Identifying Vulnerable Displaced Workers: The Role of State-Level Occupation Conditions

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Abstract

Displaced workers experience a range of earnings changes after displacement. Using comprehensive occupational employment data, I estimate the effect of the state-level occupation growth rate in the worker's pre-displacement occupation on subsequent labor market outcomes and find that adverse labor market conditions in a worker's occupation at the time of displacement have negative consequences. Displacement from a shrinking occupation is associated with decreased earnings and longer durations of joblessness. Furthermore, holding the occupation growth rate constant, there is only a small effect of the worker's industry growth rate on their labor market outcomes. These results suggests that vulnerable displaced workers' difficulties in the labor market are a function of their skills and less related to the goods and services they were previously producing. (JEL: J24, J64, J65)

1 Introduction

Policymakers often worry about the impact of job destruction on workers. Concerns for displaced workers, those laid off as a result of a firm or plant closing, reflect in part the sizable earnings losses that they experience. Even among those re-employed three years after displacement, 25% of displaced workers suffer an earnings loss greater than 41% and another

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25% suffer an earnings loss of between 6 and 41%.[1] With the other half of workers experiencing small earnings losses or earnings gains, it is clear there is substantial heterogeneity in the impact of displacement.

Understanding *which* displaced workers experience the largest losses is important for two reasons. The first is to more effectively target re-employment assistance and other services to unemployed job losers. Indeed, identifying and assisting vulnerable displaced workers is the objective of policies such as the Unemployment Compensation Amendments of 1993. These amendments created state-level systems to identify and target services to workers who are likely to exhaust their unemployment compensation and need job search assistance. These systems, called Worker Profiling and Reemployment Systems (WPRS), use a variety of methods to identify variables relevant to unemployment exhaustion such as education, job tenure, and the local unemployment rate.

Second, to the extent that job displacement destroys specific skills, designing effective policy responses requires an understanding of what aspects of pre-displacement employment (such as industry, occupation or region) that specificity is attached to. For example, policies targeted at declining industries may be poorly focused if displaced workers' difficulties are more related to their skills than the goods and services they were producing. In this respect, less is known. While it does appear that displaced workers who change occupations, or skill portfolios, lose more than displaced workers who change industries (Kambourov and Manovskii, 2009; Poletaev and Robinson, 2008), the decision to change occupations or industries is endogenous, making it difficult to attach a causal interpretation to these differences. In addition, because industry- and occupation-switching are outcomes of the post-displacement job search process, the act of switching cannot be used to target re-employment assistance to displaced workers. Indeed, if industry- or occupation-switching are costly for workers, it is at least as important to identify the observable factors that *cause* costly switching than the consequences of switching per se.

To this end, I use data from the Current Population Survey Displaced Worker Supplement

[1] Analysis using the 2004-2014 waves of the Current Population Survey's Displaced Workers Supplement.

to study the effects of poor state labor market conditions in a displaced worker's occupation of origin on a number of labor market outcomes, treating the decision to switch occupations as endogenous. In models comparing workers displaced from different occupations in the same state and year, those displaced from shrinking occupations suffer significantly longer durations of joblessness and lower earnings conditional on being re-employed. A one standard deviation decrease in the worker's occupation growth rate (which is approximately four percentage points) is associated with a 12.5 percent increase in the duration of joblessness and a 5.5 percent decrease in weekly earnings. Adding occupation fixed effects to this specification implies a one standard deviation decrease is associated with a 11.2 percent increase in the duration of joblessness and a 7.1 percent decrease in weekly earnings. Additionally, I find that state-level occupation growth impacts duration of joblessness and changes in earnings significantly more than state-level industry growth. The power of the industry growth rate also diminishes in models including occupation growth rate. This is consistent with other research including Blinder et al. (2009) and Jensen and Kletzer (2010) that emphasizes that employment prospects depend much more on workers' occupation (the set of activities or tasks that employees are paid to perform) than their industry (the primary business activity of their establishment).

To contextualize the size of my estimated effects, I note that a one standard deviation decrease in the occupation growth rate (approximately four percentage points) is similar to the change in the national unemployment rate during a typical recession. In fact, the magnitude of the main estimate in this paper (a 7.1 percent decrease in weekly earnings per standard deviation decrease in occupation growth rate) is similar to the short-run effects of graduating during a typical recession found in Oreopoulos et al. (2012) and Altonji et al. (2016). As this effect is strongest for the contemporaneous occupation growth rate and not the occupation growth rate in the prior year or two years ago, it appears that this loss can be attributed to *temporary* adverse labor market conditions and is quite comparable to this related literature. That said, unlike recessions, the types of shocks examined here are both state- and occupation-dependent. They are also net of controls for year of displacement, state of residence, and minor occupation group, and therefore demonstrate the impact of conditions even more localized to the worker.

These shocks are consistent with, for example, the model described in Huckfeldt (2016) where hiring is endogeneously more selective during recessions. However, my paper suggests that a recession is not necessary. Instead, declines in occupational employment that come from declines in the industries where the occupation is concentrated affect labor market outcomes net of year fixed effects. These occupation-level growth rates, likely exogenous to the worker, reveal a significant impact of adverse labor market conditions at the time of displacement on displaced workers' outcomes. Aggregate indicators like the national unemployment rate mask the heterogeneity in employment prospects within occupations, across states, and over time.

The idea that state-level occupation conditions matter is quite intuitive, but their importance has not been measured due to data limitations on occupation growth. Unlike industry codes, which employers report when submitting information for unemployment insurance, regularly produced comprehensive occupational employment data is only available from the Bureau of Labor Statistics (BLS) Occupational Employment Statistics program, and suffers from a significant limitation. The occupational employment estimates for a given year are created using three consecutive years of data, limiting the data's usefulness for time series analysis. I overcome this limitation by constructing an occupation growth rate measure using a shift-share method based on states' different industry compositions. This measure of occupation growth rate takes into account the growth of all industries that employ workers in a particular occupation in the state to assess potential employment opportunities within a displaced worker's occupation. To the best of my knowledge, this is the first study to create a measure of local conditions within an occupation and to estimate its importance for displaced workers' labor market outcomes. This new evidence that the relevant employment conditions are at the occupation level suggests a significant role for occupation-specific human capital over industry-specific human capital. In contrast to workers displaced from shrinking industries, there appears to be considerably less scope for workers from shrinking occupations to find work with similar earnings.

Importantly, even though my occupation growth rate is constructed, in part, from national industry growth rates, my estimates of its effects are robust to a variety of controls for industry

growth, and are more important determinants of displaced workers' outcomes than industry growth in all specifications. Thus, while industry growth rates matter (consistent with previous research), my results show that industry growth rate matters mostly because it changes the mix of occupations demanded in state labor markets. Consequently, predicting the local occupation growth rate from national industry growth yields a more powerful predictor of displaced workers' outcomes than either national or local industry growth measures on their own.

The remainder of the paper is as follows: section two discusses the literature, section three discusses the data, section four explains the empirical approach, section five reports the main results, section six discusses the robustness of the results, and section seven concludes.

2 Literature

This paper contributes to a long line of literature interested in understanding displaced workers' labor market outcomes. A series of empirical regularities has emerged, documented by Carrington and Fallick (2015). First, displaced workers' earnings losses are persistent and large, on average. This finding, initially in Ruhm (1991), shows that relative to their non-displaced peers, a displaced workers' earnings are reduced by 10 percent on average for more than twenty years after displacement (Jacobson, LaLonde, and Sullivan, 1993; Von Wachter, Song, and Manchester, 2007; Couch, Jolly, and Placzek, 2011). The second key empirical regularity, that the range of earnings changes is wide, has encouraged researchers to compare the experiences of different displaced workers to understand what is driving the earnings changes. Jacobson, LaLonde, and Sullivan (1993) found that workers' losses increased when workers were displaced in weak local labor markets. This heterogeneity was substantial: the long-term differential between the losses suffered in the strongest and weakest labor markets corresponds to about one-third of the average loss. That earnings losses are dependent on macroeconomic conditions has become another empirical regularity, supported by Couch, Jolly, and Placzek (2011), Davis and von Wachter (2011), and others.

This paper relates most closely to Carrington (1993), who argued that the wage losses of high tenure displaced workers can be attributed to downturns in industry, occupation, and state labor market conditions. The major insight of Carrington's paper, echoed by Neal (1995), is that workers displaced from declining industries experienced significantly greater wage losses than workers displaced from growing industries. Part of this loss is driven by the increased probability that workers from declining industries would change industries. Because of the historically strong data on industry growth, employment growth at the industry level was much better measured than employment growth at the occupation level in the Carrington (1993) study, which suggested a strong role of industry conditions and, potentially, industry-specific human capital.

Not until Poletaev and Robinson (2008) and Kambourov and Manovskii (2009) did the focus of displaced workers' earnings losses return to occupations and their skill content. These papers emphasize the strong correlation between earnings losses and changes in pre- and post-displacement tasks performed at work. While Poletaev and Robinson (2008) and Kambourov and Manovskii (2009)' analyses have done much to our understanding of displaced workers' earnings losses, still unanswered is why many displaced workers change occupations or relevant skills, and how much of a role occupation and industry conditions play in this decision.

A few papers that have started to ask similar questions include Kandilov (2010) and Crinò (2010), who study the sources of displaced workers' earnings losses in the manufacturing industry. They find, respectively, that greater low-wage country import competition and offshoring in the displaced worker's pre-displacement industry decrease the re-employment wage. Along these lines, Ebenstein et al. (2014) look at the impact of increased trade and offshoring on all workers' probability of occupation change amongst all workers using the Current Population Survey. They find that trade-induced occupation switching led to real wage losses of 12 to 17 percentage points. Tschopp (2017) looks at the relationship between worker's outside options in wage determination, exploiting the differences in industry employment composition across cities in Germany and mobility across occupation-industry cells. She finds that a 10% increase in the outside options of a worker generates a 7% wage increase.

