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

Sarah H. Bana*

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Abstract

Some displaced workers experience larger earnings changes after displacement than others. 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. I 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 suggest 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)

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1 Introduction

Displaced workers, workers who lose their job as a result of their firm or plant closing or moving, have large earnings losses on average. These large average losses, however, mask substantial variation in earnings changes. Understanding the ex ante correlates of these earnings changes is important for two reasons. The first is to more effectively target re-employment assistance and other services to those unemployed job losers most in need of assistance. Indeed, identifying and assisting vulnerable displaced workers is the objective of policies such as the Unemployment Compensation Amendments of 1993. These amendments created systems to predict which workers were more likely to exhaust their unemployment benefits, with the aim of targeting job search assistance to those workers.

Second, understanding which workers are likely to experience the largest earnings losses may shed light on why these workers experience such large losses. For example, the devaluation of specific human capital is widely considered to be a major source of displaced workers' earnings losses. But is that specific human capital a function of industry, occupation, region, or some combination of these pre-displacement employment attributes? And, what are the circumstances in which the human capital is less valuable?

To answer these questions, I use data from the Current Population Survey Displaced Worker 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. In models comparing workers displaced from different occupations in the same state and year net of occupation fixed effects, 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 16.1 percent increase in the duration of joblessness and a 9.2 percent decrease in weekly earnings. Additionally, I find that state-level occupation growth impacts durations of joblessness significantly more than state-level industry growth does. The estimated effect of the industry growth rate also diminishes in all models including the occupation growth rate. This supports the claim 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).

The idea that state-level occupation conditions matter is quite intuitive, but their importance has not been measured due to data limitations. Unlike industry codes, which employers report when submitting information for unemployment insurance, regularly produced comprehensive occupational employment data are only available from the Bureau of Labor Statistics (BLS) Occupational Employment Statistics program, and suffers from a significant limitation. The data used to produce occupation employment estimates for each year are collected in a three year sampling cycle, which means independent annual occupation employment estimates are not produced. As a result, existing estimates cannot capture short-term fluctuations in occupational employment. I address this limitation by constructing an occupation growth rate measure using a shift-share method based on states' different occupation and industry compositions and national industry growth rates. This measure of the 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 relative to 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.

This research builds on literature on specific human capital, which shows 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). However, the decision to change occupations or industries is endogenous, making it difficult to attach a causal interpretation to these differences. By identifying the occupation growth rate, an observable factor associated with costly switching, I demonstrate a clear relationship between decreased demand for occupational services and its labor market consequences.

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. In this way, this paper contributes to the literature on targeting workers who are likely to experience longer unemployment durations or large earnings losses, while speaking to the efficacy of certain re-employment policies in the United States. For example, this paper suggests that policies targeted at declining industries are poorly focused because displaced workers' difficulties are more related to their skills than the goods and services they were producing. The findings are consistent with Ebenstein et al. (2014), who find that occupational exposure to globalization is associated with significant wage effects, while industry exposure has no impact. The shocks examined in this paper apply to a broader measure of employment conditions and thus the occupations affected are likely a different, and potentially more representative, sample of workers than those affected by offshoring.

The effect of the occupation growth rate on displaced workers' labor market outcomes in this paper complements existing research on the effects of adverse labor market conditions on various groups, including displaced workers Davis and von Wachter (2011), economists (Oyer, 2006) and college graduates (Oreopoulos et al., 2012; Altonji et al., 2016). In fact, the magnitude of the main estimate in this paper (a 9.2 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. That said, unlike economy-wide recessions, the types of shocks examined here depend also on workers' state of residence and occupation. 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. While the occupation growth rate can decline during a recession, a full-blown 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. As workers' employment prospects are dependent on conditions at the state and occupation level, aggregate indicators like the national unemployment rate mask the heterogeneity in employment prospects within occupations, across states, and over time.

Finally, this paper contributes to a long line of literature interested in understanding displaced workers' labor market outcomes. It 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. Based on the data available at the time, the Carrington (1993) study uses only ten occupation categories, admitting that this grouping is coarse, while the industry employment measures are finer. As a result of these data limitations, relevant employment growth at the industry level was much better measured than relevant employment growth at the occupation level, which suggested a strong role of industry conditions and, potentially, industry-specific human capital.

With better data and a new method to identify an occupation growth rate, I find that occupation growth has a significantly larger role than industry growth in determining durations of joblessness, and has a significant relationship with earnings changes, holding constant the industry growth rate. 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.

2 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.

