) using German data. These patterns are depicted in figure 3.1, details of which are discussed in chapter 3. Then, using the richness of the dataset, I study sectoral variation of the earning loss. Specifically, I document for the first time in the literature, to the best of my knowledge, how earning loss - associated with job displacement - differs across sectors by doing two exercises. First I show how the frequency of earning loss is correlated with both aggregate and sectoral economic performance. Then I compare the earning loss of displaced workers across sectors by comparing the earning loss of workers displaced from relatively growing sectors to those displaced from relatively declining ones. The core finding of this paper is that once we look at the top growing and top declining sectors, aggregate economic conditions - measured by the real GDP growth rate, or the unemployment rate or by periods of recession and expansion - have less influence in explaining earning loss of displaced workers.

I also show that upon receiving the displacement shock, workers' probability of switching their industry and occupation increases significantly. Furthermore, I find that this increase in the likelihood of switching sectors is also counter-cyclical: significantly more workers displaced during recessions switch their industry and occupation. Figure 3.7 depicts the ratio of switchers after displacement. Then using a regression framework, I show that while displacements in recession are on average associated with 24.5% higher earning loss, sectoral shocks accounts for more than half of the observed variation in earning loss. In other words, once controlling for sectoral shocks, recessions can merely explain 10.8% larger earning loss.

In order to distinguish pure sectoral performance from aggregate performance, I decompose measures of sectoral performance (such as the employment growth rate) in two parts: an aggregate growth rate which changes over time but is uniform across all sectors and locations, as well as another idiosyncratic term that varies across location, sectors and time. I call the latter part the Relative Sectoral Performance (hereafter RSP). Sectors, identified by a 3-digit NACE industry classification, are reported as the main economic activity of the establishment in which the worker is being employed. By construction, recessions are periods of downward aggregate economic activity. Therefore, to measure how each sector is performing relative to the average economy, I use the above decomposition of performance measures. The idiosyncratic sectoral performance, measured by RSP, is found to be more prevailing during recessions which is consistent with the literature on a possible "cleansing effect" of recessions or the idea that firms and sectors increase their productivity-enhancing activities in recessions because of relatively low opportunity costs of their resources (e.g., Davis and Haltiwanger, 1990; Caballero and Hammour, 1994; Aghion and Saint-Paul, 1998; Foster et al., 2016). These productivity enhancing activities can include large-scale layoff events which in this paper are used to identify displaced workers.

1.1 Related Literature

To the best of my knowledge, my paper is the first one to study the role of sector-specific human capital on the magnitude of earning loss associated with displacement and its countercyclicality. Recent studies, such as Jarosch (forthcoming) show that the huge earning loss post displacement could be explained by loss of general human capital due to joblessness after displacement as well as loss of job security post displacement. Jarosch argues that the longer periods of joblessness upon displacement is associated with larger loss of human capital and therefore larger earning loss. The other mechanism that he suggests is the loss of job security after displacement. Empirical studies such as Lilien (1982), Topel (1985), Murphy and Topel (1987) as well as Jarosch (forthcoming) well document less attachment of displaced workers to labor force after a mass layoff event. Jarosch (forthcoming) uses these evidence to argue that displaced workers not only lose their human capital but also have less wage bargaining power in their new employment offers. In a similar paper, Krolikowski (2017) explains the large and presistent earning loss of displaced workers by introducing search frictions in the form of job ladder and increased separation rate for the recently hired workers. My paper adds loss of sector-specific human capital to this literature.

Although Jarosch (forthcoming) and Krolikowski (2017) are silent about the counter-cyclicality of earning loss, one can extend their argument using the fact that displaced workers are on average more jobless if displacement happens during recession. Therefore, one can expect more loss of general human capital which can explain counter-cyclicality of earning loss associated with displacement. However, using micro data of German workers, I find that this channel can not explain the large lifetime earning losses during recessions. For instance, it is shown that duration of joblessness is very similar for displacements in recession and expansion. In addition, as more than 63% of displaced workers find full-time job in the same year of job loss, it is shown that even for this group of displaced workers, wage loss is 47% higher if job loss happens in recession. This fact can not be explained by the effect of longer periods of joblessness on loss of human capital. Therefore, this channel can not be the main reason for counter cyclicality of earning loss. A salient finding of this paper is to identify sectoral shocks as the main source of the gap between earning loss associated with displacements during recession and those during expansions.

Furthermore, this paper is related to the literature of asymmetric information in the labor market which is developed after the seminal paper of Gibbons and Katz (1991). They develop and empirically test a model that if asymmetric information is important, one should expect a larger fall in earnings at layoff than at plant closing. The main reason for this prediction is that layoff is more related to the characteristics of the worker, while plant closing is demand-driven and perhaps uncorrelated with the worker's quality. Therefore, if prospective employers have less information about the quality of the worker than the last employer, they may perceive a layoff as a negative signal about the quality of the worker while a plant closing may lack any such negative information. Gibbons and Katz (1991) and more recently, Hu and Taber (2011) and Sorensen (2017) find evidence in support of the hypothesis of asymmetric information. This hypothesis, if true, suggests higher earning loss would be associated with job displacements during expansion as the information contained in a separation during expansion is more valuable than the information in job loss during a recession, since recessions are periods in which many jobs are lost. However, my findings as well as Davis and von Wachter (2012), Jarosch (2017) and many others show exactly the opposite: job loss in recessions are associated with larger earning loss. Notice that in this paper, I do not claim to provide evidence against the asymmetric information hypothesis in the labor market. However, I suggest that even if the hypothesis is correct, it does not have first order effect on the earning loss of displaced workers.

To summarize, this paper claims that recessions are worse for job displacement for two reasons. First, since job loss is more common and job vacancies are fewer during recessions, finding a new job is harder and on average it takes longer to find a new job after a job loss. This channel, related to the first moment of the economy, causes for workers longer periods of joblessness and less job security in recessions relative to expansions. The second property of recessions, related to the second moment of the economy, is the higher dispersion of sectors in terms of their economic performance such as employment growth rates, job creation or job destruction. This property of recessions translates into existence of more sectors with relatively fast declining employment during economic downturns. Consequently, sectoral skills of many displaced workers become less valuable. The main finding is that the first property of recessions has very limited contribution on earning loss while the second property explains about more than half of the associated earning loss of displaced workers.

This paper is organized as follows. Chapter 2 discusses the dataset and empirical methodology that I use. Chapter 3 measures consequences of displacement using German data and studies the effect of business cycle and sectoral properties of job displacement. Chapter 4 lays out a simple theoretical framework which emphasizes the importance of sector-specific human capital and endogenous decision of workers to stay or switch to motivate my empirical work. Chapter 5 concludes and provides final thoughts. Appendices contain details on data and additional empirical results.

CHAPTER 2

DATA

To study labor market outcomes of displaced workers relative to other workers, I used two German administrative data sources provided by the German Federal Employment Agency's Institute for Employment Research, IAB. The first database is the *Sample of Integrated Labor Market Biographies* (SIAB) which is a two percent random sample of all individuals in Germany employed in non-public sectors and subject to social security between 1975 and 2014. SIAB comes in spell format and reports exact dates for the start and end of each employment spell. It also reports age, gender, level of vocational training, and education of the workers as well as the occupation of the worker at each job. I restricted the main sample to workers with full-time and full-year jobs as hours of work is not observable which would be necessary to include part-time workers.

The second administrative data source is the *Establishment History Panel* (BHP) which is a 50% random sample of all establishments in Germany between 1975 and 2010. This panel data reports the number of employed workers, median wage, and location of an establishment for each year. It also provides an establishment's 3-digit Nomenclature of Economic Activities (NACE) industry classification (European statistical classification of economic activities). SIAB and BHP data can be merged together using the unique establishment ID and year of activity. See Data Appendix A for details of data preparation.

2.1 Mass Layoff Events

Following the literature in job displacement such as Davis and von Wachter (2011) I use mass layoff events to identify permanent shocks to employments. It is crucial to distinguish mass layoff events from individual layoffs as the latter are endogenous decisions of firms which involve qualities of the individual worker that cannot be observed by the researcher though observable by an establishment's managers. For instance, in a seminal paper, Gibbons and Katz (1991) compare the earning loss of separations due to individual layoff with those separations in plant closings. They found that post-separation wages are lower and post-separation unemployment spells are longer for those separated by individual layoffs than for those displaced by plant closings, while pre-separation wages do not differ by cause of separation. Therefore, to prevent the lemon problem of layoffs due to asymmetric information, it is necessary to focus only on mass layoff job losses.

The large-scale, permanent loss of employment at the establishment level, or a mass layoff event, at year y occurs when an employer meets all four of the following conditions at the same time: 1) 30 or more employee in year $y-2$, 2) employment contracts by 30 to 99% from $y-2$ to y, 3) employment in $y-2$ is no more than 130% of employment in $y-3$ and 4) employment in $y+1$ is less than 90% of employment in $y-2$. These conditions are set to exclude temporary contractions of establishments. Davis and von Wachter (2012) provide more details on these conditions.

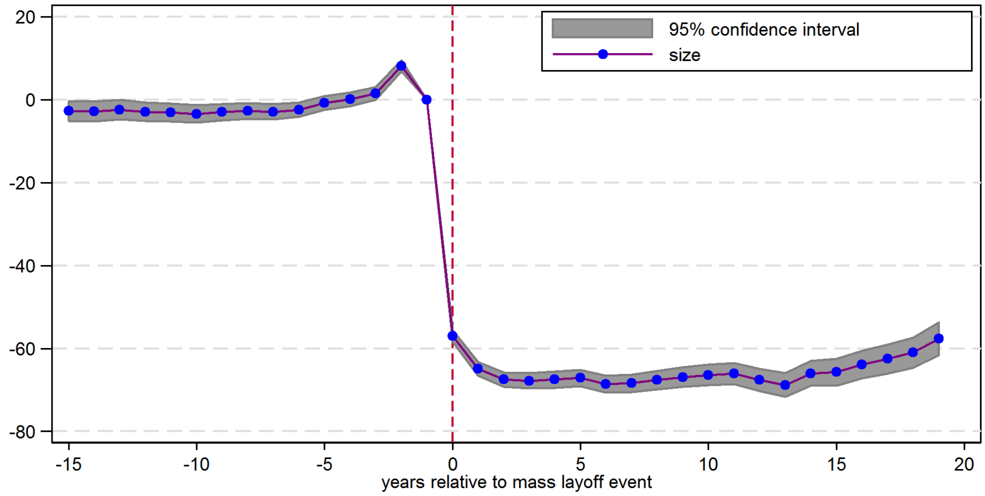
Using the BHP files provide by the IAB, I used the above four conditions to identify large scale layoff events. To test if these identified events, truly represent permanent negative employment shock to the treated establishments, I estimate average employment size of establishments before and after the identified incidence of mass layoff. In order to do that, I estimate the following distributed lag model:

$$EMP_{ey} = \sum_{k=-15}^{20} \delta_k D_{ey}^k + \epsilon_{et} \tag{2.1}$$

where EMP_{ey} is the employment size of the establishment e at year y[1]. Dummy variables D_{ey}^k switch on only at k-years relative to the mass layoff event for establishment e. Then δ_k coefficients capture average employment size of these treated establishments k-years relative to the incidence of mass layoff, and relative to the baseline year, which is one year prior the mass layoff event. Therefore, by construction $\delta_{-1} = 0$. Estimated δ_k coefficients are depicted in figure 2.1. This figure shows how each establishment's size evolves before and after incident of mass layoff. On average, these establishments have relatively stable employment size before and after the mass layoff event. However, during the year of the incident, employment size drops drastically. The shaded gray area represents 95% confidence interval for the relative size of these establishments.

1. The results are very similar if one adds α_j and β_l as industry and location fixed effects to this specification

Figure 2.1: Change in the size of establishments due to a mass layoff event.



Notes: Changes in employment size of establishments experiencing a mass layoff event relative to the one year prior to the incident. Blue dots are the average and the gray area represent 95% confidence interval. This graph ensures that the mass layoff event is a permanent negative shock to the employment of these establishments.

2.2 Job Displacement

Job displacement is defined as involuntary and permanent separation of long-tenured workers during mass layoff events. Throughout this paper I consider workers with more than 24 consecutive months of job tenure in a single establishment as long-tenured employees. As explained earlier, mass layoff events are used to filter out individual layoffs to make sure that lay off is demand-side driven and not confounded with supply-side characteristics of workers.

SIAB data, provided by IAB, is the main source for identifying job loss of tenured workers. However to specify job displacements, which is defined as job loss of tenured workers in a large scale layoff event, I need interaction of job loss and mass-layoff events which are identified using the BHP file. I regard a worker as "displaced" in year y if he separates from his employer in y and the employer experiences a mass-layoff event in y. I say a worker "separates" from an employer in year y if his employment spell with the employer ends in y and a new spell with the same employer does not start at the same year y. In addition, I follow workers up to 9 months to make sure that I do not count recalls as separations and

Table 2.1: Summary statistics of job separations and displacement

	total	high tenured separators		displaced workers	
		Rec	Exp	Rec	Exp
unique workers	$2,639,010$	$209,037$	$212,517$	$31,846$	$42,780$
observations	$221,631,833$	$118,938,018$	$46,135,894$	$4,865,606$	$5,566,445$

Notes: *Sample of Integrated Labor Market Biographies* (SIAB) provides a 2% random sample of all individuals in Germany employed in non public sectors and subject to social security between 1975 and 2014. Among $2,639,010$ workers in this sample only $321,554$ employees separate from establishments while they have more than two years of job tenure. Only $33,665$ workers experience *displacement* which is defined as permanent separation of high tenured workers during a mass-layoff event.

new employment. To meet the prior job tenure requirement, the worker must have positive earnings from the employer in question in at least 730 days prior the day of separation. In Data Appendix A I provide more information on identifying job displacements.

This way, I identify job displacements in the German economy from 1975 to 2014. Among $2,639,010$ unique workers in SIAB, only $421,554$ employees separate from establishments while they have more than two years of job tenure. In addition, only $74,626$ workers experience *job displacement* which is permanent separation of long-tenured workers during mass layoff event. Table 2.1 presents number of workers in the sample that experience job loss and job displacement separately for separations during recessions and expansions.

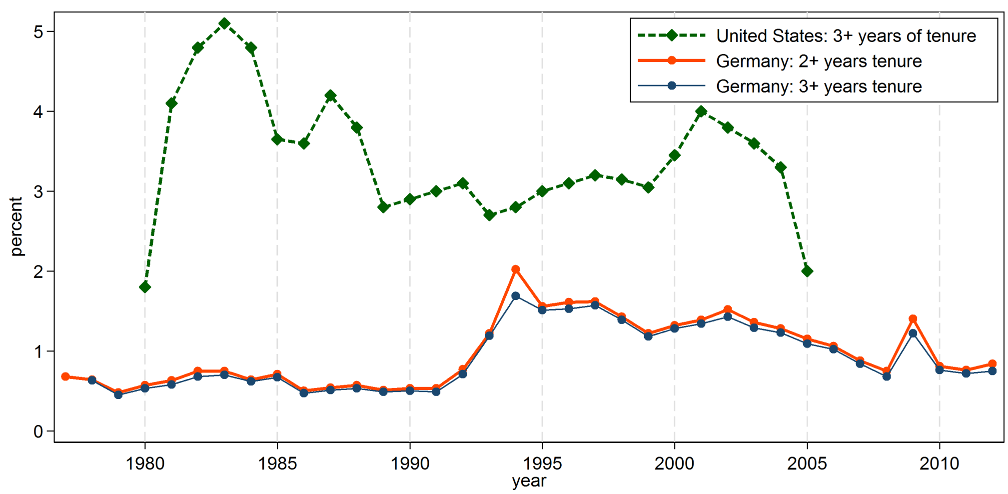
2.3 Job Displacement in Germany versus the United States

It is interesting to compare job displacements in Germany with that in the U.S. economy. In order to have comparable measures, the displacement rate for each year y is defined as the share of high tenured workers, employed in large establishments (those with more than 50 employees at year $y-2$) that experience job displacement in y, i.e.

$$\text{Displacement Rate}_y = \frac{\#\text{ of displacements in } y}{\#\text{ of high tenured workers in large establishments in } y}$$

Figure 2.2 depicts the displacement rate in the United States and in Germany over time. I used Davis and von Wachter (2012) data for the U.S. displacement rate and SIAB data for Germany's displacement rate. Davis and von Wachter identify high tenure workers as workers with at least three years of tenure at the establishment prior to mass layoff. However, throughout this paper I use two years as the threshold for job tenure in order to include more displaced workers in the sample, as the German economy is smaller than the U.S. economy. Therefore, in order to have comparable measures for the displaced rate in the U.S. and in Germany, one should use the same definitions. In figure 2.2 the German displacement rate is depicted using both criteria. While the two German rates follow each other, it is clear that the U.S. economy has systematically larger displacement rates. The reasons for this large difference can be a topic for further studies.

Figure 2.2: Displacement rate in the U.S. versus Germany



Notes: Displacement rate, defined as ratio of high tenured workers employed in large establishments who lose job in a mass layoff event, is depicted here for the US and Germany. Displacement rate in the US comes from Davis and von Wachter (2012). Displacement rate in Germany is based on my calculation from SIAB data. This graph shows systematically larger displacement rate in the US than in Germany.

CHAPTER 3
THE CONSEQUENCES OF JOB LOSS

In this chapter, first I present methods for measuring the consequences of job loss in recessions and expansions which is similar to the recent growing literature on the consequences of job loss, pioneered by Davis and von Wachter (2011) and followed by many others such as Jarosch (2016), Krolikowski (2017), and Sorenson (2017). Then I present findings consistent with the proposed mechanism for explaining the observed counter-cyclicality of earning loss: Earning loss (similarly wage loss) is higher if job loss happens during recession (or higher unemployment rate) than the case of job loss in expansion (or lower unemployment rate), because recessions are not only periods with more job loss but also periods in which sectors with poor performance relative to the mean are more frequent.

3.1 Measuring the Consequences of Job Loss

To estimate the consequences of job loss, I use the following empirical model similar to Davis and von Wachter (2011). The model is a distributed lag using yearly observations on labor market outcomes such as wages and earnings. I use the following regression as the main specification for measuring consequences of job displacement:

$$e^y_{it} = \alpha_i + \beta^y X^y_{it} + \gamma_t + \bar{e}^y_i \lambda_t + \sum_{k=-5}^{20} \delta^y_k D^k_{it} + u^y_{it} \tag{3.1}$$

Each $y \in (1977, 2012)$ fixes a displacement year as defined earlier. I restrict the sample to workers displaced in that year (treatment group) and non-displaced workers similar to the displaced workers (control group). I will explain how the control group is constructed later. I regress dependent variable, e^y_{it} (e.g. real earnings or wages of individual worker i in year t in 2001 Euros, deflated by the consumer price index), for all individuals i in years $t \in (y-5, y+20)$ on person fixed effects, α_i, and polynomial of degree 4 of age, X^y_{it}, year dummy variables, γ_t. In addition, as workers' education level may change over time, X_{it} include education level dummies. Furthermore, the model also allows for differential year effects, λ_t, depending on the worker's average earnings in the five years prior to displacement, $\bar{e}_i^y$.

Coefficients of interest are δ_k^y on the dummies D_{it}^y and are designed to measure the time path of the dependent variables from 5 years before and up to 20 years after the separation year, relative to baseline and relative to the change in earnings of the control group. The baseline consists of two years prior job displacement. Therefore, by construction $\delta_{-2} = 0$. Dummies D_{it}^k take 1 only if individual i is displaced in year y and $t = y + k$. In the 1985 displacement-year regression, for example, $D_{it}^2 = 1$ for $t = 1987$ and zero otherwise for a worker displaced during 1985. Using this specification, δ_k^y can be interpreted as the average earning loss of workers displaced in year y relative to the control group, k years after (or before) displacement.

I estimate equation 3.1 for all 36 years $y \in (1977, 2012)$ to create a panel of average effects of displacement from 5 years before to 20 years after for each displacement year. The weighted average of these effects over 36 years, measures the average effect of displacement on earnings. By splitting years y into two groups of years in which the German economy was in recession and in expansion, I can estimate the average effect of job displacement during years of recession and during years of expansion[1].

I use Organisation for Economic Co-operation and Development (OECD) based Recession Indicators for Germany, reported by the federal reserve bank of St. Louis [2], to identify months in which the German economy was in recession and expansion. To better study the effect of displacement, I have to compare the treatment group of displaced workers relative to a control group of similar workers. This gives the counterfactual interpretation of workers not being displaced. In the next section, I explain how I create a control group for displaced workers and then represent the consequences of job displacement relative to this control

1. More precisely, I construct the weighted average of those values for recession and expansion years as follows:

$$\bar{\delta}_k^{rec} = \frac{\sum_{y=1977}^{2012} I_{[rec]}(y) \times DW^y \times \delta_k^y}{\sum_{y=1977}^{2012} I_{[rec]}(y) \times DW^y}$$

where DW^y is the number of total displaced workers during year y and $I_{[rec]}(.)$ is number of months in year y that the German economy was in recession.

2. https://fred.stlouisfed.org/series/DEUREC

group.

