Mismatch and the Consequence of Job Loss

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Abstract: This paper asks whether mismatch—or a misalignment in the places where new jobs are created and old jobs are lost—can explain the heterogeneity in earnings losses following job displacement. I offer an empirical answer to this question by building on previous research that uses mass layoff notifications as a worker-level shock; longitudinal administrative data to compare the labor market outcomes of displaced workers with non-displaced workers; and three new data sets on vacant jobs. I first document that the level and persistence of earnings losses is strongly associated with workers’ displacement location: the earnings loss at the 90th percentile is about twice as large as in the 10th percentile of commuting zones. I then assess the extent to which the dispersion in earnings losses depend on the availability of relevant job openings. Using vacancy-unemployment ratios defined by local labor markets, I find that skill and geographic mismatch explain 10-30 percent of the average earnings loss, and more than half of the dispersion in earnings losses across commuting zones. To help interpret the results, I estimate how employment depends on mismatch. I find that full-time employment is five percentage points lower among mismatched workers. By comparison, I find that part-time employment decreases by a smaller amount. These findings suggest that mismatch reduces earnings due to lower job-finding rates, and through fewer hours worked. Moreover, the results imply that the unequal labor market outcomes could be reduced by policies that move jobs or workers across space.

Keywords: Job Displacement; Unemployment Insurance; Labor Market Mismatch.
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1 Introduction

A large body of empirical research documents that job loss is a persistent and negative shock to workers’ labor market careers. At the same time, the consequence of job loss varies greatly across workers with different skills; between those who stay or leave their previous industry; as well as between otherwise similar workers who lose their job at different times and geographic locations (see e.g. Jacobson et al., 1993; Neal, 1995; Davis & von Wachter, 2011; Yagan, 2016; Huckfeldt, 2016). Understanding the economic mechanisms that shape the adverse consequences of job loss lies at the heart of policies concerned with aggregate labor markets and unemployment—yet, the relative importance of the many explanations remains unclear (Carrington & Fallick, 2014). This paper investigates the empirical importance of availability of jobs that match a worker’s specific skills, and asks whether mismatch in the geographic locations of jobs and displaced workers can explain the persistence and level of earnings losses. Several debates—ranging from the role of policies aimed at improving labor market outcomes in disadvantaged areas, to the importance of job training programs to mitigate skill losses—hinge directly on the empirical answer to this question.

The primary challenge in assessing this question is that firms may selectively lay off less productive workers, and that workers may voluntarily leave for better job offers elsewhere. As a result, a comparison of the average earnings of displaced and non-displaced workers will reflect unobserved factors that are priced differently across the labor market, in addition to the causal impact of job loss. Another challenge is measuring the joint distribution of vacant jobs and displaced workers, while both accounting for the specificity of human capital, and how far individuals are willing to travel for work.

I overcome the empirical challenges by building on the strengths of administrative registers in the context of Norwegian labor markets, and three unique data sets on vacant jobs. The first key strength facilitates a research design used in prior work that uses mass layoff events as a worker-level shock to those who subsequently leave. I identify exposed workers using information on the universe of mass layoffs reported to authorities during the period 2009-2013. Second, using matched employer-employee data, I can track the outcomes of displaced and non-displaced workers spanning several quarters around the mass layoff date. The administrative nature of the data ensures that there is little measurement error in the coding of workers’ earnings and job-seeker status, and provides the complete history of transitions between 3000 residential locations and 250 occupations. Third, I apply a machine learning method to construct a measure of the closeness of jobs in terms of their underlying tasks and skill levels. This information allows me to distinguish between available jobs in a worker’s occupation—and, other jobs that are likely to match a worker’s occupation-specific human capital. Finally, I combine data on travel distance and the universe of job openings to characterize labor market tightness for every occupation (e.g. the number of vacant jobs over unemployed workers) within an hour’s drive from where the worker resides. The extent to which earnings losses depend on dispersion in these ratios at the time of job loss provides direct evidence on the importance of mismatch.

The insights from my empirical analysis can be summarized with three broad conclusions. The first result echoes evidence from other contexts: The average earnings losses associated with job loss are large and persistent, and much of the earnings loss is explained by a decline in full-time employment. In the first quarters after mass layoff, the earnings loss amounts to about 35 percent of pre-displacement earnings. Earnings
rise rapidly during the next four quarters. After this point, average earnings recover slowly, and stabilize at around 80 percent of their pre-displacement earnings. Second, the level and persistence of earnings losses is strongly associated with workers’ displacement location: four years after mass layoff, the earnings loss at the 90th percentile is about twice as large as in the 10th percentile of commuting zones. At the annual level, this difference equals about two monthly pay checks. Third, I find that the consequences of job loss are strongly associated with mismatch. A worker who loses her job in a market with high demand for her specific skills experiences a significantly faster earnings recovery. Geographic and skill mismatch account for about 10-30 percent of the average earnings loss. These estimates suggest that more than half of the earnings inequality across commuting zones could be explained by a misalignment between vacant jobs and unemployed workers. I take several steps to assess the sensitivity of these results. The main conclusions do not change appreciably if I flexibly control for a range of individual and local labor market characteristics, or use alternative definitions of local labor markets.

In interpreting these results, there are several things to keep in mind. The target of my empirical analysis is the impact of losing a job in a labor market that matches a worker’s skills and geographic location well. Any estimated earnings losses would therefore reflect the combination of several distinct mechanisms. One is the decision to accept a lower paid job; another is the depreciation of human capital while looking for better jobs; as well as any changes to the overall chances of finding a job.¹ While I do not have information on hourly wages or exact hours worked, I estimate how employment rates depend on mismatch. I find that a worker who loses her job in a market that matches her skills well are five percentage point more likely to be fully employed than workers who are mismatched. By comparison, I find that part-time employment increases by a smaller amount. These two findings provide suggestive evidence that mismatch reduces earnings due to extensive margin responses, and through fewer hours worked.

The paper is primarily related to a growing empirical literature that investigates the long run implications of job loss in weak labor markets (see Davis & von Wachter, 2011, for a review). Most closely related is the study by Yagan (2016), which compares the post-recession employment outcomes of workers in large retail chains spread throughout the US. The data allows him to compare outcomes of workers who perform identical tasks—where some workers happened to live in regions with severe employment fluctuations during the 2007-2009 recession. He finds that a worker’s location during the Great Recession has an enduring impact on employment outcomes. These results are consistent with a spatial mismatch hypothesis, where the unequal distribution of employment could be mitigated by moving workers across locations. I complement this study by providing direct evidence on how the consequence of job loss depends on mismatch, and that much of the spatial dispersion in earnings losses is due to geographic mismatch. Another strand of the literature considers excess unemployment that arises because there may be too many job seekers relative to vacancies in some local labor markets (Andersson et al., 2014; Sahin et al., 2014; Marinescu & Rathelot, 2016). While evidence is mixed, geographic mismatch may have prevented 2-5 percent of potential hires among unemployed workers from being realized. I contribute to this literature by showing that mismatch explains more than half of the unemployment spells of displaced workers, and has long-lasting impacts on

¹A growing literature studies how the level and duration of unemployment benefits affects the quality of subsequent job matches. These studies usually define match quality as the subsequent job-tenure or level of wages (see e.g. Lalive, 2007; Card et al., 2007; Chetty et al., 2008; Nekoei & Weber, 2015; Schmieder et al., 2016).
employment that extend beyond the initial periods of unemployment.

My empirical approach is similar to empirical studies of occupational mismatch (Gathmann & Schonberg, 2010; Guvenen et al., 2015). These studies use a multidimensional index of the similarity of occupations in terms of tasks, formal skills, cognitive and non-cognitive abilities, and show that occupational switches between jobs that are close or poor substitutes are important in understanding both cross sectional wage dispersion and wage growth over the life cycle. Relatedly, Neal (1995), Stevens (1997) and Poletaev & Robinson (2008) show that a large portion of the earnings losses of displaced workers is explained by workers who switch industries and occupations. In line with these results, Huckfeldt (2016) finds that the excess earnings loss during recessions is primarily driven by workers who switch to occupations that pay lower wages. I add to this literature by showing that access to jobs other than their own has a persistent impact on the earnings of displaced workers. This finding is broadly consistent with the view that labor market skills are quite portable.

Finally, the paper contributes to the large literature that studies the consequences of job loss. The majority of these studies focus on the US (see Couch & Placzek, 2010, for a review), and find that earnings losses are in the range of 10-25 percent after five years, and that the loss persists even 10 to 15 years after displacement.\(^2\) Evidence from European countries provides similar results for annual earnings losses, where relatively more of the earnings loss is explained by declines in employment and hours worked than changes to lower-paying jobs (Bender et al., 2002; Von Wachter & Bender, 2006; Eliason & Storrie, 2006; Huttunen et al., 2011; Jarosch, 2014). While my findings mirror the evidence from other countries and time periods, the main contribution of this paper is to provide direct evidence on one economic mechanism underlying the large earnings losses.

This paper proceeds as follows. I begin with a description of the institutional setting and data on employers, workers and vacant jobs. The next section presents estimates of average earnings losses, and how these losses are dispersed across commuting zones. I then describe how I measure two types of labor market frictions for the empirical analysis of mismatch. The following two sections present the main empirical results. The last section offers some concluding remarks and possible future extensions to this paper.

2 Data and Institutional Setting

I begin this section by describing the institutional details surrounding mass layoffs and unemployment insurance in Norway. Next, I describe the data sources on workers and employers, and illustrate the quality and representativeness of three novel sources on job openings.

2.1 Institutional Setting

The Norwegian labor market is characterized by institutional regulation and flexibility. Most private sector jobs are covered by collective bargaining agreements and are negotiated by unions and employer associations

\(^2\)Other studies focus on the impact of job loss on other outcomes than earnings, including applications for disability insurance benefits (see Black et al., 2002; Autor & Duggan, 2003; Rege et al., 2009), socioeconomic outcomes (e.g. Charles & Stephens Jr, 2004; Rege et al., 2011), labor mobility (e.g. Huttunen et al., 2016), and mortality (e.g. Sullivan & von Wachter, 2009). This research is summarized in Davis & von Wachter (2011).
at national and industry level. Employment protection in Norway draws on European labor relation laws, and firms can dismiss workers when the firms are operating at a loss or are under-performing relative to their peers (see Huttunen et al., 2011, for details). 3

European labor relations law defines a mass layoff event as a situation in which a firm downsizes its stock of workers by at least 10 during a period of 30 days. During a mass layoff, the state body shall be notified at the latest one month prior to the start of the mass layoff, and the Norwegian Labour and Welfare Administration (henceforth, the UI agency) requires employers to submit the dismissal notification in writing. Such a notification is valid if it includes information on the number of affected workers, relevant dates and the selection criteria used. General agreements between employers and labor unions form the basis for selection and typically suggest tenure- and age-based selection criteria. The earliest time that an employee can be dismissed varies by age and tenure: at the earliest one month after notification and at most six months for elderly workers with long tenure. Firms face large financial risks in the event of wrongful discharge; for example, if the notification to the UI agency was incomplete, or if the selection criteria were unsubstantiated, dismissed workers may file a lawsuit against the firm.

Figure 1 shows that despite a high degree of regulation, the rates of job turnover in Norway are relatively high. The rates of job creation and job destruction in the private sector are comparable to those in many other countries. For example, the turnover rate in Norway is about 20 percent lower than corresponding numbers in the US private sector (see Davis et al., 2006).

**Figure 1: Gross labor market flows**

Notes: This figure shows hires and separations in the private sector in Norway for workers aged 25-66. The time series are seasonally adjusted, and smoothed using a three month moving average.

**Unemployment insurance.** Workers who are laid off by their employers are eligible for unemployment

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3Norway became subject to EU Directive 92/56/EEC on becoming a party to the European Economic Area Agreement.
insurance (UI) benefits after a three-day waiting period, while those who quit or are fired for cause have an eight-week waiting period. All unemployed workers below retirement age are eligible for 52 weeks of benefits if their previous earnings are above a fairly low threshold (see e.g. Røed & Zhang, 2003). The potential benefit period is extended to 104 weeks for workers who have earned more than twice the National Insurance basic amount for the last three years, and unemployment benefit replaces 62 percent of workers’ past earnings.\(^4\) The UI system is financed by payroll taxes, and there is no experience rating on the firm.

To remain eligible for benefits, recipients are required to actively look for jobs and to be willing to take any type of employment (e.g. full-time and part-time) at any geographic location (e.g. within and across commuting zones). To assist in matching workers to vacant jobs, the UI agency requires unemployed workers to report their previous and preferred occupation. If workers don’t comply with these rules, the UI agency can impose sanctions by canceling benefit payments for up to 26 weeks. In practice, however, the geographic mobility requirement is rarely invoked.