2.1 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).[1] 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.[2] The 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 42.82 years, with 6.75 years of firm tenure. The sample is 41.9 percent female. The mean weekly earnings loss after displacement was $108.1 or 25.3 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. 70.4

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

[2] 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.

percent of workers worked for pay since displacement.

Additionally, I exclude workers who do not report key variables including pre-displacement occupation, year displaced, full-time status at pre-displacement job and whether the worker moved after displacement.[3] The first two variables are necessary to create the occupation growth rate, which is the focus of my analysis, and the other two variables are key sample selection criteria.[4] This is not a trivial restriction: 15.9 percent of the respondents do not respond to these questions. 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 and have longer pre-displacement tenures.

For confidentiality reasons, the DWS does not report finer geography than state for some non-trivial fraction of the sample (approximately 30 percent). As such, state is the geographic labor market used for the analysis.

2.2 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. Ideally, I would create occupation growth rates using an administrative dataset where employers reported employment levels by occupation annually.

Unfortunately, such dataset does not exist in the United States. 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 (BLS) that collects detailed infor-

[3] Very few survey respondents seem to be selectively responding to certain questions. Instead, the respondents appear to stop answering questions altogether.

[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.

mation 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. 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 are not independently drawn, and therefore cannot be used to create an annual growth rate.[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 and 2003 to construct an alternative occupation growth rate, along with the industry employment numbers discussed in the next subsection.[6] 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 estimate produced using consecutive years of survey data very different, especially at the local level.

[6]The use of weights at the beginning is accordance with common practice. However, the results are not sensitive to weights, for example, based on the middle of the sample.

2.3 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.

3 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.

To overcome these obstacles, I 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 different goods and services.

If the relevant occupation conditions are at the state level, then the occupation growth rate can be predicted using a 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 involved in this analysis. My measure of state-level occupation growth rates in this paper is at the most detailed level available in the Displaced Worker Survey, the Census occupation code. This classification, which comprises 324 Census occupation categories in the estimation sample, is more detailed than the Standard Occupation Classification (SOC) minor group (88 categories) or major group (10 categories). It is also much more detailed than the measure used in existing estimates of the occupation growth rate effects on displaced workers' outcomes (Carrington, 1993). I use these most detailed codes because it is not clear that occupations within a minor group would have the same growth rate. To see this, consider for example, Table 3, which lists examples of major, minor, broad and detailed SOC occupation categories, and Census occupation categories. Using one occupation growth rate for the minor group would assume 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). My approach has the advantage of not imposing this assumption and allowing workers in different Census occupation categories to have different growth rates.

3.1 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.

More concretely, 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 employment 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. Furthermore, this statement has empirical support – the correlation between national estimates of $\alpha_{o,j,2002}$ and $\alpha_{o,j,2013}$, the first and last year, is 0.9 in my sample. I use a fixed weight from the beginning of the sample to measure α, which I will refer to as $\alpha_{s,o,j,beginning}$.[7]

Then,

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

However, I'm interested in a growth rate, as opposed to a pure change in employment. A traditional growth rate measure would use adjacent years of occupation data, treating them as independent. However, recall that the adjacent years of occupation data are not actually independent. To avoid this problem, I use a fixed employment level at the beginning of the

[7] The first year in which the North American Industry Classification (NAICS) is used in the OES data is 2002. I use a mean of 2002 and 2003 for the weight, although results are quite similar using only 2002, or some mean of years from the middle of the sample, say 2006-2008.

data period as the denominator for occupation o's growth rate in state s.

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

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

The state-level estimates are a function of two potentially noisy measures. 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 14% of the state-industry-year cells have zero employees, and around 20% have fewer than 100 workers. Because of this characteristic, the state-level industry growth rate is highly variable for small industries and small states. Additionally, the displaced workers in my DWS sample may be directly affected by firms closing in their industries, heading to an endogeneity concern. 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, in the spirit of Bartik (1991), has two major advantages: first, it is not reliant on a single state's noisy industry employment, and second, it decreases the 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 starting in 2012, 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:

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

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

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

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(a) 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. Because this figure is less informative because of a small number of large (in absolute value) occupation growth rates at the tail, Figure 1(b) plots the distribution excluding the occupation growth rates above the 99th percentile and below the 1st percentile. The figures also show that the distribution is left-skewed.

For comparison, Figure 1(c) and (d) plot the distribution of industry growth rates, constructed analogously and discussed in greater detail below in Section 3.3. The mean industry growth rate is -0.01, and the standard deviation is 0.05 (a little larger than the standard deviation of the occupation growth rate at 0.05).