3.1.1 Control Group

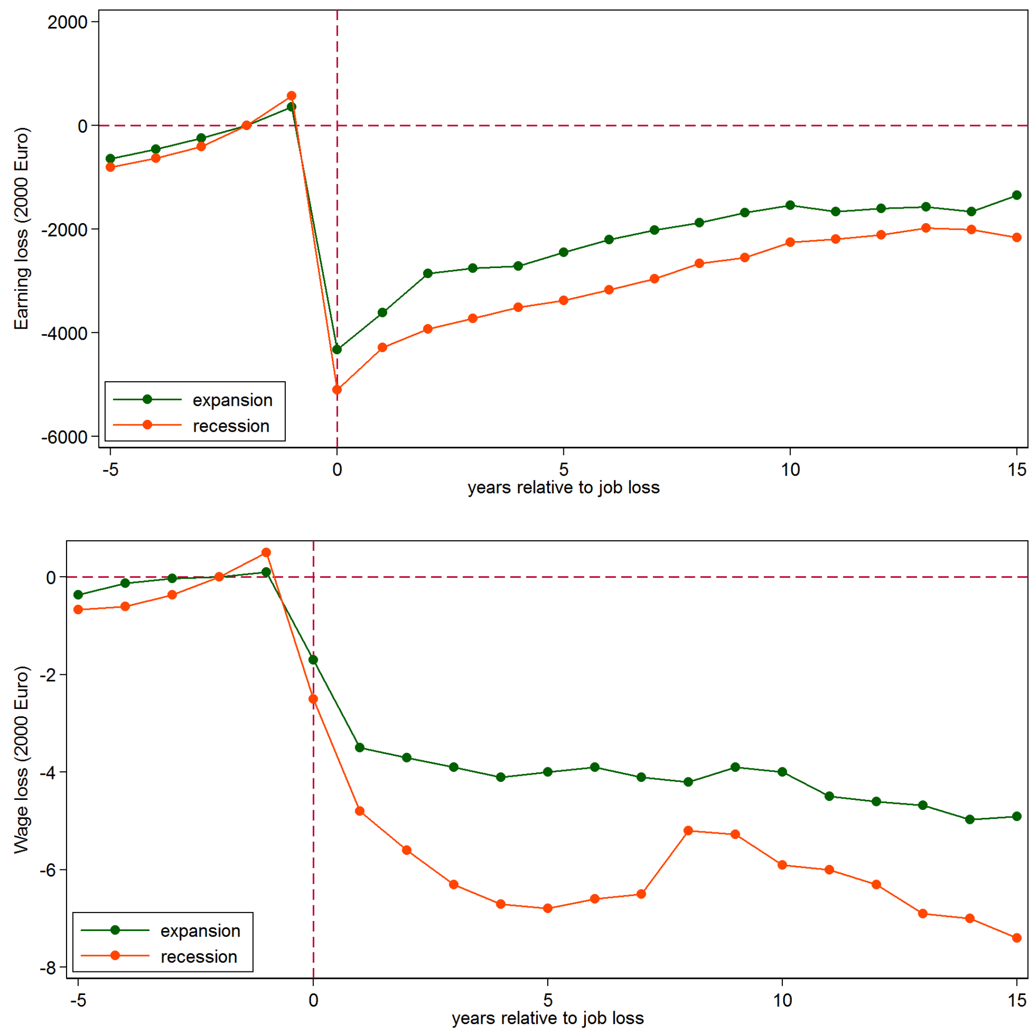
For each regression year y, the treatment group consists of all workers displaced at year y, who are defined earlier by year y separation of long-tenured workers due to a mass layoff event during year y. To create a control group for these workers I select workers in SIAB with the following properties:

1. being employed in a large establishment (with more than 30 employees) during year y,
2. older than 20 and younger than 50 years of age in year y,
3. having at least two years of job tenure at their current establishment prior to year y,
4. staying in the establishment for the next 2 years, to exclude any non-mass layoff separators.

Figure 3.1 depicts the consequences of job displacement on earnings and wages of displaced workers, relative to the earnings and wages of the control group. All earning and wages used in this paper are deflated by the consumer price index to reflect real 2001 Euros. Year-t earnings are calculated by summation over earnings of all full-time jobs of the worker during year t. Wages are the average reported daily wages of the individual worker in any full-time job in year t wighted by days at each job. Once workers do not have a full-time job, I consider it as zero earning and not available information for wages. For instance, in the displacement regression of year y, if a worker was employed in January of year t for 20 days with wage w_{it}^{Jan}, then separated by the end of January and found another full-time job in December of year t in which 15 days are worked with daily wage of w_{it}^{Dec}, then his total earnings is calculated by $e_{it}^{y} = 20 \times w_{it}^{Jan} + 15 \times w_{it}^{Dec}$ and his daily wage is $w_{it}^{y} = \frac{e_{it}^{y}}{20+15}$ Therefore, it is more precise to call w_{it}^{y} and e_{it}^{y} as the average daily earnings of worker i in year t and total full-time earnings for that worker, respectively. However, for simplicity, I refer to them as daily wages or even more simply the wages and earnings of worker i, throughout this paper. For more detail on the calculation of daily wages and earnings read the Data Appendix A.

Two main facts are clear from this graph: 1) Both wages and earnings of displaced workers drop on the incidence of job loss and never catch up even after 20 years; and 2) If job displacement takes place in recession, both wage-loss and earning-loss are higher than those in the case of displacement during expansion. These two findings are consistent with findings of Davis and von Wachter (2012) who used U.S. data to measure consequences of job displacement. Therefore, it seems that these empirical findings are robust across different times and across countries.

Figure 3.1: Effect of displacement relative to the counterfactual of not separation



Notes: These figures plot the mean effect of displacement relative to the counterfactual of not being displaced using non-separators similar to the control group. For detail on selection of the control group and calculation of the average effects refer to section 3.1. All these graphs are the author's calculations using the German SIAB data made available by the German Federal Employment Agency's research institute, IAB. In each panel the curve labeled *In recession* shows the average outcome for workers displaced in recession years from 1977 to 2012, and the curve labeled *In expansion* shows average for those displaced in expansion years. Business cycle indicators are derived from OECD-based recession indicators from the period following the peak through the trough. Displaced workers are workers with at least two years of job tenure, separated in a mass layoff event. The top panel depicts annual earning loss from 5 years before until 20 years after displacement, including zeros for non-employed workers. The bottom panel shows the average wage loss associated with job displacement. The average is over the daily wages of only employed workers, hence it excludes zeros. Earning and daily wage loss is reported in 2001 Euro, deflated by the consumer price index.

Moreover, these two figures present another important fact: earnings of displaced workers may start recovering at least after a few years, but average wage loss remains forever and never recovers. Notice that if days at a full-time job total zero for a worker during a year t, then year-t earnings are simply zero while wages are missing, therefore dropped. This explains the difference between the trends we see in earnings and wage loss of displaced workers in figure 3.1. While earning sharply drops to its lowest level at $k = 0$, and starts to recover from $k = 1$, average wages only partially drop at $k = 0$ and drop even more in the proceeding years. The reason is that wages in the displacement year y in which $k = 0$, are the average over wages of any jobs before and after displacement in year y. For instance if a worker displaced in June and remains jobless to the end of calendar year y, their average wage would be their pre-displacement wage only. Moreover conditioned on finding a full job earlier after separation, average wages are higher than conditioned on finding job in later years. In other words, the information used to calculate δ_k at $k = 0$ in the top panel includes earnings of all workers but in the bottom panel it summarizes both the wages of displaced workers who find jobs in the same year of separation and the wages of all displaced workers before separation.

The main purpose of this paper is to provide explanations for these observed losses in earning and wages of displaced workers and the gap between recession and expansion. It is worthwhile, however, to study how some groups differ in their wage and earning losses post-job displacement. In the next chapter, wage and earning losses of different groups of workers are documented.

3.2 Earning and Wage Losses of Different Groups

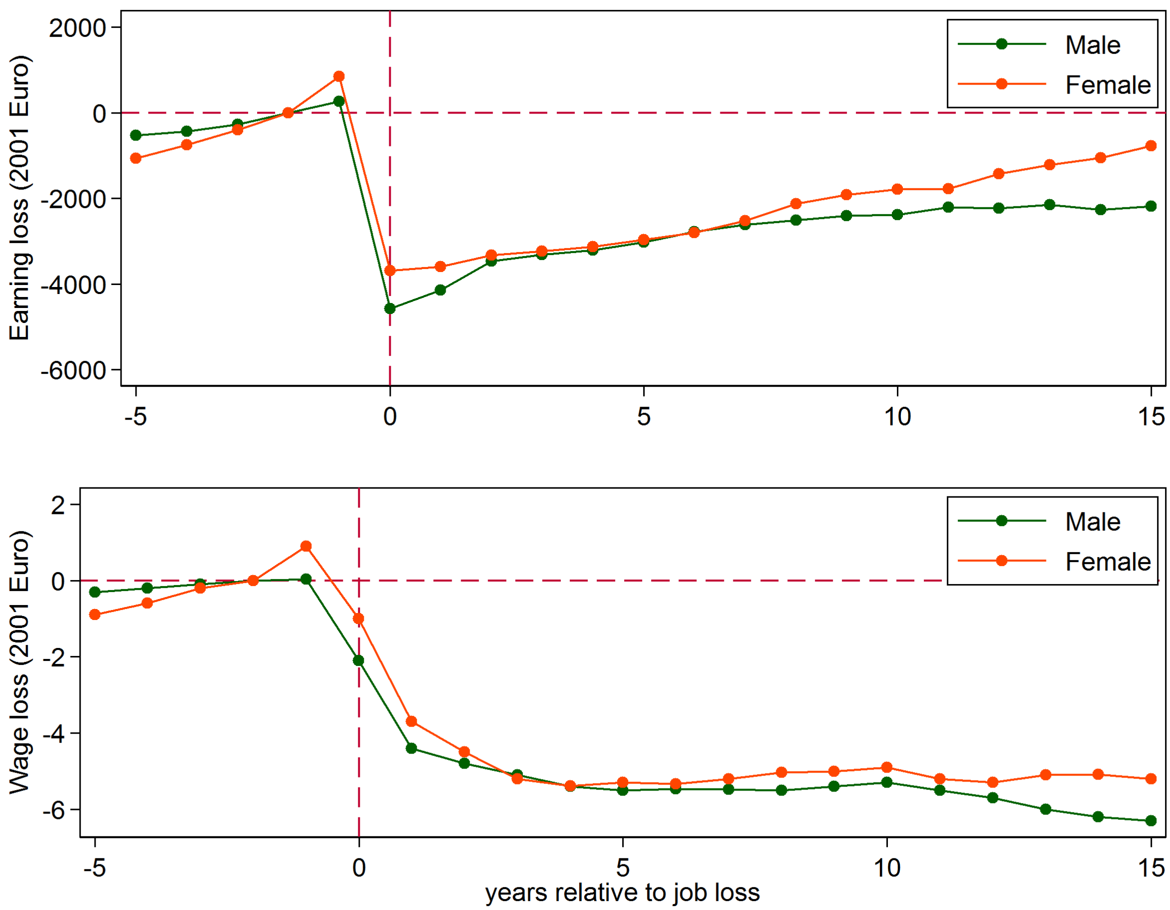
To better understand the consequences of job displacement, I reestimate equation 3.1 not only for earnings as the dependent variable but also for wages as the left-hand side variable. It is important to recall that earnings is derived from summation over earnings of all full-time jobs and wages are actually average daily earnings of the employed workers. The main shortcoming of SIAB data is that hours of work are not reported and it is assumed that daily wage is fixed for all days within any employment spell. Therefore, I use the weighted average of the employed workers' daily earnings as their daily wage. More detail about data is available in the appendix.

In the next subsections, earning and wage loss for different subgroups of the whole sample are estimated using equation 3.1 while e_{it}^{y} and w_{it}^{y} are used as the dependent variable, respectively.

3.2.1 Job Loss by Gender

To compare effects of job loss between male and female workers, I split the sample between all male and all female groups. Notice that as gender does not have any variation within each workers, we can not identify gender effect once we have individual fixed effects in the panel regression of equation 3.1. I choose to include individual fixed effects in the main specifications as there ought to be more unobservable information in these fixed effects rather than in the gender variable. Figure 3.2 depicts earning and wage loss associated with job displacement for male and female workers. I do not find a gender gap on earning and wage loss after job displacement. However, it is important to interpret this finding not as a rejection of a gender gap in their earnings. After comparing earnings and wages of male displaced workers with other male workers, and juxtaposing to the comparison of earnings and wages of female displaced workers to other female workers, I find almost similar wage and earning loss. This finding rejects the hypothesis that gender explains the level of earning and wage loss after job displacement. On average, both male and female workers suffer from job displacement at the same level.

Figure 3.2: Consequences of displacement for males and females



Notes: The top panel depicts average earning loss of displaced workers after job loss in a mass layoff event, relative to the control group of non-displaced workers. Notice that by construction, displaced workers have at least two years of job tenure before separation. The bottom panel shows wage loss of displaced workers after job loss in a mass layoff event, relative to the control group of non-displaced workers.

3.2.2 Education and Vocational Training

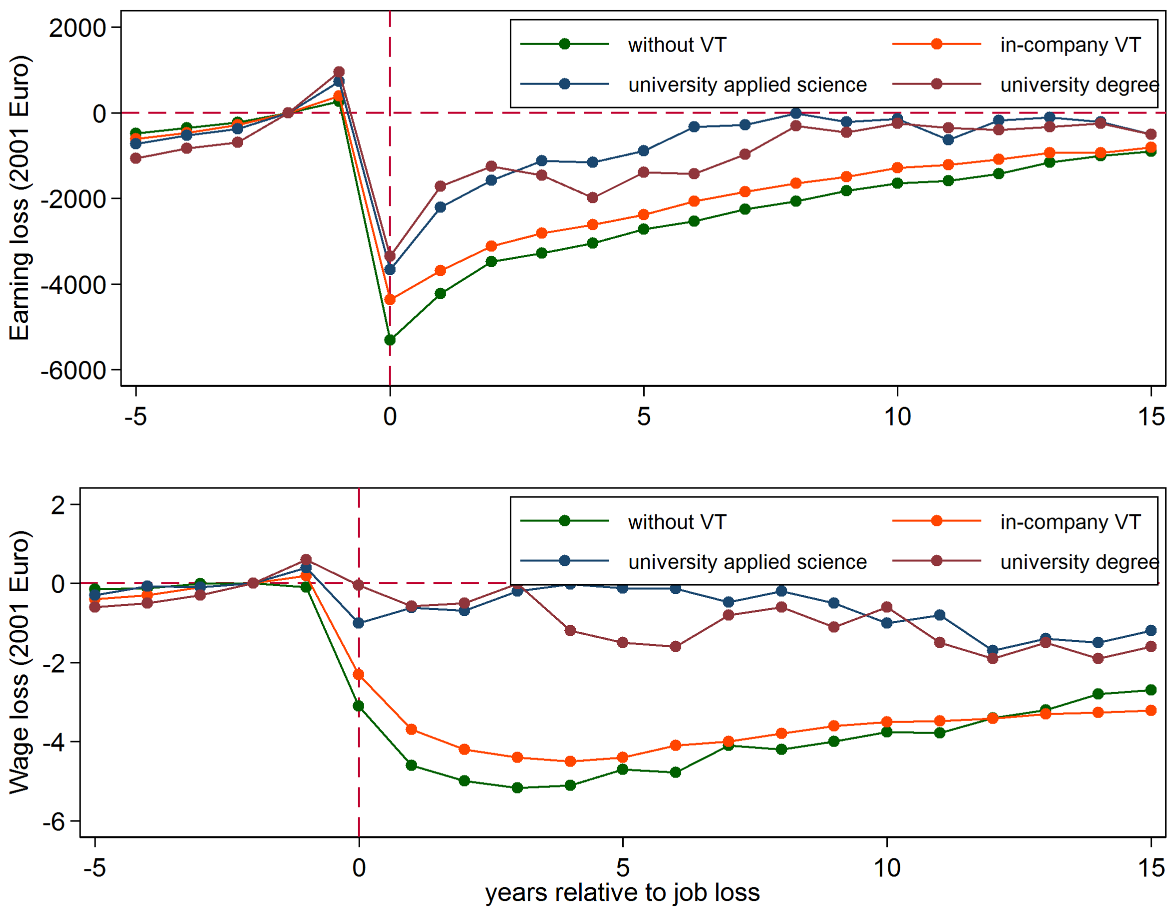
It is also interesting to see how earning and wage loss of displaced workers differ by education level and type of vocational training. In order to assess this, workers are grouped based on their education and level of vocational training at the time of displacement and are compare to the control group similar to them at the year of displacement[3].

Figure 3.3 depicts the consequences of job displacement for each of the four groups of vocational training. The most striking fact is that the group with highest wage and earning drop are workers with in-company vocational training or no training at all. And workers with university degree very slightly suffer from the job loss. This finding supports the idea of Becker (1962) that emphasizes the importance of specific human capital and the role of on-the-job training on future decision of firms and workers. In-company training is by far the most specific human capital and switching the establishment causes more harm to the workers. In contrast, workers with university degrees are less affected by job loss as they acquired more general human capital and are more flexible between other jobs. It is worth emphasizing that there is not endogeneity here as it may in general be the case. Since ability and other unobservables may affect a worker's choice of vocational training, the estimated effect of vocational training on outcome variables may be biased. However, in this exercise, I'm comparing workers with similar levels of vocational training. For instance, I compare workers with no vocational training who were displaced in year y with similar workers without vocational training but employed at year y in large establishments. I then calculate average wage and earning loss using equation 3.1 and present the results for different levels of vocational training in figure 3.3.

Another important fact is that workers with a university degree, either science or applied, on average experience almost no wage loss provided they are employed. However, their earnings drop due to periods of joblessness. In other words, conditioned on being employed, their earning is almost at the same level of not displaced workers. The fact that skills learned in college are very general and cause to increase in productivity in many different industries and occupations, suggests that workers with relatively higher general human capital experience almost no wage loss and very limited earning loss. This evidence is in support of the idea of this paper that emphasizes the role of sector-specific human capital on the observed earning and wage loss of displaced workers.

3. In the new version of SIAB data that covers 1975–2014, education and vocational training comes in separate variables for each worker.

Figure 3.3: Consequences of displacement with different levels of vocational training

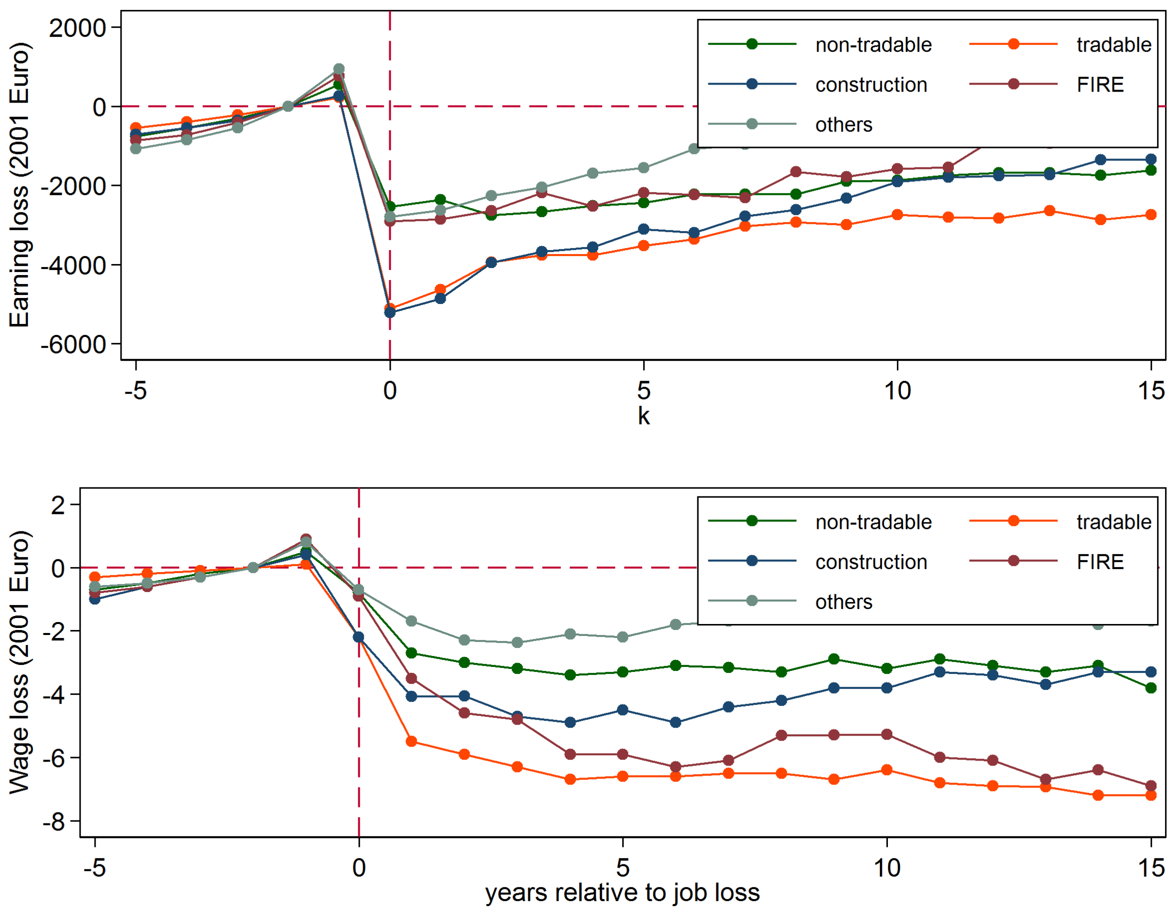


Notes: The top panel depicts the average earning loss of workers displaced with different categories of vocational training. The bottom panel shows wage loss for the same groups.