After reaching the end of their unemployment benefit period, workers can apply for other mean-tested transfer programs available through the social safety net. Social assistance (i.e. traditional welfare benefits) replaces on average 30 percent of previous earnings, and eligibility requirements (activity and means-testing) vary across geographic administrative units. Vocational rehabilitation and early retirement programs provide cash transfers that cover about 60 percent of past earnings. While eligibility for early retirement benefits requires workers to be above the age of 62 and affiliated to industries and firms covered by general agreements, vocational rehabilitation depends on workers’ health status, educational attainment and the transferability of skills to other occupations.

Previous research has documented that displacement and labor market conditions affect the entry rate into disability insurance (DI) programs; see Autor & Duggan (2003) for US evidence, and Rege et al. (2009) for evidence from Norway. Hence, workers who find themselves unable to engage in substantial gainful activity because of a medically verifiable physical or mental impairment can apply for DI benefits. Applicants who are awarded benefits rarely return fully to the labor force, and are transferred to the old age retirement program at age 67 (see Kostol & Mogstad, 2014). Finally, displaced workers may withdraw from the labor force and rely on savings or informal insurance from the family.

### 2.2 Administrative Data on Workers and Employers

In the empirical analysis, I combine several administrative data sources that can be linked by unique and anonymized identifiers for every labor force participant. I collect earnings and the history of workers’ transitions between jobs and occupations using the Norwegian Employer-Employee Register. This data set covers all employment contracts from 1995 to 2015, and contains unique identifiers for every worker and each establishment and firm. Every worker-level contract is reported by the employer to the authorities at the end of the year, and includes information on the dates of alterations to the contract, and the corresponding wage, industry and occupational codes, geographic location and tenure at the establishment. From this source,\(^4\) The National Insurance basic amount is currently set at approximately USD 12,000 p.a., and benefits are capped at a maximum level of previous earnings at six times the basic amount. All monetary figures in the paper are fixed at the 2015 level. For figures expressed in US dollars ($), I have used the following exchange rate: NOK/$ = 8.
I construct time series of monthly (and quarterly) earnings for each worker, and the transitions between establishments and occupations.

Next, I link the employer-employee data to dismissal notifications from establishments that downsize their operations over the period 2009-2015. The notifications are collected by the UI agency’s regional offices, which keep records of the date on which the notification was received and the number of workers the establishment is planning to dismiss. These combined data sources permit the construction of a sample of workers in a downsizing establishment from whom I can identify those who involuntarily separate (i.e. displaced workers), and workers who remain employed or quit for a reason in the overall population of establishments.

I collect information on participation in the UI program from administrative registers containing the complete records for all individuals who entered the program during the period 1992-2015. The data encompasses every job seeker, including both the fully unemployed and those who have a part-time job but are looking for full-time work, and workers who are participating in active labor market programs. Specifically, caseworkers record details on the unemployed workers’ previous occupation, and their stated preference for occupations to assist workers in seeking work.

To capture complete information on workers’ geographic locations, annual earnings, assets, and household income, social security data is merged with longitudinal administrative registers provided by Statistics Norway and covering every Norwegian resident from 1967 to 2015. These administrative data sources contain individual demographic information (including sex, age, zip codes, and education) and, since 1993, all sources of annual income, including earnings, self employment income, capital income, and cash transfers. Household assets include most types of assets holdings and liabilities, such as real estate, financial portfolio, and debt. Income data are reported in annual amounts, while the values of assets and liabilities are measured as of the last day of each year.

The Norwegian administrative data have several distinct advantages over data from many other countries. First, the administrative nature of our data ensures that there is little error in occupational coding. Second, because most income and wealth components are third-party reported (e.g. by employers, banks and financial intermediaries), the coverage and reliability are rated as exceptional by international quality assessments (see e.g Atkinson et al. 1995). Finally, because most register data are a matter of public record, there is no attrition of the original sample due to non-response or non-consent; and income and wealth data pertain to all Norwegian residents and are therefore not limited to those employed in jobs covered by social security, individuals who respond to wealth surveys, or households that file estate tax returns.

2.3 Data on Job Postings and Vacancies

The Norwegian Working Environment Act requires employers to report vacant positions to the UI agency. The data are used for statistical purposes and to match unemployed workers to potential employers. In practice, however, the extent to which firms comply with the rules is difficult to monitor. A natural question is then how representative the vacancies data are for all job openings. I return to this question below.

At monthly level, the UI agency classifies a vacant job by the geographic location of the hiring establishment and a corresponding four-digit occupational code. The locations corresponds to 430 municipalities,
each of which has its own UI office. Occupational codes are based on the International Standard Classifica-
tion of Occupations (ISCO). The UI agency counts the number of positions the establishment is trying to
fill, and the data are available at vacancy level from 2004 to early 2016. Unfortunately there is no information
on the time it takes to fill a job or identifiers for the hiring establishment.

In order to comply with a requirement from the European Union to report vacancies at industry level,
Statistics Norway surveys a representative sample of 8000 establishments – or around five percent of the
total population of establishments – to collect information on the vacant positions. The definition of a vacant
position is that it can start within 30 days, recruitment must be from outside the firm, and full-time, part-
time, permanent, temporary, and short-term job opening are included. The survey arguably provides the
most reliable data on the aggregate level of vacancies. The data set is available at the quarterly level from
2010 until mid-2016, and includes industry code, the number of employees and vacant positions as well as
firm and establishment identifiers.

Finally, I collect information on all vacancies posted on the major online job board (FINN) in Norway
from 2001 to 2016, linking an ad to the hiring firm, its four digit industry code and geographic location.
FINN also provides a full text description of the job, the number of online applications and unique views per
job posting, as well as the dates on which the vacancy entered and exited the market. As online recruitment
has become increasingly common in recent decades (Autor, 2001), the aggregate flow of vacancies from the
online job board appears to be comparable to the UI agency from after the financial crisis (see Appendix
Figure A.5).

Assessing the Quality of Data on Job Openings. To assess the quality and representatives of the three
sources of vacancy data, the vacancy flows need be transformed into stocks. To achieve this, I first collect the
dates on which a vacancy enters and exits FINN, and combine it with information on the firm’s geographic
location and industry in order to compute the average time it takes to fill a vacant job. Next, the industrial
mix of hires is used to compute a weighted average duration of vacancies at each combination of geographic
location and occupation. Finally, the combination of flows and average duration of vacancies is used to
impute the corresponding stock.6

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5ISCO has been adapted to Norwegian labor markets by Statistics Norway and the UI agency. The Norwegian version deviates
from the official version for a handful of occupations, and vacant jobs are recorded using the ISCO08 version, in which there are
403 unique occupational codes. The occupational codes used in the employer-employee register use the ISCO88 standard. Hence,
the two standards must be crosswalked in order to match vacant jobs to workers. The crosswalk procedure reduces the number of
unique, non-overlapping occupations from 403 (354) to 259, detailed in appendix A.5.

6Appendix A.3 describes the approach in more detail.
Figure 2: Trends in vacancy rates

The aggregate trends in stocks of vacancies are presented in Figure 2, starting in 2010, from when the survey data are available. The stock of vacancies is divided by the labor force, comprising every worker aged between 25 to 66 who is either employed or unemployed but actively looking for work. The time pattern shows a clear seasonality in the vacancy postings: the survey shows a distinct peak in the second quarter, while the two other sources have peaks that vary between the first two quarters of the year. More importantly, the graph shows that the three sources track each other well over time when the relative differences between the sources are stable over time.\footnote{The aggregate numbers from the UI agency and FINN are approximately 20 percent below the survey at their respective peaks.}

Figure 3 plots the aggregate unemployment and vacancy rate using jobs reported to the UI agency, adjusted for seasonality by month. The plot reveals a strongly inverse relationship between the two series: during the booming economy prior to the financial crises, the vacancy rate increases while the unemployment rate falls quickly. By the end of 2007, both series abruptly reverse and unemployment rises sharply to about four percentage points, while the vacancy rate steadily declines. Autor & Duggan (2003) provide compelling evidence from the US suggesting that disability insurance benefits have provided many workers with a viable alternative to UI benefits. The low unemployment rates should therefore be viewed in light of the relatively large share of the working age population enrolled on the DI program, peaking in 2004 at around 10 percent (see Kostol & Mogstad, 2014).
Notes: This figure shows the monthly unemployment rate among workers aged 25-66, and includes workers who are partially employed and participating in active labor market programs. The vacancy rate combines data on vacancy flows from the UI agency and duration from the online job board (see Section 4 for details).

Using establishment level data from JOLTS, Davis et al. (2013) find that about 40 percent of hires take place without a corresponding vacancy from the month before the survey date. The authors estimate that about two thirds of the “missing vacancies” are posted and filled within a given month; thus, even at the monthly level, a substantial fraction of hires remains unmeasured because of the frequency at which employers are surveyed.8 Thus the authors find that a majority of the establishments fill a vacancy by more than one hire. As a final test of the quality of the data, I follow Davis et al. (2013) in estimating the vacancy yield – that is, the number of hires per vacancy. I deviate from prior work by employing a methodology typically used in public finance to identify earnings responses to marginal tax changes using bunching of income around kinks in individual budget sets (Kleven, 2016). The idea behind this approach is that in the absence of a particular vacancy, the total number of hires should be smooth around the date at which an ad exits or enters the market. Estimating a counterfactual trend of total hires allows me to calculate an excess mass of hires in a short time interval after the ad exits the markets, where the yield is the ratio of excess hires over the total number of vacancies in the sample. I obtain vacancy yields in the range of 0.4–0.6 for my sample of vacancies. The approach is described in Appendix A.3.

Despite a certain degree of consensus on the measurement and interpretation of unemployment, much less is understood about vacancies. Elsby et al. (2015) discuss both conceptual and measurement issues. Taken together, the finding that vacancies of the UI agency are comparable and consistent with aggregate

8In a related study, Hansen (2016) combines a Swedish survey on vacancies at the quarterly level with administrative data on hiring, finding only a weak relationship between the reported number of vacant positions and subsequent hires at establishment level.
time trends from both the survey and the online job board speaks to a concern that “registered vacancies fail to be representative of all job openings” (Elsby et al., 2015). Furthermore, I show that vacancies are highly correlated with hires at the firm level, and consistent with the notion that a vacancy represents a firm’s effort to hire (Sahin et al., 2014). As my empirical analysis requires information on geographic location and the skill requirement of a job, I will restrict my attention to vacancies from the UI agency for the rest of the paper.

3 Mass Layoffs and Job Displacement

In this section, I follow the initial research design of Jacobson et al. (1993) in order to estimate the average earnings losses associated with job loss, and present estimates of how earnings losses vary across commuting zones.

3.1 Sample Restrictions

My empirical analysis uses the universe of mass layoffs from 2009 to 2016 reported by establishments to the local UI agencies. This data allows me to link the downsizing establishments to a matched employer-employee data set which provides information on the workers who were employed the month before the mass layoff event began. I build on a previous research design that uses the mass layoff event as a worker-level shock to those who subsequently leave. Furthermore, the data contains information on the exact time at which workers report to start looking for vacant jobs. By comparison, because mass layoffs in Norway often last for several months, and the earliest time that an employee can be dismissed varies by age and tenure, administrative data alone can only provide a noisy measure of the time at which the mass layoff event begins. As employers are required to report events that include at least 10 workers, my estimation sample also includes “small” mass layoffs. The share of displaced workers in my baseline sample is 15 percent.

To avoid issues of entry and exit from the labor force from schooling or to retirement, I restrict my sample to workers aged between 24 to 62. I follow prior work that focuses on workers with long tenure on the job, and exclude workers with less than two years of experience at the time the mass layoff begins. In the empirical part that uses non-displaced workers as comparison group, I follow the example of Davis & von Wachter (2011) in restricting the sample to full-time workers, and exclude non-displaced workers who are observed at least one quarter without work. Finally, I exclude events after 2013 in order to follow all workers for at least two years. Summary statistics of the estimation sample are presented in Table 1. The table displays summary statistics of displaced and non-displaced workers, and confirm findings from prior work that displaced workers are younger, have shorter tenure and lower average earnings than non-displaced workers.