I add to this literature by estimating the effects of pre-displacement occupation and industry growth rates on displaced workers' labor market outcomes. I focus on these pre-displacement characteristics, which are ex ante classifications of worker vulnerability. These underlying labor market conditions may contribute to industry change, occupation change, and skill portfolio change, which are endogenous variables correlated with earnings losses in the literature.

3 Data

My dataset of individual-level outcomes comes from the Current Population Survey (CPS) Displaced Workers Survey (DWS). I link the displaced worker's pre-displacement occupation to state-level occupation conditions, created using the Occupational Employment Statistics and the Quarterly Census of Employment and Wages.

3.1 Displaced Workers Data

The Displaced Workers Survey is a CPS supplement administered biennially. Respondents to the CPS were asked if in the past three years, they lost or left a job because their plant or company closed or moved, their position or shift was abolished, there was insufficient work or another similar reason. I use the survey years from 2004 to 2014, so workers surveyed were displaced between 2001 and 2013.

I limit my sample to individuals displaced because their plant or company closed down or moved as a plant or company closure may be less likely to spare high quality workers than mass layoffs (Gibbons and Katz, 1991).[2] Following Neal (1995), I also exclude workers reporting less than $40 of pre-displacement weekly earnings. I also limit my sample to workers who have not moved since displacement. This is because the data does not specify the state in which the worker was displaced, and therefore, it is not possible to connect workers to the appropriate state-level occupation growth rate for workers who have moved since displacement.[3] The

[2]There is some research suggesting this may be a function of firm size (Krashinsky, 2002).

[3]I show my results are very similar when including all workers - both those who have moved and those who have not moved in the Online Appendix.

main analysis sample consists of workers who have been displaced from a full-time job. The descriptive statistics for the main analysis sample are reported in Table 1.

Displaced workers come from all education categories and races. The average age in the sample is 41.8 years, with 6.3 years of firm tenure. The sample is 41.3 percent female. The mean weekly earnings loss after displacement was $103.8 or 24.6 percent for workers who had been re-employed. This is in the range of previous research on displaced workers and is consistent with the unusually poor labor market conditions following the Great Recession. 78.1 percent of workers worked for pay since displacement.

Additionally, I exclude workers who do not report their pre-displacement occupation. This variable is necessary to create the occupation growth rate, which is the focus of my analysis.[4] This is not a trivial restriction: 14.9 percent of the respondents who were displaced from full-time jobs because of firm closure do not report their pre-displacement occupation. In Table 2, I report tests for differences in observable characteristics between individuals reporting and not reporting pre-displacement occupations. Those reporting, as described, are more educated, younger, more likely to be male, have been displaced closer to the time of survey, and are much more likely to have worked for pay since displacement.

3.2 Occupation-Industry Composition from the Occupational Employment Statistics

To estimate the effect of the occupation growth rate, I need an annual measure at the state or local level. The American Community Survey (ACS) and other commonly used micro-data cannot be used to calculate a growth rate for most detailed occupations at the state level, since their sample size is inadequate to calculate reliable growth rates for many smaller occupations.

The alternative data source for occupation level data is the Occupational Employment Statistics (OES). The OES is a large employer survey conducted by the Bureau of Labor Statistics that

[4]Occupation growth rates can also not be calculated for workers with sufficiently vague occupations – if an engineer is not one of the 17 types of engineers listed in the Standard Occupation Classification, he/she falls into the "Engineers, All Other" category, for which the data necessary for a growth rate does not exist. These workers are also excluded from the analysis.

collects detailed information on employment by occupation, covering 1.2 million establishments and 57 percent of employment in the United States. With a much larger sample size, it is designed to produce detailed estimates of occupation level employment and wages, though these estimates are not suitable for the study of short- term changes. To minimize sampling error, the survey design selected by the BLS divides the establishments surveyed for each set of estimates into panels spread across three years of data. That is, the samples for two adjacent years, which would be used to create an annual growth rate, are not independently drawn.[5] The OES estimates reported by the BLS for a given year are moving averages based on three years of survey data.

Even if adjacent years of data were independently drawn, estimates of a single year have greater sampling error, which may be problematic when studying detailed occupations. In fact, Abraham and Spletzer (2009) use the confidential microdata at the detailed occupation level to assess the suitability of the OES for studying the effects of offshoring. They conclude that "employment time series for detailed occupations that are created from single-year micro data are likely to be highly volatile... Increases in the size of the OES sample would be needed to reduce the variance of annual employment estimates" (p. 11).

Because of these limitations, the lack of independence across adjacent years in the sample, and the sampling error associated with a single year's estimates, the OES cannot be used by itself to produce a state-level occupation growth rate.

The OES also produces estimates of occupation by industry employment at the national level for all years. I use the estimate of occupation by industry employment in 2002 to construct an alternative occupation growth rate, along with the industry employment numbers discussed in the next subsection. The OES also produces research estimates of occupation by industry employment at the state level for 2012-2014, which I will use for robustness checks.

[5]For example, even a very large private employer will be surveyed every three years. This can make an occupational estimates produced using consecutive years of survey data very different, especially at the local level.

3.3 Industry Growth Rates from the Quarterly Census of Employment and Wages

The Quarterly Census of Employment and Wages (QCEW) is a tabulation of employment of all establishments that report to the Unemployment Insurance programs in the United States. This employment covers 97% of all wage and salary civilian employment in the U.S. Because every establishment is assigned to an industry, these data are reported at the industry level. I use the annual version of this dataset as the DWS respondents only report their year of displacement. Annual state-level industry employment is used in tandem with the occupation by industry employment composition to construct an estimate of changes in occupational employment. Annual state-level industry employment is also used independently to create a measure of industry growth rate. Occupation data is not available in the QCEW.

4 Empirical Approach

My goal is to estimate the effect of the state-level growth rate of a displaced workers' pre-displacement occupation on his or her labor market outcomes. However, as described earlier, a key challenge is that the OES occupation counts for a single year are estimated using the prior three years of data. Consequentially, major issues – lack of independence across adjacent years, and sampling error associated with a single year's estimates – impede the estimation of an unbiased coefficient.[6]

To overcome these obstacles, I will predict occupation growth from the higher quality data that are available for industry growth. In contrast to occupation level employment, industry level employment is well-measured on a yearly basis. This is because a firm's product or service determines its industry and this information is easily aggregated using administrative data from unemployment insurance records. Occupations are distributed in different proportions across industries because the composition of labor inputs varies across the production of

[6]To see why estimates will be biased, note for example that a three-year moving average of occupation employment counts will underestimate the growth rate of occupations with convex growth, and will overestimate the growth rates of occupations with concave growth.

different goods and services.

If the relevant occupation conditions are at the state level, then the occupation growth rate can be predicted using state's industry employment composition, the state-level occupation-industry distribution, and the growth rate of the industries within the state. In the following subsection, I explain the construction of this state level occupation growth rate measure.

Before continuing, it is important to discuss the level of occupation and industry involved in this analysis. The Standard Occupation Classification system has four levels: major group, minor group, broad group, and detailed occupation. Table 3 lists some occupation codes and their associated titles. The Census occupation classification, which is utilized for in CPS, reports either broad or detailed occupations. In this paper, I will construct the occupation growth rate at either the broad or detailed level, as fine as is available. This is because it is not clear that the growth rate of word processors and typists (43-9022) is the same as the growth rate of insurance claims and policy processing clerks (43-9031), and using the growth rate of the minor group (43-9000) will confound potential differences.

4.1 Construction of the State Occupation Growth Rate Measure

To proceed, I create an estimate of the occupation growth rate that does not use the OES as time series data. My decomposition is based on the fact that a given occupation's employment in a state is the sum of the occupation's employment in each of the state's industries.

In words, occupation o's employment in state s at year t, $E_{s,o,t}$, will be the sum of state employment in each industry j in that year, $E_{s,j,t}$, times the fraction of industry employment in that state and year that belongs to that occupation, $\alpha_{s,o,j,t}$.

$$E_{s,o,t} = \sum_j \alpha_{s,o,j,t} E_{s,j,t} \tag{1}$$

Because we are interested in growth rates, we can describe the change in occupational em-

ployment in state s and year t as

$$\Delta E_{s,o,t} = \sum_j \alpha_{s,o,j,t} E_{s,j,t} - \sum_j \alpha_{s,o,j,t-1} E_{s,j,t-1} \tag{2}$$

Unfortunately, equation 2 suffers from the limitations inherent using OES data for time series analysis, as both $\alpha_{s,o,j,t}$ and $\alpha_{s,o,j,t-1}$ come from adjacent years of the OES. For the reasons discussed earlier, this implies that the same employment data is used to determine these two estimates, and these estimates are not independent. However, assuming $\alpha_{s,o,j,t} = \alpha_{s,o,j,t-1} \forall t$, i.e. the share of occupation o in industry j in state s does not change over time, avoids this issue. This would be true if the production function of various goods and services and the costs of various types of labor are not changing over the sample period. I use year 2002 to measure α because it is the first year in which the North American Industry Classification (NAICS) is used in the OES data.