3.2.3 Industry

Another important factor for displaced workers is the industry from which they experienced a mass layoff event. If they have a long attachment to a specific industry, and if that industry has required them to develop more sector-specific human capital, they would lose more wages and earnings in an incident of job displacement. The less specific the skills required in the sector, the less we expect to see earning loss associated with displacement from that sector. I study this hypothesis by estimating earning and wage loss of workers displaced from each of the five sectors of the German economy using the regression framework of equation 3.1. These sectors are: 1) non-tradable such as service, fishing, and so forth; 2) tradable sectors that include all manufacturing and mining; 3) construction, both residential and commercial; 4) finance, insurance and real state (FIRE); and 5) others. Figure 3.4 represents earning and wage loss of displaced workers from these sectors. As we expected, the most earning and wage loss is associated with the workers displaced from manufacturing sectors in which they have acquired more sector-specific skills. In contrast, construction workers are harmed less by the mass layoff event. Again, it is important to emphasize that for each sector, I compare workers displaced from the sector with the control group consists of workers employed in the same sector at the time of displacement.

Figure 3.4: Consequences of displacement from different sectors

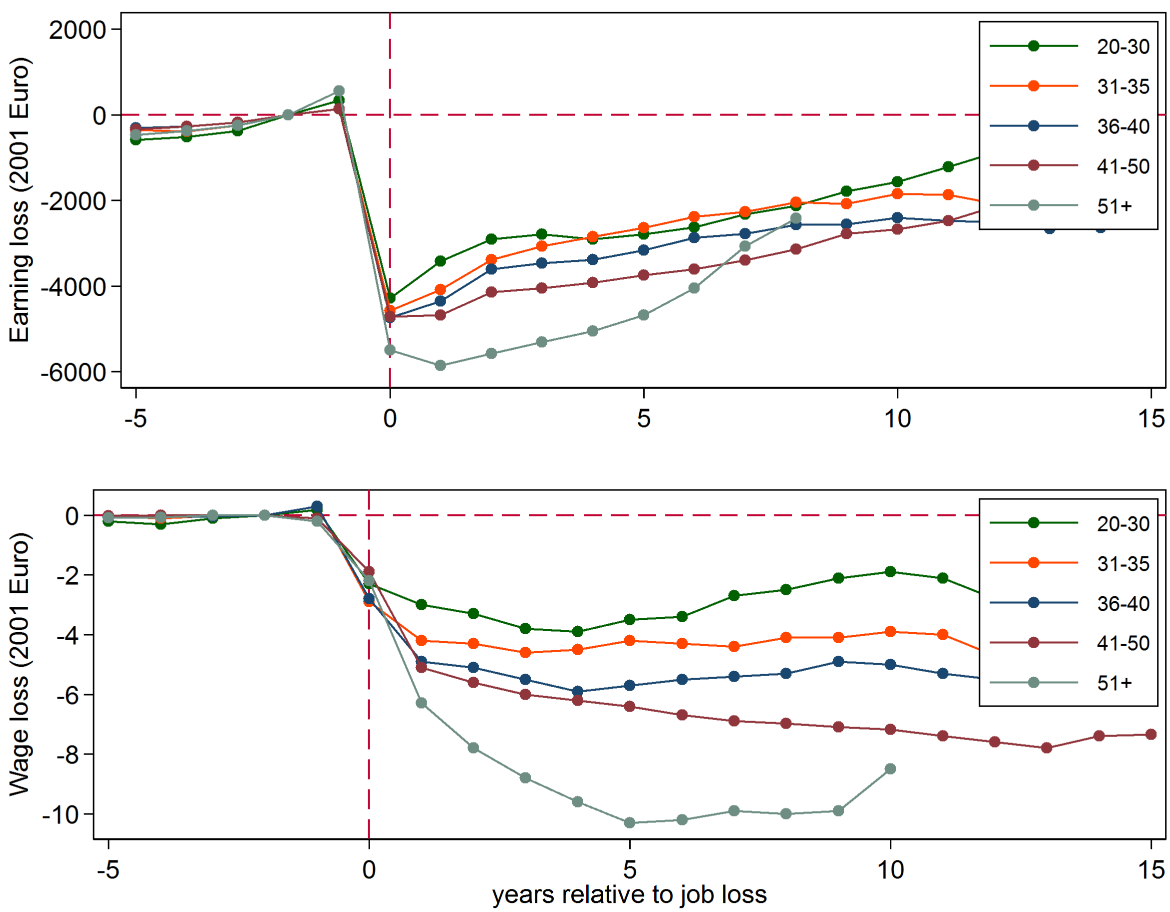


Notes: The top panel depicts average earning loss of workers displaced in the following different industries: 1) non-tradable such as service, fishing, etc; 2) tradable sectors that include all manufacturing; 3) construction, both residential and commercial; 4) finance, insurance and real state (FIRE); and 5) others. The bottom panel shows wage loss of the same groups of displaced workers.

3.2.4 Age of Displacement

Younger workers experience less earning and wage loss in both the short and long run. The theoretical analysis in the next chapter suggests that this finding can also be explained by a combination of general and sector-specific human capital. Figure 3.5 depicts earning and wage loss of displaced workers. Two features of this analysis are worth noting. First, as it was expected younger workers experience less earning and wage loss, both in the short run and long run. Second, wages of older workers largely drop after mass layoff. For instance workers displaced at ages older than 51, after 5 years, experience 25.9 (=39.25-13.37) percentage points larger wage loss than younger workers in their 20s.

Figure 3.5: Consequences of displacement at different ages



Notes: The top panel depicts average earning loss of workers displaced at different ages: 1) younger workers aged 20-30, 2) 30-35, 3) 41-50, and 4) older than 51. The bottom panel shows wage loss of the same groups of displaced workers.

This finding is consistent with other findings such as Topel (1990) that older workers are less mobile both between sectors and across regions which can explain the observed larger wage loss. This can also be explained by the theory of general and specific human capital. As the older workers have relatively more sector-specific human capital than young workers graduated from high school, they are less mobile between sectors and experience more earning and wage loss after displacement.

3.3 Length of Non-Employment and Switchers versus Stayers

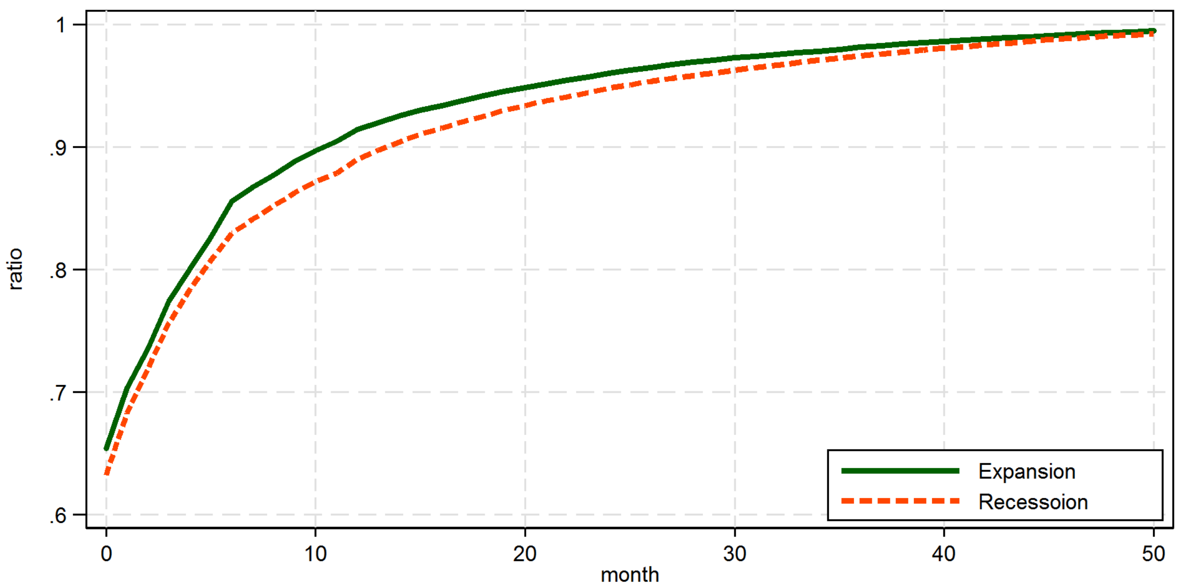
Two important labor market outcomes are *duration of unemployment* and *ratio of workers switching* their industry and occupation after job loss. Economic analysis in chapter 4 suggests that longer periods of joblessness causes more depreciation of human capital. Switching sector can lead to decline in sector-specific human capital. Furthermore, by construction, earning is a byproduct of wages and duration of employment. Switching industry and occupation affects earnings through wages. Therefore, in order to shed light for the reasons of the counter-cyclicality of earning-loss, it is necessary to investigate the impact of aggregate and industry-wide economic performances on the duration of joblessness and the ratio of switchers after displacement. To do so, I follow two exercises. First I estimate job finding hazard rate for displaced workers. Then I study cumulative duration of joblessness and ratio of switchers.

3.3.1 Hazard Rate of Finding Job

First, length of joblessness for displaced workers is estimated non-parametrically then following Gibbons and Katz (1991) a Weibull proportional hazard model is used to analyze the effect of economic performance on the duration of joblessness. The main goal here is to assess to what extent characteristics of workers as well as demand shocks are correlated with the duration of their unemployment after job loss in a mass layoff event.

To estimate the length of joblessness non-parametrically, I calculate the share of displaced workers that find full-time employment m month after the mass layoff for each $0 \leq m \leq 60$. I then draw the cumulative length of joblessness in figure 3.6 for workers displaced in recessions and expansions. First note that displacement in recessions is on average associated with longer duration of joblessness, but the difference is very minuscule and for many months is statistically insignificant. Second, note that 62% and 65% of workers displaced in recession and expansion find a job in the same month of job loss respectively. This number is large when compared to the rate of workers in general who have lost jobs and seek new employment, but the fact is that these are long-tenured workers who have been displaced due to demand shock from a mass layoff event. Although this ratio is conditional on finding full-time job within 5 years post-displacement, the unconditional rate is almost identical.[4]

Figure 3.6: Length of joblessness for displaced workers



Notes: Conditional on finding a job within 60 months post job displacement, the cumulative ratio of workers who find full-time jobs is calculated from SIAB. The green solid line represents job losses during expansions and the red dashed line represents job losses during recessions.

Notice that figure 3.6 presents an important evidence that non-employment duration after job loss can not be the main source of the counter-cyclicality of earning loss. For instance, workers with zero years of joblessness have almost very short and similar periods of joblessness. However, those displaced during recessions experience 47% more wage loss. For this group that makes almost 73% of all displaced workers, length of joblessness is the same but wage loss is different. Therefore, longer periods of joblessness could not be the main reason for larger earning and wage loss in recessions and expansions.

4. The reason that I conditioned rates to those workers who find job within 60 months is the data disclosure rules by IAB, as the number of displaced workers with more than 60 months of joblessness for many months become less than 20. IAB requires that each statistics be aggregated for more than 20 individuals.

I follow Gibbons and Katz (1991) by using a Weibull proportional hazard model to analyze duration of the first spell of joblessness for displaced workers. The hazard for individual i can be specified as $\lambda_i(t) = \mu_i \lambda_0(t)$ where $\lambda_0(t)$ is the baseline hazard. Thus the hazard for each individual has the same shape over time, but is shifted up or down proportionally by the covariates X_i. Moreover, I assume the individual level is specified as an exponential regression function for convenience $\mu_i = e^{X_i' \beta}$. Therefore,

$$\lambda_i(t) = \mu_i \lambda_0(t) = \gamma t^{\gamma - 1} e^{X_i' \beta} \tag{3.2}$$

where (γ, β) are parameters to be estimated. The nice aspect of the Weibull model is that the expected value of the log duration is linear, so that if T_i represents the duration of unemployment for individual i,

$$\frac{\partial E(\log(T_i))}{\partial X_i} = -\frac{\beta}{\gamma}$$

If γ, the shape parameter, is less than one then hazard rate is decreasing over time, which is shown to be the case for displaced workers. This means that the longer is the duration of joblessness, the lower is the chance of finding a full-time job.

Table 3.1 reports estimates of proportional hazard model with different covariates. Exponential coefficients as well as the t-statistics are reported in parentheses. For instance, the first column reports the hazard rate model once the only covariate is a dummy for recession at the month of job loss. The estimated parameter of 0.941 states that, on average, workers displaced in recessions have six percent lower hazard rate than workers displaced in expansions. Columns 2 and 3 report the effect of high and low unemployment and GDP growth rate. These results state that, on average, displacement during high unemployment and low GDP growth are associated with 8.4 and 8.3% lower hazard of finding employment after job loss. Then in column 4, the same proportional hazard model is estimated once the covariates include gender, location, age, level of vocational training, and industry categorical dummy variables. The results are very interesting. For instance, female workers, on average have a 30 percent lower hazard rate. This can explain, at least partially, the observed gender gap as the longer periods of joblessness can depreciate more of their human capital. I should also note that workers in east Germany and Berlin have 23.3% and 7.5% higher rates of finding jobs than workers in east Germany.

Moreover, older workers, equipped with more general and specific human capital, have much higher hazard rate s for finding a job. For instance, workers displaced at the age of 40–45 have on average 35.8% higher hazard rate. Additionally, workers with university degrees, either applied or scientific, are more likely to find jobs faster than workers with no or limited training. Columns 5 and 6 study to what extent the effect of recessions is important once we include the GDP growth rate and the unemployment rate, as well as the covariates. This finding suggests that while still recessions are important but the effect is merely 2%.

3.3.2 Cumulative Length of Joblessness and Ratio of Switchers

In this section I estimate equation 3.1 while taking the cumulative duration of unemployment and ratio of switchers as the dependent left-hand side variable, separately. Then I compute the weighted average of the δ coefficients as before. The result could be interpreted as an average longer period of unemployment and higher rate of switchers relative to the counterfactual of not being displaced.

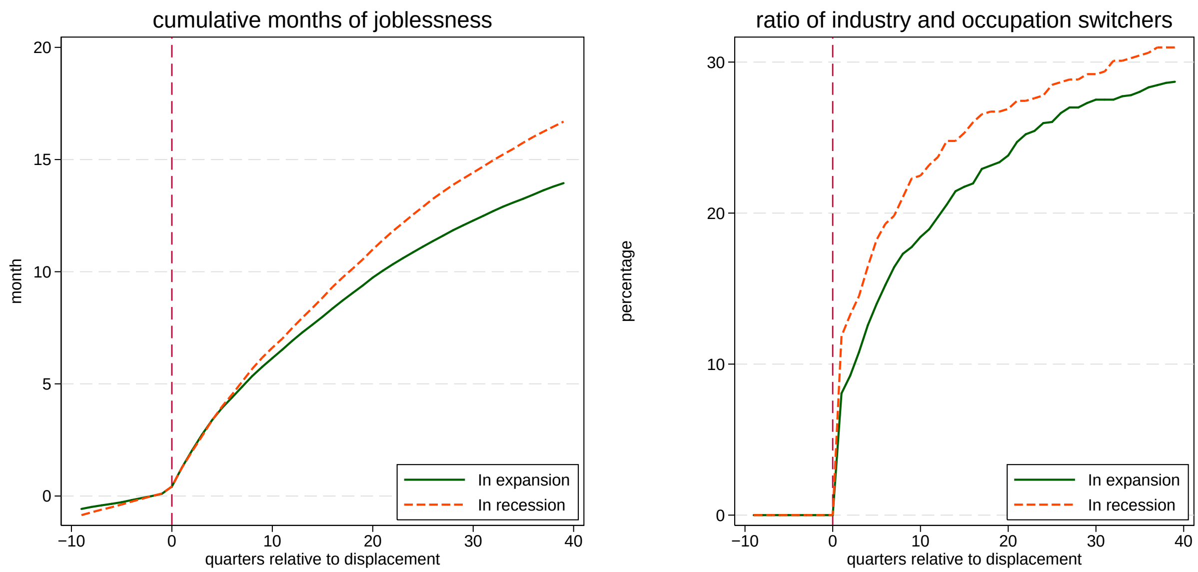
The cumulative months of joblessness are closely related to the hazard model that already studied so we expect similar results. Figure 3.7 depicts these effects. The left panel compares cumulative months of joblessness for displaced workers in recessions and expansion with the counterfactual of not being displaced. At least in the short run, this figure does not show much difference between joblessness in recessions and expansion. This is another evidence that at least in the short run, a longer duration of joblessness can not be the main reason for larger earning loss associated with displacements in recessions. However, the right panel depicts a clear difference between the ratio of switchers both in the short and long run. These findings, together with the fact that earning and wage loss of switchers are larger, suggest that the main reason for larger earning loss associated with job loss during recessions is due to devaluation of sector-specific skills in response to relatively worse industry-wide economic conditions rather than longer periods of unemployment due to the aggregate economic contraction.

Table 3.1: Hazard rate of finding a job for displaced workers

	proportional hazard rate model: $\lambda_i(t) = \gamma t^{\gamma-1} e^{X_i'\beta}$					
	(1)	(2)	(3)	(4)	(5)	(6)
recession	0.941***			0.944***	0.979***	0.963***
	(10.72)			(-9.70)	(-4.18)	(-6.33)
high UR		0.916***			0.913***	0.911***
		(-11.57)			(-10.68)	(-12.30)
high GDP growth			1.083***		1.074***	1.051***
			(10.49)		(7.32)	(5.41)
female				0.699***	0.697***	
				(-38.21)	(-38.41)	
East				1.000	1.000	
				(.)	(.)	
West				1.233***	1.190*	
				(18.54)	(14.73)	
Berlin				1.075***	1.051***	
				(3.51)	(2.42)	
aged 20-30 years				1.000	1.000	
				(.)	(.)	
aged 31-35 years				1.184***	1.198***	
				(12.43)	(13.27)	
aged 36-40 years				1.250***	1.267***	
				(16.53)	(17.45)	
aged 41-50 years				1.358***	1.373***	
				(26.45)	(27.36)	
aged 50+ years				1.512***	1.524***	
				(31.60)	(32.18)	
without VT				1.000	1.000	
				(.)	(.)	
in company VT				1.202***	1.209***	
				(17.13)	(17.59)	
university applied science				1.000	1.000	
				(13.69)	(14.15)	
university degree				1.315***	1.326***	
				(14.00)	(14.42)	
non-tradable				1.000	1.000	
				(.)	(.)	
tradable				0.972*	0.975*	
				(-2.27)	(-2.4)	
construction				0.889***	0.891***	
				(-7.36)	(-7.22)	
FIRE				1.110***	1.120***	
				(4.39)	(4.79)	
others				1.063***	1.072***	
				(4.58)	(5.19)	
Observations	69,878	69,878	69,878	62,498	62,498	69,878

Notes: This table reports estimated coefficients of a proportional hazard rate model for duration of joblessness for workers after their job displacement. Exponential coefficients are reported and t-statistics are in parentheses. $^*(p < 0.05)$, ** $(p < 0.01)$, *** $(p < 0.001)$

Figure 3.7: Displacement impact on duration of unemployment and likelihood of switching occupation/industry



Notes: The left panel depicts average cumulative months of joblessness for displaced workers after separation, relative to the control group of non-displaced workers. Notice that by construction, displaced workers have at least two years of job tenure before separation.
The right panel shows the fraction of industry and occupation switchers after job displacement. Industry is defined as: 1) tradable; 2) non-tradable; 3) construction; 4) finance, insurance and real estate; and 5) others. It can be shown that if switchers for 1, 2, and 3 digit NACE classification are studied, the pattern would be similar but, as expected, there would be more workers switching at 3-digit level rather than 1-digit level of industry classification.

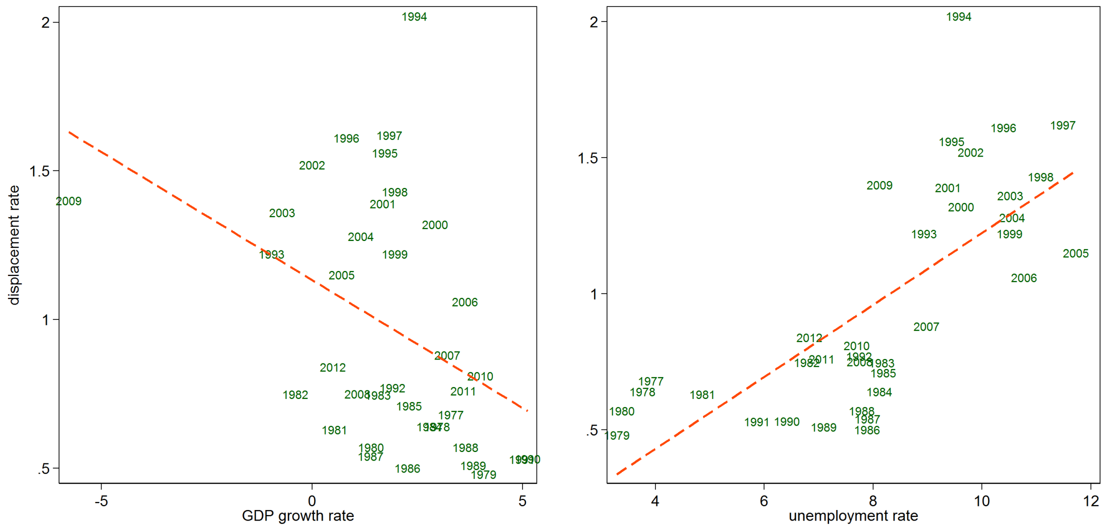
All measures of the consequences of job loss, studied so far, depict a larger negative effect for displacements which took place in recessions. Therefore, it is crucial to study how aggregate conditions affects the outcome of job loss. This will be the topic of the next subsection.