Because I measure vacant jobs at the zip code, occupation, and monthly level, I exclude a small number of workers with missing occupation or geographic location.
Table 1: Summary Statistics: Mass Layoffs

<table>
<thead>
<tr>
<th>Worker characteristics</th>
<th>Non-displaced Mean</th>
<th>Non-displaced Std. Dev.</th>
<th>Displaced Mean</th>
<th>Displaced Std. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>43.8 [8.92]</td>
<td>42.6 [10.1]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tenure at the establishment (months)</td>
<td>114 [89.1]</td>
<td>88.3 [79.0]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>0.2 [0.40]</td>
<td>0.22 [0.41]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Married</td>
<td>0.62 [0.48]</td>
<td>0.57 [0.49]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of kids below age 18</td>
<td>1.0 [1.08]</td>
<td>0.87 [1.05]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Level of education: High school</td>
<td>0.48 [0.50]</td>
<td>0.44 [0.50]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Level of education: Some College</td>
<td>0.25 [0.43]</td>
<td>0.23 [0.42]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Occupation: Skilled</td>
<td>0.46 [0.50]</td>
<td>0.38 [0.49]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Occupation: Vocational</td>
<td>0.46 [0.50]</td>
<td>0.53 [0.50]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Quarterly earnings ($)</td>
<td>20,514 [8,835]</td>
<td>17,900 [8,303]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of observations</td>
<td>53,393</td>
<td>10,164</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: Baseline sample of displaced workers aged 25-62 with at least two years of tenure during the period 2009-2013. Characteristics and earnings is measured four quarters before mass layoff.

3.2 Estimated Earnings Losses Associated with Job Displacement.

I begin by estimating the association between quarterly earnings losses and displacement for the pooled sample of workers described above. Following the statistical specification in Davis & von Wachter (2011), I compare the earnings of displaced to non-displaced workers, and let the (conditional) difference vary across the eight quarters before and sixteen quarters after displacement. Worker characteristics are restricted to influencing earnings the same way over all quarters relative to displacement notice, \( q \), and include a quadratic polynomial in age, tenure, and a moving average of pre-displacement earnings over \( q \in \{-8, 0\} \) to capture differences in earnings levels before displacement. I implement this comparison by running ordinary least squares (OLS) regressions on the following distributed lag model

\[
E_{iq} = \alpha_j + \alpha_t + \gamma_q + \beta X_{iq} + \sum_{q=-8}^{16} \delta_q D_{iq} + u_{iq}
\]  

where \( E_{iq} \) denotes individual \( i \)'s labor income in a quarter relative to when notice was received by a UI office. The occupation fixed effects, \( \alpha_j \), removes average earnings for all workers in the same four digit occupation—irrespective of whether they are displaced or not. For example, if all machine operators lose their jobs, the displacement indicator \( D_{iq} \) would be fully absorbed by the fixed effect and not contribute to the average impact. Fixed effects for each mass layoff year are included in \( \alpha_t \), and the quarterly dummies in the vector \( \gamma_q \) capture the mean earnings for non-displaced workers. The characteristics of workers are included in the vector \( X_{iq} \). Finally, \( D_{iq} \) represents the interaction of a quarter and a dummy which is equal to 1 for displaced workers, and zero for non-displaced workers; thus the parameter \( \delta_q \) captures the conditional difference in earnings in a quarter (e.g. sixteen quarters after displacement).

Estimates of the earnings losses due to job displacement are plotted together with 95 percent confidence intervals in Figure 4a. To facilitate comparisons with prior work, I divide the estimates by the average
earnings of displaced workers in the period before mass layoff. The graph shows that the difference between non-displaced and displaced workers is relatively stable and close to zero for the first eight quarters, but abruptly increases as mass layoffs begin. The earnings loss reaches its maximum two quarters after mass layoff, a time when most displaced workers have separated from their employer. During the next four quarters, displaced workers’ earnings rise rapidly during the next four quarters, after which the earnings loss appears to stabilize at around 20 percent. By comparison, prior research finds that job displacement reduces average earnings in the range from 10 to 25 percent after five years (see Davis & von Wachter, 2011; Couch & Placzek, 2010, for extensive reviews). Thus the estimates presented here are broadly consistent with what researchers have found in other countries and for different time periods (Rege et al., 2009; Huttunen et al., 2011). These numbers shed light on the external validity of job loss experiences in the context of Norwegian labor markets, suggesting that the consequences of job loss are comparable to findings from many other countries.

Figure 4b shows that a large part of the earnings losses are driven by a decline in the number of workers who find full-time employment. This is similar to much of the evidence from Europe, while much of the earnings losses in the US are explained by wage reductions (Bender et al., 2002).

Figure 4: Average impacts of job loss

(a) Quarterly earnings

(b) Full time employment

Notes: Left figure shows the estimated earnings loss associated with job displacement, and right figure shows estimated loss of full time employment for workers aged 25-62 with at least two years of tenure during the period 2009-2013. Regressions include indicators for each quarter, their interaction with a dummy for whether a person is displaced, occupational clusters fixed effects, and worker-characteristics (age, tenure, and pre-displacement average earnings). Dashed lines show 95 percent confidence intervals, and robust standard errors are clustered at the level of commuting zones.

3.3 Regional Dispersion in Earnings Recoveries.

To assess the geographic dispersion of earnings recovery, I re-estimate equation 1 separately by the commuting zones (CZ) in which a worker was resident the year before displacement. There are 46 commuting zones.
in total that comprise several municipalities and are defined by aggregate commuting statistics and physical barriers such as mountains, lakes and fjords (see Huttunen et al., 2016). I exclude CZs with less than 1000 affected workers, and keep workers whose occupation is employed in at least two distinct CZ before and after the mass layoff event. I divide each estimate by the average wage before displacement at national level, and display the median, 10th and 90th percentiles of the estimated quarterly earnings losses in Figure 5a.

The results show that the level and persistence of earnings losses appear to be strongly associated with workers’ displacement location: four years after mass layoff, the earnings loss at the 90th percentile CZ is about twice as large as in the 10th percentile CZ. The difference in the earnings loss accounts for approximately 15 percent of quarterly earnings, or about two monthly pay checks at annual level. Over the first four years, the cumulative effect of living in a 10th percentile region as compared to a 90th percentile exceeds 60 percent of the average annual earnings level before displacement. Extrapolating the difference beyond the last quarter, a worker pays an annual wage premium for being displaced in the worst displacement region after six years.

**Figure 5:** Average impacts of job loss by commuting zones

(a) Quarterly earnings

(b) Full-time employment

Notes: Left figure shows the estimated earnings loss associated with job displacement, and right figure shows estimated loss of full-time employment for workers aged 25-62 with at least two years of tenure during the period 2009-2013. Regressions include indicators for each quarter, their interaction with a dummy for whether a person is displaced, occupational clusters fixed effects, and worker-characteristics (age, tenure, and pre-displacement average earnings). The graph shows the 90th, 50th and 10th percentiles of earnings losses by quarter since mass layoff begins.

The dispersion in post-displacement employment is presented in Figure 5b. The 90th to 10th percentile difference in the probability of finding a full-time job is somewhat smaller than for earnings. This suggests that some of the earnings dispersion may be due to differences in wages, or part-time employment. In the remainder of the paper, I will investigate whether the spatial heterogeneity in the consequences of job loss can be attributed to mismatch in the demand and supply of labor at the time of job displacement.
4 Measuring Labor Market Frictions

In this section I develop a measure of how closely related jobs are in terms of their underlying tasks and skill levels, and the physical distance between displaced workers and vacant jobs.

4.1 Transferability of Skills Across Jobs

The premise of this paper is that occupations are able to capture critical elements of the specificity of a worker’s human capital. A large empirical literature supports this view. Kambourov & Manovskii (2009) emphasize the importance of occupation in wage determination, Gibbons et al. (2005) show that employee sorting across jobs is consistent with comparative advantages based on human capital accumulated by occupational tenure, and Gathmann & Schonberg (2010) demonstrate that distinguishing between general and task-specific human capital is key to understanding differential wage growth in Germany. Autor & Dorn (2013) show that the task content of occupations is an important factor in explaining the rising wage inequality in the US.

I begin by describing the occupational structure in Norway and the complexity of job search using the occupations in which unemployed workers are actively looking for work. The basic question is whether job seekers direct their search efforts to finding jobs with similar tasks and that employ similar skills to their previous occupation? Figure 6 displays every four digit occupation, layered vertically by their first digit and then grouped horizontally by the next two digits. The first digits of an occupational code are meant to capture the similarity of occupations in terms of skill and tasks: Occupations for workers with some years at college or a university degree (e.g. mechanical engineer and medical professionals) are found in the bottom two layers, and occupations that require the vocational track at secondary school level are in the second and third layer from the top (e.g. machine operators and plumbers). The remaining occupations have no formal skill requirement.

The lines between occupational nodes represent the share of unemployed workers from occupation $j$ that are currently looking for work in occupation $j'$. A thin (thick) line represents a switch that accounts for at least 15 (25) percent of the total occupational moves from either occupation $j$ or $j'$. The sample is constructed from the last month of every unemployment spell for workers above age 25 in which an unemployed worker reports herself to be looking for a job in a different occupation from her previous one. The figure shows that switches across 1-digit occupational codes may be equally as important as switches within these codes. For example, if the occupational structure captures the essence of the transferability of human capital, most of the transitions should be horizontal, as in the case of clerical workers (third layer from bottom). On the contrary, the figure shows that most of the major switches occur vertically and across 1-digit codes. Similar patterns are found for job-to-job transitions that are less prone to measurement errors from workers’ stated preferences, and are available upon request.
Notes: This figure shows the occupational structure of the International Standard Classification of Occupations, where vertical layers represent the first digit (excluding managers), and two digit occupational clusters are displayed horizontally. A single node is a four digit occupation, and the lines between nodes represent the share of unemployed workers from occupation \( j \) stating a preference for a job in occupation \( j' \) or vice versa for the sample of unemployed worker’s whose preferred occupation differs from her previous occupation in the period 2003-2011. Thin (thick) lines are for pairs of occupations where the share of workers’ destination \( j' \) represents 15 (25) percent of occupation \( j \)’s overall switches.

Learning from Dictionaries of Occupational Titles. To move beyond the bare structure of occupational codes, I follow prior research in using the occupational content of jobs. The approach that I take builds on the general idea from Autor et al. (2003), Gathmann & Schonberg (2010) and Poletaev & Robinson (2008), that output in an occupation is produced by combining multiple tasks, for example lift, build, advice, and manage personnel. While the first two tasks are arguably more specific in the sense that they are employed in jobs where workers perform certain manual tasks, the latter two are more general and can be used in a wider range of occupations. Gathmann & Schonberg (2010) formulate a model in which a worker’s productivity in an occupation \( j \) – or let’s say earnings – is determined by the intensity of tasks and experience in performing each specific task. In the model, the share of time spent performing analytic tasks, \( A \), is \( \beta \), and that spent on manual tasks, \( M \) equals \( 1 - \beta \). Hence, earnings vary due to differences in the amount of time they spend on abstract and manual tasks, and a worker \( i \)’s years of experience in a particular occupation

\[
E_{i,j,t} = \beta_{j} t_{i,j,t}^{A} + (1 - \beta_{j}) t_{i,j,t}^{M}
\]  

Earnings, \( E_{i,j,t} \) increase over time due to learning on the job. This learning accrues through accumulation of task-specific tenure, which is determined by the intensity of each task in an occupation, and a worker’s initial human capital investment (i.e. medicine or engineering). The key point is that occupations can be ranked according to the absolute distance \( d_{j,j'} = |\beta_{j} - \beta_{j'}| \), where this “skill distance” determines how well a worker’s task-specific human capital from job \( j \) is transferred to a new occupation \( j' \); and, therefore how earnings are affected by occupational switches.