Then,

$$\widehat{\Delta E_{s,o,t}} = \sum_j (E_{s,j,t} - E_{s,j,t-1}) \alpha_{s,o,j,2002} \tag{3}$$

My analysis, however, requires a growth rate, as opposed to the pure change in employment. To avoid relying on adjacent years of occupation data to compute the growth rate, I use a fixed year at the beginning of the data period, 2001, as the denominator for occupation o's growth rate in state s.

$$\frac{\widehat{\Delta E_{s,o,t}}}{E_{s,o,2001}} = \frac{1}{E_{s,o,2001}} \sum_j (E_{s,j,t} - E_{s,j,t-1}) \alpha_{s,o,j,2002} \tag{4}$$

$$= \sum_j \frac{E_{s,j,2001}}{E_{s,o,2001}} \frac{E_{s,j,t} - E_{s,j,t-1}}{E_{s,j,2001}} \alpha_{s,o,j,2002} \tag{5}$$

It is possible to create variants of this occupation growth rate measure to decrease noise associated with certain state-level estimates. There are two reasons why state level estimates

may be substantially noisier than national level estimates: noise in the industry growth rate and noise in the occupation-industry composition.

The 4 digit NAICS industry growth rate at the state level is fairly noisy. Over 11% of the state-industry-year cells have zero employees, and over 16% have fewer than 100 workers. Because of this characteristic, the state-level industry growth rate is highly variable for small industries and states. Additionally, the displaced workers in my DWS sample may be directly affected by firms closing in their industries. To deal with these problems, researchers including Autor and Duggan (2003) have used national-level industry changes in employment, excluding the focal state's industry employment. This method, a type of shift-share Bartik instrument, has two major advantages: first, it is not reliant on a single state's noisy industry employment, and second, it removes any chance of a mechanical correlation between the displaced worker's job loss and the relevant employment conditions.

State-level occupation-industry composition suffers from a more significant limitation. Namely, the data only exists from 2012 to 2014, and has been published as "research estimates." This designation implies a higher variability due to smaller samples. Additionally, these estimates are limited to state-occupation-industry cells with sufficient employment to disclose an estimate. As fewer estimates are withheld as employment numbers are aggregated to the national level, national estimates are available for far more occupation-industry cells and for every year in the sample.

Motivated by these concerns, my preferred estimate of the occupation growth rate uses national estimates of both the industry growth rate and occupation by industry composition:

$$\pi_{s,o,t} = \frac{\widehat{\Delta E_{s,o,t}}}{E_{s,o,2001}} = \sum_j \frac{E_{s,j,2001}}{E_{s,o,2001}} \alpha_{o,j,2002} \frac{E_{-s,j,t} - E_{-s,j,t-1}}{E_{-s,j,2001}} \tag{6}$$

For clarity, the three components of the measure can be labeled as follows:

$$\pi_{s,o,t} = \frac{\widehat{\Delta E_{s,o,t}}}{E_{s,o,2001}} = \sum_j \underbrace{\gamma_{s,o,j,2001}}_{\substack{\text{State-specific}\\ \text{weight}}} \underbrace{\alpha_{o,j,2002}}_{\substack{\text{Fraction}\\ \text{of occ } o\\ \text{in ind } j}} \underbrace{\frac{E_{-s,j,t} - E_{-s,j,t-1}}{E_{-s,j,t-1}}}_{\substack{\text{Growth rate of ind } j\\ \text{nationally}}}$$

I will use this measure, $\pi_{s,o,t}$, the predicted state-level occupation growth rate, condensed to "occupation growth rate" as my main regressor of interest for the remainder of the paper.

Figure 1 plots the distribution of occupation growth rates amongst the displaced workers in the sample. The mean worker-weighted occupation growth rate is -0.008 and the standard deviation is .04. The figure also shows that the distribution is left-skewed.

4.2 Estimation of the Impact of Occupation Growth Rates

I estimate the impact of the occupation growth rate on a displaced worker's labor market outcomes as follows:

$$Y_{i,s,o,t} = \beta \pi_{s,o,t} + \delta X_{i,s,o,t} + \lambda_s + \lambda_t + \varepsilon_{i,s,o,t} \tag{7}$$

where $\pi_{s,o,t}$ is the occupation growth rate, defined above. $X_{i,s,o,t}$ is a vector of individual characteristics including sex, race, education, years since displacement, indicators for different age categories, and a quadratic of tenure at the pre-displacement job. λ_s and λ_t are state of residence and year of displacement fixed effects. The primary outcomes of interest, $Y_{i,s,o,t}$, are the worker's re-employment status after displacement, occupation change, log duration of joblessness, and the change in log earnings. The regressions are weighted by the Displaced Worker Supplement Weights, and standard errors are clustered at the state level. This regression specification compares two observationally identical displaced workers who have been displaced in the same state and same year from occupations growing at different rates.

The identifying assumption in equation (7) is that unobservable characteristics of displaced workers are uncorrelated with their occupation growth rate, conditional on observable individual characteristics, state, and year of displacement. This specification directly addresses the

challenge of state workforce agencies, who are interested in targeting services to workers and need to decide between workers displaced in a state at similar times.

A potential disadvantage of the specification in equation (7) is that workers who select into different occupations may have different unobservable characteristics that affect labor market outcomes, which might be correlated with the occupation growth rate. This might be true, for example, if the most able workers recognize their occupation is shrinking, or vulnerable to shrinking, and change into more stable occupations. To allay concerns about differences in unobservable characteristics across displaced workers in different occupations, I also present estimates that add three digit SOC occupation fixed effects. This specification is as follows:

$$Y_{i,s,o,t} = \beta\pi_{s,o,t} + \delta X_{i,s,o,t} + \lambda_s + \lambda_t + \lambda_o + \varepsilon_{i,s,o,t} \tag{8}$$

These fixed effects control for the situation in which certain occupation categories have longer unemployment durations or lower post-displacement earnings, independent of the occupation growth rate. In this specification, the variation is coming from differences within occupations, controlling for state and year fixed effects. The identifying assumption is that unobservable characteristics of the worker are uncorrelated with the occupation growth rate, conditional on observable individual characteristics, pre-displacement occupation, state, and year of displacement. Of course, while alleviating concerns about bias, equation (8) relies on considerably less identifying variation, so it has a cost in terms of statistical power.

As the focus of this paper is displaced workers, I will discuss the magnitude of the effects for a one percentage point *decrease* in the occupation growth rate.

4.3 Comparison with Industry Growth Rate

Previous literature, including Carrington (1993), Kandilov (2010), and Crinò (2010), has found a significant effect of pre-displacement industry decline on displaced workers' labor market outcomes. However, there are few estimates of the relative impact of occupation growth compared to industry growth in the displaced workers' literature. Additionally, more state

workforce agencies use historical data on changes in industry employment (59%) compared to historical data on changes in occupation employment (25%) in their prediction models (Dickinson et al., 1997).

To compare the impact of industry growth versus occupation growth on displaced workers' labor market outcomes, I run the following two regressions:

$$Y_{i,s,o,t} = \gamma \pi_{s,j,t} + \delta X_{i,s,o,t} + \lambda_s + \lambda_t + \varepsilon_{i,s,o,t} \tag{9}$$

$$Y_{i,s,o,t} = \gamma \pi_{s,j,t} + \beta \pi_{s,o,t} + \delta X_{i,s,o,t} + \lambda_s + \lambda_t + \varepsilon_{i,s,o,t} \tag{10}$$

where the first equation replaces the occupation growth rate with the state-level industry growth rate. The industry growth rate is analogously predicted from national industry growth.[7] This measure is constructed using the same approach as the occupation growth rate and therefore has the same advantages: it is not reliant on a single state's noisy industry employment, and it removes any chance of a mechanical correlation between the displaced worker's job loss and the relevant employment conditions.

The second equation adds the occupation growth rate back in. In the second equation, the coefficient on occupation growth rate will be the impact of occupation growth holding industry growth constant. Similarly, the coefficient on industry growth rate will be the impact of industry growth holding occupation growth constant.

The labor market outcomes discussed in this context are the log duration of joblessness and change in log earnings. Industry growth is at the three digit NAICS level.

5 Results

5.1 Variation in the Occupation Growth Rate

To illustrate the source of my identifying variation, Figure 2 plots the state-level occupation growth rate measure, net of state fixed effects and year of displacement fixed effects for two

[7] More formally, $\pi_{s,j,t} = \sum_j \frac{E_{s,j,2001}}{E_{s,2001}} \left(\frac{E_{-s,j,t} - E_{-s,j,t-1}}{E_{-s,j,2001}} \right)$

years, 2009 and 2010, and for two occupations, mechanical engineers (17-2141) and accountants/auditors (13-2011). Several comparisons emerge: First, the net occupation growth rate of mechanical engineers was much lower in Georgia than in California in 2009. This difference comes partially from the manufacturing industry, which is a bigger share of employment in Georgia than in California. However, the prospects for mechanical engineers in Georgia also recovered much more quickly than in California. A different story emerges looking at accountants/auditors. The economic prospects became relatively worse for accountants/auditors from 2009 to 2010. The decline was similar in California and Georgia. Looking across the panels, the decline in manufacturing in 2009 had a greater effect on mechanical engineers, as the share of mechanical engineering employment in manufacturing is 58 percent, while the share of accounting/auditing employment in manufacturing is 45 percent. The decline of services, which came later, lead to worse employment outcomes for accountants/auditors in 2010. This example illustrates how changes in the natural industrial employment can give rise to very different occupation employment growth rates in different states in the same year.

The variation in the occupation growth rate over this time period (2001-2013) is substantial. Figure 3 compares the minimum and maximum occupation growth rates for state-occupation combinations represented in my displaced workers' sample. The mean difference between the minimum and maximum growth rate is 0.098 and the standard deviation is 0.078.