3.2 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,[8] 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 SOC minor group (3 digit) occupation fixed effects. This specification is as

[8] Results are similar without weights.

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 durations of joblessness 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 that affect their durations of joblessness and earnings losses are uncorrelated with their 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.

3.3 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.[9] 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.

Equation 10 adds the occupation growth rate back in. In this 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.

4 Results

4.1 Variation in the Occupation Growth Rate

Recent research on Bartik instruments by Goldsmith-Pinkham et al. (2018) finds that a number of empirical applications rely heavily on a few industries for identifying variation. In my dataset, this is not the case. The variation in the occupation growth rate in my data is calculated from 291 NAICS 4 digit industries. Figure 2 displays a histogram of the number of industries used to derive each occupation growth rate. The figure highlights a key descriptive statistic of the paper: most displaced workers' occupations exist in a wide number of industries. The

[9] More formally, $\pi_{s,j,t} = \frac{E_{-s,j,t} - E_{-s,j,t-1}}{E_{-s,j,beginning}}$

mean (median) worker in the sample has an occupation growth rate that is a function of 125 (124) industries. In the extreme, if each occupation is represented in one industry, the occupation growth rate is exactly equal to the industry growth rate. However, this figure demonstrates that this is not likely to be the case and there is substantial room for worker's pre-displacement occupation growth and pre-displacement industry growth to have little correlation.

The occupation growth rate also varies substantially over this time period (2001 - 2013). Figure 3 compares the minimum and maximum occupation growth rates for state-occupation combinations represented in my displaced workers' sample (i.e. the within-state and occupation across time variation I exploit). The mean difference between the minimum and maximum growth rate is 0.10 and the standard deviation is 0.07.

A second potential problem is that these industries may have characteristics that are correlated with observables, which may suggest potential unobserved confounders. In my context, these are not concerns for the following reasons: First, the fact that different occupations are concentrated in different industries and to different extents is a characteristic of the labor market and an important empirical fact. Second, if a few industries in an occupation are driving occupation growth, occupation growth and industry growth would be highly correlated. The resulting coefficients and standard errors from the regression model would take into account the correlation between the growth rates through the covariance terms in the standard errors. This empirical finding would have an implication for the relative importance of occupation and industry specific human capital – namely, that because of the structure of the labor market, it is difficult to separately identify the effects of occupation and industry specific human capital, and the distinction between the two may be unnecessary.

Because my context is not an instrumental variables context, I cannot measure the sensitivity-to-misspecification elasticity as recommended in the Goldsmith-Pinkham et al. (2018). Finally, in the Robustness section, I show that the estimates are similar when excluding one industry at a time.

4.2 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 calendar year of displacement, this is only a rough control for elapsed time.[10] Working for pay is assumed for workers currently employed, and asked of individuals who are both unemployed and not in the labor force. Approximately 71 percent of the sample had worked for pay by the time they were surveyed. In Column (1), the specification with state and year of displacement fixed effects, the occupation growth rate does not have a statistically significant, or economically significant, relationship with working for pay after displacement. The biggest determinant of working since displacement is the time elapsed since displacement – workers who were displaced three (two) years ago are approximately 27 (9) percentage points more likely to have worked for pay after displacement, respectively, compared to workers displaced one year ago. 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. In Column (2), the specification adding minor group occupation fixed effects, the occupation growth rate continues to have an insignificant relationship with working for pay 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.[11] For other workers, those who have not worked for pay since displacement, the DWS unfortunately does not ask duration of joblessness. Because the DWS only asks year of displacement, any statements about jobless durations of workers who are not re-employed are highly imprecise.Thus I omit these workers from my main estimates, working with the sample of self-reported completed durations only.[12] Approximately 70 percent of

[10]Workers are asked which calendar year they were displaced in January. In all regressions, I include indicators for two calendar years ago and three calendar years ago, with the omitted category being one calendar year ago.

[11]It is topcoded at 100 weeks, although this affects a small fraction (2%) of the sample.

[12]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. Indeed, this is what I find.

workers have worked for pay after displacement, and as discussed earlier, ever working for pay after displacement is largely a function of time elapsed since displacement. 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 4.5 percent increase in the duration of joblessness conditional on having been re-employed after displacement. The estimate is similar with minor group occupation fixed effects in Column (2) – a one percentage point decrease is associated with a 3.9 percent increase in the duration of joblessness. This translates into a one standard deviation decrease (approximately four percentage points) is associated with a 16.1 percent increase in the duration of joblessness conditional on having been re-employed after displacement.