Precisely because human capital may be specific to an occupation, Poletaev & Robinson (2008) argue
that the transferability of skills across occupations is central to explaining the costs of job loss. Because workers have different sets of skills, a measure of the similarity of jobs contributes to understanding how occupational mobility affects earnings recovery. The authors use the US dictionary of occupational titles (DOT) with detailed descriptions of the tasks and skills needed for several thousands of jobs to construct a vector of inputs for each job, from which they can distinguish between occupational switches that use different skills and those that require higher levels of skills. Similarly, I use detailed job descriptions from dictionaries of ISCO titles to compute a ranking of how similar occupations are in terms of the context of the job, the tasks performed and the skills needed at a granular level. In contrast to Gathmann & Schonberg (2010), my approach characterizes a job by the full textual description of the job, and generalizes Equation 2 to K dimensions $E_{i,j,t} = \sum_k \beta_{j,k} t_{i,j,t}^k$. To see how this basic idea works, consider the description of a mechanical engineer, which includes a broad description such as

“Mechanical engineers conduct research; advise on, design, and direct production of machines, aircraft, ships, machinery and industrial plant, equipment and systems; advise on and direct their functioning, maintenance and repair; or study and advise on mechanical aspects of particular materials, products or processes.”

together with an exhaustive list of the types of tasks a mechanical engineer may perform. The descriptions typically vary in levels of detail, the number of sentences and unique words. For example, the words describing a shop assistant have several words that overlap with those describing a shelf filler (e.g., wholesale, shop, and goods), and the description of a shoemaker is similar to a sewing machine operator (e.g. sewing, leather, stitching). The approach I take will compare the verbs and nouns that describe the job of a mechanical engineer to a chemical engineer, computer technician, machine operator, and shop sales assistant. As some words appear very frequently in the job descriptions (e.g. “do”) and have little importance in describing the specificity of different jobs, I follow a weighting scheme commonly used by computer scientists that attach less weight to the words used frequently within and across descriptions.

To compare the vast number of comparisons, I provide an algorithm that proceeds as follows. First, I vectorize words from job descriptions and re-weight each word according to the inverse of their document frequency, leaving a vector of 4,500 words, $w_j$. Second, for each pair of occupations $j$ and $j'$, I tell the computer to calculate the weighted distance, and follow standard practice in using the euclidean distance (Friedman et al., 2009). More formally, the distance is calculated from

$$d(w_j, w_{j'}) = \sqrt{\sum_{k=1}^{K} (\tilde{w}_{jk} - \tilde{w}_{j'k})^2}$$

where $\tilde{w}_{jk}$ is the weighted frequency of the $k$-th word in the description of occupation $j$, and $K$ is the total number of words to evaluate. The computer performs the calculation from equation (3) for every pair $(j, j')$, and outputs a pairwise distance matrix of size 259 × 259. Appendix A.4 provide further details on the steps of this procedure.

10Neal (1995) makes a related point, but limits his empirical investigation to industry-specific tasks. Ljungqvist & Sargent (1998) show that a search model with depreciation of occupation-specific human capital provides patterns that are consistent with the level of earnings losses found in Jacobson et al. (1993).
Figure 7: Skill distance and search patterns

Notes: This figure shows the relationship between skill distance and occupational switches among unemployed workers from occupation \( j \) who are actively looking for a job in a different occupation \( j' \). The sample is all unemployed workers in the age 25-66 who are actively looking for work in a different occupation than their previous occupation. The distance is based on dissimilarity of the words from dictionaries of occupational titles between any pair of occupations \( j \), \( j' \), and are grouped by percentiles (see Section 4).

To test how well the distance variable performs in explaining the direction of job seekers’ search effort, I sort pairs of occupations by distance and aggregate pairs into percentiles. Next, I count the number of periods in which workers from occupation \( j \) are actively looking for work in (percentile) destination \( j' \) using the same data on unemployed workers as above. Finally, I aggregate the number of switches by percentile distance, and divide by the total number of switches in the sample. Figure 7 shows that the distance in the skill and task content between occupations explains a large portion of the occupations in which unemployed workers are currently looking for work. Moreover, the smoothed solid line shows that the most likely moves are to the closest occupations: Overall, the three (ten) closest occupations explain almost twenty (forty) percent of all transitions. The greater the distance, the less likely a worker is to look for a job in that occupation, and the relationship decreases monotonically in skill distance. Moving to the far end of the scale, the relationship reverses abruptly. To investigate whether the reversals can be explained by a larger share of vacant jobs relative to unemployed workers looking for jobs in that occupation, the gray bars display the average vacancy-unemployment ratio by skill distance. The ratio does not display a marked difference when the 100th percentile is compared with alternatives that are ranked closer to the origin. Instead, as illustrated in Figure 7, the most prevalent occupation at the 100th percentile is shop sales assistants. Thus the reversal appears to be explained by occupations that are relatively easy to fill, and whose textual description is limited to a few generic words. Finally, Appendix Figure A.6 tests separately the performance of workers who are actively looking for jobs in occupations from different 1-digit occupational codes. The search pattern is quantitatively similar, and shows that skill distance is a powerful tool for understanding the direction of occupational mobility independently of the embedded occupational structure from ISCO.\(^{11}\)

\(^{11}\)The pattern is quantitatively similar, and more pronounced if I instead consider occupational switches in job-to-job transitions.
Despite delivering empirically reasonable patterns of job search, the dimensions of the pairwise skill distance matrix remain prohibitively large. The next step involves reducing the dimensions of the skill portfolio to make it empirically tractable while preserving the information contained in the skill distance. I address this challenge using a hierarchical clustering approach that starts with each occupation and sequentially looks for pairs of occupations to join that minimize the increase in total within-cluster skill distance (e.g. the Ward method; see Friedman et al., 2009, and Appendix for details). The algorithm continues to join occupations until there are two clusters left, leaving a traversable tree of potential clusters from which the researcher in practice is left to choose among. A natural starting point is to find the branch of the tree in which all occupations have been matched to a cluster. Occupations whose tasks and skills are relatively more similar to other jobs will tend to enter a cluster early in the process (e.g. engineers), whereas skills that are hard to substitute enter late (e.g. undertakers). As a result, jobs that require general skills and tasks tend to end up in larger clusters. Note that the pairwise skill distance allows for asymmetry – e.g. a baker’s closest substitute is a food product worker, but the food product worker’s closest occupation is butcher. The clustering approach imposes symmetry and ignores the relative skill distances within clusters. As a result, the clustering approach suggests that a baker is equally likely to take a job as a butcher or as a food product worker.

**Robustness and Comparison with Other Task-Based Approaches.** Building on the work of Autor et al. (2003), Autor & Dorn (2013) measure an occupation’s demand for manual, routine and abstract tasks from dictionaries of occupational titles. Manual tasks are measured as the need for “eye-hand-foot coordination” in performing a job. Routine tasks are the average of the scales measuring the need for “set limits, tolerances, and standards” and “finger dexterity”, and abstract tasks are measured as the average of “direction control and planning” and “GED Math”, which measures the managerial, interactive and mathematical skill requirement of jobs. While these measures are not readily available from Norwegian job descriptions, the occupational codes can be matched to these three measures using the crosswalk made available by Autor & Dorn (2013). Figure 8 shows how the demand for routine, abstract and manual tasks varies with the skill distance for occupations with abstract skill requirements above the 75th percentile. The skill distance captures differences in the task content of jobs well: with increasing distance from the origin, the content of jobs becomes less abstract, and requires more routine and manual tasks.

Because equation (3) will increase mechanically when two occupations vary in the number of words describing them, it is natural to ask how the approach performs for unskilled occupations or jobs with sparse descriptions. To investigate this, Appendix Figure A.7 partitions the sample into groups by skill level. First, the figure shows that the reversal at the 100th percentile is fully accounted for by unskilled occupations. Second, and consistent with the findings of Gathmann & Schonberg (2010), the figure suggests that the transferability of task-specific human capital is more important for workers with a high skills level: the higher the skills level, the more directed the search is towards similar occupations. Nonetheless, the skill distance remains strongly associated with the number of workers looking for jobs in a particular occupation across all skill types.

The results are available upon request.
Figure 8: Skill distance for jobs with abstract tasks

Notes: This figure shows the relationship between tasks scores and the skill distance between pairs of occupations \((j,j')\). The sample of occupations have with abstract content above the 75th percentile. The tasks scores are based on measures of abstract, routine and manual tasks performed in occupation \(j'\) (see Section 4 and Autor & Dorn (2013) for details).

In the baseline specifications I use the 80 clusters that are left after all occupations have been allocated to a cluster. Importantly, the approach delivers patterns of substitutability entirely based on comparative advantages ensuing from the human capital accumulated through occupational tenure. A mechanical engineer is relatively better at chemical engineering because of his technical insights and mathematical skills. The approach is therefore unable to deal with comparative advantages based on unobserved abilities (see e.g. Heckman & Honore, 1990), nor is it able to capture that the next best alternatives may vary across workers (e.g. Kirkeboen et al., 2016).

4.2 The Geography of Vacant Jobs and Workers

The last measurement issue of this section pertains to the geography of a worker’s labor market. Specifically, how far is an unemployed worker willing to commute for work?

To shed light on this issue I collect travel distances between every zip code in Norway. Using this data I can calculate the travel time in minutes between the place where displaced workers live and their previous workplace. Appendix Figure A.9 shows a histogram of travel times for displaced workers. It illustrates that the vast majority spend less than 60 minutes commuting to work, and that one third live within a 10 minutes drive of their workplace. As in Marinescu & Rathelot (2016), the pattern suggests a clear distaste for travel time. In contrast, in the context of Norwegian labor markets, travel distance may exceed three hours in commuting zones that are defined by aggregate commuting statistics and physical barriers. To address these facts, I follow Manning & Petrongolo (2016) in allowing local labor markets to overlap, that relaxes the implicit assumption of zero cost of travel time within a commuting zone. Instead, I assume that a local labor
market is defined by the vacant jobs that can be reached an hour’s drive from where the worker resides.\textsuperscript{12} Taken to the data, this definition amounts to counting the number of job openings that can be reached by an hour’s drive from a worker’s home, while at the same accounting for the competition from other job seekers that can reach the same jobs by an hour’s drive from their home.\textsuperscript{13}

Figure 9 illustrates the marginal distributions of vacant jobs and potential competition from other job seekers in local labor markets. The sample is restricted to the baseline sample of displaced workers, and the distribution of vacant jobs and job seekers are measured two months after mass layoff. The left panel shows the number of vacancies and unemployed workers for all jobs, whereas the right panel shows the number of jobs in a displaced worker’s own occupation. The next section shows how I integrate these numbers to form a measure of mismatch.

Figure 9: Distribution of jobs and competition from other job seekers

Notes: This figure shows a histogram of the number of available jobs the baseline sample of displaced workers have in their local labor market two quarters after mass layoff (see Table 1). The left panel counts all jobs and the right panel counts the number of jobs in their own occupations. The gray bars reflect the number of unemployed workers from overlapping local labor markets that may apply for the same jobs. A local labor market is measured as the jobs that can be reached from an hour’s drive from home.

5 Empirical Analysis

This section describes how I integrate the econometric specification from Section 3 with the measures from Section 4, and presents the main empirical results of the paper.

\textsuperscript{12}In practice, the location of the vacant job is an aggregate of zip codes, as the administrative unit of the UI agency contains on average 10 zip codes. Travel time does not account for traffic congestion.

\textsuperscript{13}I do not consider competition from workers who are employed. Jarosch (2014) and Krolikowski (2014) show that accounting for on-the-job search is important in explaining the earnings losses for displaced workers. However, accounting for such behavior is challenging both computationally and conceptually in the setting of this paper.
5.1 Research Design and Parameters of Interest

The goal of this paper is to understand how the consequence of job loss depends on mismatch. Everything else equal, I want to compare two states. One in which workers’ skills match what hiring firms need, and another where they don’t. To implement this comparison, I take the baseline sample of displaced workers and run OLS regressions on the following extension of equation (1)

\[ E_{i,q}^D = \alpha + \alpha_j + \gamma_q + \beta X_i,q + \rho m_i + \sum_{q=-8}^{16} \mathcal{M}_q m_{i,q} + u_{i,q} \] (4)

where \( E_{i,q}^D \) denotes the post-displacement quarterly labor market earnings (or employment). The dummies for occupational clusters \( \alpha_j \) account for geographic concentration of different types of jobs, and permanent differences in earnings across occupations.\(^{14}\) As in Section 3, \( \alpha_t \) captures the calendar year fixed effects, \( \gamma_q \) captures the average earnings loss at quarter \( q \), and \( X_i \) is a vector of controls, including the workers age, tenure, pre-displacement average earnings and a set of pre-determined local labor market characteristics. Any remaining pre-determined differences in the level of earnings for mismatched workers are captured by \( \rho \). The main independent variable, or vector \( m_{i,q} \), measures average mismatch after displacement for individual \( i \), and is equal to 1 in quarter \( q \) and zero for all other quarters.

The key parameter of interest \( \mathcal{M}_q \), gives the effect of being displaced in a labor market with many jobs compared to a market with few jobs. This parameter is estimated separately for each quarter, which allows earnings to depend on mismatch differently over time. When estimating the relative importance of geographic and skill mismatch, \( \mathcal{M}_q \) is a vector of two parameters. For example, \( \mathcal{M}_q^{s} \) would determine how earnings depend on skill mismatch while holding the geographic distribution of jobs fixed (and vice versa).