3.4 Aggregate Economy and the Effects of Job Displacement

Following Davis and von Wachter (2012) part of the literature on the consequences of displacement is concentrated on recessions and expansions. In previous chapters I have compared job losses during recessions with those in expansions and find similar results to Davis and von Wachter (2012). In this section, I use a similar empirical framework to show how the aggregate economy at the time of job loss is crucial to the consequences of the job displacement. I use two other measures of aggregate economy, real GDP growth rate and the unemployment rate. First I show that job displacement is more frequent during economic downturns. Then by splitting the data between four quartiles of annual output growth rate and four quartiles of unemployment rates, I compare the estimated earning and wage loss of displaced workers in the top and bottom quartiles. The main goal of this exercise is to show that economic downturns, which could be measured by real GDP growth rate or unemployment rate or recession and expansion, are not only periods of more job loss, but also periods of job loss with larger earning and wage loss.

First step is to show how number of displacements vary over business cycles. Figure 3.8 depicts the displacement rate, defined earlier as the ratio of long-tenure workers separated in a mass layoff events, for each year of 1977–2012, versus its real GDP growth rate and unemployment rate. Negative correlation between real GDP growth rate and displacement rate depicted in the left panel documents the higher likelihood of displacement during economic downturns. The right panel presents positive correlation between unemployment rates and the displacement rate which is consistent with the negative correlation in the left panel. This finding is robust if one modifies the way that I identified displaced workers. For instance if one uses three years as thejob tenure requirement for long-tenured workers instead of two years, results are similar.

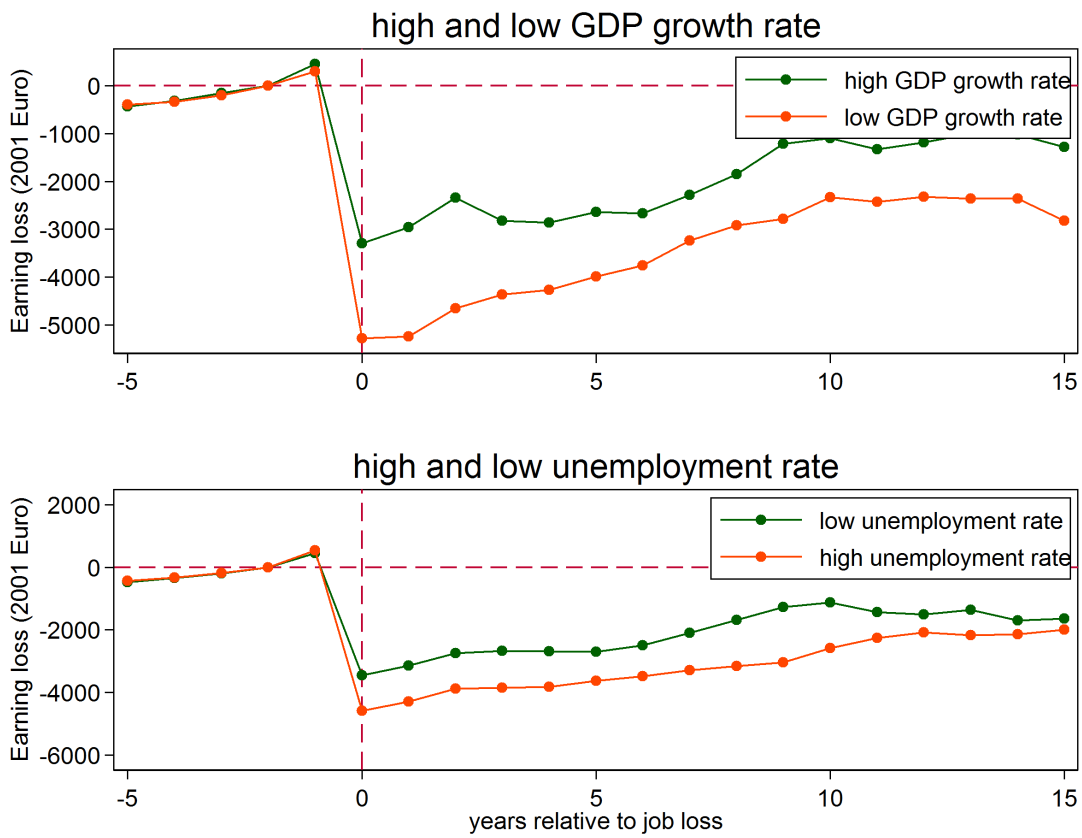
Figure 3.8: Displacement rate and aggregate economy



Notes: The left panel depicts the displacement rate versus the real GDP growth rate of Germany for 1977-2012. Displacement rate is defined as the number of displacements in each year over the number of high tenured workers employed in large establishments. The right panel presents the positive correlation between unemployment rate and displacement rate.

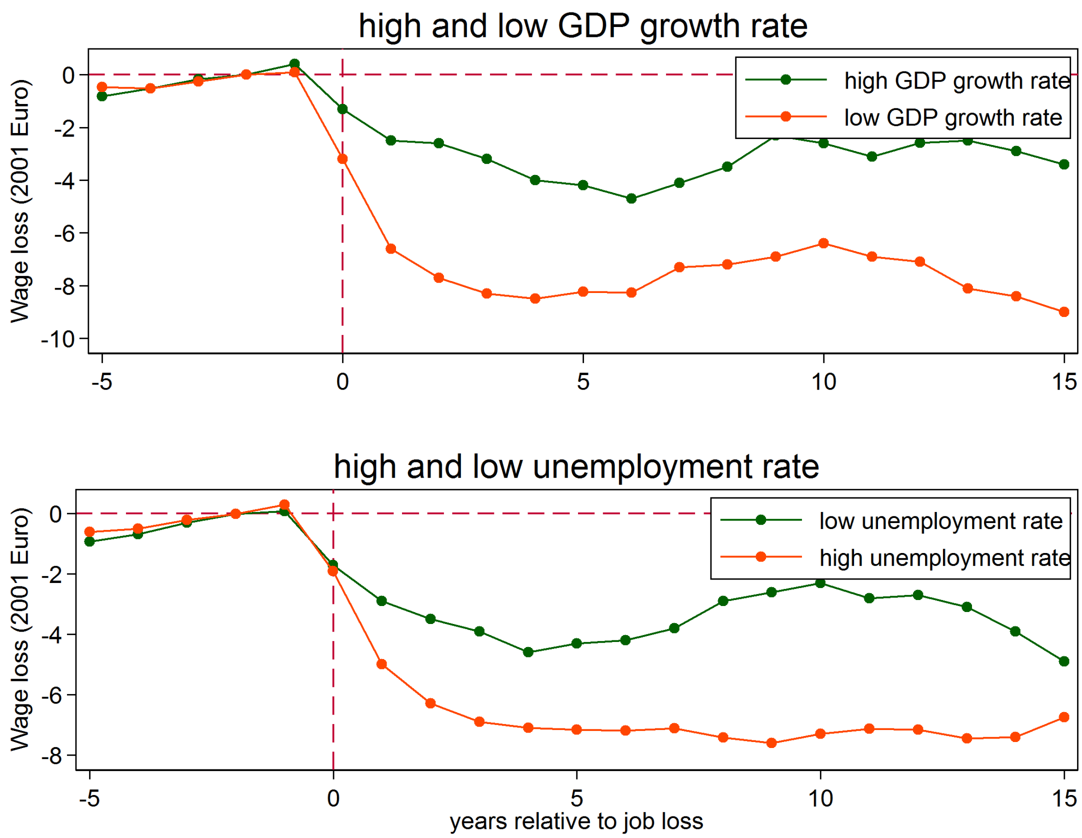
Additionally, I split the sample of displaced workers based on year of displacement into four quartiles in terms of real GDP growth rate and another set of four quartiles for unemployment rate to estimate average earning loss associated with job displacement for each quartile. In figures 3.9 and 3.10 I show these estimates and depict the fact that economic downturns are not only periods in which there are more job losses, but also periods in which job loss has a more severe effect on both short-term and long-term earnings of displaced workers as well as their wages. These findings are consistent with my earlier findings as well as Davis and von Wachter (2012) that document different earning losses for job displacements in recession and expansion using U.S. data.

Figure 3.9: Earning loss of workers displaced in years with high versus low GDP growth rate



Notes: Average earning loss of displaced workers are estimated by equation 3.1 for top and bottom quartiles of GDP growth rates. Years from 1977 to 2012 are grouped into 4 quartiles based on the real GDP growth rate (for the top panel) and unemployment rate (for the bottom panel). Then earning and wage loss of workers in top an bottom quartile are studied.

Figure 3.10: Wage loss of workers displaced in years with high versus low GDP growth rate



Notes: Average wage loss of displaced workers are estimated by equation 3.1 for top and bottom quartiles of GDP growth rates. Years from 1977 to 2012 are grouped into 4 quartiles based on the real GDP growth rate (for the top panel) and unemployment rate (for the bottom panel). Then earning and wage loss of workers in top an bottom quartile are studied.

3.5 Relative Sectoral Performance and Job Displacement

In the previous section, I measured the consequences of job displacement and re-established the fact that job displacement is more disastrous if it happens during recession or in general if it happens during aggregate economic downturns. In this section, I want to study whether and to what extent consequences of job displacement depends on the performance of the sector at the time of job loss. The main idea, corroborated by a theoretical framework of sectoral human capital, is that if demand for sectoral skill declines, earning loss associated with job loss would be larger since those specific skills would become less valuable. In this view, the main reason that aggregate poor economic performance, such as recession versus expansion, exacerbates earning and wage loss of displaced workers is that those are times with more frequent poor sectoral performance too. Hence, if this view is correct, then we expect that the aggregate economy would be less crucial in determining the consequences of job less once we control for sectoral performance.

In order to study this hypothesis, first I need to measure sectoral performance. So, I build a few measures for relative sectoral performance based on job creation, job destruction, and net job growth rate of each sector for a three-year time frame that includes the year of displacement. Then, using these measures, I study variation of job loss across sectors to measure how relative sectoral performance is correlated with earning loss of displaced workers.

3.5.1 Quantifying Sectoral Performance

To measure performance of each sector j at each year y I follow Davis and Haltiwanger (1999) measures for size, job creation, job destruction, and net growth rate with a little modification to measure sectoral performance for a longer period, such as three, four or five years. This choice of a longer time window is to make sure that we capture sectoral trends not transitory sectoral shocks. For the rest of this paper, I use a three-year window to measure sectoral performances, while results are robust if one uses other three- or five-year windows instead.

Lets define gross job creation at year y as employment gains summed over all establishments that expand or start up between year $y-2$ and $y+1$.

$$C_{jy} = \sum_{e \in S^+_{jy}} Emp_{e,y+1} - Emp_{e,y-2}$$

where the sum is over all establishments e in sector j that have employment level at $y+1$ which is more than their employment at $y-2$, i.e. $e \in S^+_{jy}$. Similarly, let's define gross job destruction at year y as employment losses summed over all establishments that contract or shut down between year $y-2$ and $y+1$:

$$D_{jy} = \sum_{e \in S^-_{jy}} |Emp_{e,y+1} - Emp_{e,y-2}|$$

where S^-_{jy} includes all establishments in sector j with less employment in $y+1$ than $y-2$.

To express the job flow measures as rates, I divide by a measure of size. Sectoral size is measured by a modified version of Davis and Haltiwanger (1999) to match the three-year window. Define year-y size of an industry j as the simple average of its employment in $y-2$ and $y+1$: $Z_{jy} = 0.5(EMP_{jy+1} + EMP_{jy-2})$, where $EMP_{jt} = \sum_{e \in S_{jt}} Emp_{et}$ and S_{jt} include all establishments in sector j and year t. In terms of this notation, year-y growth rate of sector j can be written as

$$g_{jy} = \frac{EMP_{jy+1} - EMP_{jy-2}}{Z_{jy}}$$

As mentioned in Davis and Haltiwanger, these growth rate measures lie in the closed interval $[-2, 2]$, are symmetric around zero and with endpoints corresponding to exit and entry. Then the job creation rate and job destruction rate can be expressed as $c_{jy} = \frac{C_{jy}}{Z_{jy}}$ and $d_{jy} = \frac{D_{jy}}{Z_{jy}}$ respectively.

By definition, economic downturns are periods in which more sectors are declining. Therefore, given earlier presented evidence that job loss in recession is more harmful for lifetime earning than job loss in expansion, if one looks at consequences of job displacement across sectors, it is not unexpected to find more earning loss associated with sectors which experienced poorer performance, as they are more likely to be in poor aggregate economic conditions too. Instead, what is more interesting is to capture sectoral performance relative to the average sector in each year. In other words, what we want to study is over and beyond aggregate boom and bust cycles of the aggregate economy, whether and to what extent sectoral performances are crucial in earning and wage loss of displaced workers. In order to do that, for each year y, and for each performance measure c_{jy}, d_{jy}, g_{jy}, I calculate average performance of the economy as the size-weighted average of all sectoral performances: $\bar{x}_y = \sum_j \frac{Z_{jy}}{Z_y} x_{jy} = \frac{X_y}{Z_y}$ where $X_y = \sum_j X_j y$ and $Z_y = \sum_j Z_j y$. Then I define year-y relative performance change in sector j as

$$\tilde{x}_{jy} = x_{jy} - \bar{x}_y$$

In other words, I decompose sectoral performances into two parts: The first part, which is uniform across all sectors but changes over time and captures the aggregate fluctuations of the economy. The second part that varies over both time and industry and captures idiosyncratic performance of sectors relative to the average sector in the economy. In this way for each NACE industry classification I can build a measure of relative performance.

While sectoral performance should be an important factor in determining earning loss of displaced workers, if workers are not perfectly mobile across regions then regional variation of sectoral performance should be important too. Consequently, it is crucial to define a measure that not only captures inter-industry performances but also varies across regions. Using the variation of establishment data across 16 provinces in Germany, I can measure job creation, C_{ljy}, job destruction, D_{ljy}, and net employment growth rate, g_{ljy}, for each region l and industry j. Then, I express *relative sectoral performance* (RSP hereafter) of sector j in location l as $\tilde{x}_{ljy} = x_{ljy} - \bar{x}_y$ where $\bar{x}_y$ is weighted average of sectoral performances in all sectors and all regions. For instance,

$$\tilde{g}_{ljy} = \frac{EMP_{ljy+1} - EMP_{ljy-2}}{Z_{ljy}} - \bar{g}_y$$

where $EMP_{ljy+1} = \sum_{e \in l,j} Emp_{ey+1}$ is the sum of employment of all establishments j in location l in year $y+1$ and $Z_{ljy} = 0.5(Emp_{ljy+1} + Emp_{ljy-2})$

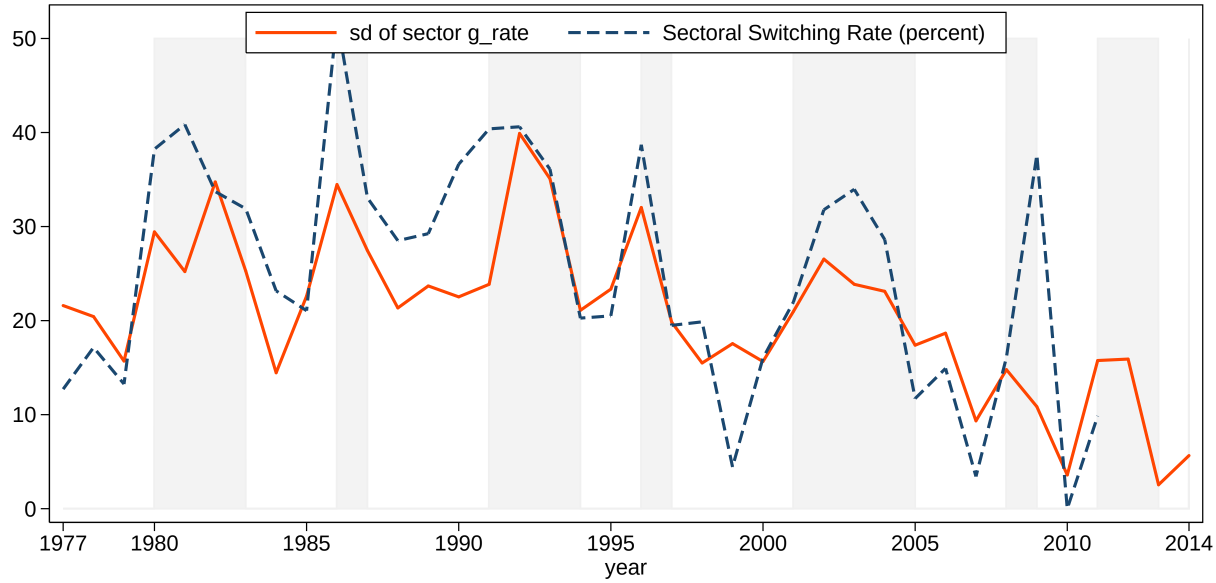
Before studying the effect of the relative sectoral performance on the consequences of job loss, I present the fact that these measures of relative sectoral performance are correlated with the performance of the aggregate economy. In other words, I show that economic downturns are not only periods in which on average sectors are declining (first moment property), but also the spread between sectors increases (second moment property). Therefore, it will not be coincidental to find larger earning and wage loss associated with sectors with relatively poor economic performance, which is studied in detail in later sections.

3.5.2 Relative Sectoral Performance and Aggregate Shocks

Typically business cycles are defined and identified by the first moment behavior of total output. Predictably, the first moment of labor employment is declining in recessions; meaning that, on average, sectors are shrinking their employment during any economic downturn. However, properties of its second moment are less studied. In figure 3.11, I present the standard deviation of employment growth rate of different sectors in the German economy from 1975 to 2014 (shaded areas depict recession periods). This figure clearly presents the second important but less emphasized property of recessions: sectoral dispersion increases during recessions and declines in expansions.

To measure sectoral dispersion I follow these steps. Year-y growth rate of industry j at location l is measured by $g_{ljt} = \frac{Emp_{ljy+1} - Emp_{ljy-2}}{.5(Emp_{ljy+1} - Emp_{ljy-2})}$. Then standard deviation of g_{ljy} for all $2,390$ industry-locations (16 provinces and 324 NACE 3-digit industries) is calculated for each year y. Notice that year-y standard deviation of industry growth rates are the same as year-y standard error of the relative sectoral performance, $\tilde{g}_{ljy}$, as they differ only to a constant term $\bar{g}_y$.

Figure 3.11: SD of sector growth rates and switching rate: Germany 1970-2014



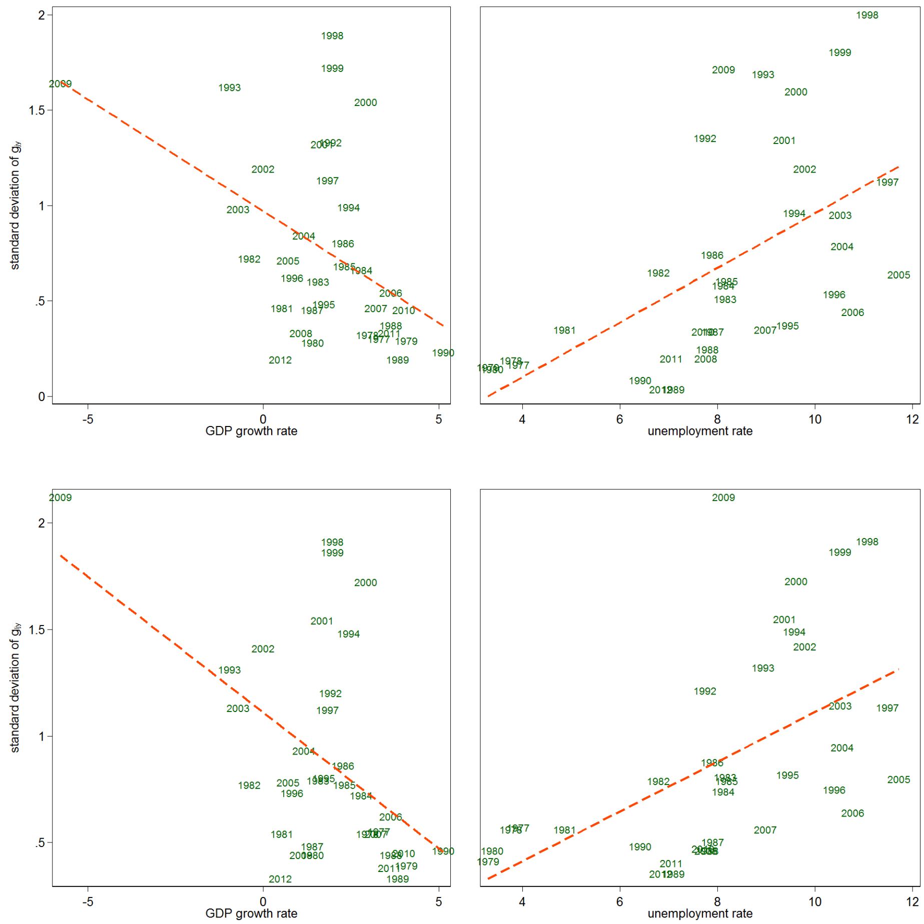
Notes: For each year, standard deviation of employment growth rate for 2,390 location-industry combinations is computed and depicted in the red solid line. The dashed blue line shows percentage of displaced workers that switch their industry at each year.