Previous literature by Poletaev and Robinson (2008) and Kambourov and Manovskii (2009) 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 (64 percent) change occupations after displacement. Linear probability models with occupation change as the dependent variable are displayed in Column (1), and show that a one percentage point decrease in the occupation growth rate is associated with a 0.95 percentage point increase in the probability of an occupation change. Column (2) adds minor group occupation fixed effects, which decrease the magnitude of the point estimate but the new estimate is not statistically different. It appears that workers change occupations because their occupations are shrinking – a one standard deviation lower occupation growth rate is associated with a 3.7 to 4.1 percentage point (5.7-6.4 percent) increase in the probability of changing occupations. This is a large effect of temporary conditions in a worker's pre-displacement occupation.

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 1.5 percent decrease in post-displacement earnings. This effect is similar when adding minor goup occupation fixed effects – a one percentage point decrease in the occupation growth rate is associated with a 2.2 percent decrease in post-displacement earnings. The standard deviation of the occupation growth rate amongst this sample is 0.042, suggesting that a worker who is displaced in conditions one standard deviation below the mean suffers, all else equal, a 9.2 percent larger earnings loss than a worker displaced in conditions at the mean.

4.3 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. Before presenting regression results on these relationships, I begin by showing descriptive evidence. In Figure 4, the occupation and industry growth rate are split into five categories: shrinking substantially, shrinking, neutral, growing slightly, and growing substantially. The mean and 95% confidence interval is displayed for workers in each of these categories. In Figure 4(a), the range spanned by the means and confidence intervals of the occupation growth rate is larger than the range spanned by the means and confidence intervals of the industry growth rate. A similar story appears in Figure 4(b), the equivalent figure for change in log earnings. Workers displaced when their occupation is shrinking substantially have larger earnings losses than when their occupation is growing substantially ($p = 0.0757$). This is not true of workers displaced when their industry is shrinking substantially compared to workers displaced when their industry is growing substantially ($p = 0.3938$). However, these results can be driven only by differences amongst workers in these samples and/or state and year of displacement characteristics. Table 8 more formally tests the relative effects of occupation and industry growth rates.

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 4.5 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 is associated with a 2.1 percent increase in the duration of joblessness. These coefficients, in Columns (1) and (2), are also statistically different. Column (3) includes both the occupation and industry growth rates in the same regression. While the magnitude of the occupation growth rate shrinks slightly, 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 ten times the size of the point estimate on the industry growth rate. The test of equality between the two coefficients in the regression shows that we can reject the null hypothesis that these growth rates are the same at the 1% level.

Columns (4) - (6) add minor group 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 3.9 percent longer duration of joblessness. On the other hand, the effect of a one percentage point decrease in the industry growth rate is a statistically insignificant 1.2 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 has a quite small 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 0.70 in this sample. Despite this fact, the estimated occupation growth rate effect is statistically different in both comparisons in Table 8.

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 1.5 percent decrease in earnings. A one percentage point decrease in the industry growth rate is associated with a 0.9 percent decrease in weekly earnings. The coefficient on the occupation growth rate is larger, though not significantly larger, than 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 ($p = 0.0037$). A similar story can be told with occupation fixed effects in columns (4)-(6).

5 Robustness

This section assesses the robustness of these results to a variety of potential concerns.

The first concern is whether the occupation growth rate used is truly a measure of temporary conditions at the time of displacement, or if it reflects something systematic about the occupational labor market. If the effect is truly the effect of displacement during poor labor market conditions, then it should be largest for the contemporaneous occupation growth rate, and not the occupation growth rate in years prior to displacement. 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 contemporaneous growth rate, in Table 9 Panel A Columns (1) and (5), has the largest effect on the worker's duration of joblessness, followed by the mean 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 (Column 8).