The next question is how to measure mismatch. Most of the empirical and theoretical literature uses vacancy-unemployment ratios that approximate the way in which unemployment and vacancies are transformed into hires (see Jackman & Roper, 1987; Shimer, 2007; Sahin et al., 2014; Marinescu & Rathelot, 2016). This ratio would reflect the basic idea that there may be too many job seekers relative to vacancies in some places and too few job seekers in other places. To fix ideas, consider labor markets that are segmented by geography where workers are perfectly substitutable across jobs. In such a situation, geographic mismatch could be captured by the ratio of vacant jobs to unemployed workers in a local labor market, \( m_g = \frac{V}{U} \). An increase in the number of jobs, while holding the number of workers fixed would increase the chance of finding a job. Conversely, increasing the number of unemployed workers within the same labor market reduces the probability of finding a job.

Similarly, aggregate skill mismatch could be defined as a labor market completely segmented by occupation, where labor moves freely between locations. Here, mismatch arises because workers are attached to an occupation, where job search would be more efficient in occupations with more jobs relative to unemployed workers. I measure such skill mismatch at the local labor market, since the goal of this paper is to understand dispersion in earnings losses over different geographic locations. This form of mismatch is computed

---

\(^{14}\)Removing the time-invariant fixed effects amounts to assuming that matching efficiency is constant across occupational clusters. Importantly, while the fixed effects control for some of the permanent differences across groups of occupations, it also leaves some variation in mismatch within the occupational cluster (i.e. a mechanical engineer is mismatched if there are relatively more jobs in chemical engineering).
by counting the number of jobs and unemployed workers in occupation $j$ at local labor market $g$, $m_{g,j} = \frac{V_{g,j}}{U_{g,j}}$. I will also consider the close substitutes from the previous section, and compute the ratio at the level of an occupational cluster $\hat{j}$.\textsuperscript{15}

Table 2 shows the means and standard deviations of vacancy-unemployment ratios. The ratios are economy-wide, and at the level of local labor markets, for all jobs and for jobs in workers’ previous occupation. The vacancy-unemployment ratios are counted at the quarterly level and averaged over the eight quarters before and the sixteen quarters after mass layoffs begin. These numbers echo the decline in job openings and increasing rate of unemployment from Figure 3. Most displaced workers therefore experience a decline in available jobs—or, an increase in the competition for a given job. Whereas aggregate ratios depend on the time in which a worker loses her job, the ratios at the local level depend on the availability of jobs at different times and locations. The size of the ratios thus reflects that most workers live close to where jobs are created (e.g. job loss typically occurs in larger cities).

Table 2: Summary Statistics: Mismatch

<table>
<thead>
<tr>
<th>Vacancy-unemployment ratios</th>
<th>Before</th>
<th>After</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Std. Dev.</td>
</tr>
<tr>
<td>Vacancy-unemployment ratios, national level</td>
<td></td>
<td></td>
</tr>
<tr>
<td>All jobs</td>
<td>0.81</td>
<td>[0.27]</td>
</tr>
<tr>
<td>Own occupation</td>
<td>0.77</td>
<td>[0.83]</td>
</tr>
<tr>
<td>Vacancy-unemployment ratios, local labor markets</td>
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<td></td>
</tr>
<tr>
<td>All jobs</td>
<td>2.34</td>
<td>[2.06]</td>
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<tr>
<td>Own occupation</td>
<td>1.31</td>
<td>[1.54]</td>
</tr>
<tr>
<td>Substitutable occupation</td>
<td>1.67</td>
<td>[1.93]</td>
</tr>
<tr>
<td>Number of observations</td>
<td>10,164</td>
<td></td>
</tr>
</tbody>
</table>

Notes: Baseline sample of displaced workers (see Section 3 for details). Vacancy-unemployment ratios at the aggregate level are measured as the total flow of vacancies over the total number of unemployed workers who are unemployed at some point during a quarter. The ratios at the level of local labor markets are measured as the number of jobs that can be reached within an hour’s drive from home in a quarter, over the total number of workers that can reach the same jobs by an hour’s drive from their residential zip code. The ratios are averaged over the pre- and post-displacement periods.

The second and fourth columns show the corresponding standard deviations. As expected, the standard deviations at the aggregate level are quite small, but gradually increase as ratios are measured at finer levels. The standard deviations of vacancy-unemployment ratios in the places where workers lose their job suggest that the variation in the relative demand and supply of labor is large.

Throughout the rest of the paper, I measure the vacancy-unemployment ratios in the local labor market where a worker lives at the time of displacement. I take the average of the ratio over the sixteen quarters after displacement as in Table 2, and divide the sample into two equally sized groups. A worker is “well matched” if the ratio is above the median value for workers who lost their job in the same year and occupational cluster.\textsuperscript{16} Conversely, a worker is “poorly matched” if her ratio is below the median. Since I measure

\textsuperscript{15}Thus, the vacancy-unemployment ratio includes a worker’s own occupation, and her close substitute $m_{\hat{j},g} = \frac{V_{\hat{j},g}}{U_{\hat{j},g}}$.

\textsuperscript{16}If there are no unemployed workers in a local labor market, I set the denominator equal to one $m_g = \frac{V_g}{\max(V_g,1)}$. The results are unchanged if I define the median as within an occupation instead of occupational cluster.
mismatch at the pre-displacement location, no matter where they move, it allows me to directly control for any post-displacement composition changes.

**Graphical evidence**

The three panels of Figure 10 illustrate how this variation can be used to estimate $M$. The figure displays aggregate labor market earnings by quarters since displacement separately for workers who are mismatched and workers who are well matched. I compute the difference in pre-displacement earnings for the two groups, and illustrate the difference by the light blue area (e.g. $\rho$). Panel 10a shows the evolution of earnings around mass layoffs for workers who are well matched to the overall demand for labor, compared with displaced workers who are poorly matched (e.g. geographic mismatch). The figure shows that there is little, if any, difference in pre-displacement earnings between the two groups, and that trends in earnings before displacement are similar. Panel 10b displays how earnings evolve for displaced workers who are well and poorly matched to the demand for their own occupations. Here, the pre-displacement levels of earnings is larger for workers who are well matched, but the pre-trends in earnings are fairly stable and aligned. This model assumes extreme market segmentation, and completely ignores the availability of other jobs in their local labor market. By comparison, Panel 10c adds the close substitute from the occupational clusters developed in Section 4, so a worker is well matched if there are relatively many jobs in her own occupation or in the close substitute.

**Figure 10: Estimated average earnings loss**

(a) All jobs  
(b) Own occupation  
(c) Close substitute

**Notes:** This figure displays the evolution in earnings for the baseline sample of displaced workers (see Section 3 for details) who are poorly and well matched. Vacancy-unemployment ratios are measured in the period after mass layoff. Panel 10a shows earnings for workers by geographic mismatch, Panel 10c for workers by occupational and geographic mismatch, and 10b for workers by skill and geographic mismatch, where close substitutes are included as a relevant job. The groups are divided by the median value within an occupation and year. Pre-displacement differences in earnings are depicted in light blue.

Common to all three graphs is that after displacement, the earnings of the two groups diverge and that the difference persists over the sixteen quarters after mass layoff.

In a simple OLS regression of earnings on Equation (4), the estimate of $M$ would reflect the post-
displacement differences in Figure 10. To help understand the mechanisms underlying these differences, I estimate the vector $M$ jointly to assess the relative importance of mismatch in skills and geography. By changing the dependent variable in equation (4), I can also examine how mismatch affects outcomes other than earnings. For example, changing the dependent variable to indicators for whether a worker is employed or is currently seeking work will help explain the extent to which earnings losses depend on mismatch due to longer spells of unemployment, or exits from the labor force.

### 5.2 Empirical Evidence on Mismatch

I now turn to the main empirical analysis, and present estimates of how earnings losses depend on mismatch.

I begin with a regression analysis of the raw data plot in Figure 10, where I aggregate earnings into a pre- and a post-displacement period. Equation (4) is estimated for the two periods and the estimates of $M_q$ quantify how average quarterly earnings depend on mismatch.

#### Table 3: Estimates of how average post-displacement earnings depend on mismatch

<table>
<thead>
<tr>
<th>Labor market segmentation</th>
<th>I</th>
<th>II</th>
<th>III</th>
<th>IV</th>
<th>V</th>
<th>VI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average quarterly earnings ($)</td>
<td>651</td>
<td>582</td>
<td>476</td>
<td>487</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1-16 quarters after displacement</td>
<td>(202)</td>
<td>(199)</td>
<td>(226)</td>
<td>(225)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Geographic mismatch, all jobs</td>
<td>509</td>
<td>409</td>
<td>283</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mismatch, own occupation</td>
<td>(316)</td>
<td>(309)</td>
<td>(276)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mismatch, incl. close substitute</td>
<td>625</td>
<td>431</td>
<td>287</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pre-displacement average quarterly earnings</td>
<td>17,899</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Post-displacement average quarterly earnings</td>
<td>13,337</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of observations</td>
<td>20,330</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: Baseline sample of displaced workers aged 25-62 with at least two years of tenure during the period 2009-2013. Average earnings are measured eight quarters prior to displacement and sixteen quarters after mass layoff begins. Mismatch is measured over the period after displacement at the pre-displacement zip code and occupation. The measures are divided into two equally sized groups based on within occupation and year median vacancy-unemployment ratios. All regressions include mismatch indicators and an indicator for the post-displacement period, their interaction (reported in table) and occupational clusters fixed effects, worker-characteristics (age, tenure, and pre-displacement average earnings), labor market characteristics (aggregate quarterly flow of vacancies at national and local labor market level) and year fixed effects in Equation 4 (see Sections 3 and 5 for details). The control variables are measured the month before mass layoff was notified to the UI agency. Robust standard errors (in parenthesis) are clustered at the commuting zone.

Each column of Table 3 reports estimates of how average quarterly earnings over the sixteen quarters depend on mismatch. The estimates of Columns I-III correspond to the raw differences shown in Figure 10, and confirms that there are substantial and significant differences between the two groups. The first column says that when a worker loses her job in a local labor market with many jobs relative to job seekers, average quarterly earnings are $650 higher than among workers in markets with relatively few jobs. Geographic
mismatch thus accounts for about five percent of the post-displacement earnings. This is approximately 15 percent of the average earnings loss (obtained from the bottom rows of Column I). In contrast, Column II assumes that a worker’s human capital is only productive in one occupation, where earnings depend on the geographic variation in the vacancy-unemployment ratios of workers’ own occupation. The estimate for earnings is somewhat smaller as compared to the figure for all jobs in Column I. The estimate says that most of the earnings loss due to mismatch is explained by a workers’ previous occupation. In column III, I include jobs that are likely to be close substitutes to the vacancy-unemployment ratio.

Turning to Panel IV, I combine the models from the first two columns. This model compares two workers who are displaced in different labor markets with equal vacancy-unemployment ratios for all jobs. The only difference is the fraction of vacant jobs in their own occupation. These estimates say that—fixing the demand for all types of jobs at the local level, a larger number of jobs in her own occupation reduces the earnings loss by an additional $400. Panel V performs a similar comparison, but combines available jobs in a worker’s own and occupations that are close substitutes. Panel VI uses all three measures of mismatch. This model compares two workers who are displaced in different labor markets with equal vacancy-unemployment ratios for all jobs and their own occupation. While many of the figures are imprecisely estimated, the third row of Panel VI gives the additional earnings gain from having access to jobs that are close substitutes.

Table 4: Quarterly estimates of how earnings recoveries depend on mismatch

<table>
<thead>
<tr>
<th>Quarterly earnings ($)</th>
<th>Quarters relative to mass layoff</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-4</td>
</tr>
<tr>
<td>I: Geographic mismatch</td>
<td>4</td>
</tr>
<tr>
<td></td>
<td>(107)</td>
</tr>
<tr>
<td>II: Skill mismatch</td>
<td>-158</td>
</tr>
<tr>
<td></td>
<td>(91 )</td>
</tr>
<tr>
<td>Dependent mean</td>
<td>17,900</td>
</tr>
<tr>
<td>Number of observations</td>
<td>10,165</td>
</tr>
</tbody>
</table>

Notes: Baseline sample of displaced workers aged 25-62 with at least two years of tenure during the period 2009-2013. Quarterly earnings are relative to the date in which mass layoff begins, for the quarters \( q \in [-8, 16] \). Mismatch is measured over the period after displacement at the pre-displacement zip code and occupation, are divided into two equally sized groups based on within occupation and year median vacancy-unemployment ratios. All regressions include mismatch indicators and indicators for each quarter (from \( q = -4 \)), their interaction (reported in table) and occupational clusters fixed effects, worker-characteristics (age, tenure, and pre-displacement average earnings), labor market characteristics (aggregate quarterly flow of vacancies at national and local labor market level) and year fixed effects in Equation 4 (see Sections 3 and 5 for details). The control variables are measured the month before mass layoff was notified to the UI agency. Robust standard errors (in parenthesis) are clustered at the commuting zone.