Furthermore, I define the sectoral job switching rate as the ratio of displaced workers in each year y, that switch to another sector within six years prior job loss, $SR_y = \frac{S_y}{D_y}$ where S_y is the number of workers, displaced at year y, and find permanent full-time jobs at years $y, y+1, y+2, ..., y+6$ in another sector measured by a 2-digit NACE industry classification. D_y is the total number of long-tenured employees, displaced at year y due to a mass layoff event. Figure 3.11 presents the counter-cyclical behavior of this rate as well. This measure is observable only after six years that most displaced workers find a full-time job. In SIAB, 84% of high-tenured workers find a new full-time job after six years, conditional on not leaving the labor market forever.

Another way to depict the correlation between aggregate economic performance and the prevalence of poor sectoral performances is to look at the scatter plot of measures for dispersion of sectoral performance and a measure for performance of the aggregate economy. In figure 3.12, the correlation between standard deviation of different measures of RSP, defined in previous subsection as $\tilde{g}_{jy}$ and $\tilde{g}_{ljy}$, with real GDP growth rate and unemployment rate as measures of aggregate economic activity are presented. In the top panel, standard deviation of employment growth rate for 235 NACE 3-digit industries is computed at each year and presented versus the corresponding real GDP growth and unemployment rates in the left and right panels. In the bottom panel, standard deviation for 3,170 location-industry combinations is computed. The positive correlation between unemployment rate (as well as the negative correlation between GDP growth rate) and standard deviation of sectoral performance is robust once we look at inter-industry variation or once we look at regional variation or one uses a different measure for industry performances.

This finding corroborates the conjecture that job displacements in recessions (or in general in economic downturns) are more likely to be originated from relatively shrinking sectors. Therefore specific skills of these displaced workers are more likely to become less valuable, compared to those workers who experience mass layoff event in years where standard deviation of sectoral growth rates are smaller and there is less sectoral deviation from the mean.

Figure 3.12: Standard deviation of relative sectoral growth rates versus unemployment: Germany 1970-2014

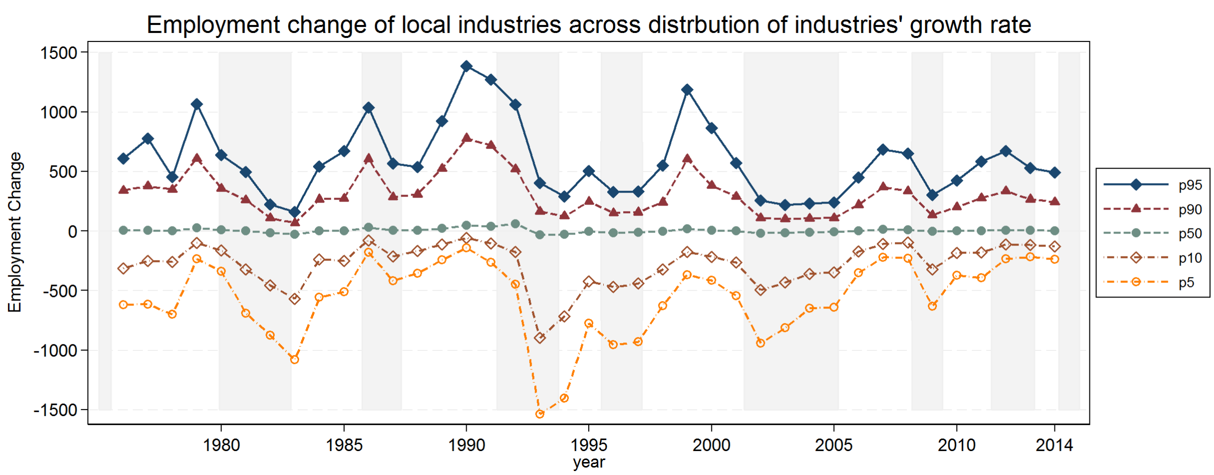


Notes: In the top panel, standard deviation of employment growth rate for 235 NACE 3-digit industries is computed at each year and depicted versus the corresponding real GDP growth and unemployment rates. In the bottom panel, standard deviation for 3,170 location-industry combinations is computed.

In addition, it is interesting to see how employment of growing and declining sectors evolve over time. The BHP file provides employment levels for Germany's establishments in 16 provinces and in 324 NACE 3-digit industries which creates a total combinations of $3,170$ location-industries. For each year, I identify the 5th, 10th, 50th, 90th and 95th percentiles from the distribution of local industries' growth rate, g_{ljy}, formally defined earlier. Then for each percentile, I count its net employment change. Figure 3.13 depicts these employment changes over time. For instance, in 1996, the 3-digit industry-location at the bottom 5th percentile has a net employment change of roughly -1,500 workers, and at the same time the 3-digit industry-location-year on the top 95th percentile's net employment increased by almost 500 workers.

It is very interesting that the median industry, the industry which has the same number of industries with a faster growth rate as the number of industries with a slower growth rate, has observed only slightly changes in employment. This level of employment change is not affected by the aggregate economic conditions such as recessions and expansions. However, in expansions, the fastest growing industries expand more rapidly and in recessions, the fastest declining industries shrink at much higher rates such that, on average, we observe more positive net employment growth in expansions and negative employment growth in recessions. This finding is consistent with the observed higher standard deviation of employment growth rates in recessions depicted in figure 3.11.

Figure 3.13: Employment change of local industries

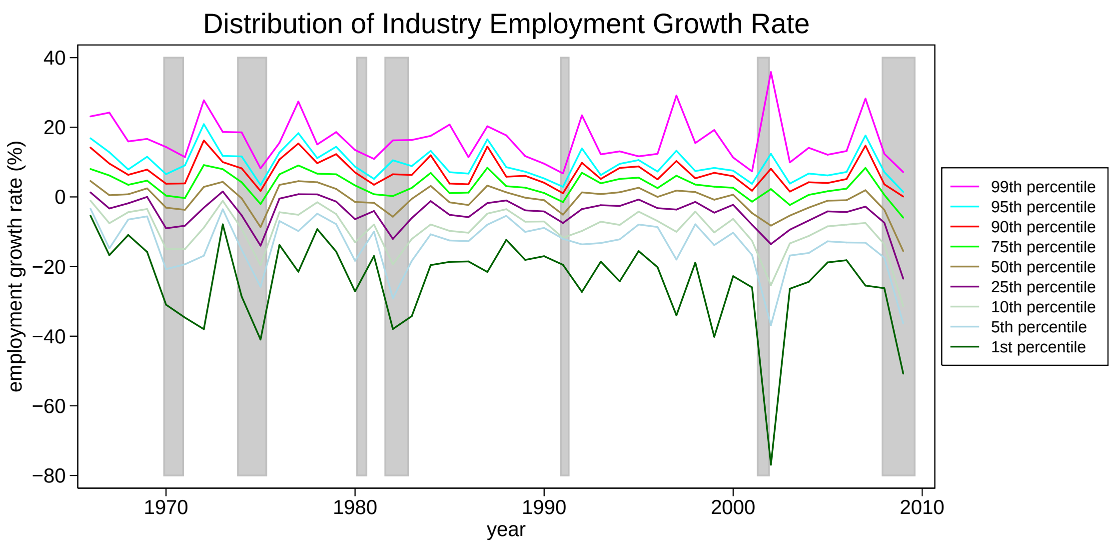


Notes: Each year, 95th, 90th, 50th, 10th and 5th percentile from the distribution of employment growth for the $3,179$ local industries is identified. Then for each of the above percentiles employment change is depicted in this figure.

Notice that in figure 3.13 number of employment changes not shares are reported to emphasize the fact that once we look at all workers displaced in recessions, most of them are separated from sectors with relatively low net employment growth rates. One would get a similar result if drawing the same graph for employment change as a share of sectoral employment. But then it would not be directly clear that whether there are greater number of displacements from bad sectors, as extremely bad sectors may be very small and the absolute number of displaced workers from these sectors may be negligible.

Furthermore, these findings are robust if one uses similar U.S. data. Figure 3.14 is based on a panel of 473 industries within the U.S. manufacturing sector. The lines are based on the industry's employment growth rate and they show how different percentiles perform across these industries. Gray bars are NBER recessions. This graph along with other studies such as Bloom (2014) suggest that recessions are not only periods of economic downturn, but also periods of sharp increase in dispersion of sectoral performances.

Figure 3.14: Dispersion of U.S. manufacturing industries over time



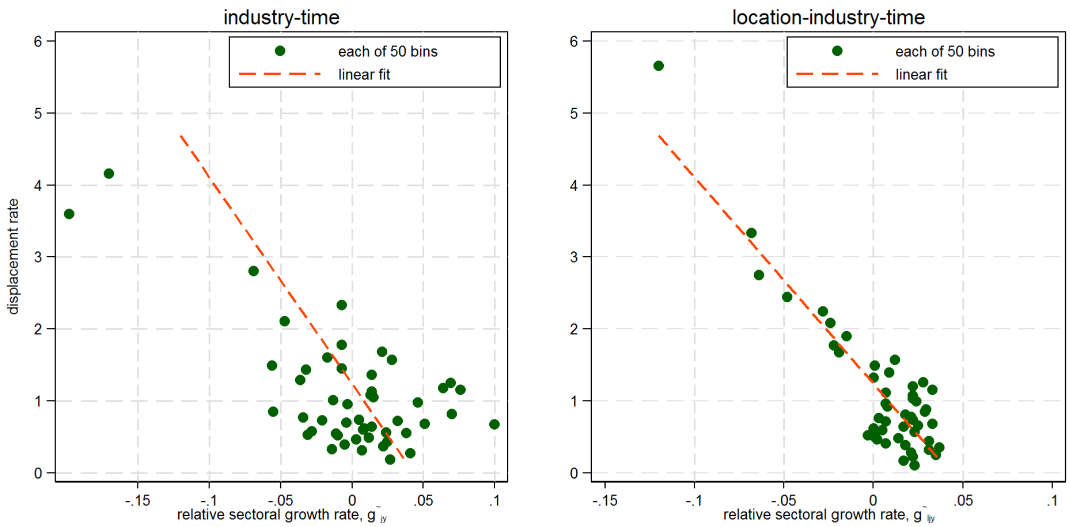
Notes: Using U.S data, this figure shows 1st, 5th, 10th, 25th, 50th, 75th, 90th, 95th, and 99th employment weighted percentiles of annual growth rate of employment for all 473 NAICS sectors in the NBER-CES Manufacturing Industry Database. Data spans 1958-2009. Gray bars are NBER recessions.

The findings of this section are consistent with literature on a possible "cleansing effect" of recessions: the idea that firms and sectors increase their productivity-enhancing activities in recessions because of relatively low opportunity costs (e.g., Davis and Haltiwanger, 1990; Caballero and Hammour, 1994; Aghion and Saint-Paul, 1998; Foster et al., 2016). The fact that a three-year window for measuring sectoral performance has been used guarantees that these findings are not driven by short term and transitory shocks to the sectors. Now that the properties of relative sectoral performance and its relation with aggregate performance measures have been studied, we should study the relationship between sectoral performance and sectoral displacement rate and finally we can study its effect on earning and wage loss of displaced workers, which is the topic of the next section.

3.5.3 Relative Sectoral Performances and Job Displacement

In this section, the relative sectoral performance (hereafter RSP) and its regional variation is used to study whether and to what extent, the displacement rate is correlated with relative sectoral performances. In the previous sections, it was shown that the displacement rate in the aggregate economy is negatively correlated with the real GDP growth rate and positively correlated with the unemployment rate. Here, it is shown that similar correlation exists at both the industry and the region-industry level. The main goal is to show that displacements are more frequent from sectors which are shrinking relatively faster. This step is very crucial as it states that not only relatively shrinking sectors are more common in economic downturns but also there are more displaced workers from these sectors. The left panel of figure 3.15 depicts the correlation between the relative sectoral performance and the displacement rate for each of the 50 bins of the distribution of $\tilde{g}_{jy}$, as well as the fitted line. All 185 (5×37) industry-years are summarized in the 50 bins. The right panel depicts the same correlation for the 2,390 combination of sectors, locations and years. Each dot in these plots represent one bin of the 50 bins for the distribution of $\tilde{g}_{jy}$ and $\tilde{g}_{ljy}$.

Figure 3.15: Displacement Rate and Relative Sectoral Performance (RSP)



Notes: Correlation between the sectoral displacement rate and the relative sectoral growth rate is presented. In the left panel 185 (5×37) combinations of NACE 1-digit industry and year are studied. In the right panel regional variation is added to create 2,390 combinations. In order to produce these graphs Stata's `binscatter` command is used. Each dot in these plots represents one of the 50 bins from the distribution of $\tilde{g}_{jy}$ and $\tilde{g}_{ljy}$. For each bin, average displacement rate and average RSP is used for the scatter plot.

Notice that this finding is crucial in corroborating my main argument that displaced workers are more likely to be displaced from relatively declining sectors, irrespective of aggregate economy's fluctuations. Table 3.2 shows that the same correlation exists even if one controls for aggregate measures such as the real GDP growth and unemployment rates. In other words, controlling for the performance of the aggregate economy by the real GDP growth rate and/or the unemployment rate, still more workers experience job loss due to mass layoff events from sectors which declining at relatively faster rates. This finding confirms the main idea of more displacements happening from relatively bad sectors.

So far, it is shown that: 1) Relatively declining sectors are more frequent in economic downturns, and 2) more workers are displaced from relatively declining sectors. In the next section the effect of RSP on the earning and wage loss of displaced workers is studied.

Table 3.2: More displacements in bad times and industries

	Dependent Variable					
	d_y	d_{jy}	d_{jy}	d_{ljy}	d_{ljy}	d_{ljy}
GDP growth rate	-0.059^{**}		-0.01			-0.01^{*}
	(0.021)		(0.008)			(0.005)
Unemployment rate	0.113^{***}		0.149^{***}		0.192^{***}	0.192^{***}
	(0.017)		(0.018)		(0.010)	(0.010)
$\tilde{g}_{jy}$		-4.764^{***}	-4.764^{***}			0.15
		(.591)	(.498)			(0.392)
$\tilde{g}_{ljy}$				-6.693^{***}	-6.686^{***}	-6.695^{***}
				(.236)	(.220)	(.318)
Observations	35	185	185	2,390	2,390	2,390
R^2	0.65	0.26	0.48	0.25	0.35	0.35

Notes: This table studies effects of aggregate and sectoral performance on the displacement rate. In the first column, aggregate displacement rate is studied as the dependent variable. The second and third columns study 185 combinations of NACE 1-digit industry and year. The last three columns study displacement rate for the 2,390 location-industry and year combinations. Standard Errors are in parentheses.
* ($p < 0.05$), ** ($p < 0.01$), *** ($p < 0.001$)

3.6 Aggregate versus Sectoral Performance

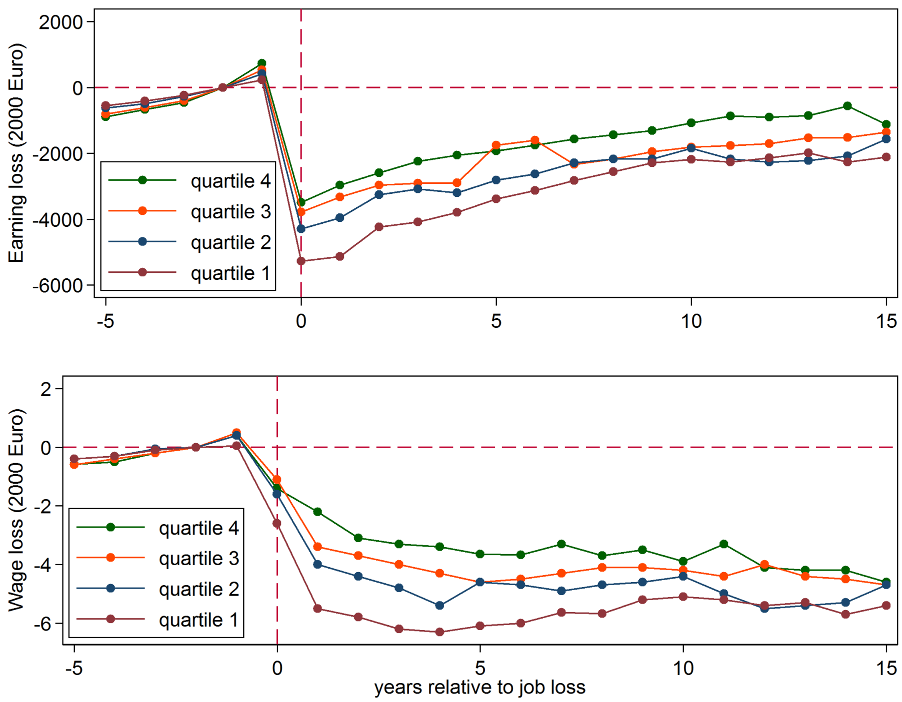
The main goal of this section is to identify to what extent the observed earning and wage loss of displaced workers are due to the aggregate economic conditions and how much can be explained by sectoral performance at the time of job loss. In order to study this question, I do two exercises. First, I split displaced workers into four quartiles based on the RSP at the location, industry and year of their job loss. Then I compare consequences of job displacement for the top and the bottom quartiles. Moreover, by estimating consequences of job loss for those in recession and expansion in each quartile, I study whether aggregate economy is important even within each group of sectoral performance. If poor aggregate economic conditions cause larger earning loss through a channel other than the more prevalence of sectors with relatively poor performances during economic downturns, then we should find a large difference between the consequence of job loss in recession and those in expansion even once we focus on each quartile. If the counter-cyclicality of earning loss diminishes within the RSP quartiles, then one can conclude that sectoral performance at the time of job loss is more important than aggregate economic conditions. On the other hand, if within each of the RSP quartiles, we still observe large difference between recession and expansion, one can conclude that there are more reasons for the counter cyclicality of earning loss other than the prevalence of sectors with relatively poor performance.

Second, in order to assess whether and to what extent, observed earning loss associated with job displacement is explained by the relative sectoral performances, I change the main specification designed for estimating earning and wage loss such that it includes a control variable for the sectoral performance. Then I compare the difference between results of the two specifications. If sectoral performance are not an important factor at the time of job loss, then the two specifications should estimate similar earning losses. However, as it is shown bellow, adding sectoral performance to the main specification, sharply diminishes estimated earning loss for displaced workers, though not completely eliminates it. This finding suggest that sectoral performance is crucial on life time earning of displaced workers even more than the aggregate economic conditions, while it is not the only determinant factor. Additionally, it is shown that including this term largely, but not completely, eliminates the counter-cyclicality of earning losses.

3.6.1 Job Loss From Good versus Bad Sectors

Using the RSP at the time of job loss, I split displaced workers into four groups based on the quartiles of $\tilde{g}_{ljy}$. The earning and wage loss for displaced workers in these four groups are depicted in figure 3.16. There is a large difference between earning and wage loss of workers from the top and the bottom quartiles of the RSP. Recall that the relative sectoral performance is derived by employment growth rate within a three-year window, which states that workers from the top quartile are in sectors that net employment growth rate are very high during that four years. This finding is consistent with the hypothesis that job loss from declining sectors proceeds with more earning and wage loss since the sector-specific skills of the workers has become less valuable. But this finding is not enough to prove the effect of sectoral performance on earning and wage loss of workers. Since it could be the case that these job displacements are associated with larger earning losses because they are more likely to be in recessions. For this reason, it is necessary to study how recessions and expansions alter this finding.