To ensure that this effect is truly the effect of temporary labor market conditions at displacement, 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 duration of joblessness. 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. In Table 10, the occupation growth rate four years after displacement has a significant effect on duration of joblessness in the absence of controls for occupation. This is surprising as the occupation growth rate four years later is negatively correlated with the contemporaneous occupation growth rate ($\rho = -0.2385$). In Column (4), which adds minor group occupation fixed effects, the estimate of the occupation growth rate four years later becomes much smaller and is statistically insignificant.[13]

As previously discussed, recent literature on shift-share approaches by Goldsmith-Pinkham et al. (2018) suggests that many empirical applications rely on a few industries for identifying variation. If one industry is driving the results, it also may be true that this industry's growth or decline is not exogenous to the worker and/or is correlated with the unobservable characteristics related to the worker's labor market conditions. To show that the occupation growth rate is not being driven by a singular industry's employment changes, I construct the occupation growth rate leaving out one industry at a time, then run the main regressions with these new "leave-one-out" growth rates. The result is 291 estimates of the occupation growth rate's effect on each outcome. Figure 5 displays histograms of the estimates for the four primary outcomes: log duration of joblessness and change in log earnings, with and without occupation fixed effects. The original estimate of the occupation growth rate (with all industries) is denoted by a dashed line. The 95 percent confidence interval of "leave-one-out" estimates is denoted by solid lines. From these figures, it is clear that the occupation growth rate is insensitive to any

[13]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 suggestive evidence of search and bargaining effects in local labor markets.

single industry's employment.

Another concern may be the sensitivity to the way the occupation growth rate is specified. To address this concern, 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 $\alpha_{o,j,beginning}$ 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 slightly 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 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, a concern may be that my estimated effects of the occupation growth rate are affected by right-censoring of observed durations. This concern is addressed in Table 12, which demonstrates robustness of the log duration of joblessness result by including workers who have not been re-employed. The DWS asks respondents the calendar year they were displaced. Workers who are not re-employed at the time of the survey will have been jobless for some minimum amount of time. 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 12. In Column (1), a one percentage point decrease in the occupation growth rate is associated with a 3.9 percent increase in duration of joblessness, an effect that is similar to the estimated 4.5 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 -3.84 and -4.20. 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.

Finally, I test the robustness of the results for duration of joblessness and earnings losses to different functional forms of the dependent variable. For duration of joblessness, the functional forms I consider are commonly used by various State Workforce Agencies in their profiling systems. Table 13 Panel A Columns (1) and (2) look at levels of duration of joblessness, instead of logs, and thus includes workers who have 0 weeks of joblessness. A one percentage point lower occupation growth rate is associated with 0.64 to 0.74 weeks longer duration of joblessness, similar to the effect in Table 5. The Displaced Workers Survey asks those who said they claimed unemployment benefits whether they exhausted their unemployment benefits. This outcome is displayed in Columns (3) and (4). The sample size is smaller for this group as workers may not have taken unemployment benefits for various reasons. Though only marginally significant in one specification, this outcome provides some suggestive evidence that the occupation growth rate is related to exhausting formal unemployment benefits. Column (5) and (6) attempt to proxy for a binary indicator of unemployment duration – the most common measure used by State Workforce Agencies. 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 be jobless for more than 26 weeks. 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. A one percentage point decrease in the occupation growth rate is associated with a .008 to .012 percentage point (2.4 percent to 3.6 percent) increase in the probability of having 26 or more weeks without a job. Overall, this panel provides further evidence supporting the claim that the occupation growth rate is a predictor of the duration of joblessness and suggests that states looking to improve their targeting of displaced workers should use this information.

Table 13 Panel B tests the robustness of the earnings results to functional form, and including workers who have not been re-employed. Instead of using change in log weekly earnings, Panel B uses change in weekly earnings. The results using levels in Columns (1) show that a one percentage point decrease in the occupation growth rate is associated with a \$6.24 decrease in weekly earnings. Given the mean lost job earnings in this sample, this translates to a 0.8 percent decrease at the mean, a little smaller than the 1.5 percent change in Table 7. The effect is larger when including minor group occupation fixed effects in Column (2), a one percentage point decrease is associated with a \$11.53 decrease in weekly earnings, or a 1.5 percent decrease at the mean. This specification, using levels instead of logs, has the added advantage of including the entire lost job earnings of displaced workers who have not been re-employed. In Columns (3) and (4), I include these workers. Unsurprisingly, the mean earnings loss in this sample is much higher. The result without occupation fixed effects, in Column (3), is similar.

However, in Column (4), the result is no longer significant because of the large standard errors. Further inspection of the data suggests that these large standard errors are driven by outliers – some workers who had extremely high lost job earnings prior to displacement have not been re-employed, while other workers experienced massive earnings gains after displacement. The change in log earnings outcome was not as sensitive to these outliers. Adding a restriction to exclude workers at the bottom 1st percentile or top 99th percentile of the change in weekly earnings distribution yields estimates similar to the estimate in Column (1). This assurance that the results are not incredibly sensitive to functional form, and hold when including most workers who have not been re-employed, supports the claim that the occupation growth rate affects displaced workers' earnings losses.