5.2 The Effect of the Occupation Growth Rate

Table 4 shows the effect of the pre-displacement occupation growth rate on the probability of working for pay after displacement, controlling for elapsed time between displacement and the survey date. As the DWS only asks year of displacement, this is only a rough control for elapsed time. Working for pay is assumed for workers currently employed, and asked of individuals who are both unemployed and not in the labor force. Approximately 79 percent of the sample had worked for pay by the time they were surveyed. The occupation growth rate is not associated with working for pay by the survey date in either specification. The biggest determinant of working since displacement is the time elapsed since displacement – workers

who were displaced three (two) years ago are approximately 31 (15) percentage points more likely to have worked for pay after displacement, respectively. The other coefficients in this regression follow expected patterns – older workers are less likely to work after displacement, more educated workers are more likely to work after displacement.

The next outcome is log duration of joblessness. Duration of joblessness is defined as the number of weeks that went by between displacement and when the respondent started working again. This is self-reported by all displaced workers who have worked for pay at some time since displacement.[8] For other workers, the DWS survey unfortunately allows us only to make highly imprecise statements about their jobless durations. Thus I omit these workers from my main estimates, working with the sample of self-reported completed durations only.[9] In the Robustness section, I report the results from censored duration regressions that include non-re-employed workers under various assumptions for calculating their incomplete durations.

Table 5 Column (1) shows that a one percentage point decrease in the growth rate of a worker's occupation in the state and year of displacement is associated with a 3.1 percent increase in the duration of joblessness conditional on having been re-employed after displacement. The estimate is similar with occupation fixed effects in Column (2) – a one percentage point decrease is associated with a 2.8 percent increase in the duration of joblessness. This suggests that a one standard deviation decrease is associated with a 11.5 percent increase in the duration of joblessness conditional on having been re-employed after displacement.

Previous literature has focused extensively on the correlation between occupation change and displaced workers' earnings and employment outcomes. But under what conditions do displaced workers' change occupations? Table 6 analyzes the effect of the occupation growth rate on the probability of an occupation change for workers who are currently employed. The majority of workers in the sample (67.8 percent) change occupations after displacement. Linear probability models with occupation change as the dependent variable are displayed in Column

[8] It is topcoded at 100 weeks, although this affects a very small fraction of the sample.

[9] As in most censored regression contexts, I expect the exclusion of these incomplete durations (which will be longer, on average) to attenuate my estimates of occupation growth rates on duration of joblessness.

(1), and show that a one percentage point decrease in the occupation growth rate is associated with a 1.2 percentage point increase in the probability of an occupation change. Column (2) adds occupation fixed effects, which decrease the magnitude of the point estimate but the new estimate is not statistically different. We may, however, be concerned that workers are temporarily changing occupations to work part-time, and this negative outcome may not hold over time. This does not appear to be the case. Column (3) includes only workers who report having a full-time job after displacement. This selected sample of workers looks equally likely to change occupations as a function of the occupation growth rate. The coefficient is still statistically significant and meaningful in column (4). A one percentage point decrease in the growth rate is associated with a 1.1 percentage point increase in the probability of changing occupations.

Table 7 looks at the change in log earnings between pre- and post-displacement jobs, conditional on re-employment. Earnings changes are related to the worker's occupation growth rate: a one percentage point decrease in the occupation growth rate is associated with a 1.4 percent decrease in post-displacement earnings. This effect is similar when adding occupation fixed effects – a one percentage point decrease in the occupation growth rate is associated with a 1.8 percent decrease in post-displacement earnings. The standard deviation of the occupation growth rate amongst this sample is .039, suggesting that a worker who is displaced in conditions one standard deviation below the mean suffers, all else equal, a 14.2 percent larger earnings loss than a worker displaced in conditions one standard deviation above the mean.

5.3 Comparison with Industry Growth

With a clear understanding of the negative impact of the occupation growth rate on displaced workers' labor market outcomes, I now turn to understanding its role relative to the industry growth rate.

Table 8 Panel A compares the impact of occupation versus industry growth on the duration of joblessness. Column (1) shows that a one percentage point decrease in the occupation growth rate is associated with a 3.1 percent longer duration of joblessness. Column (2) shows

that a decrease in the industry growth rate has a smaller effect on duration of joblessness, but still lengthens it – a one percentage point decrease in the industry growth rate has a 0.9 percent increase in the duration of joblessness. Column (3) includes both occupation growth rate and industry growth rate in the same regression. While the magnitude of the occupation growth rate shrinks, it is still statistically and economically significant. The industry growth rate coefficient is also smaller, and now not statistically significant. The relative magnitudes here are important – the point estimate on the occupation growth rate is five times the size of the point estimate on the industry growth rate. The test of equality shows that we can reject the null hypothesis that these growth rates are the same at the 1% level.

Column (4) - (6) add occupation fixed effects to the specifications in Columns (1) - (3). These fixed effects do not significantly change the magnitude of the estimates. A one percentage point decrease in the occupation growth rate is associated with a 2.8 percent longer duration of joblessness. On the other hand, the effect of a one percentage point decrease in the industry growth rate is .7 percent. Column (6) shows the "horse race" regression specified in Equation 8. Again, the effect of the occupation growth rate is much larger than the effect of industry growth rate. As in Column (3), the industry growth rate no longer has a significant impact on duration of joblessness. It is valuable to remember that the occupation growth rate is constructed using industry growth rates. As such, it should not be surprising that the correlation between the occupation growth rate and the industry growth rate is 0.46 in this sample. Despite this fact, the occupation growth rate is statistically different in both comparisons in Table 8. It is dominant in determining the duration of joblessness.

Table 8 Panel B compares the impact of industry and occupation growth on the displaced workers' change in log earnings. A one percentage point decrease in the occupation growth rate is associated with a 1.4 percent decrease in earnings. A one percentage point decrease in the industry growth rate is associated with a 0.4 percent decrease in weekly earnings. The coefficient on the occupation growth rate is more than three times the size of the coefficient on industry growth rate. When the occupation growth rate and industry growth rate are in the same regression, as in column (3), neither effect is statistically significant although we can

reject the null hypothesis that they are jointly equal to zero ($p = .0092$). A similar story can be told with occupation fixed effects in columns (4)-(6). For this specification, the test of equality demonstrates that the occupation growth rate plays a larger role (we can reject the null hypothesis that these two estimates are the same at the 10% level).

6 Robustness

This section looks at the robustness of these results. The occupation growth rate in the above regressions is based on the year the worker was displaced. Table 9 compares the specification based on the contemporaneous occupation growth rate with the occupation growth rate last year, the occupation growth rate two years ago, and the mean occupation growth rate in the three years leading up to the displacement (the contemporaneous year, the year prior and two years prior). To make comparisons across these four specifications, the sample is limited to workers who have all four measures, decreasing the sample size by excluding workers displaced in 2001 and 2002. The mean growth rate, in Table 9 Panel A Columns (4) and (8), has the largest effect on the worker's duration of joblessness, followed closely by the contemporaneous growth rate. Panel B, which changes the focus to change in log earnings, provides more support for the contemporaneous growth rate. Here, the contemporaneous growth rate is the only statistically significant estimate. The mean growth rate, in this case, even has the 'wrong' sign. While the mean growth rate might provide information on the length of joblessness, earnings changes are more related to contemporaneous conditions.

Next, I run a placebo test, comparing the effect of the contemporaneous occupation growth rate with the effect of the occupation growth rate four years after displacement on the worker's labor market outcomes. The sample is limited to workers for whom both contemporaneous and four year later occupation growth rates are available, and therefore, workers displaced after 2010 are excluded. By four years after the reported calendar year of displacement, the vast majority of displaced workers have been re-employed, and therefore the occupation growth rate should have little effect on the worker's duration of joblessness. This is certainly the case –

in Table 10, the occupation growth rate four years after displacement has an insignificant effect on duration of joblessness. The test of equality rejects the null hypothesis that the estimates in Column (1) and (2) are the same at the 5% level. Adding occupation fixed effects makes these results a bit noisier although quite similar.[10]

Next, I vary the method by which I estimate the occupation growth rate. Table 11 shows the effect of the occupation growth rate measured in four different ways on log duration of joblessness and change in log earnings. As discussed in section 4.1, my preferred measure of the occupation growth rate uses Equation 6, displayed in Columns (1) and (2) of Table 11. The three components of this measure are the state-specific weight and national estimates of the industry growth rate and national estimates of occupation by industry composition. To show robustness to different measures, I replace the national occupation by industry composition term with a state-specific occupation by industry composition term. This comes from the OES research estimates of state-level occupation by industry employment, which started in 2012. In other words, I replace $\alpha_{o,j,2002}$ with $\alpha_{s,o,j,2012}$ in Equation 6. This estimate is displayed in Column (3) and (4) in Table 11 with and without occupation fixed effects. The estimate is smaller than the corresponding estimates using the national occupation by industry composition term but still statistically significant.

The next measure of occupation growth rate returns to Equation 6 and replaces national industry growth with state s's industry growth. This estimate is displayed in Columns (5) and (6). The estimate is smaller than the estimates from Column (1) and (2) but still economically meaningful (notably, bigger than the estimates of the industry growth rate from 8). Finally, in Columns (7) and (8), the occupation growth rate measure combines the two changes. This

[10]While it seems plausible to expect no effects of the growth rate of a worker's pre-displacement occupation four years after displacement on the length of the worker's first post-displacement jobless spell (an outcome that is most likely determined by that time), a similar null effect does not seem likely on the worker's earnings at the DWS survey date, which can be up to three years after displacement. Employment growth (estimated by the growth of occupation o between $t+3$ and $t+4$) in the pre-displacement occupation should still be correlated with the worker's outside options, since he or she has skills related to that occupation, for reasons explored by Beaudry et al. (2012) and Tschopp (2017). For these reasons, Table 10 type regressions do not constitute a valid placebo test when earnings are the outcome of interest. Interestingly, while the standard errors are large, four-year-later occupation growth rates in those regressions have consistently positive coefficients, regardless of whether the worker has switched occupations. I interpret this as weak evidence of search and bargaining effects in local labor markets.

estimate is the smallest of the four, but still statistically significant. The pattern is similar when considering changes in weekly earnings, though the results become insignificant when using the own state industry growth rate. The weaker estimates when using state level industry growth may be evidence of greater measurement error in these values.