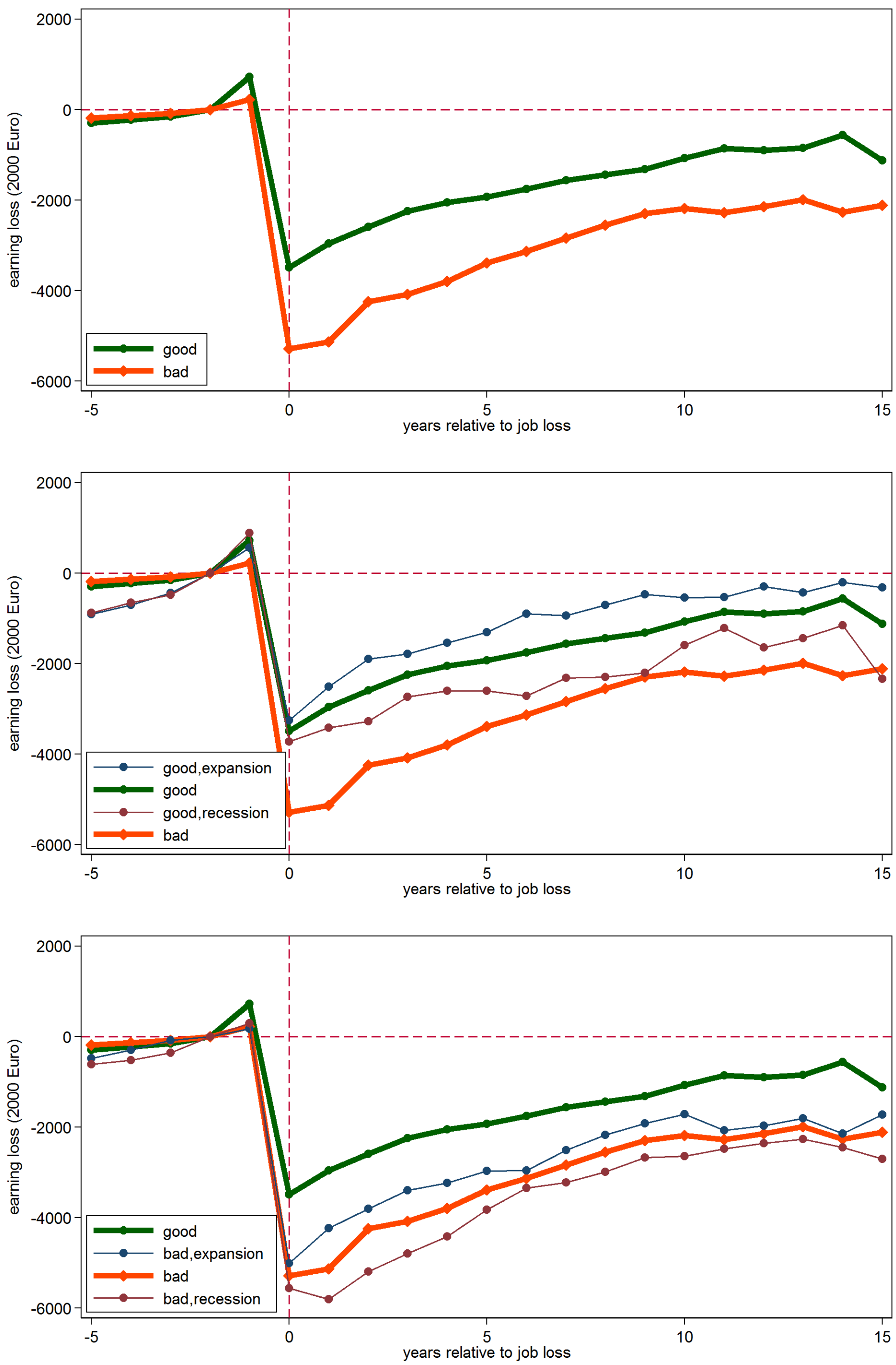
Figure 3.16: Earning loss of displaced workers from each quartile of relative sectoral performance



Notes: The top panel presents earning loss of workers, displaced from each of the four quartiles of relative sectoral performance $\tilde{g}_{ljy}$. The fourth quartile represents sectors with relatively higher growth rate and sectors with relatively lowest growth rate are represented by the first quartile.

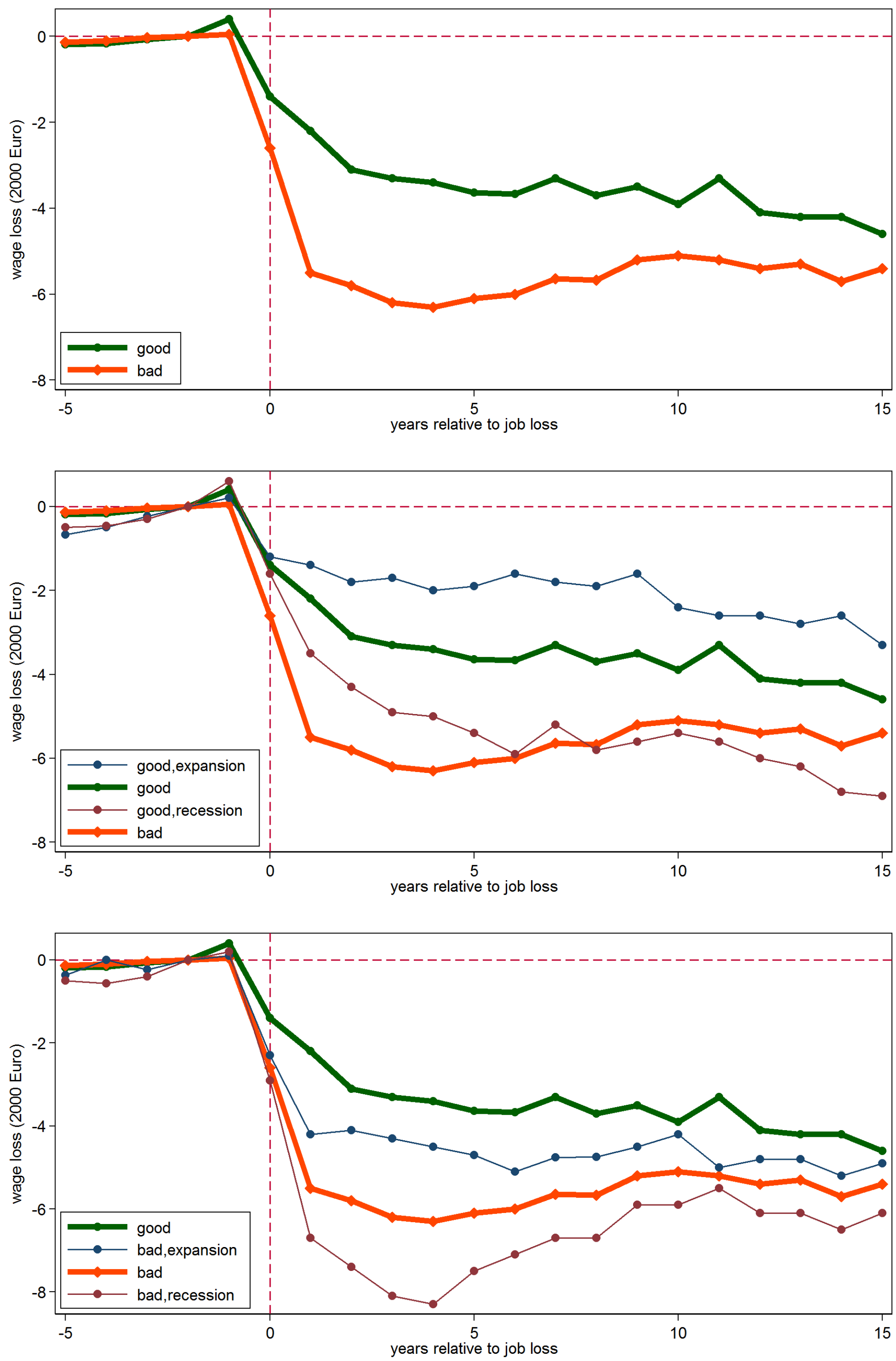
To better see the difference, I concentrate only on the top and the bottom quartiles. I call those sectors in the top quartile as the good sectors and in the bottom quartiles as the bad sectors and then estimate earning loss of workers in these two groups of good and bad sectors. The top panel of figure 3.17 depicts earning loss of displaced workers using the same specification of equation 3.1 for workers displaced from the good and the bad sectors. Similarly the top panel of figure 3.18 depicts wage loss for the same two groups. These graphs depict the fact that relative sectoral performance at the time of job loss has both short term and long term effect on earnings of workers. In addition, the effect is even larger than the effect of aggregate performances such as the real GDP growth rate or recession and expansion.

Figure 3.17: Earning loss of displaced workers for good and bad sectors



Notes: Good sectors are defined as those sectors in the top quartile of relative sectoral performance measured by $\tilde{g}_{ljy}$. Bad sectors are those in the bottom quartile. Top panel, depicts earning loss for good and bad sectors. The middle panel adds expansion and recession for good sectors and the bottom panel adds for the bad sectors.

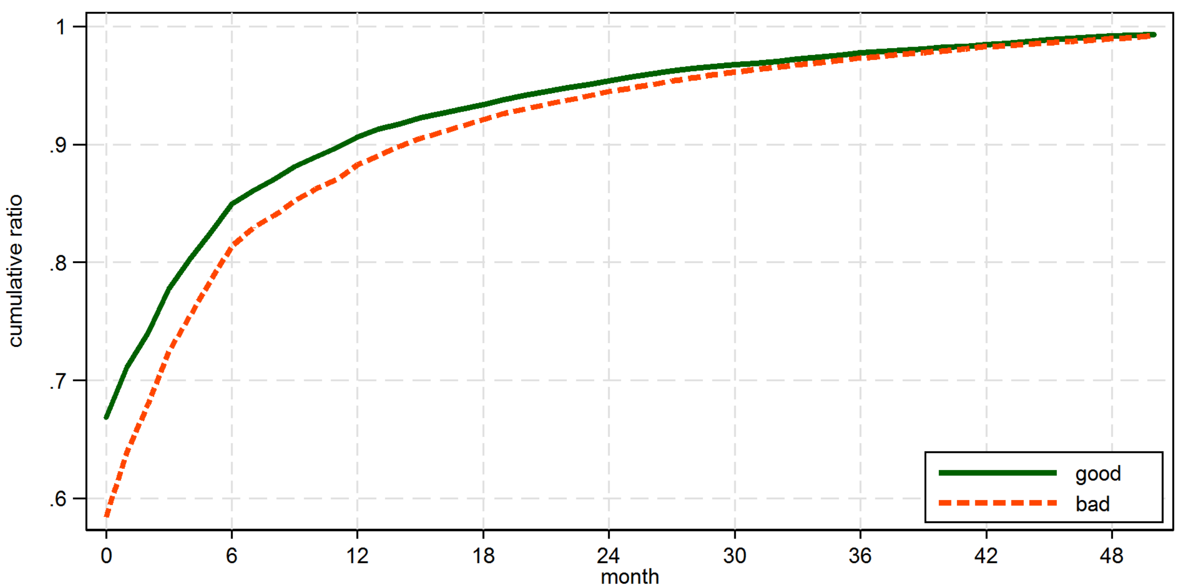
Figure 3.18: Wage loss of displaced workers for good and bad sectors



Notes: Good sectors are defined as those sectors in the top quartile of relative sectoral performance measured by $\tilde{g}_{ljy}$. Bad sectors are those in the bottom quartile. Top panel, depicts wage loss for good and bad sectors. The middle panel adds expansion and recession for good sectors and the bottom panel adds for the bad sectors.

Besides earning and wage loss, it is useful to compare length of joblessness for workers displaced from good and bad sectors and compare it with those in recessions and expansions. In figure 3.6 it was shown that recession and expansions are not much different on the duration of joblessness. In figure 3.19 cumulative length of joblessness is depicted for displaced workers in good and bad sectors. Workers displaced from good sectors, find a full-time jobs relatively faster and the difference between the length of these two groups is larger than the difference between recession versus expansion, but still the difference is not enough to explain all earning and wage loss of displaced workers. For instance, workers who find job in the same year, who are 58% of workers displaced from bad sectors and 67% of workers displaced from good sectors, have almost very short period of joblessness. However, those displaced from bad sectors experience 85% more wage loss. Therefore, the longer periods of joblessness could not be the main reason for the larger earning and wage loss.

Figure 3.19: Cumulative Length of joblessness for displaced workers

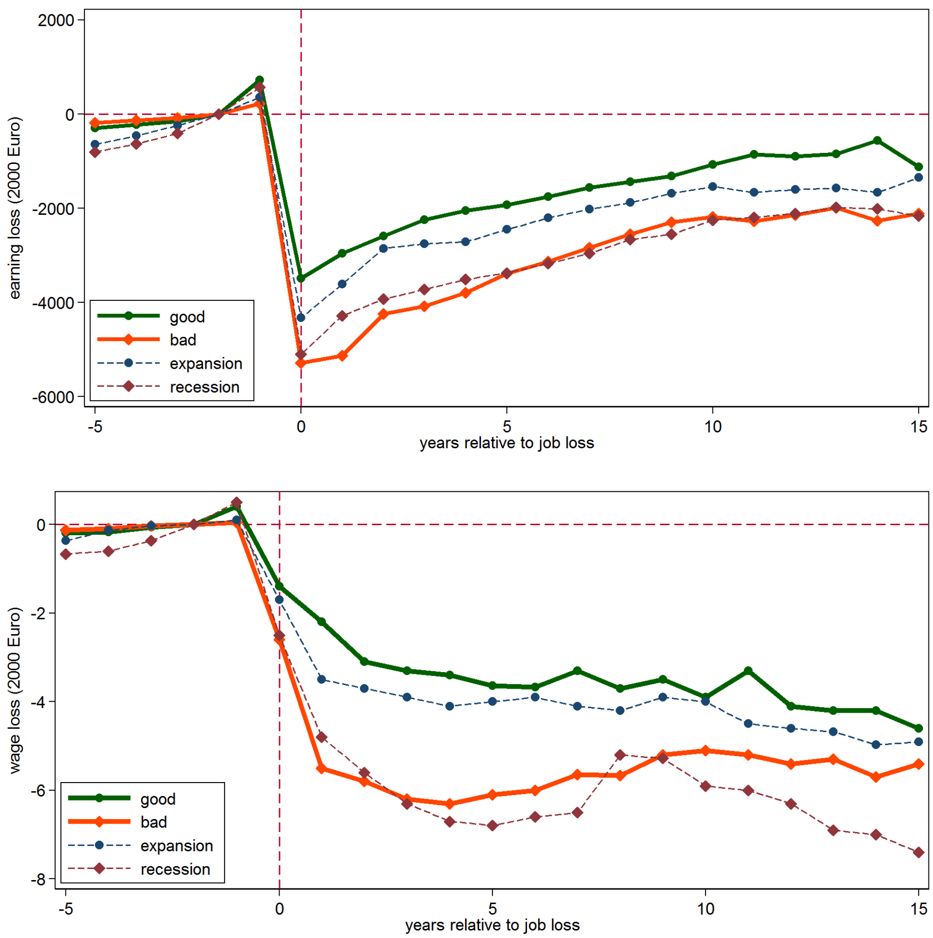


Notes: Conditional on finding job within 60 month post job displacement, cumulative ratio of workers find full-time job is calculated from SIAB. Green solid line represent those job loss from good sectors, top quartile of $\tilde{g}_{ljy}$, and red dashed line present job loss from bad sectors, bottom quartile of $\tilde{g}_{ljy}$.

How business cycle fluctuations affect earning loss of workers displaced from good sectors, and those displaced from bad sectors? To answer this question, earning and wage loss for each of the following 4 groups is estimated: job loss from good sector during a recession and an expansion, job loss from a bad sector during a recession and an expansion. The middle and bottom panels of figure 3.17 depict associated earning loss for these four groups. Similarly, middle and bottom panels of figure 3.18 present wage loss of these four groups. These figures support the idea that the sectoral performance at the time of job loss can explain much of the earning and wage loss associated with job displacement. While sectoral performance explains much of earning and wage loss, it is worth noting that recession and expansion are still an important factor.

To compare effects of the aggregate and sectoral performance at the time of job loss, figure 3.20 depicts earning and wage loss for good and bad sectors alongside those for recession and expansion. Couple of important facts from these graphs. First, note that not only the trends for wage and earning loss is similar for good/bad sectors and recession/expansions years but also the level of these effects are very similar. Second, the difference between recession and expansion has almost the same wage and earning loss as good and bad sectors have. Consequently, a displacement during recessions is on average similar to a displacement from a bad sector, and a displacement in expansion is very similar to those job loss from a good sector in terms of their wage and earning loss.

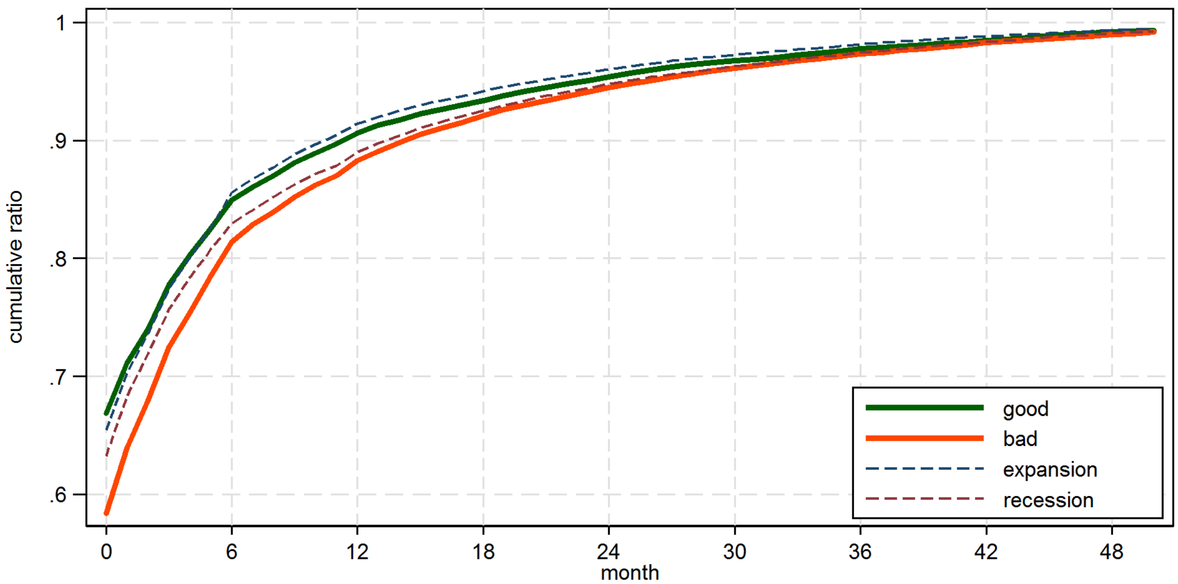
Figure 3.20: Wage loss of displaced workers for good and bad sectors



Notes: This graph depicts the effect of job displacement from good and bad sectors, in solid lines, alongside displacements in recession and expansion, in dashed line.

In addition, the cumulative length of joblessness is depicted in figure 3.21 for each of the four groups of workers displaced either from a good or a bad sectors, or displaced during recessions or expansions. Results are similar to wage and earning loss, except that the length of joblessness for workers displaced from bad sectors is longer than those of workers displaced in recessions. Note that displacement from good sectors has almost the same consequences as displacement during expansion. A displacement from the bad sectors takes more time to find a new full-time job than a job loss in recession. Again, these differences are not large and this channel alone can not explain the large difference between earning and wage loss of displaced workers.

Figure 3.21: Cumulative length of joblessness for displaced workers



Notes: Conditional on finding a job within 60 months post-job displacement, cumulative ratio of workers find full-time job is calculated from SIAB. Green solid line represent those job loss from good sectors, top quartile of $\tilde{g}_{ljy}$, and red dashed line present job loss from bad sectors, bottom quartile of $\tilde{g}_{ljy}$.

3.6.2 Controlling for sectoral performance

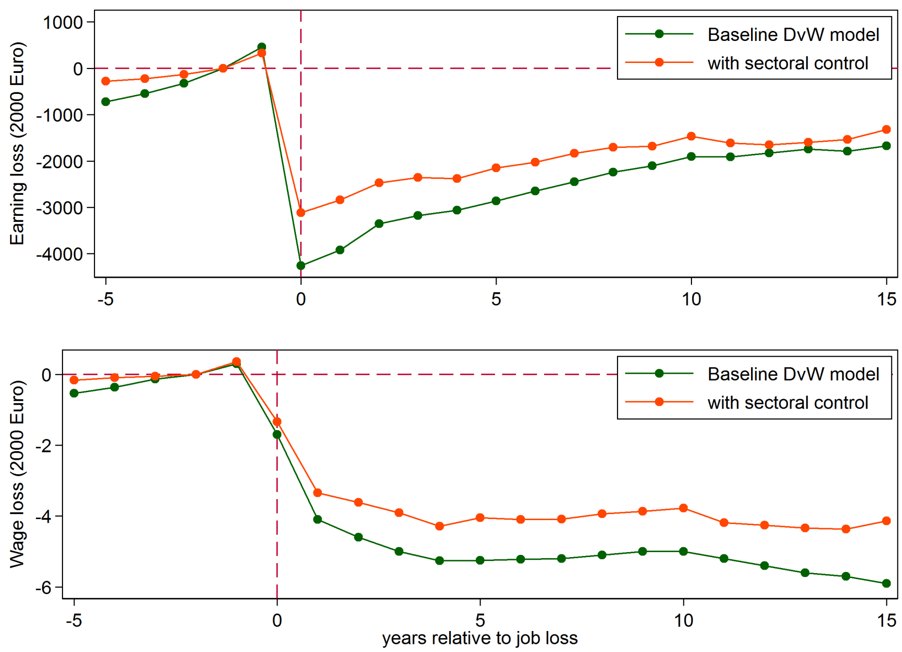
Findings in the previous section suggest that sectoral performance at the time of job loss is a crucial determinant of lifetime earnings of displaced workers. However, in this section I want to quantitatively assess to what extent RSP affects earning loss of displaced workers and moreover, once we control for RSP, whether the aggregate economic conditions could anymore explain variation in the observed earning loss. In order to do that I estimate the following model:

$$e^y_{it} = \alpha_i + \beta^y X^y_{it} + \gamma_t + \bar{e}^y_i \lambda_t + \sum_{k=-5}^{20} \delta^y_k D^k_{it} + \sum_{k=-5}^{20} \theta^y_k (\tilde{g}^i_{ljy} \times D^k_{it}) + u^y_{it} \tag{3.3}$$

where $\tilde{g}^i_{ljy}$ is a constant for each worker and determines relative sectoral performance at the location and industry at which the worker was displaced in year y. Notice that this specification is similar to equation 3.1 except for the term that includes the interaction of the dummy variables with the RSP at the time of displacement. This interaction term is all zero for the control group of non-displaced workers.