For the remainder of this paper, I define skill mismatch as the additional loss from having few relevant jobs in a labor market while at the same time holding the vacancy-unemployment ratio of all jobs constant. I therefore restrict attention to the model from Panel V in Table 3, that I refer to as the baseline model throughout the rest of the paper. Here, a worker is skill mismatched if there are few jobs in either her own occupation or in the close substitutes relative to other job seekers in her local labor market.

Table 4 presents quarterly estimates of the impacts of mismatch on earnings at four quarter intervals,
beginning one year before mass layoff and ending sixteen quarters after. The bottom row of Table 4 shows that the number of observations is smaller for the last eight quarters. This is because my sample becomes slightly unbalanced as the earnings data is only covered until 2015. The last eight quarters are therefore not directly comparable to the first eight quarters. The first row shows that earnings strongly depend on geographic mismatch, and that the dependence increases during the first year. After this point, the estimated impacts of geographic mismatch remain statistically and economically significant throughout the period I consider. By comparison, the evidence for skill mismatch shows a more temporary pattern. Taken together, mismatch due to skills and geography jointly accounts for nearly 25 percent of the earnings loss four years after job loss.

5.3 Robustness

Before turning to the interpretation of my findings, I ask what other factors could explain why the earnings loss is persistently higher in places with relatively many jobs. If such factors affect both earnings and the supply and demand for labor in different times and places, the relationship between earnings and the vacancy-unemployment rate that I estimate would be biased.

I begin by copying the main results from Table 4 into the second row of Appendix Table A.1. The baseline model controls for both worker and labor market characteristics, including aggregate flows of vacancies at the local labor market and at the national level. By comparison, the model of Row I is estimated without these measures of labor demand. Comparing the first two rows show that controlling for the scale of a labor market reduces the estimated impacts slightly (see Petrongolo & Pissarides, 2006). Still, the association between mismatch and earnings remains strong. However, if depressed regions are disproportionately populated by workers in declining sectors or occupations that face lower economy-wide demand for the skills they supply, these labor market characteristics may not fully account for such composition effects. To address issues of composition and agglomeration spillovers (e.g., employee poaching), I fully interact indicators for each commuting zone with indicators for occupational clusters. Adding nearly 4,000 fixed effects to the model does not alter the main conclusions.

I implicitly assume that productive workers are not systematically laid off by their employers in good times—or, that less productive workers are not systematically more likely to be laid off at times in which the labor market poorly matches their skills. Fortunately, I observe the exact month in which an establishment reports a mass layoff to the authorities, so I can sample vacant jobs around this date instead of using the actual date that a worker leaves the firm. Recall that workers of different age and tenure can be dismissed at various times relative to the notice, and a worker may voluntarily leave earlier if she observes the market is getting sour — or on the contrary, sit the whole period out to wait for better times. As such, assuming that the timing of mass layoff is exogenous to the individual worker appears more reasonable than the actual date in which she leaves.

While the parallel trend assumption is supported by the empirical patterns in earnings in Figure 10, trends in earnings could differ after displacement for other reasons than mismatch. For example, the demand for some occupations may be more sensitive to aggregate fluctuations than others (e.g. Abraham & Katz, 1986). To investigate whether the estimated effects are primarily driven by cyclical variations in the demand for
certain occupations, I fully interact the occupation dummies with aggregate demand for their skill. Another concern is that the estimates may be sensitive to how I control for any pre-displacement differences. For example, the slightly significant pre-displacement association between skill mismatch and earnings indicates that trends might diverge after controlling for individual characteristics. I address this concern by estimating the pre-determined difference in earnings for mismatched workers using all quarters before mass layoff. Reassuringly, Rows V and VI shows that the estimates do no change appreciably after addressing these two issues.

In Row VII, I add fully interacted establishment and month of mass layoffs fixed effects to address the concern that establishments might discharge different workers at different times. For example, if the establishment expects the demand shock for their product to be temporary, they might selectively retain key personnel. The results are quantitatively similar, and the main findings are qualitatively the same.

Another concern is that job seekers selectively sort into areas with good access to jobs. This type of selection would lead to a type of reverse causality. However, I measure geographic mismatch in the local labor market a worker live at the time of displacement. This means that I can track workers over time no matter where they move, and directly addresses any post-displacement sorting across zip-codes. Still, certain certain zip codes may be predominantly populated by certain types of workers—e.g., liquidity constrained workers who are less likely to draw on accumulated assets while searching for a better match. Controlling for zip code fixed effects would remove time invariant common components of earnings. While the zip-code fixed effects removes large amounts of variation in the data, the results in Row VII show that the main conclusions remain the same.

Finally, in Row VIII I show that the results are quantitatively similar if I instead measure a local labor market as the administrative unit of a municipality.

6 Interpreting Mismatch

This section explores the possible mechanisms through which mismatch influences labor market earnings. I first investigate how employment and unemployment spells depend on mismatch. I then assess the relative importance of vacancy-unemployment ratios of all jobs, jobs in a worker’s own occupation, and jobs that are likely to match her human capital well, and how this dependence evolves with time.

6.1 Employment, Job Search, and Labor Force Participation

Previous work on skill mismatch finds that wages falls as workers switch to industries and occupations that poorly match their human capital (see e.g. Neal, 1995; Poletaev & Robinson, 2008; Kambourov & Manovskii, 2009; Gathmann & Schonberg, 2010). Unfortunately, I do not have good measures of hourly wages or the exact number of hours worked. However, I can investigate how the probability of full-time and part-time employment depends on mismatch. This will help understand whether mismatch affects earnings mainly through intensive or extensive margin responses in labor supply. I can also investigate whether workers stay longer unemployed, and whether workers exit the labor force at a higher rate when they are poorly matched to their local labor markets.
Table 5: Quarterly estimates of how (un)employment depends on mismatch

<table>
<thead>
<tr>
<th>Panel A: Full-time employment</th>
<th>Quarters relative to mass layoff</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-4</td>
</tr>
<tr>
<td>I: Geographic mismatch</td>
<td>-0.002</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
</tr>
<tr>
<td>II: Skill mismatch</td>
<td>-0.001</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
</tr>
<tr>
<td>Dependent mean:</td>
<td>0.990</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B: Any employment</th>
<th>-4</th>
<th>0</th>
<th>4</th>
<th>8</th>
<th>12</th>
<th>16</th>
</tr>
</thead>
<tbody>
<tr>
<td>I: Geographic mismatch</td>
<td>0.001</td>
<td>0.022</td>
<td>0.021</td>
<td>0.019</td>
<td>0.012</td>
<td>0.013</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.014)</td>
<td>(0.013)</td>
<td>(0.010)</td>
<td>(0.012)</td>
<td>(0.011)</td>
</tr>
<tr>
<td>II: Skill mismatch</td>
<td>0.000</td>
<td>0.005</td>
<td>0.034</td>
<td>0.027</td>
<td>0.026</td>
<td>0.012</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.011)</td>
<td>(0.017)</td>
<td>(0.011)</td>
<td>(0.011)</td>
<td>(0.012)</td>
</tr>
<tr>
<td>Dependent mean:</td>
<td>0.999</td>
<td>0.917</td>
<td>0.733</td>
<td>0.761</td>
<td>0.765</td>
<td>0.756</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel C: Unemployment</th>
<th>-4</th>
<th>0</th>
<th>4</th>
<th>8</th>
<th>12</th>
<th>16</th>
</tr>
</thead>
<tbody>
<tr>
<td>I: Geographic mismatch</td>
<td>-0.001</td>
<td>-0.004</td>
<td>0.010</td>
<td>0.009</td>
<td>0.003</td>
<td>-0.002</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.012)</td>
<td>(0.020)</td>
<td>(0.009)</td>
<td>(0.007)</td>
<td>(0.007)</td>
</tr>
<tr>
<td>II: Skill mismatch</td>
<td>-0.000</td>
<td>0.007</td>
<td>-0.059</td>
<td>-0.051</td>
<td>-0.033</td>
<td>-0.023</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.015)</td>
<td>(0.017)</td>
<td>(0.008)</td>
<td>(0.006)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>Dependent mean:</td>
<td>0.012</td>
<td>0.101</td>
<td>0.107</td>
<td>0.074</td>
<td>0.039</td>
<td>0.038</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel D: Labor Force Participation</th>
<th>-4</th>
<th>0</th>
<th>4</th>
<th>8</th>
<th>12</th>
<th>16</th>
</tr>
</thead>
<tbody>
<tr>
<td>I: Geographic mismatch</td>
<td>0.001</td>
<td>0.013</td>
<td>0.024</td>
<td>0.024</td>
<td>0.014</td>
<td>0.014</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.008)</td>
<td>(0.013)</td>
<td>(0.009)</td>
<td>(0.011)</td>
<td>(0.010)</td>
</tr>
<tr>
<td>II: Skill mismatch</td>
<td>0.000</td>
<td>-0.002</td>
<td>-0.006</td>
<td>-0.012</td>
<td>0.003</td>
<td>-0.003</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.006)</td>
<td>(0.010)</td>
<td>(0.010)</td>
<td>(0.010)</td>
<td>(0.011)</td>
</tr>
<tr>
<td>Dependent mean:</td>
<td>0.999</td>
<td>0.949</td>
<td>0.805</td>
<td>0.814</td>
<td>0.790</td>
<td>0.784</td>
</tr>
<tr>
<td>Number of observations:</td>
<td>10,165</td>
<td>10,165</td>
<td>10,165</td>
<td>10,165</td>
<td>9,071</td>
<td>7,858</td>
</tr>
</tbody>
</table>

**Notes:** Baseline sample of displaced workers aged 25-62 with at least two years of tenure during the period 2009-2013. Quarterly earnings are relative to the date in which mass layoff begins, for the quarters $q \in [-8, 16]$. Mismatch is measured over the period after displacement at the pre-displacement zip code and occupation, are divided into two equally sized groups based on within occupation and year median vacancy-unemployment ratios. All regressions include mismatch indicators and indicators for each quarter (from $q = -4$), their interaction (reported in table) and occupational clusters fixed effects, worker-characteristics (age, tenure, and pre-displacement average earnings), labor market characteristics (aggregate quarterly flow of vacancies at national and local labor market level) and year fixed effects in Equation 4 (see Sections 3 and 5 for details). The control variables are measured the month before mass layoff was notified to the UI agency. Robust standard errors (in parenthesis) are clustered at the commuting zone.

Panel A of Table 5 reports estimates of the baseline model on full-time employment. The estimates show that employment mainly depends on the relative number of jobs to which a worker’s human capital transfers well: Four quarters after mass layoff, employment is five percentage points higher for workers who are well matched. Relative to the dependent mean, the increase corresponds to around seven percent, or 15 percent of the average employment loss. By comparison, geographic mismatch only explains a small portion of the
variation in full-time employment among displaced workers, and the figures are less precisely estimated.

Panel B shows how any employment—that is, full-time or any part-time work—depends on the two types of mismatch. A worker is more likely to be employment if there are many jobs that matches her skills well, but the magnitude of these estimates are about half of the size as for full-time employment. The estimates from Panel A and B thus provide suggestive evidence that the earnings response from the previous section is driven by extensive margin, and that workers are offered jobs with longer hours in when there are many suitable jobs available.

Panel C complements the evidence by replacing the dependent variable with an indicator which is equal to one if a worker is registered as an active job seeker. The majority of job seekers receive UI benefits, where the maximum period of benefit entitlement is limited to eight quarters. Row II of Panel C shows that a skill mismatched worker is nearly six percentage points more likely to be unemployed and actively seeking work. This explains more than half of the average quarterly unemployment rates four quarters after mass layoff—and, over time, skill mismatch explains an even greater fraction of unemployment. By comparison, the is no relationship between unemployment and the vacancy-unemployment ratio of all jobs. These results are consistent with at least two explanations. One is that repeated unemployment spells are more prevalent among workers who are skill mismatched at the time of job loss. Another is that the results reflect labor market mismatch that occur at later dates since I measure mismatch over the sixteen quarters after mass layoff.