As the Displaced Workers Survey does not ask duration of joblessness for individuals who have not been re-employed by the CPS survey date, my main results on duration of joblessness did not include those who have not been re-employed. While Table 4 shows that the occupation growth rate does not have a significant effect on the probability of working for pay after displacement, Table 13 demonstrates robustness of the log duration of joblessness result by including workers who have not been re-employed. The DWS asks year of displacement, so workers who have not been re-employed at the time of the survey will have been jobless for a minimum amount of time depending on the year they were displaced. To incorporate this information, I first treat all workers with incomplete durations as being displaced in the middle of their displacement year. Then, workers who were displaced one, two and three years ago have minimum durations of 26, 78, and 130 weeks, respectively. I then include these minimum durations in a right-censored regression that includes both complete and incomplete spells. The results are reported in Table 13. In Column (1), a one percentage point decrease in the occupation growth rate is associated with a 2.6 percent increase in duration of joblessness, an effect that is quite similar to the estimated 3.1 percent in Table 5. This result is also quite robust to supposing that all workers were displaced in any other month of the year: the estimates range between -2.64 and -2.71. In Column (2), the specification with occupation fixed effects, the estimate is however much smaller and statistically insignificant. Since these censored regressions must be estimated by maximum likelihood, the low power of this estimate may reflect an incidental parameters problem associated with the large number of occupation fixed effects.

Next, I test the robustness of the results for earnings changes. In Table 12 Columns (1) and (2), I change the functional form of the outcome to levels – the change in weekly earnings. These results are quite similar to the log specification. A one percentage point decrease in the

occupation growth rate is associated with a $6.17 decrease in weekly earnings. This translates to a 0.8 percent change in earnings. The results with occupation fixed effects show that a one percentage point decrease in the occupation growth rate is associated with a $9.75 (1.3 percent) decrease in weekly earnings. Next, I address the concern that the change in log earnings results described in Table 7 are limited to workers who are re-employed. In Table 12 Columns (3) and (4), I replace the outcome, change in weekly earnings, to the full lost earnings of workers who have not been re-employed.[11] The mean change in earnings is more than twice as large, and the occupation growth rate has a similar impact, though only statistically significant in the occupation fixed effects specification. Further analysis shows that the weaker effect is partially driven by unemployed workers who had earnings inconsistent with full-time work prior to displacement. Excluding workers who had less than $150 in lost job weekly earnings (suggesting these workers were not full-time workers despite reporting 35 usual hours of work), the results are significant in both specifications, and consistent with the main results.

Finally, Table 14 looks at the effects of the occupation growth rate on proxies for the four most common dependent variables used by various State Workforce Agencies in their profiling systems: fraction of unemployment benefits exhausted, an indicator for an unemployment duration greater than or equal to 26 weeks, an indicator for exhausting formal unemployment compensation benefits, and unemployment duration. As the Displaced Workers Survey does not explicitly ask for the duration of unemployment, I proxy for duration of unemployment with duration of joblessness. I create a proxy for the fraction of benefits exhausted by dividing the duration of joblessness by 26, with a maximum value of one. Workers who were displaced two or three years ago and have not worked since displacement were also considered to completely exhaust unemployment compensation. While the maximum number of weeks for which unemployment benefits were provided changed during this time period, the DWS does not provide detailed timing information, and so this is a rough proxy.

Some states use a binary variable in their profiling system, so in Columns (3) and (4), I replace this proxy with a binary for unemployment duration greater than or equal to 26

[11] I exclude the small number of workers who have top-coded lost job earnings and are not re-employed. The top-coded value is $2884.61.

weeks. The Displaced Workers Survey asks those who said they claimed unemployment benefits whether they exhausted their unemployment benefits. This outcome is displayed in Columns (5) and (6). The sample size is smaller for this group as workers may not have taken unemployment benefits for various reasons. The fourth dependent variable, in Columns (7) and (8), is unemployment duration in weeks, censored at 100 weeks.[12]

The results all appear to be consistent: there appears to be a negative effect of occupation growth on the fraction of unemployment benefits exhausted, the probability of exhausting benefits, and unemployment duration. A one percentage point decrease in the occupation growth rate is associated with a .006 to .01 decrease in the fraction of unemployment benefits exhausted, which is the equivalent to a 1.4-2.2 percent reduction in the probability of exhausting benefits. This is also true using a binary dependent variable for a duration longer than or equal to 26 weeks, although not statistically significant for the regression using occupation fixed effects. This result is also consistent with evidence that a continuous dependent variable performs better shown in other WPRS related work such as Black et al. (2003). The indicator for a worker reporting they exhausted benefits, in Column (5) and (6), provides results in a similar direction but they are underpowered. Columns (7) and (8) find significant, negative effects of a shrinking occupation on unemployment duration. A one percentage point decrease in the occupation growth rate is associated with a .46-.57 week longer duration. Overall, this table provides further evidence supporting the claim that the occupation growth rate is a predictor of the duration of joblessness and states looking to improve their targeting of displaced workers should use this information.

7 Conclusion

Policymakers and researchers alike have contemplated causes of displaced workers' earnings losses and attempted to identify vulnerable displaced workers. While it is well established that older and high tenure workers lose more, much less is known about other determinants

[12]This restriction is only because the DWS censors duration of joblessness at 100 weeks. However, it only affects less than 2 percent of the respondents.

of displaced workers' earnings losses. This is additionally problematic as recent literature has focused on ex post determinants of earnings losses, such as industry and occupation change, which do not have a clear causal interpretation and are less helpful to states' worker-targeting decisions. While the role of occupation growth is quite intuitive, data limitations have hindered this analysis.

This paper shows that the growth rate of a displaced worker's pre-displacement occupation significantly impacts workers' durations of joblessness and earnings losses. Importantly, the effect of industry growth holding occupation growth constant is quite small in comparison. This implies that workers' difficulties are less related to the goods and services they were producing, and more related to the activities they were performing at work. Thus, being a worker in a declining occupation at the time of displacement leads to worse labor market outcomes. This information may be useful in improving the provision of scarce resources for re-employment assistance, based on information available to the states at the time of displacement.

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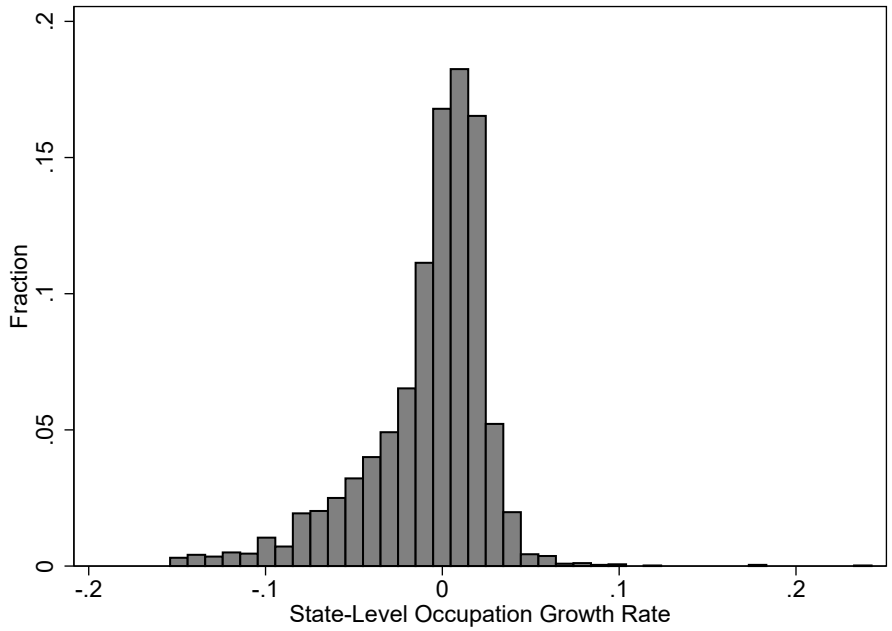
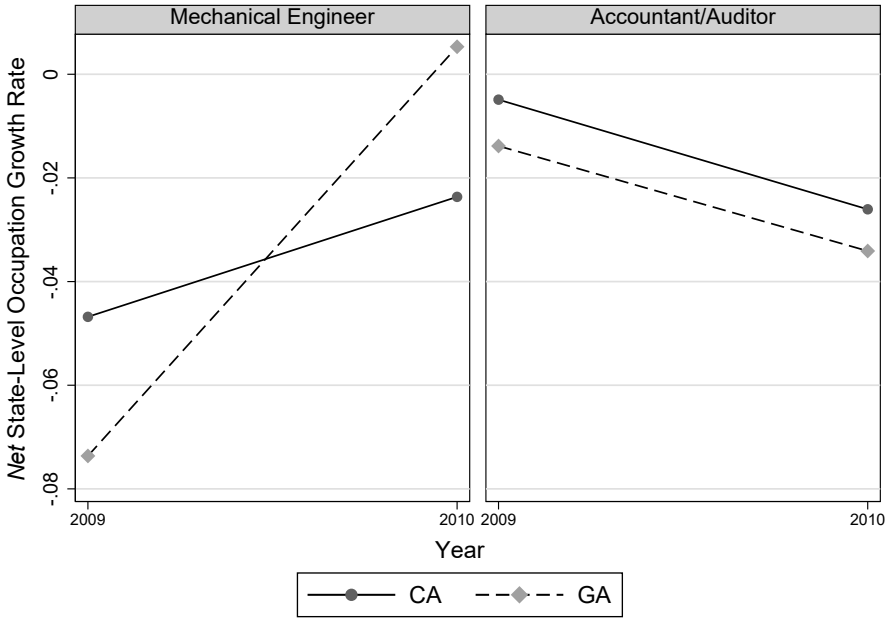
8 Figures