Then θ_k^y captures amount of earning (or wage) loss associated with RSP of workers displaced in year y and δ_k^y are the average earning loss of workers displaced in year y relative to the control group, k years after (or before) displacement, once we control for RSP. If RSP is not crucial in determining earning loss of displaced workers we expect to find similar δ_k^y from the two specifications of 3.1 and 3.3. Figure 3.22 compares the results of these two models. The green line shows the baseline Davis and von Wachter (2012) framework that I have already used in this paper, and the red line shows the results of the modified model in 3.3. The difference between the two curves depict the importance of the relative sectoral performance (RSP) at the time of displacement. Notice that this difference is non-zero, which states that relative sectoral performance is non-trivial.

Figure 3.22: Consequences of job loss, with and without controlling for sectoral performance



Notes: Earning and wage loss of displaced workers are estimated using the two specifications of equation 3.1 and 3.3 which are the same except for that the latter include a control term with interaction of RSP for displaced workers.

We can also quantitatively measure the extent to which RSP affects the average earning loss by the decline in estimated δ_k^y. Let's define average present discounted value of earning loss for workers displaced in year y as follows:

$$PDV^y = \sum_{k=0}^{20} \frac{\hat{\delta}_k^y}{(1+r)^k} \tag{3.4}$$

where $\frac{1}{1+r} = 0.95$ represents yearly discount rate. Furthermore, define aggregate present discounted value earning loss of all displaced workers as the weighted average of PDV^y once weighted by the number of displaced workers in each year y:

$$PDV = \frac{1}{\sum_y D^y} \sum_{y=1977}^{2012} D^y PDV^y \tag{3.5}$$

and define PDV^0 and PDV^1 as the present discounted value earning loss, estimated from the model of 3.1 and 3.3 respectively. Then one can measure the extent to which RSP affects earning losses by

$$\rho = 1 - \frac{PDV^1}{PDV^0}$$

The larger is this number there are less variation in earning loss that can not be explained by RSP. In other words, the more important is RSP the larger is ρ. Using this measure I find that 23.6% of the present discounted value of earning loss of displaced workers can be explained by the RSP (relative sectoral performance) at the time of job loss.

But the main reason we defined RSP is to capture whether and to what extent, the sectoral performance can explain the gap between the earning loss associated with displacements in recessions and those in expansions, the counter cyclicality of earning loss puzzle. To answer this question, earning and wage loss are estimated using these specifications for recessions and expansions. Without controlling for RSP, earning loss is 24.5% less if job loss happens in expansion than job loss in recession. However, once the RSP at the time of displacement is controlled for, earning loss difference drops to only 10.8%. In other words, 55% of the gap between recession and expansions are explained by relative sectoral performance. Table 3.3 summarizes the findings of this chapter. While average earning of displaced workers in the last 5 years prior to job loss is 30,842 Euro, average PDV of earning loss using the baseline specification is 34,595 Euro while including the RSP in the specification declines this earning loss by 23.6%.

Table 3.3: PDV Earning Loss

Description	Coefficient	$\bar{e}_i$	PDV^0	PDV^1	ρ
All sample	δ_k	30,842	34,595	26,422	23.6%
Recession	δ_k^{Rec}	30,642	40,648	28,371	30.2%
Expansion	δ_k^{Exp}	31,010	30,306	23,821	21.4%
Recession - Expansion	$(\delta_k^{Rec} - \delta_k^{Exp})$	-	10,341	4,551	55.9%

Notes: This table compares present discounted value of the earning loss associated with job displacements. The first row uses all sample of displaced workers. The second and third row reports PDV for workers displaced during recessions and expansions respectively. The last row presents PDV of the gap between recessions and expansions.

This finding concludes empirical findings of this paper. In the next chapter, a simple model of sector-specific human capital is presented and shown how loss of sector-specif human capital can explain not only the earning loss of displaced workers but also the counter-cyclicality of earning losses.

CHAPTER 4

A MODEL OF SECTOR SPECIFIC HUMAN CAPITAL

In this chapter, I introduce a simple model of sector-specific human capital. The model can be extended in many dimensions such as on-the-job search, heterogeneous agents, more than 2 sectors, uncertainty in many outcomes and etc. However, this very simple model predicts many moments of the data very well. Therefore, I leave all the above extensions of the model either to the appendix or for future research.

4.1 Basic Model

4.1.1 Baseline model

There are 2 sectors in the economy that workers can chose to work. While employed, they acquire human capital specific to the sector as well as general skills. Initially, I assume there is no on-the-job search, and all workers are the same ex-ante. Hence they are only different in levels of their sectoral and general human capital (x, y) and the sector they have attachment to. Production takes place in firms which transform only human capital into output. Sectoral and general specific human capital are substitutable with constant elasticity of substitution of σ. Wage of workers are given as

$$w_i(x,y) = (p_i x^{\frac{\sigma-1}{\sigma}} + y^{\frac{\sigma-1}{\sigma}})^{\frac{\sigma}{\sigma-1}} \tag{4.1}$$

where p_i is the relative price of sectoral human capital in sector i.

Employed workers are subject to the hazard of job loss at rate λ_i and discount future earnings at rate β. Then value of employed workers are

$$V_1(x,y) = w_1(x,y) + \beta\Big[(1-\lambda_1)V_1(x',y') + \lambda_1 U_1(x',y')\Big] \tag{4.2}$$

$$V_2(x,y) = w_2(x,y) + \beta\Big[(1-\lambda_2)V_2(x',y') + \lambda_2 U_2(x',y')\Big] \tag{4.3}$$

I also assume that different types of workers' human capital evolve deterministically at a constant rate as long as they are employed:

$$x' = \min\{x + \triangle x, \bar{X}\}$$
$$y' = \min\{y + \triangle y, \bar{Y}\}$$

This is another dimension that could be extended to include stochastic evolutions. However the deterministic model predicts the important moments of data, therefore I leave this extension for future research.

On the other hand, unemployed workers have three choices. They can leave the labor force and enjoy their leisure while receiving unemployment insurance of z. Moreover, they can pay a search cost to search for a new job in the same sector or they can either pay extra search cost to search the other sector as well. If they search in sector i, there is a μ_i probability of not finding a job in sector i and $(1 - \mu_i)$ chance of finding job in sector i. I also assume that job finding rate in any sector is independent of search in the other sectors. Therefore chance of finding job in sector 1 is the same whether the unemployed worker is searching only in sector 1 or searching in both sectors. If they are lucky to find a job in both sectors, they will chose the one with highest continuation value. Searching costs are $c_1 < c_2$ for searching in 1 sector or 2 sectors respectively, which implicitly assumes that search costs are uniform across all workers and sectors and is not a function of their time value.

While unemployed, sector-specific and general human capital depreciate at rate δ_x and δ_y respectively. If workers chose to start a new job in their previous sector, they will retain their depreciated level of sector-specific human capital as well as their general human capital. But, if they chose to start a new job in the other sector they have to forgo their accumulated sector-specific human capital and start with much smaller sector-specific human capital, while retaining their depreciated general human capital. If workers switch to the other sector their sector-specific human capital worth only partially that depends on transferability of sectoral skills, which is measured by constant $0 \leq \psi \leq 1$. The higher is ψ the lower is the specificity of sectoral skill.

Workers are memoryless in the sense that if they move to the other sector and switch back afterwards they do not remember their old sector-specific skills and shall start from x_0 level of sector-specific human capital. This assumption is crucial in simplifying the problem at the same time seems reasonable as in the SIAB data only 6.7% of those workers switching 2 digit NACE industry, will ultimately return to the same 2 digit industry again. In summary, value of unemployed workers can be expressed as:

$$\begin{aligned} U_1(x,y) =& z + \max\Bigg\{\beta U_1(\delta x,\delta y), -c_1 + \beta\Big[\mu_1 U_1(\delta x,\delta y) + (1-\mu_1)V_1(\delta x,\delta y)\Big], \\ & - c_2 + \beta\Big[\mu_1\mu_2 U_1(\delta x,\delta y) + (1-\mu_1)\mu_2 V_1(\delta x,\delta y) + \mu_1(1-\mu_2)V_2\psi x,\delta y) \\ & + (1-\mu_1)(1-\mu_2)\max\{V_1(\delta x,\delta y), V_2(\psi x,\delta y)\}\Big]\Bigg\} \end{aligned} \tag{4.4}$$

$$\begin{aligned} U_2(x,y) =& z + \max\Bigg\{\beta U_2(\delta x,\delta y), -c_1 + \beta\Big[\mu_2 U_2(\delta x,\delta y) + (1-\mu_2)V_2(\delta x,\delta y)\Big], \\ & - c_2 + \beta\Big[\mu_1\mu_2 U_1(\delta x,\delta y) + (1-\mu_1)\mu_2 V_1(\psi x,\delta y) + \mu_1(1-\mu_2)V_2(\delta x,\delta y) \\ & + (1-\mu_1)(1-\mu_2)\max\{V_1(\psi x,\delta y), V_2(\delta x,\delta y)\}\Big]\Bigg\} \end{aligned} \tag{4.5}$$

Since the sectoral prices are different, value of employment (and similarly value of unemployment) differs among sectors. I use iterations over the value function to solve for the above Bellman equations, then use the computed value functions to find the optimal policy functions for unemployed workers. Figure 4.1 depicts the optimal policy of unemployed workers having attachment to sector 1 (left panel) and 2 (right panel). The model is solved for the baseline parameters reported in table 4.1. Notice that unemployed workers have three options to chose: leaving the labor market, searching within their initial sector, searching both sectors.

Notice that since the two sectors have similar parameters, unemployed workers in two sectors follow the same policy rule. Most of the workers search only within their initial sector, represented by the green area (also shaded with '\' lines) as there is a fixed cost for searching the other sector as well. But those with relatively less sectoral attachment (i.e. less sector-specific human capital relative to their general human capital) are willing to pay extra search cost and search other sectors too. These workers are depicted by the

Table 4.1: Baseline parameters of the basic model

description	parameter	base value
discount rate	β	0.985
elasticity of substitution between x and y	σ	3
unemployment insurance	z	20
accumulation of human capital	$(\Delta x, \Delta y)$	$(0.1, 0.1)$
depreciation rate of human capital	(δ_x, δ_y)	$(0.8, 0.95)$
hazard of losing job	(λ_1, λ_1)	$(0.0025, 0.0025)$
job finding rate	$(1-\mu_1, 1-\mu_2)$	$(0.5, 0.5)$
search cost	(c_1, c_2)	$(10, 20)$
price of good	(p_1, p_2)	$(1, 1)$
transferability of specific human capital	ψ	0.3
maximum level of human capital	$(\bar{x}, \bar{y})$	$(20, 20)$

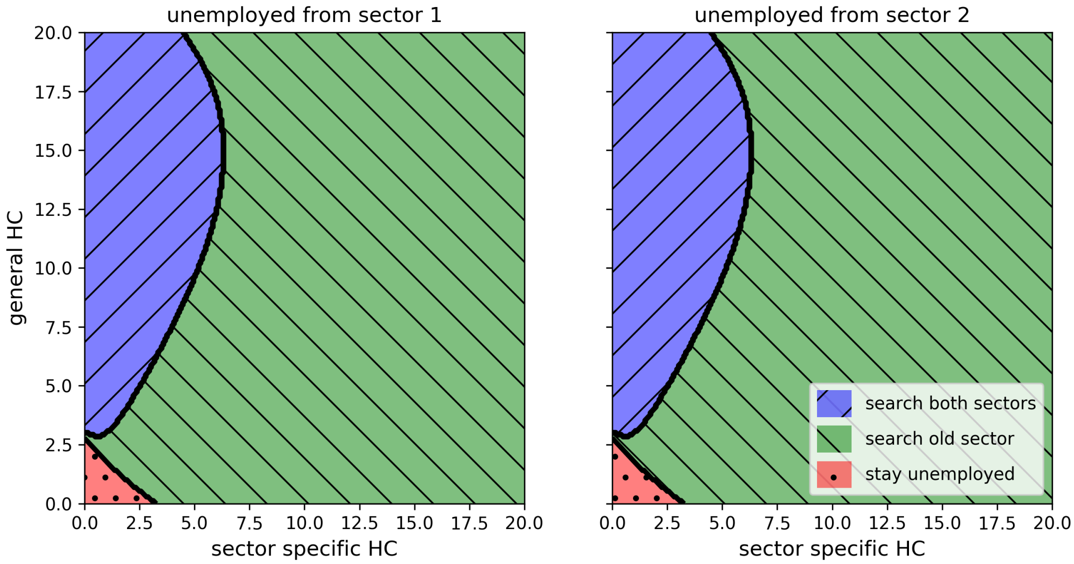
Notes: Baseline parameters used for simulation of the base model.

blue area on the top left corner of the policy rule graph (also shaded with '/' lines). Some of them will find a job in the other sector and choose to switch their sector. Rest of these workers will remain unemployed or find job in the same sector. There is another group of unemployed workers with very low levels of general and sectoral human capital who will leave the labor force. These workers will either stay out of labor force forever or acquire enough skills through education or apprenticeship. Red area in the bottom left corner of the graph represents these workers (also depicted with dots).

Also notice that in the baseline calibration of the model where the two sectors rewarding human capital exactly the same, the only reason that unemployed workers are willing to forgo their sector-specific human capital and search other sectors is that searching more sectors increases the chance of finding jobs, which is beneficial for two reasons: First, fewer periods of unemployment is better because of the accrued earnings. Second, the shorter is the unemployment period, the less depreciation of human capital declines future earnings of the worker.

One testable prediction of this simple model is that everything else equal, workers with relatively higher general human capital are more likely to switch their sector after job loss than workers with higher sector-specific human capital. Also workers with more sectoral attachment are less likely to switch sectors.

Figure 4.1: Optimal policy rule of unemployed workers.



Notes: Left panel shows optimal policy of workers separated from sector 1. Workers with high enough level of sector-specific human capital prefer to search their own sector only. Green area represent these workers. But unemployed workers with relatively high general human capital and low sector-specific human capital, represented by the blue area, are willing to pay higher search cost and search other sectors too. Workers need a minimum level of human capital to enter the labor force. Workers in the red area will remain out of labor force. Right panel shows the policy rule for workers unemployed from sector 2. The two panels are the same since the two sectors have the same parameters.

4.1.2 Invariant Distribution

Initially there is a continuum of workers between 0 and 1, half of them employed in sector 1 and half are employed in sector 2 and no unemployed worker. Moreover each half are uniformly distributed with initial sector and general human capital. Theorem 1 shows that there is a unique invariant distribution for this model in which distribution of employed and unemployed workers remains the same over time.

Theorem 1. *There is a unique stationary distribution in which there are both employed and unemployed workers in both sectors.*

Proof. Form the Markov transition matrix P. Then find the invariant distribution as the eigenvector associated with the unit eigenvalue of the transition matrix. For uniqueness use theorem 2.2.2 of Sargent and Ljungquist (2012). □

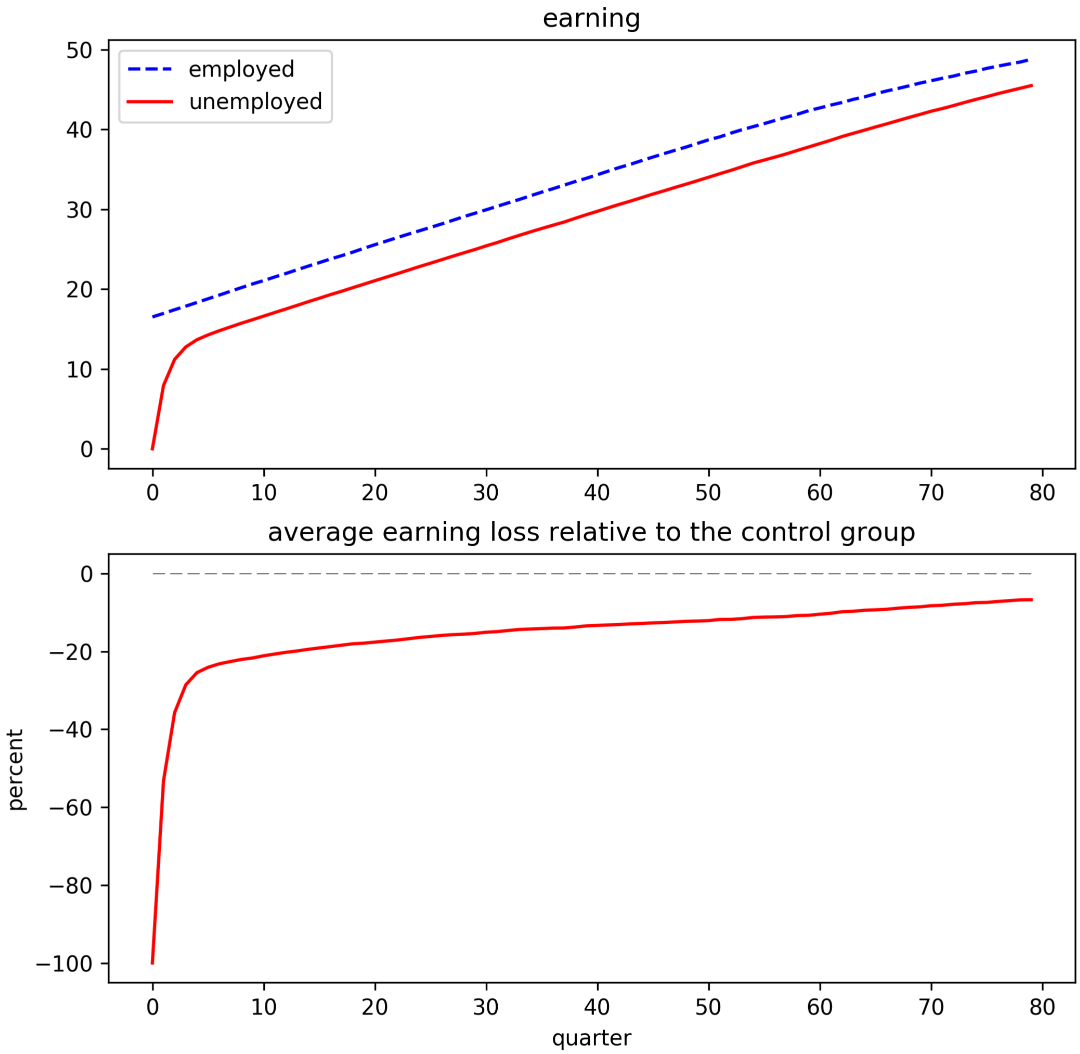
Given the initial distribution, I use iteration method to find the invariant distribution.

4.2 Consequences of job loss

Here I study effects of job loss. Since the two sectors are similar there is no difference between workers displaced from each of them. Even in this economy there will be shown that loss of human capital, either general or specific, causes permanent earning loss. However, this model can not explain the gap between earning loss of workers displaced in recessions and those displaced in expansions. In the next section I will study the consequences of job loss under non uniform sectoral shocks to accommodate this finding.

In order to compare wage profile of unemployed workers, I use the computed policy rule of unemployed workers, once calibrated for the baseline parameters. Then, I compare average earning of workers for the two groups of employed and unemployed workers. To do that, I simulate earning profile of 200,000 workers employed before entering period 0, while half of them receiving unemployment shock at time 0. I follow earning of each worker for the next 80 periods and compare the average earning of the two groups during each period. The former group of employed workers are my control group and the latter group of unemployed ones are the treatment group.

Figure 4.2: Wage loss of displaced workers.



Notes: This figure depicts simulated wage loss of displaced workers for the basic model of this chapter that is calibrated for parameters of table 4.1. Top panel shows wage profile of employed workers in the blue dashed line while the solid red line depicts wage of similar workers with the same level of sectoral and general human capital become unemployed at time 0. Bottom panel depicts the wage loss as the percentage of the wage of employed workers over time.

Figure 4.2 depicts simulated earning loss of displaced workers. Top panel shows earning profile of employed workers in the blue dashed line while the solid red line depicts earning of workers who become unemployed at time 0. In order to be comparable, I restrict the observations to the workers with similar level of sectoral and general human capital at the time 0, right before the job loss. Therefore, control and treatment groups have similar distribution before displacement. Bottom panel of this figure depicts the earning loss as a percentage of the earning of employed workers over time. This result is consistent with the first empirical fact, introduced in the introduction chapter: job loss has permanent negative impact on earning profile of workers. Consistent with the empirical findings of Davis and von Wachter (2012) this simple model of sectoral human capital predicts persistent and large amount of wage loss upon job loss.