In the last panel I combine the two dependent variables from Panel B and C, and define labor force participation to be equal to one if a worker is either employed or is actively looking for work. Row II of Panel D says that skill mismatch does not significantly affect the probability of staying in the labor force. On the other hand, Row I says that availability of other jobs keeps a worker in the labor force. Taken together, the results presented in Panels A, B, and C are consistent with the idea that workers are more likely to receive an offer if the jobs matches her skills. But, when there are few jobs both in general and the type of jobs that matches her skills, Panel D suggests that workers are less inclined to be active in the labor force. The results thus sheds light on the importance of mismatch and labor market exists, and is consistent with existing evidence from job displacements and evidence from the literature that studies how labor force participation responds to local labor market shocks (Black et al., 2002; Autor & Duggan, 2003; Rege et al., 2009; Moretti, 2011; Huttunen et al., 2011; Bratsberg et al., 2013).

6.2 The Relative Importance of Substitutable Jobs

I now investigate the relative importance of geographic and skill mismatch, where I distinguish between vacant jobs in a worker’s own occupation and other jobs that are likely to match her human capital well.

In Appendix Table A.2, I present estimates of how quarterly earnings depend on the three measures of mismatch. The results complement the evidence on average earnings reported in Panel VI of Table 3, and allow earnings to depend differently on mismatch over time. The second and third rows show that—holding the overall demand for labor fixed, skill mismatch has a more temporary impact on earnings, but indicate

Note that if a worker is unemployed, his influence on the vacancy-unemployment ratio is removed. All vacancy-unemployment ratios use a leave-out-mean in the denominator.
that displaced workers’ earnings recover faster when there are relatively many jobs that match their human capital well. The results presented in Table 5 suggest that much of the earnings response due to mismatch is accounted for by extensive and intensive margin response. By comparison, the results presented in Table A.2 suggest that earnings may be determined by important interactions of the overall and the composition of demand in a local labor market.

Figure 11 summarize the findings from Appendix Table 3 by plotting the estimates over time. The point estimates are divided by pre-displacement average earnings, and I add the average earnings loss for comparison. The figure displays that three sources of mismatch explain about 25 percent of the average earnings over the period covered by my data. While earnings depends less on the availability of jobs in a worker’s own occupation over time, the overall number of jobs and close substitutes appear to have a persistent impact on the level of earnings losses. These results suggests that human capital may be quite portable across occupations.

Figure 11: Estimated average earnings loss

Notes: This figure displays the estimates from the baseline model in Table A.2 together with the average earnings loss normalized by average pre-displacement earnings.

7 Conclusion and Future Extensions

This paper asks whether mismatch can explain the large and persistent heterogeneity in earnings losses of displaced workers. Three novel data sets on vacancies combined with rich Norwegian administrative data allows me to offer an empirical answer to this question.

The research design that I implement uses mass layoffs as a worker-level shock, and longitudinal administrative data to compare the labor market outcomes of displaced workers to non-displaced workers. My first set of results show that average earnings losses following job displacement are both large and persistent: In the first quarters after mass layoff, the earnings loss amounts to about 35 percent of pre-displacement
earnings. Earnings rise rapidly during the next four quarters and stabilize at around 80 percent of pre-displacement earnings. I next show that the level and persistence of earnings losses is strongly associated with workers’ displacement location: four years after mass layoff, the earnings loss at the 90th percentile is about twice as large as in the 10th percentile of commuting zones.

To investigate whether the spatial heterogeneity in the consequences of job loss can be attributed to mismatch, I ask whether areas with large earnings losses also have lower ratios of vacancy-unemployment ratios. The key empirical result of this paper is that mismatch explains a significant amount of the dispersion in earnings losses. Geographic mismatch has a persistent impact on earnings losses. Skill mismatch—or, job loss in places with few jobs that match a workers’ occupation-specific human capital—adds to the earnings loss, but its influence is limited to the first three years after displacement. Taken together, mismatch explains 10-30 percent of the average earnings loss, which amounts to about half of the dispersion in earnings losses across commuting zones. I take several steps to assess the sensitivity of these results, and find that the main conclusions do not change appreciably if I flexibly control for a range of individual and local labor market characteristics, or use alternative definitions of local labor markets. To help interpret the results, I estimate how employment depends on mismatch. I find that full-time employment is five percentage points lower among “skill mismatched” workers. By comparison, I find that part-time employment decreases by a smaller amount. These two findings provide suggestive evidence that mismatch reduces earnings due to both extensive margin responses, and through fewer hours worked.

The empirical evidence on the importance of labor market mismatch raises two key issues. First, on the empirical side, the social safety net in Norway is generous compared to many other countries. These institutional differences may lead to stronger impacts on labor market earnings, while attenuating net impacts of mismatch on a household’s disposable income. At the same time, characteristics at the level of a household may attenuate the economic impacts, such as spousal labor supply, or the level of wealth that a worker may draw upon. Similarly, some workers may be unable to move in response to local labor demand shocks. For example, homeowners with limited or negative home equity, low levels of financial assets and restricted opportunities to borrow are likelier to be unable to respond to geographic shifts in the distribution of labor demand. Another important barrier may arise due to having children in school age, where non-monetary costs associated with moving may be particularly high. Direct evidence on geographic and occupational mobility would be useful to understand the precise nature of the frictions that prevent worker mobility from offsetting the consequences of mismatch. Second, on the theoretical side, a natural question is what model of job search would predict the empirical evidence presented here. In future versions of this paper I plan to do address these important issues.
References


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Nekoei, Arash, & Weber, Andrea. 2015. Does Extending Unemployment Benefits Improve Job Quality?


A Appendix Material

This section provides details of the sources of job openings from Section 2.3 and the approach described in Section 4.

A.1 FINN - the Online Job Board.

FINN (www.finn.no) is the largest online job board in Norway, and has a market share that is close to complete. Figure A.5 plots the flow of vacancies from FINN compared to the numbers from the UI agency, suggesting that shortly after the financial crisis the two provide similar aggregate trends.

The job board provides an online application service, that allows users to send an application directly to the requiring firm. Users can subscribe for relevant jobs by e-mail notifications (i.e. occupation or industry), and the site records traffic on each posted vacancy, including the number of viewings, applications, and e-mails sent. The data includes the information detailed above, as well as information on the firm that posted the vacant job, the dates on which the vacancy was posted, and the date on which it exited the market. Also included are a full description of the job, including utility posting and in rare cases wages offered.

Figure A.1: Distribution of Vacancy-durations

Notes: This figure shows the density of vacancy-durations from FINN over the period 2010-2016.

For ads lacking identifiers for firm or establishment (typically for public sector), I run a sequence matching algorithm that compares the company title in the ad with registered company names from the administrative data (the VoF database; also publicly available at www.brreg.no). The processed data file has identifiers at firm or establishment level for approximately 95 percent of ads, the vast majority of them at the firm level. I use the firm identifier to identify the location of the job for about 15 percent of ads that lack a zip code.
Many of these zip codes are the level of the firm, which typically has headquarters in a large city, but may be hiring at establishments located elsewhere.

Key to the procedure for transforming flows into stocks, described in the main text and below, is the length of time an ad is active online. This is a useful statistic for understanding how quickly jobs are filled, and for considering the discrepancy between the three time series shown in Figure 2. The distribution of the times that ads are active is plotted in Appendix Figure A.1 for the period 2010 to April 2016. The histogram suggest that some firms have highly systematic recruitment patterns, indicated by the spikes at two weeks, 1 and 1.5 months.

A.2 Cross-Validation of Vacancy Data

In order to compare the aggregate numbers from the online job board and UI agency with the weighted aggregate stocks of vacancies in the vacancies survey provided by Statistics Norway, I need to transform flows of vacancies into stocks.\(^{A.1}\) To achieve this, I start by collecting the dates on which a vacancy enters and exits the market and information on the firm’s geographic location and industry from FINN. This information allows me to compute the average time it takes to fill a vacant job within cells of four-digit industry codes and 430 geographic locations. This is defined as

\[ D_{k,g,q} = \frac{1}{N_{k,g,q}} \sum_{n} \text{time}_{k,g,q,n}, \]

where \( N_{k,g,q} \) is the number of vacancies per cell, and \( n \) is a particular vacancy. Next, using the matched employee-employer data, I calculate the industrial mix of recent hires. This gives me, for each occupation \( j \), quarter \( q \), and municipality \( g \), the number of hires in an industry \( k \). This sum equals

\[ h_{j,g,q} = \sum_{k} h_{k,j,g,q} \]

that is, the total number of hires of occupation \( j \) in each municipality.

Note that if all steel workers in Oslo are hired by manufacturing firms, then the average duration of steel worker vacancies is equal to the average time that an ad is active for manufacturing firms in Oslo, \( D_{k,g,q} \). Next, I assume that within the same industry, the average time it takes to recruit a worker is independent of skill levels. This allows me to compute a weighted vacancy duration

\[ D_{j,g,q} = \frac{1}{h_{j,g,q}} \sum_{k=1}^{K} h_{k,j,g,q} D_{k,g,q} \]

I transform the vacancy flow from the UI agency to stocks using the weighted vacancy duration, and assume that vacancies arrive in the middle of a month, on average. For example, a vacancy arrives in mid May, and the average duration is 25 days; then, the corresponding stock would count this particular vacancy in May and June. By comparison, the vacancy stock using only vacancies from FINN is exact.

A.3 Vacancy Yields.

I follow the example of Davis et al. (2013) in estimating the vacancy yield: that is, the number of hires per vacancy posting. However, I deviate from prior work in two important ways. First, I link the ads from the online job board to the hiring firm, and use dates to create an event study around the times at which an ad enters and exits the market, to investigate the total number of hires. For a subset of ads, I can also identify

the firm’s preferred start-date for a job, which proves useful when isolating a particular vacancy among firms that are actively trying to fill more than one position (i.e. more than one active vacancy at any point in time). Second, because the time on which a worker can start depends on her employment status, the terms of her previous work contract and the requirement of the hiring firm, the actual hires are noisy around these dates. To circumvent this issue, I employ a methodology typically used in public finance to identify earnings responses to marginal tax changes, using bunching of income around kinks in individual budget sets (Kleven, 2016). The idea behind this approach is that in the absence of a particular vacancy, the total number of hires should be smooth around the date on which an ad exits or enters the market. Estimating a counterfactual trend of total hires allows me to calculate an excess mass of hires in a short time interval after the ad enters the markets. The vacancy yield equals the ratio of excess hires over the total number of vacancies in the sample.

To estimate vacancy yields, I restrict my attention to the subset of vacancies with a preferred start-date. For the remaining vacancies, I exclude firms with more than five vacancy postings during a calendar year, which helps to reduce the noise in the number of hires around the dates on which the ad enters and exits the market. The time period is 2010-2015, the same as that used to create Figure 2. The vacant jobs are matched to the employer-employee register using the unique firm identifier to create a panel of hires. For each firm and unique vacancy, I collect every hire in the period between 12 months before and 24 months after the job was posted and exclude a handful of jobs in which the firm hired more than 50 workers in a given month within the time window. The resulting number of ads is about 44 thousand, and 14 thousand firms. In contrast, I do not impose any restrictions on hired workers (e.g. previously employed at the firm, short-term or part-time contracts).

I next normalize the hires relative to i) the subset of ads with information on the month in which the firm wants the job to start, ii) the month a job entered the market, and iii) the month in which the job exits the market. Next, I aggregate the total number of hires from 12 months prior to 12 months after these dates. A counterfactual hire trend is estimated by fitting a flexible polynomial to the empirical density, excluding observations from the month in which the job entered the market and up to six months afterwards. This is similar to Kleven & Waseem (2013), who assume that the distribution of earnings would be smooth in the absence of notches in the individual budget sets. In this setting, I need to assume that a vacancy only affects hires in the excluded region. When estimating excess hires around the entry date, I exclude i) a narrow window, from one month before to two months after the firm’s preferred start date, ii) the period from the date on which the vacancy entered and up to six months afterwards, and iii) two months prior to and up to five months after the vacancy exits the market.

A.2 For the subset of vacancies with a corresponding start date, I include all firms; that is, also firms that post more than five vacancies in a given calendar year.
Figure A.2: Vacancies and hires at the firm level

Notes: This figure shows total hires at the firm level, normalized around the specified job start from vacant jobs from FINN, and the implied vacancy-yield (see Section 4 for details).

Figure A.3: Hires at the firm level around the time a vacant job enters the market

Notes: This figure shows total hires at the firm level, normalized around the entry of a vacant job ad on FINN, and the implied vacancy-yield (see Section 4 for details).
Figure A.4: Hires at the firm level around the time a vacant job exits the market

Notes: This figure shows total hires at the firm level, normalized around the exit of a vacant job ad on FINN, and the implied vacancy-yield (see Section 4 for details).