Figure 1: Distribution of Predicted Pre-Displacement Occupation Growth Rates for Workers Displaced From Full-Time Jobs



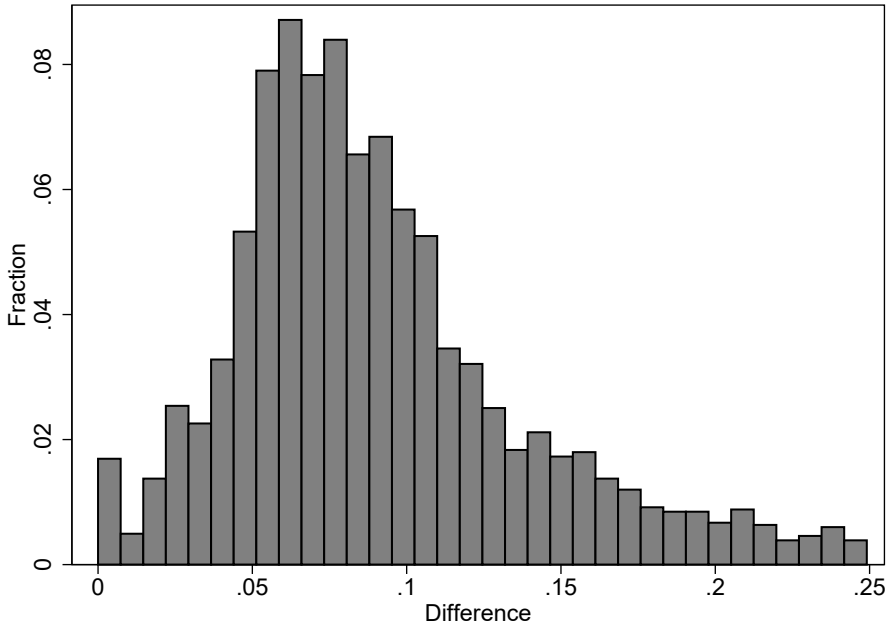
Notes: The sample is limited to workers responding to the Current Population Survey Displaced Workers Survey Supplement between 2004 and 2014. Workers have been displaced because their plant or firm closed or moved, and be displaced from a full-time occupation. Workers in this sample must report pre-displacement occupation and have a pre-displacement occupation growth rate.

Figure 2: Illustrative Example of the Differences Between State-Level Occupation Growth Rates



Notes: This is an illustrative example of net state-level occupation growth rates in 2009 annd 2010 for mechanical engineers (17-2141) and accountants/auditors (13-2011).

Figure 3: Difference between Highest and Lowest Growth Rate within Occupation-State Cell



Notes: The sample is limited to occupation-state combinations that correspond to workers responding to the Current Population Survey Displaced Workers Survey Supplement between 2004 and 2014. Workers have been displaced because their plant or firm closed or moved, and be displaced from a full-time occupation and report their occupation.

9 Tables

Table 1: Summary Statistics

Less Than HS	0.124
	(0.330)
HS Diploma	0.357
	(0.479)
Some College	0.296
	(0.456)
BA/BS	0.170
	(0.376)
Graduate Degree	0.0531
	(0.224)
White	0.797
	(0.402)
Black	0.136
	(0.342)
Asian	0.0102
	(0.101)
Other Race	0.0572
	(0.232)
Age	41.82
	(11.60)
Tenure	6.302
	(7.300)
Female	0.413
	(0.492)
Displaced 3 Years Ago	0.311
	(0.463)
Displaced 2 Years Ago	0.305
	(0.461)
Displaced Last Year	0.383
	(0.486)
Change in Wage	-103.8
	(453.6)
Change in Log Earnings	-0.246
	(0.904)
Worked for Pay Since Displacement	0.781
	(0.414)
Duration of Joblessness in Weeks	15.42
	(21.33)
Year Displaced	2006.6
	(3.472)
Pre-Displacement Occupation Bartik State Growth Rate	-0.00918
	(0.0417)
Observations	4771

Notes: The sample is limited to workers responding to the Current Population Survey Displaced Workers Survey Supplement between 2004 and 2014. Workers have been displaced because their plant or firm closed or moved. Workers in this sample must report pre-displacement occupation. The main sample is workers who were working full-time prior to displacement. Summary statistics are weighted using Displaced Workers Survey Supplement weights. Means are reported, and standard deviations are in parentheses.

Table 2: Differences between workers reporting and not reporting occupation

	(1)	(2)	(3)
Less Than HS	0.124	0.173	-0.041
	(0.330)	(0.378)	(0.013)
HS Diploma	0.357	0.407	-0.044
	(0.479)	(0.492)	(0.018)
Some College	0.296	0.279	0.013
	(0.456)	(0.449)	(0.017)
BA/BS	0.170	0.106	0.059
	(0.376)	(0.308)	(0.012)
Graduate Degree	0.053	0.036	0.013
	(0.224)	(0.186)	(0.007)
White	0.797	0.772	0.043
	(0.402)	(0.420)	(0.015)
Black	0.136	0.147	-0.015
	(0.342)	(0.354)	(0.012)
Asian	0.010	0.007	-0.001
	(0.101)	(0.081)	(0.004)
Other Race	0.057	0.075	-0.027
	(0.232)	(0.263)	(0.010)
Age	41.823	47.265	-5.873
	(11.597)	(14.579)	(0.532)
Tenure	6.302	8.962	-2.980
	(7.300)	(9.644)	(0.380)
Female	0.413	0.490	-0.072
	(0.492)	(0.500)	(0.019)
Displaced 3 Years Ago	0.311	0.349	-0.050
	(0.463)	(0.477)	(0.018)
Displaced 2 Years Ago	0.305	0.323	-0.007
	(0.461)	(0.468)	(0.017)
Displaced Last Year	0.383	0.328	0.056
	(0.486)	(0.470)	(0.018)
Change in Weekly Earnings	-103.770	102.914	-150.513
	(453.645)	(500.761)	(117.917)
Change in Log Earnings	-0.246	0.012	-0.161
	(0.904)	(0.604)	(0.156)
Worked for Pay Since Displacement	0.781	0.204	0.566
	(0.414)	(0.403)	(0.016)
Duration of Joblessness in Weeks	15.424	17.938	-3.603
	(21.327)	(24.997)	(2.150)
Year Displaced	2006.614	2006.711	-0.092
	(3.472)	(3.493)	(0.132)
Observations	4771	835	5606

Notes: This table compares workers who have been displaced from a full-time job who do report (Column 1) and do not report (Column 2) pre-displacement occupation. The standard deviations are reported in parentheses. Column (3) is the difference between the two columns, with the standard error of the difference in parentheses.

Table 3: Examples of Occupation Categorization

Major	Minor	Broad	Detailed	
43-0000				Office and Administrative Support Occupations
	43-6000			Secretaries and Administrative Assistants
	43-9000			Other Office and Administrative Support Workers
		43-9010		Computer Operators
			43-9011	Computer Operators
		43-9020		Data Entry and Information Processing Workers
			43-9021	Data Entry Keyers
			43-9022	Word Processors and Typists
			43-9030	Desktop Publishers
			43-9031	Desktop Publishers
		43-9040		Insurance Claims and Policy Processing Clerks
			43-9041	Insurance Claims and Policy Processing Clerks
		43-9050		Mail Clerks and Mail Machine Operators, Except Postal Service
			43-9051	Mail Clerks and Mail Machine Operators, Except Postal Service
		43-9060		Office Clerks, General
			43-9061	Office Clerks, General
		43-9070		Office Machine Operators, Except Computer
			43-9071	Office Machine Operators, Except Computer
		43-9080		Proofreaders and Copy Markers
			43-9081	Proofreaders and Copy Markers
		43-9110		Statistical Assistants
			43-9111	Statistical Assistants

Notes:

Table 4: Worked For Pay Since Displacement

	(1)	(2)
Occupation	0.0831	-0.0802
Growth Rate	(0.211)	(0.270)
HS Diploma	0.0495***	0.0497***
	(0.0167)	(0.0165)
Some College	0.0497***	0.0381**
	(0.0165)	(0.0175)
BA/BS	0.0855***	0.0597**
	(0.0193)	(0.0256)
Graduate Degree	0.140***	0.0945***
	(0.0276)	(0.0342)
Displaced 3	0.313***	0.317***
Years Ago	(0.0204)	(0.0184)
Displaced 2	0.152***	0.148***
Years Ago	(0.0439)	(0.0419)
Black	-0.0702***	-0.0591**
	(0.0232)	(0.0257)
Asian	-0.0758	-0.0806
	(0.0585)	(0.0571)
Other Race	-0.0234	-0.00823
	(0.0241)	(0.0215)
Age 20-29	0.00575	0.00669
	(0.0188)	(0.0165)
Age 40-49	-0.0377*	-0.0352**
	(0.0193)	(0.0175)
Age 50 Plus	-0.103***	-0.104***
	(0.0188)	(0.0171)
Female	-0.00618	0.00173
	(0.0184)	(0.0157)
Tenure	0.00352*	0.00378*
	(0.00204)	(0.00209)
Tenure Squared	-0.000195***	-0.000203***
	(0.0000633)	(0.0000644)
Dept. var mean	0.788	0.788
Observations	4644	4644
State and Year FE	Yes	Yes
Occupation FE	No	Yes