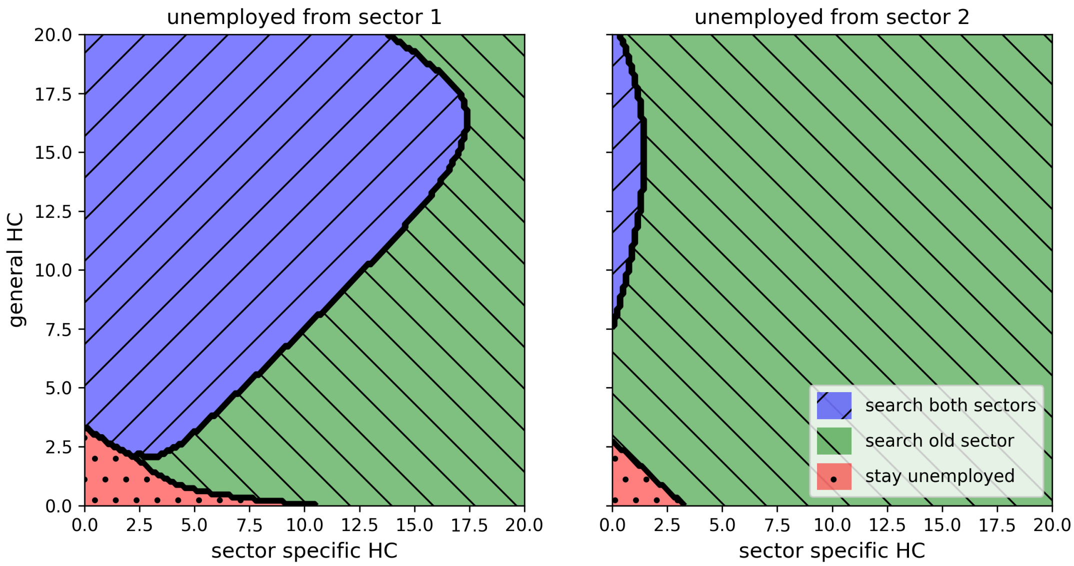
However, this model is incapable of replicating the second or third fact as all sectors are the same and negative shock uniformly affect workers. In order to explain the other two empirical findings we need to study the model under non-uniform sectoral performance. The next section studies the model with such sectoral dispersion.

4.2.1 Declining Sector

So far I have assumed that prices are constant and uniform across the two sectors. Here the goal is to study effects of a negative (or positive) sectoral shocks to employed and unemployed workers in both sectors. For simplicity I assume that there is a permanent negative shock to sector 1's prices that drops value of sector 1's human capital by 20%. I study the optimal policy rule and the consequences of job loss under this shock. This shock is counterpart of the relative sectoral performance measure we studied earlier which represent the fact that the sector is declining or growing relative to the average sector.

I use the same iteration method to solve for value functions and optimal policy rules. Right panel in figure 4.3 shows optimal policy of workers separated from sector 2. Now, unemployed workers in sector 2 are less willing to search in sector 1 for new jobs. After all, sector 1 become less valuable and less desirable. Even in this case, workers with very limited sectoral attachment but with high level of general human capital are willing to switch as the cost of staying unemployed is very high for them. If this negative shock to sector 1 was large enough no one in sector will choose to search for jobs in the declining sector. However, in sector 1, many more workers find it optimal to search within sector 2 and forgo their accumulated human capital specific to sector 1 since these skills are now less valuable. This fact is shown in the left panel of figure 4.3. Another important result of the model is that more workers from sector 1 will leave the labor force due to the decline in the market value of their skills.

Figure 4.3: Optimal policy of unemployed workers in response to a negative permanent shock to sector 1

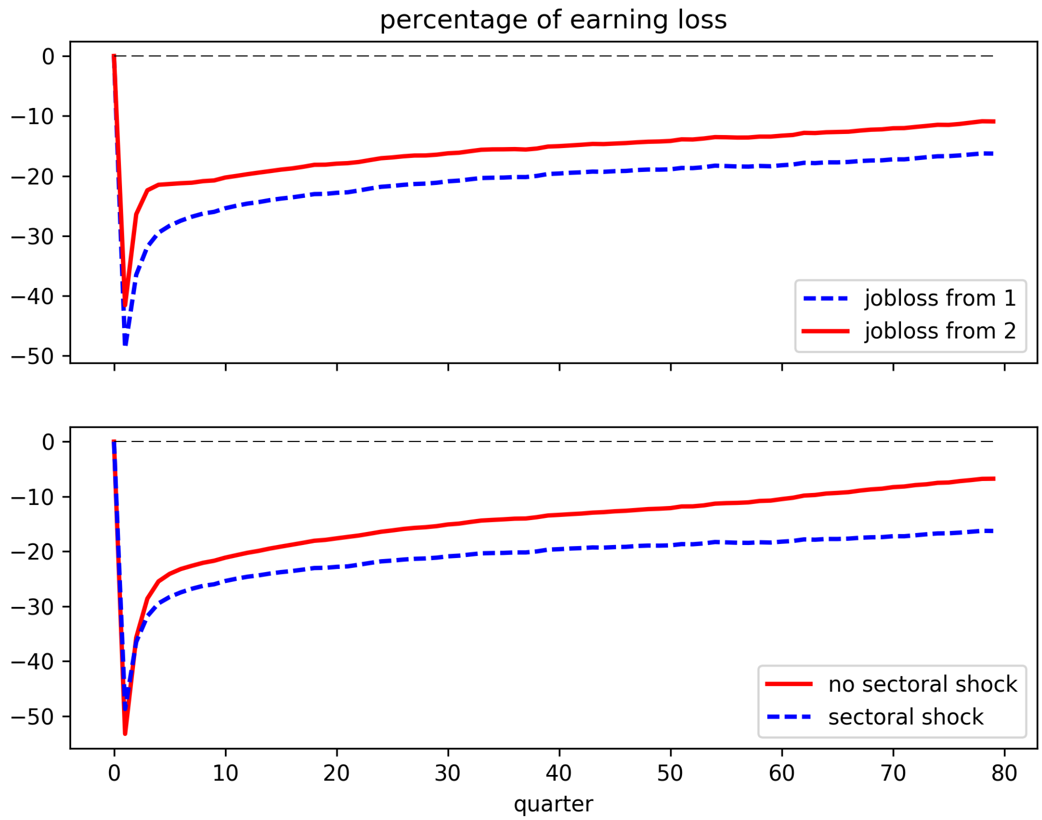


Notes: Left panel shows optimal policy of workers separated from sector 1 and the right panel depicts optimal rule for workers in sector 2. Now, unemployed workers in sector 1 are more willing to search in sector 2 for new jobs.

Using this policy rule, I simulate wage profile of workers employed in these two sectors. Top panel of the figure 4.4 depicts the percentage wage loss for workers displaced from sector 1 and 2 at time 0, relative to similar workers being employed in the same sector, once the shock happens. While the two groups of displaced workers experience huge and persistent earning-loss, those workers from the declining sector experience even larger earning loss, which remains forever.

Bottom panel compares the earning loss of workers separated after a sectoral shock with those job loss occurred in the absence of any sectoral shock. This result of the model is consistent with the second empirical finding that displaced workers experience larger wage and earning loss if the job loss happens during a recession. As in the previous chapter, I empirically show that recessions are not only period of economic downturn, but also periods of more sectoral shocks. Therefore, displaced workers are more faced with sectoral shocks during recessions.

Figure 4.4: Optimal policy of unemployed workers in response to a negative permanent shock to sector 1



Notes: Top panel represents the percentage of wage loss for workers displaced from sector 1 and 2 at time 0, relative to similar workers being employed in the same sector. Bottom panel compares the earning loss of these workers with those job loss in the absence of sectoral shock.

CHAPTER 5
CONCLUSION

To summarize, recessions are worse for displacement for two reasons. First, since job loss is more common and job vacancies are fewer during recessions, finding a new job is harder and on average takes longer after a job loss. This channel causes workers longer periods of joblessness and less job security in recessions relative to job losses in expansions. While this channel may be important for typical separators, it cannot explain the large difference between earning and wage loss of displaced workers since displaced workers are very special separators. For instance, in this paper it is shown that duration of joblessness is not very different for workers displaced in recession than those displaced in expansions.

The second property of recessions is the higher dispersion of sectors in terms of their employment growth rates. In other words, there are more sectoral differences in recessions than in expansions. Therefore, there are more job displacements from relatively declining sectors in recessions. This property of recessions, which makes sector-specific skills of many displaced workers less valuable and exacerbates earning and wage losses associated with the job loss if it happens from a declining sector.

This paper extends the literature on displaced workers in at least two dimensions. First, it documents that displacements not only differ by aggregate properties of the economy at job loss, but also differ based on the relative performance of the sector. Second, it shows that the relative sectoral performance can explain more than half of the observed gap between earning loss in recessions and expansions. In other words, at least half of the reason that recessions are worse for displaced workers is due to the fact that more of the displacements in recessions are happening from relatively declining sectors which makes sector-specific human capital of these workers less valuable. What can explain the other half of the gap should be the topic of future research.

APPENDIX A
DATA

The data basis of this paper is the weakly anonymous Sample of Integrated Labour Market Biographies (SIAB) 1975 - 2014. The data were accessed on-site at the Research Data Centre (FDZ) of the Federal Employment Agency (BA) at the Institute for Employment Research (IAB) and/or via remote data access at the FDZ.

The Institute for Employment Research (IAB) at the Federal Employment Agency of Germany, BA, provides Sample of Integrated Labor Biographies (SIAB) data in spell format which is a 2% random sample of all workers subject to social security in Germany from 1975 to 2014. I convert the main dataset into a monthly panel which I use to compute the job tenure and identify high-tenured workers. In addition, IAB provides Establishment History Panel (BHP) which is a 50% random sample from the universe of all establishments in Germany from 1975 to 2014. The BHP data is used to identify large scale layoff events. Section B.1 describes the construction of the main monthly panel dataset and how I use it to construct the quarterly moments that are used in calibration of the model. I collapse the monthly panel into an annual panel which is used in the regressions to measure consequences of job displacement. Section B.2 describes how the BHP data is used for identifying mass layoff and creating relative sectoral performance measures.

A.1 Monthly Panel of Employees

Original SIAB data report employment spell for each individual worker identified by person unique ID number. Workers may have multiple employment spells at each point in time. These employment spells report the starting and ending date as well as average daily wage, her occupation, and the establishment of the worker identified by establishment unique ID number. In the new version of SIAB that covers 1975 to 2014, a new variable is added to recored whether the employment spell was full-time or part time job. The shortcoming of the data is that it does not record hours of work for each spell. Therefore, I only focus on the full-time workers. I also exclude students during internship or vocational training. Employment spells longer than 1 year are reported in separate spells. Therefore, maximum duration of employment spells reported in the SIAB data is designed to be 1 year. During any employment spell, daily wage is assumed to be constant. If a worker reports wage change, IAB creates a new employment spell starting from the first day of wage change.

To create a monthly panel for wage and earning of workers, I identify the job with most earning at each month. Then I report daily wage of that job as the the wage of worker for the specific month and then calculate total earning of the person from summation of all full-time employment spells which is derived by summation over days at work times their respective daily wages. Notice that I excluded all other types of incomes, such as part time earning, training, or social security benefit from the calculation of full-time earning. This way I can count exact number of days each worker was working for a establishment. This is also used to identify workers with long on-the-job tenure. If a worker does not have any full-time job in a month, I report zero earning and not available daily wage for that month. Hence, earning and wage are different for periods of joblessness.

All earning and wages used in this paper are deflated by consumer price index to reflect real 2001 Euros. From the monthly panel, year-t earnings are calculated by summation over earnings of all full-time jobs of the worker during year t. Wages are the average of reported daily wages of the individual worker in any full-time job in year t. Once workers do not have full-time job, I consider it as zero earning and not available information for wage. Hence, it is possible that a worker has a relatively high wage but very low earning in a year. For instance, in the displacement regression of year y, if a worker was employed in January of year t for 20 days with wage w_{it}^{Jan}, then separated by the end of January and find another full-time job in December of year t in which he worked for 15 days with daily wage of w_{it}^{Dec}, then his earning is $e_{it}^{y} = 20 \times w_{it}^{Jan} + 15 \times w_{it}^{Dec}$ and his average daily wage is $w_{it}^{y} = \frac{e_{it}^{y}}{20+15}$.

Therefore, it is more precise to call w_{it}^{y} and e_{it}^{y} as the average daily earning of worker i in year t and his total full-time earning respectively. However, for simplicity, I refer to them as daily wage or even more simply the wage of worker i and his earning throughout this paper.

A.2 Establishment Panel

Main source for information of employers is the Establishment History Panel (BHP) that is also provided by IAB. The original BHP data include exact employment for each of its workers as well as many other useful information. However, it is forbidden by IAB to merge the original BHP with the original SIAB data. Instead, IAB provides a supplement annual panel aggregated from the original BHP that can be merged with SIAB data. Throughout this paper, I refer to the supplement file as the BHP, while it is more precise to call it BHP supplement for SIAB.

The BHP data is a 50% random sample of all establishments in Germany from 1975 to 2014. Therefore, for each employment spell in the SIAB, we can identify properties of the establishment such as employment size, median wage and the industry at which the establishment has the its main activities. The BHP supplement for SIAB is used in this paper to identify sectoral growth rates, relative sectoral performances, and mass layoff events.

APPENDIX B
EXTENSIONS OF THE MODEL

In chapter 4, I introduced a very simple model of labor market with 2 sectors. Here I want to extend the model in another dimension. On the job search is added to the baseline model to incorporate the fact that employed workers in low performance are willing to pay the search cost and forgoe thier specific skill in return for hihger wages and earning in the other sectors. However, including this feature to the model does not affect the two main results of the basic model that were consistent with the empirical findings of Davis and von Wachter (2012).

B.1 on-the-job search

Now assume that employed workers are free to search jobs in the other sector. Recall that all firms in her sector pay her the same as the only determinant of wages are sector and general human capital. Therefore, the only jobs she can search for are the jobs in the other sector.

$$\begin{aligned}
V_1(x,y) =& w_1(x,y) + \beta \max \Bigg\{ (1-\lambda_1)V_1(x',y') + \lambda_1 U_1(x',y') \\
& , -c_2 + (1-\mu_2)V_2(\phi x, y') + \mu_2 \Big[(1-\lambda_1)V_1(x',y') + \lambda_1 U_1(x',y') \Big] \Bigg\} \\
V_2(x,y) =& w_2(x,y) + \beta \max \Bigg\{ \Big[(1-\lambda_2)V_2(x',y') + \lambda_2 U_2(x',y') \Big] \\
& , -c_1 + (1-\mu_1)V_1(\phi x, y') + \mu_1 \Big[(1-\lambda_2)V_2(x',y') + \lambda_2 U_2(x',y') \Big] \Bigg\}
\end{aligned} \tag{B.1}$$

I assume low of motion for sector-specific and general human capital as well the value function for unemployed workers remains the same. Then, value functions and optimal policy function are solved using the iteration method. Now there are four possible states for workers: employed in sector 1 or 2; or unemployed from sector 1 or 2. It is straight forward to show that this model predicts the same earning losses for displaced workers as the model without on-the-job search.

REFERENCES

[1] Addison, John T., and Pedro Portugal. ”Job displacement, relative wage changes, and duration of unemployment.” Journal of Labor Economics 7, no. 3 (1989): 281-302.

[2] Aghion, Philippe, and Gilles Saint-Paul. ”Virtues of bad times interaction between productivity growth and economic fluctuations.” Macroeconomic Dynamics 2, no. 03 (1998): 322-344.

[3] Antoni, Manfred; Ganzer, Andreas; vom Berge, Philipp (2016): Sample of Integrated Labour Market Biographies (SIAB) 1975-2014. FDZ-Datenreport, 04/2016 (en), Nuremberg

[4] Bartlesman, Eric, and Wayne B. Gray. ”The NBER manufacturing productivity database.” (1996).

[5] Becker, Randy, Wayne Gray, and Jordan Marvakov. ”NBER-CES Manufacturing Industry Database: Technical Notes.” (2013).

[6] Bloom, Nicholas. ”Fluctuations in Uncertainty.” The Journal of Economic Perspectives 28, no. 2 (2014): 153-175.

[7] Caballero, Ricardo J., and Mohamad L. Hammour. ”The Cleansing Effect of Recessions.” American Economic Review 84, no. 5 (1994): 1350-68.

[8] Davis, Steven J. ”Sorting, learning, and mobility when jobs have scarcity value: A comment.” In Carnegie-Rochester Conference Series on Public Policy, vol. 46, pp. 327-337. North-Holland, 1997.

[9] Davis, Steven J., and John Haltiwanger. ”Gross job flows.” Handbook of labor economics 3 (1999): 2711-2805.

[10] Davis, Steven J., R. Jason Faberman, and John C. Haltiwanger. ”The Establishment-Level Behavior of Vacancies And Hiring.” The Quarterly Journal of Economics 581 (2013): 622.

[11] Deaton, Angus, and Christina Paxson. ”Intertemporal Choice and Inequality.” The Journal of Political Economy 102, no. 3 (1994): 437-467.

[12] Diamond, Peter A. ”Wage determination and efficiency in search equilibrium.” The Review of Economic Studies 49, no. 2 (1982): 217-227.

[13] Foster, Lucia, John Haltiwanger, and Chad Syverson. ”The slow growth of new plants: Learning about demand?.” Economica 83, no. 329 (2016): 91-129.

[14] Gibbons, Robert, and Lawrence F. Katz. ”Layoffs and lemons.” Journal of labor Economics 9, no. 4 (1991): 351-380.

[15] Greenwald, Bruce C. ”Adverse selection in the labour market.” The Review of Economic Studies 53, no. 3 (1986): 325-347.

[16] Hall, Robert E. "Employment fluctuations with equilibrium wage stickiness." American economic review (2005): 50-65.

[17] Hall, Robert E., and Paul R. Milgrom. "The Limited Influence of Unemployment on the Wage Bargain." American Economic Review 98, no. 4 (2008): 1653-1674.

[18] Harris, Milton, and Yoram Weiss. "Job matching with finite horizon and risk aversion." The Journal of Political Economy (1984): 758-779.

[19] Hornstein, Andreas, Per Krusell, and Giovanni L. Violante. "Frictional wage dispersion in search models: A quantitative assessment." The American Economic Review 101, no. 7 (2011): 2873-2898.

[20] Hu, Luojia, and Christopher Taber. "Displacement, asymmetric information, and heterogeneous human capital." Journal of Labor Economics 29, no. 1 (2011): 113-152.

[21] Jarosch, Gregor, Falling off the Ladder - Earnings Losses from Job Loss. Job Market Paper, 2014.

[22] Johnson, William R. "A theory of job shopping." The Quarterly Journal of Economics (1978): 261-278.

[23] Jovanovic, Boyan. "Job matching and the theory of turnover." The Journal of Political Economy (1979): 972-990.

[24] Jovanovic, Boyan. "Firm-specific capital and turnover." The Journal of Political Economy (1979): 1246-1260.

[25] Jovanovic, Boyan, and Yaw Nyarko. "Stepping-stone mobility." In Carnegie-Rochester Conference Series on Public Policy, vol. 46, pp. 289-325. North-Holland, 1997.

[26] Katz, Lawrence F., Lawrence H. Summers, Robert E. Hall, Charles L. Schultze, and Robert H. Topel. "Industry rents: Evidence and implications." Brookings Papers on Economic Activity. Microeconomics 1989 (1989): 209-290.

[27] Kremer, Michael. "The O-ring theory of economic development." The Quarterly Journal of Economics (1993): 551-575.

[28] Krolikowski, Pawel. 2017. "Job Ladders and Earnings of Displaced Workers." American Economic Journal: Macroeconomics, 9(2): 1-31.

[29] Krolikowski, Pawel. "Choosing a Control Group for Displaced Workers" working paper

[30] Krueger, Alan B., and Lawrence H. Summers. "Efficiency wages and the inter-industry wage structure." Econometrica: Journal of the Econometric Society (1988): 259-293.

[31] Ljungqvist, Lars, and Thomas J. Sargent. "The European unemployment dilemma." Journal of Political Economy 106, no. 3 (1998): 514-550.

[32] Miller, Robert A. "Job matching and occupational choice." The Journal of Political Economy (1984): 1086-1120.

[33] Mortensen, Dale T., and Christopher A. Pissarides. "Job creation and job destruction in the theory of unemployment." The review of economic studies 61, no. 3 (1994): 397-415.

[34] Murphy, Kevin M., and Robert H. Topel. "Efficiency wages reconsidered: Theory and evidence." In Advances in the Theory and Measurement of Unemployment, pp. 204-240. Palgrave Macmillan UK, 1990.

[35] Neumuller, Seth. "Inter-industry Wage Differentials Revisited: Wage Volatility and the Option Value of Mobility." (2013).

[36] Neal, Derek, The complexity of job mobility among young men. Journal of Labor Economics 17, no. 2:237861, 1999.

[37] Pavan, Ronni. "Career choice and wage growth." University of Rochester (2006).

[38] Pissarides, Christopher A. Equilibrium unemployment theory. MIT press, 2000.

[39] Schmieder, Johannes F., Till Von Wachter, and Stefan Bender. "The effects of extended unemployment insurance over the business cycle: Evidence from regression discontinuity estimates over 20 years." The Quarterly Journal of Economics 127, no. 2 (2012): 701-752.

[40] Shimer, Robert. "The cyclical behavior of equilibrium unemployment and vacancies." American economic review (2005): 25-49.

[41] Topel, Robert. "Specific capital, mobility, and wages: Wages rise with job seniority." Journal of political Economy 99, no. 1 (1991): 145-176.

[42] Topel, Robert H., and Michael P. Ward. 1992. "Job Mobility and the Careers of Young Men." The Quarterly Journal of Economics, 107(2): 439479.

[43] Von Wachter, Till, and Steven J. Davis. "Recessions and the Costs of Job Loss." Brookings Papers on Economic Activity, 2011.