Figure A.2 plots the total number of hires relative to the firm’s preferred job start. Following Kleven & Waseem (2013), I estimate the counterfactual trend in hires at the aggregate level by fitting a fifth-order polynomial to the empirical distribution, and exclude the period from one month prior to and two months after the required start dates. The shaded area shows the calculated excess hires, equal to the sum of differences between actual and counterfactual hires in the excluded region. The vacancy yield equals the ratio of the excess hires over the total number of vacancies in the sample. The vacancy yield obtained from this approach reveals that only 61 percent of jobs are filled. In contrast, the vacancy yield implied by comparing the hires in the month in which the job is supposed to start to the number of vacancies is equal to 125 percent, which is in line with the evidence at establishment level from JOLTS (Davis et al., 2013). I repeat the exercise using the entry and exit dates of vacant jobs and obtain similar numbers, albeit slightly attenuated by noisier information around the relevant hiring dates. The results are displayed in Figures A.3 and A.4.

A.4 Transferability of Skills across Occupations

I now describe the method that measures the closeness of jobs in terms of underlying tasks and skill levels. This involves multiple steps, which I describe subsequently.

I. I collect the detailed description of every occupational code using the Norwegian adaptation of the ISCO framework (see Appendix Section A.5). These descriptions are in Norwegian, and are purged of Norwegian letters. Next, I keep nouns and verbs and replace each word with its base form using the Norwegian Linguistics database.A.3

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A.3The linguistics database is available at:
II. As the descriptions contain little information on the exact educational requirements, I collect educational requirements from an online database on educational requirements for occupations. The database is jointly maintained by a panel of 250 employers and the Norwegian Directorate of Education, and provides a description of educational codes, including field of study and the level of schooling required or needed to perform the tasks in an occupation. I link this information to occupational descriptions from step I.  

III. Because the empirical analysis requires occupations from two standards to be crosswalked, some occupations contain descriptions of multiple occupations. I address this by using a set of unique words for each crosswalked occupation.

IV. I vectorize words from III, and re-weight each word according to the inverse of their document frequency, leaving a vector of approximately 4,500 words, \( w_j \). For each pair of occupations \( j \) and \( j' \), I tell the computer to calculate the weighted pairwise distance, and follow standard practice in using the euclidean distance (Friedman et al., 2009). More formally, the distance is calculated from

\[
d(w_j, w_{j'}) = \sum_{k=1}^{K} \sqrt{\left(\tilde{w}_{jk} - \tilde{w}_{j'k}\right)^2}
\]

where \( \tilde{w}_{jk} \) is the weighted frequency of the \( k \)-th word in the description of occupation \( j \), and \( K \) is the total number of words to evaluate. The computer performs the calculation for every pair \( (j, j') \), and outputs a pairwise distance matrix of size \( 259 \times 259 \).

V. The next step involves reducing the dimensions of the skills portfolio to make it empirically tractable while preserving the information contained in the skill distance. I address this challenge using a hierarchical clustering approach that starts with each occupation and sequentially looks for pairs of clusters to join up that minimize the increase in the total within-cluster skill distance (e.g. the Ward method; see Friedman et al., 2009, and Appendix for details). The algorithm continues to link up occupations until there are two clusters left, leaving a traversable tree of potential clusters from amongst which the researcher is in practice left free to choose.

A.5 Crosswalking Occupational Codes

The International Standard Classification of Occupations (ISCO) underwent a major revision as a result of a resolution at the Meeting of Experts on Labor Statistics in 2007. Statistics Norway and the Norwegian Labour and Welfare Administration (NAV) jointly adopted the international versions, with 354 and 403 unique four digit occupations from ISCO88 and ISCO08 respectively. The Norwegian versions are named

[http://www.edd.uio.no/prosjekt/ordbanken/](http://www.edd.uio.no/prosjekt/ordbanken/).

The occupational descriptions are available at:

- [www.ssb.no/a/publikasjoner/pdf/nos_c521/nos_c521.pdf](http://www.ssb.no/a/publikasjoner/pdf/nos_c521/nos_c521.pdf)

A.4 This mapping is available at [data.norge.no/data/senter-ikt-i-utdanningen/yrkesbeskrivelser-fra-utdanningno](http://data.norge.no/data/senter-ikt-i-utdanningen/yrkesbeskrivelser-fra-utdanningno).

A.5 I use the available packages for Python described here:


STYRK98 and STYRK08. STYRK98 is currently used in the employer-employee register, available from 2003, and STYRK08 is used in vacancy data from the UI agency/NAV, and after 2011 in unemployment data.

During the revision, several occupations were split into smaller groups, e.g. computer systems designers and computer programmers. Other codes were collapsed into a larger group; for example, many types of machine operator had been made obsolete by technological change. An official version of a correspondence table from STYRK98 to STYRK08 is currently not available. In order to create a non-overlapping and consistent measure of occupations, I require a two-way correspondence table. This was obtained through the following steps:

1. Using occupational titles, I collect occupations with an exact match in the two versions. This gives a match of 50 occupations.

2. Using unemployment periods that overlap with both versions in the course of 2011/2012, I identify revised occupations. I keep 1:1 and 1:many mappings, but keep only those with at least 30 percent of each unique STYRK98 code’s total to reduce noise.

3. I keep all occupations in the ISCO correspondence table that have 1:1, 1:2 and 2:1 mappings. These are crosswalked to STYRK98.

Putting 1, 2 and 3 together, I identify the remaining occupations that lack a correspondence. These are manually identified using the available descriptions of STYRK codes and the ISCO crosswalk table. A final set of consistent occupations depends on the clinked sets of occupations with 1:many and many:1 mappings. The resulting number of occupations is reduced from a total of 403 unique versions to 259 consistent occupations. My crosswalked version can be crosswalked going from either STYRK08 or STYRK98, and is available upon request.

A.7 Statistics Norway 1998 (NOS C521); Statistics Norway 2011 (Notater 17/2011)
## B Additional Tables and Figures

### Table A.1: Robustness Checks

<table>
<thead>
<tr>
<th>Quarterly earnings ($)</th>
<th>Panel A. Geographic mismatch</th>
<th>Panel B. Skill mismatch</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>4</td>
<td>8</td>
</tr>
<tr>
<td>I: With scale effects</td>
<td>634</td>
<td>490</td>
</tr>
<tr>
<td></td>
<td>(382)</td>
<td>(270)</td>
</tr>
<tr>
<td>II: Baseline model</td>
<td>614</td>
<td>480</td>
</tr>
<tr>
<td></td>
<td>(384)</td>
<td>(295)</td>
</tr>
<tr>
<td>III: CZ×Occupation F.E.</td>
<td>581</td>
<td>443</td>
</tr>
<tr>
<td></td>
<td>(380)</td>
<td>(299)</td>
</tr>
<tr>
<td>IV: Differential pre-trend</td>
<td>609</td>
<td>473</td>
</tr>
<tr>
<td></td>
<td>(386)</td>
<td>(297)</td>
</tr>
<tr>
<td>V: Cyclical sensitivity</td>
<td>629</td>
<td>488</td>
</tr>
<tr>
<td></td>
<td>(386)</td>
<td>(293)</td>
</tr>
<tr>
<td>VI: Firm×Year F.E.</td>
<td>570</td>
<td>431</td>
</tr>
<tr>
<td></td>
<td>(381)</td>
<td>(302)</td>
</tr>
<tr>
<td>VII: Zip code F.E.</td>
<td>523</td>
<td>379</td>
</tr>
<tr>
<td></td>
<td>(376)</td>
<td>(310)</td>
</tr>
<tr>
<td>VIII: Alternative measure</td>
<td>614</td>
<td>480</td>
</tr>
<tr>
<td></td>
<td>(384)</td>
<td>(295)</td>
</tr>
</tbody>
</table>

N. obs: 10,165

*Notes*. Baseline sample of displaced workers aged 25-62 with at least two years of tenure during the period 2009-2013. Quarterly earnings are relative to the date in which mass layoff begins, for the quarters $q \in [-8, 16]$. Mismatch is measured over the period after displacement at the pre-displacement zip code and occupation, are divided into two equally sized groups based on within occupation and year median vacancy-unemployment ratios. All regressions include mismatch indicators and indicators for each quarter (from $q = -4$), their interaction (reported in table) and occupational clusters fixed effects, worker-characteristics (age, tenure, and pre-displacement average earnings), labor market characteristics (aggregate quarterly flow of vacancies at national and local labor market level) and year fixed effects in Equation 4 (see Sections 3 and 5 for details). Specification III includes fully interacted CZ and occupation fixed effect; IV omits quarter and mismatch interactions in the period before mass layoff: V interacts the flow of vacancies in an occupations with occupation indicators; VI fully interacts establishment and month of mass layoff, and VII includes more than 2000 fixed effects for residential zip codes. VIII uses municipalities as a measure of local labor markets. Robust standard errors (in parenthesis) are clustered at the commuting zone.
Table A.2: Earnings recoveries and skill mismatch

<table>
<thead>
<tr>
<th>Quarterly earnings ($)</th>
<th>Quarters relative to mass layoff</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-4</td>
</tr>
<tr>
<td>I: Geographic mismatch</td>
<td>-1</td>
</tr>
<tr>
<td></td>
<td>(108)</td>
</tr>
<tr>
<td>II: Skill mismatch, own occupation</td>
<td>-214</td>
</tr>
<tr>
<td></td>
<td>(148)</td>
</tr>
<tr>
<td>III: Skill mismatch, close substitute</td>
<td>-49</td>
</tr>
<tr>
<td></td>
<td>(70)</td>
</tr>
<tr>
<td>Dependent mean:</td>
<td>17,900</td>
</tr>
<tr>
<td>Number of observations:</td>
<td>10,165</td>
</tr>
</tbody>
</table>

Notes: Baseline sample of displaced workers aged 25-62 with at least two years of tenure during the period 2009-2013. Quarterly earnings are relative to the date in which mass layoff begins, for the quarters $q \in [-8, 16]$. Mismatch is measured over the period after displacement at the pre-displacement zip code and occupation, are divided into two equally sized groups based on within occupation and year median vacancy-unemployment ratios. All regressions include mismatch indicators and indicators for each quarter (from $q = -4$), their interaction (reported in table) and occupational clusters fixed effects, worker-characteristics (age, tenure, and pre-displacement average earnings), labor market characteristics (aggregate quarterly flow of vacancies at national and local labor market level) and year fixed effects in Equation 4 (see Sections 3 and 5 for details). The control variables are measured the month before mass layoff was notified to the UI agency. Robust standard errors (in parenthesis) are clustered at the commuting zone.

Figure A.5: Time trend vacancies from online recruitment and UI agency

Notes: This figure shows the aggregate trend of vacancy rates using data on vacant jobs from the UI agency and FINN (see Section 4 for details).
Figure A.6: Skill distance and occupational switches across 1-digit occupational codes

Notes: This figure shows the relationship between skill distance and occupational switches among unemployed workers from occupation \( j \) who are actively looking for a job in a different occupation \( j' \). The sample is all unemployed workers in the age 25-66 who actively looking for work in a occupation a different 1-digit occupational code than their previous occupation \( j \). The distance is based on dis-similarity of the words from dictionaries of occupational titles between any pair of occupations \( j, j' \), and are grouped by percentiles (see Section 4).

Figure A.7: Skill distance and occupational switch by skill requirement

Notes: This figure shows the relationship between skill distance and occupational switches among unemployed workers from occupation \( j \) who are actively looking for a job in a different occupation \( j' \). The sample is all unemployed workers in the age 25-66 who actively looking for work in a different occupation than their previous occupation, split by the skill requirement in occupation \( j \). The distance is based on dis-similarity of the words from dictionaries of occupational titles between any pair of occupations \( j, j' \), and are grouped by percentiles (see Section 4).
Figure A.8: Results from hierarchical clustering of 4-digit occupations

Notes: This figure shows the output from the hierarchical clustering approach described in Section 4. There are 82 clusters after every occupations has been allocated to a cluster. The number in parenthesis shows the number of iterations between a particular occupation entered the cluster.
Figure A.9: Travel distance between home and previous workplace

Notes: This figure shows a histogram of the actual travel time between the residential zip code of the baseline sample of displaced workers and their previous employer’s zip code (see Section 3 for details). The travel time is based on existing infrastructure and speed limits in 2010, but does not account for traffic congestion. Travel time is collapsed at 10 minute intervals.