Notes: Sample is limited to workers displaced because their plant or firm closed or moved, and have a non-missing pre-displacement occupation state growth rate. The outcome variable is worked for pay since displacement. Education categories are indicator variables, with "Less Than HS" as the omitted category. Race categories are indicator variables, with "White" as the omitted category. Workers were displaced three, two or one year ago, with one year ago as the omitted category. Regression is a linear probability model with Displaced Workers Survey sample weights. All regressions have state and year of displacement fixed effects. Standard errors clustered by state. * p<0.1 ** p<0.05 *** p<0.01

Table 5: Log Duration of Joblessness

	(1)	(2)
Occupation	-3.131***	-2.800***
Growth Rate	(0.819)	(0.995)
HS Diploma	-0.00359	-0.0148
	(0.107)	(0.104)
Some College	0.164	0.203*
	(0.125)	(0.116)
BA/BS	0.0629	0.0528
	(0.115)	(0.125)
Graduate Degree	0.0423	-0.0108
	(0.187)	(0.176)
Displaced 3	0.618***	0.595***
Years Ago	(0.0617)	(0.0653)
Displaced 2	0.447**	0.431**
Years Ago	(0.174)	(0.176)
Black	0.376***	0.350***
	(0.0749)	(0.0840)
Asian	0.00856	0.0594
	(0.372)	(0.356)
Other Race	0.251**	0.248*
	(0.122)	(0.131)
Age 20-29	-0.101	-0.107
	(0.0861)	(0.0825)
Age 40-49	0.0929	0.0693
	(0.0683)	(0.0639)
Age 50 Plus	0.192**	0.166**
	(0.0738)	(0.0718)
Female	0.0837	0.0932
	(0.0723)	(0.0931)
Tenure	0.0231*	0.0230
	(0.0127)	(0.0146)
Tenure Squared	-0.000350	-0.000387
	(0.000545)	(0.000588)
Dept. var mean	2.129	2.129
Observations	2933	2933
State and Year FE	Yes	Yes
Occupation FE	No	Yes

Notes: Sample is limited to workers displaced because their plant or firm closed or moved, and have a non-missing pre-displacement occupation state growth rate. Workers must be reemployed after displacement. The outcome variable is log duration of joblessness, censored at 100 weeks. Education categories are indicator variables, with "Less Than HS" as the omitted category. Race categories are indicator variables, with "White" as the omitted category. Workers were displaced three, two or one year ago, with one year ago as the omitted category. Column (1) is all workers, and Column (2) is limited to workers displaced from a full-time job. All regressions use Displaced Workers Survey sample weights and have state and year of displacement fixed effects. Standard errors are clustered by state. * $p<0.1$ ** $p<0.05$ *** $p<0.01$

Table 6: Occupation Change

	(1) All	(2) All	(3) Full-Time After	(4) Full-Time After
Occupation	-1.180***	-0.793**	-1.204***	-1.131***
Growth Rate	(0.262)	(0.325)	(0.345)	(0.376)
HS Diploma	0.0458	0.0312	0.0806**	0.0662*
	(0.0341)	(0.0327)	(0.0342)	(0.0330)
Some College	0.0786***	0.0637***	0.0941***	0.0757***
	(0.0288)	(0.0228)	(0.0289)	(0.0274)
BA/BS	0.0533	0.0436	0.0859*	0.0709
	(0.0428)	(0.0430)	(0.0482)	(0.0518)
Graduate Degree	-0.00315	0.0609	0.0421	0.0779
	(0.0415)	(0.0499)	(0.0476)	(0.0569)
Displaced 3	0.0813***	0.0699***	0.0835***	0.0749***
Years Ago	(0.0224)	(0.0198)	(0.0256)	(0.0222)
Displaced 2	0.0686	0.0621	0.0813	0.0713
Years Ago	(0.0472)	(0.0482)	(0.0553)	(0.0591)
Black	0.0749***	0.0837***	0.0768**	0.101***
	(0.0266)	(0.0255)	(0.0301)	(0.0283)
Asian	0.173***	0.176**	0.194***	0.138*
	(0.0565)	(0.0666)	(0.0713)	(0.0773)
Other Race	-0.0256	-0.0135	-0.0705*	-0.0564
	(0.0343)	(0.0364)	(0.0420)	(0.0432)
Age 20-29	0.0629**	0.0653***	0.0535*	0.0560**
	(0.0259)	(0.0218)	(0.0305)	(0.0259)
Age 40-49	0.0118	0.00696	0.0128	0.00721
	(0.0178)	(0.0177)	(0.0259)	(0.0256)
Age 50 Plus	0.0175	0.0190	0.00173	0.00498
	(0.0239)	(0.0200)	(0.0227)	(0.0192)
Female	0.0321	0.0132	0.0287	0.00472
	(0.0192)	(0.0213)	(0.0219)	(0.0265)
Tenure	0.00206	0.000674	0.00541	0.00334
	(0.00344)	(0.00335)	(0.00430)	(0.00435)
Tenure Squared	-0.000131	-0.000131	-0.000243	-0.000215
	(0.000118)	(0.000113)	(0.000145)	(0.000146)
Dept. var mean	0.678	0.678	0.659	0.659
Observations	3406	3406	2651	2651
State and Year FE	Yes	Yes	Yes	Yes
Occupation FE	No	Yes	No	Yes

Notes: Sample is limited to workers displaced because their plant or firm closed or moved and have a non-missing pre-displacement occupation state growth rate. Workers must be reemployed at the time of the survey and report a post-displacement occupation. The outcome variable is occupation change. Education categories are indicator variables, with "Less Than HS" as the omitted category. Race categories are indicator variables, with "White" as the omitted category. Workers were displaced three, two or one year ago, with one year ago as the omitted category. Column (1) and (3) are all workers, and Column (2) and (4) are limited to workers displaced from a full-time job. All regressions use Displaced Workers Survey sample weights and have state and year of displacement fixed effects. Standard errors are clustered by state. * $p<0.1$ ** $p<0.05$ *** $p<0.01$

Table 7: Change in Log Weekly Earnings

	(1)	(2)
Occupation	1.403*	1.824**
Growth Rate	(0.748)	(0.861)
HS Diploma	-0.0456	-0.0383
	(0.0394)	(0.0424)
Some College	-0.0733	-0.0506
	(0.0628)	(0.0616)
BA/BS	-0.109*	-0.0367
	(0.0614)	(0.0683)
Graduate Degree	-0.134	-0.0316
	(0.102)	(0.118)
Displaced 3	-0.00212	0.00841
Years Ago	(0.0536)	(0.0547)
Displaced 2	-0.0128	-0.0155
Years Ago	(0.113)	(0.120)
Black	-0.0853	-0.136*
	(0.0568)	(0.0738)
Asian	0.0957	0.105
	(0.159)	(0.160)
Other Race	0.0189	0.00908
	(0.162)	(0.156)
Age 20-29	0.0544	0.0405
	(0.0596)	(0.0717)
Age 40-49	-0.0504	-0.0299
	(0.0556)	(0.0643)
Age 50 Plus	-0.124***	-0.132***
	(0.0431)	(0.0415)
Female	-0.0175	-0.0283
	(0.0415)	(0.0536)
Tenure	-0.00770	-0.00706
	(0.00548)	(0.00566)
Tenure Squared	0.00000651	-0.0000275
	(0.000191)	(0.000199)
Dept. var mean	-0.240	-0.240
Observations	2861	2861
State and Year FE	Yes	Yes
Occupation FE	No	Yes

Notes: Sample is limited to workers displaced because their plant or firm closed or moved and have a non-missing pre-displacement occupation state growth rate. Workers must be reemployed at the time of the survey. The outcome variable is change in log earnings. Education categories are indicator variables, with "Less Than HS" as the omitted category. Race categories are indicator variables, with "White" as the omitted category. Workers were displaced three, two or one year ago, with one year ago as the omitted category. All regressions use Displaced Workers Survey sample weights and have state and year of displacement fixed effects. Standard errors are clustered by state. * p<0.1 ** p<0.05 *** p<0.01

Table 8: Horse Race Regressions

	(1)	(2)	(3)	(4)	(5)	(6)
A. Log Duration of Joblessness						
Occupation	-3.122***		-2.780***	-2.817***		-2.594**
Growth Rate	(0.820)		(0.804)	(0.999)		(0.998)
Industry		-0.942**	-0.509		-0.668	-0.401
Growth Rate		(0.415)	(0.370)		(0.421)	(0.390)
Test of Equality	p = 0.0034			p = 0.0217		
Dept. var mean	2.130	2.130	2.130	2.130	2.130	2.130
Observations	2901	2901	2901	2901	2901	2901
State and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE	No	No	No	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
B. Change in Log Earnings						
Occupation	1.448*		1.299	1.888**		1.826*
Growth Rate	(0.749)		(0.818)	(0.859)		(0.953)
Industry		0.399**	0.229		0.274*	0.109
Growth Rate		(0.160)	(0.189)		(0.155)	(0.228)
Test of Equality	p = 0.1558			p = 0.0760		
Dept. var mean	-0.241	-0.241	-0.241	-0.241	-0.241	-0.241
Observations	2836	2836	2836	2836	2836	2836
State and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE	No	No	No	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Sample is limited to workers displaced from a full-time job because their plant or firm closed or moved, and have a non-missing predicted pre-displacement occupation state growth rate and a non-missing 3 digit NAICS state indusry growth rate. Workers have worked for pay after displacement. Panel A's outcome is log unemployment duration and Panel B's outcome is change in weekly earnings. Panel B is limited to workers who were employed at the time of survey. Workers with fewer than $40 of earnings per week prior to displacement are excluded. Other controls included in all specifications are as follows: Education categories (indicator variables), race categories (indicator variables), age categories, and years since displacement. All regressions use Displaced Workers Survey sample weights and have state and year of displacement fixed effects. Standard errors are clustered by state.* p<0.1 ** p<0.05 *** p<0.01

Table 9: Prior Year Occupation Growth Rate on Log Duration of Joblessness

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. Log Duration of Joblessness								
Contemporaneous	-2.548***				-2.738**			
	(0.938)				(1.086)			
Prior Year		-1.836*				-1.793*		
		(0.964)				(0.959)		
Two Years Ago			-0.885				-0.657	
			(1.285)				(1.337)	
Mean				-2.561**				-2.879**
				(1.189)				(1.182)
Dept. var mean	2.066	2.066	2.066	2.066	2.066	2.066	2.066	2.066
Observations	2423	2423	2423	2423	2423	2423	2423	2423
State and Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE	No	No	No	No	Yes	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
B. Change in Log Earnings								
Contemporaneous	1.506*				2.598**			
	(0.887)				(1.254)			
Prior Year		0.330				-1.440		
		(0.718)				(1.477)		
Two Years Ago			0.177				-2.219	
			(0.500)				(1.761)	
Mean				0.971				-1.065
				(0.931)				(1.963)
Dept. var mean	-0.235	-0.235	-0.235	-0.235	-0.235	-0.235	-0.235	-0.235
Observations	2375	2375	2375	2375	2375	2375	2375	2375
State and Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE	No	No	No	No	Yes	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Sample is limited to workers displaced from a full-time job because their plant or firm closed or moved, and have a non-missing pre-displacement occupation state growth rate for the contemporaneous year, the year prior and two years prior. The sample, therefore, consists of workers displaced between 2003 and 2013. The outcome variable is log duration of joblessness, censored at 100 weeks. Workers must be reemployed after displacement. Workers with fewer than $40 of earnings per week prior to displacement are excluded. Other controls included in all specifications are as follows: Education categories (indicator variables), race categories (indicator variables), age categories, and years since displacement. All regressions use Displaced Workers Survey sample weights and have state and year of displacement fixed effects. Standard errors are clustered by state. * $p<0.1$ ** $p<0.05$ *** $p<0.01$

Table 10: Placebo Test- Occupation Growth Rate Four Years After Displacement on Log Duration of Joblessness

	(1)	(2)	(3)	(4)
Occupation	-3.611***		-3.068***	
Growth Rate	(0.928)		(1.138)	
4 Years Later		-1.302		-0.543
Occ Growth Rate		(0.871)		(0.924)
Test of Equality	p = 0.0413		p = 0.1289	
Dept. var mean	2.134	2.134	2.134	2.134
Observations	2509	2509	2509	2509
State and Year FE	Yes	Yes	Yes	Yes
Occupation FE	No	No	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes

Notes: Sample is limited to workers displaced from a full-time job because their plant or firm closed or moved, and have a non-missing pre-displacement occupation state growth rate, and have not moved after displacement. Workers must have worked for pay after displacement to be in the sample, which implies all durations are completed, and censored at 100 weeks. The sample is restricted to 2001-2010, to have the same sample for Columns (1) and (3) as (2) and (4). Standard errors are clustered by state. * p<0.1 ** p<0.05 *** p<0.01

Table 11: Different Measures of Occupation Growth Rate

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Nat'l Ind Emp		Nat'l Ind Emp		State Ind Emp		State Ind Emp	
	Nat'l Occ-Ind Dist		State Occ-Ind Dist		Nat'l Occ-Ind Dist		State Occ-Ind Dist	
A. Log Duration of Joblessness								
Occupation	-3.208***	-2.837***	-0.923**	-0.803**	-1.315*	-0.891	-0.601**	-0.538*
Growth Rate	(0.821)	(1.005)	(0.356)	(0.378)	(0.692)	(0.706)	(0.280)	(0.278)
Dept. var mean	2.128	2.128	2.128	2.128	2.128	2.128	2.128	2.113
Observations	2897	2897	2897	2897	2897	2897	2897	2685
State and Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE	No	Yes	No	Yes	No	Yes	No	Yes
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
B. Change in Log Earnings								
Occupation	1.438*	1.848**	0.360	0.289	0.375	0.457	-0.0453	-0.120
Growth Rate	(0.747)	(0.887)	(0.261)	(0.264)	(0.331)	(0.463)	(0.119)	(0.128)
Dept. var mean	-0.241	-0.241	-0.241	-0.241	-0.241	-0.241	-0.241	-0.241
Observations	2830	2830	2830	2830	2830	2830	2830	2830
State and Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE	No	Yes	No	Yes	No	Yes	No	Yes
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Sample is limited to workers displaced from a full-time job because their plant or firm closed or moved, and have a non-missing pre-displacement occupation state growth rate, constructed in the following four ways: Columns (1) and (2) as measured throughout the paper, Columns (3) and (4) replacing national occupation by industry composition for 2002 with state-specific occupation by industry composition for 2012, Columns (5) and (6) replacing national industry growth with state-specific industry growth, and Columns (7) and (8) making both changes. Additional details are specified in the text. The outcome variable is change in weekly earnings. Workers must be reemployed after displacement. Workers with fewer than $40 of earnings per week prior to displacement are excluded. Other controls included in all specifications are as follows: Education categories (indicator variables), race categories (indicator variables), age categories, and years since displacement. All regressions use Displaced Workers Survey sample weights and have state and year of displacement fixed effects. Standard errors are clustered by state. * $p<0.1$ ** $p<0.05$ *** $p<0.01$

Table 12: Other Methods of Computing Change in Weekly Earnings

	(1)	(2)	(3)	(4)	(5)	(6)
	Re-Employed Workers		All Workers		All Workers Excluding Pre-Displacement Earnings$\leq$ \$150	
Occupation Growth Rate	616.9*	974.5**	540.0	747.7*	585.1*	807.9*
	(354.4)	(450.2)	(339.5)	(426.3)	(343.9)	(435.8)
Dept. var mean	-98.44	-98.44	-248.2	-248.2	-251.0	-251.0
Observations	2861	2861	3839	3839	3813	3813
State and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE	No	Yes	No	Yes	No	Yes
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Sample is limited to workers displaced from a full-time job because their plant or firm closed or moved, and have a non-missing pre-displacement occupation state growth rate. Workers must be reemployed after displacement and report both pre-displacement and post-displacement earnings. The outcome variable is change in weekly earnings. If a worker is not reemployed, then their new earnings are 0. Columns (1) and (2) are specifications with and without occupation fixed effects. Columns (3) and (4) are limited to people who were displaced two or three years ago. Workers with fewer than \$40 of earnings per week prior to displacement are excluded. Education categories are indicator variables, with "Less Than HS" as the omitted category. Race categories are indicator variables, with "White" as the omitted category. Workers were displaced three, two or one year ago, with one year ago as the omitted category. All regressions use Displaced Workers Survey sample weights and have state and year of displacement fixed effects. Standard errors are clustered by state. * p<0.1 ** p<0.05 *** p<0.01

Table 13: Log Duration of Joblessness - Censored Regression

	(1)	(2)
Occupation Growth Rate	-2.709***	-1.626
	(0.833)	(1.023)
Dept. var mean	2.129	2.129
Observations	4065	4065
State and Year FE	Yes	Yes
Occupation FE	No	Yes
Other Controls	Yes	Yes

Notes: Sample is limited to workers displaced from a full-time job because their plant or firm closed or moved, and have a non-missing pre-displacement occupation state growth rate. For workers who are not reemployed, the maximum jobless duration is 52 weeks if they were displaced the year prior to the survey, 104 weeks if they were displaced two years prior to the survey, and 156 weeks if they were displaced three years prior to the survey. Columns (1) and (2) are specifications with and without occupation fixed effects. Workers with fewer than \$40 of earnings per week prior to displacement are excluded. [CONTROL VARIABLES] All regressions use Displaced Workers Survey sample weights and have state and year of displacement fixed effects. Standard errors are clustered by state. * p<0.1 ** p<0.05 *** p<0.01

Table 14: Measures Used by State Workforce Agencies

	(1) Fraction	(2) Fraction	(3) Binary	(4) Binary	(5) Duration	(6) Duration	(7) Duration	(8) Duration
Occupation Growth Rate	-0.965***	-0.626**	-0.810***	-0.424	-0.471	-0.580	-57.06***	-45.87**
	(0.229)	(0.277)	(0.236)	(0.297)	(0.309)	(0.433)	(14.72)	(18.34)
Dept. var mean	0.439	0.439	0.265	0.265	0.353	0.353	14.97	14.97
Observations	3803	3803	3803	3803	2304	2304	3495	3495
State and Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE	No	Yes	No	Yes	No	Yes	No	Yes
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Sample is limited to workers displaced from a full-time job because their plant or firm closed or moved, and have a non-missing pre-displacement occupation state growth rate. Workers must be reemployed after displacement. The outcome variable in Column (1) and (2) is the fraction of unemployment benefits exhausted, measured roughly by the number of weeks prior to working again at another job divided by 26, with a maximum of 1. The outcome variable in Column (3) and (4) is a binary indicator for unemployment benefits greater than or equal to 26 weeks. This is a rough proxy for exhausting unemployment, for all workers. Column (5) and (6) is a linear probability model, with the outcome equal to 1 if the individual reported exhausting their unemployment benefits. This sample is smaller because it is limited to those who took unemployment benefits. Column (7) and (8) are the number of weeks that went by before the respondent started working again at another job, censored at 100 weeks. Workers with fewer than $40 of earnings per week prior to displacement are excluded. Education categories are indicator variables, with "Less Than HS" as the omitted category. Race categories are indicator variables, with "White" as the omitted category. Workers were displaced three, two or one year ago, with one year ago as the omitted category. All regressions use Displaced Workers Survey sample weights and have state and year of displacement fixed effects. Standard errors are clustered by state.p<0.1 ** p<0.05 *** p<0.01