6 Conclusion

Policymakers and researchers 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 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 that worker's duration of joblessness and earnings losses. A one standard deviation decrease in the worker's occupation growth rate (which is approximately four percentage points) is associated with a 16.1 percent increase in the duration of joblessness and a 9.2 percent decrease in weekly earnings. These are large effects associated with temporary conditions in the worker's pre-displacement occupation. 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.

This result suggests a significant role of occupation specific human capital in determining displaced workers' earnings. Notably, it is similar to the short-run effect of graduating during a typical recession. It is larger than the effect found in recent work by Lachowska et al. (2018) of losses attributable to foregone employer fixed effects amongst workers displaced from employers paying top-quintile earnings premiums. This suggests a greater role of occupation specific human capital compared to firm-level rents in the debate on theories of displaced workers' earnings losses. Finally, the large effect of a temporary employment decline in one's own occupation suggests that workers are not well-adapted to doing different work. Notably, the result in this paper applies to a more representative sample of occupations and a broad measure of employment conditions, in contrast to previous work that is highly focused on the manufacturing sector or on labor market shocks related to trade.

Our current social insurance system is not targeting assistance based on occupation. In fact, not all states even collect the occupation of unemployment insurance claimants. As new technology has the potential to fundamentally affect the labor market and it appears that workers of different occupations will be affected differently (Brynjolfsson et al., 2018), this information may be increasingly useful in improving the provision of scarce resources for re-employment assistance, based on information available to the states at the time of displacement.

References

ABRAHAM, K. G. AND J. R. SPLETZER (2009): "Addressing the demand for time series and longitudinal data on occupational employment," in *conference "Measurement Issues Arising from the Growth of Globalization," held in Washington, DC, November*, Citeseer, vol. 6.

ALTONJI, J. G., L. B. KAHN, AND J. D. SPEER (2016): "Cashier or consultant? Entry labor market conditions, field of study, and career success," *Journal of Labor Economics*, 34, S361–S401.

AUTOR, D. H. AND M. G. DUGGAN (2003): "The Rise in the Disability Rolls and the Decline in Unemployment*," *The Quarterly Journal of Economics*, 118, 157.

BARTIK, T. J. (1991): *Who Benefits from State and Local Economic Development Policies?*, W.E. Upjohn Institute.

BEAUDRY, P., D. A. GREEN, AND B. SAND (2012): "Does Industrial Composition Matter for Wages? A Test of Search and Bargaining Theory," *Econometrica*, 80, 1063–1104.

BRYNJOLFSSON, E., T. MITCHELL, AND D. ROCK (2018): "What Can Machines Learn, and What Does It Mean for Occupations and the Economy?" *AEA Papers and Proceedings*, 108, 43–47.

CARRINGTON, W. J. (1993): "Wage Losses for Displaced Workers: Is It Really the Firm That Matters?" *The Journal of Human Resources*, 28, 435–462.

CRINÒ, R. (2010): "The Effects of Offshoring on Post-displacement Wages: Evidence from the United States," *The World Economy*, 33, 1836–1869.

DAVIS, S. J. AND T. VON WACHTER (2011): "Recessions and the Costs of Job Loss," *Brookings Papers on Economic Activity*.

DICKINSON, K. P., S. D. KREUTZER, AND P. T. DECKER (1997): "Evaluation of Worker Profiling and Reemployment Services Systems," Tech. rep., Report to Congress.

EBENSTEIN, A., A. HARRISON, M. MCMILLAN, AND S. PHILLIPS (2014): "Estimating the Impact of Trade and Offshoring on American Workers using the Current Population Surveys," *The Review of Economics and Statistics*, 96, 581–595.

GIBBONS, R. AND L. F. KATZ (1991): "Layoffs and Lemons," *Journal of Labor Economics*, 9, 351–380.

GOLDSMITH-PINKHAM, P., I. SORKIN, AND H. SWIFT (2018): "Bartik Instruments: What, When, Why, and How," Working Paper 24408, National Bureau of Economic Research.

KAMBOUROV, G. AND I. MANOVSKII (2009): "Occupational specificity of human capital," *International Economic Review*, 50, 63–115.

KANDILOV, I. T. (2010): "How Import Competition Affects Displaced Workers in the US," *The BE Journal of Economic Analysis & Policy*, 10.

KRASHINSKY, H. (2002): "Evidence on adverse selection and establishment size in the labor market," *Industrial & labor relations review*, 56, 84–96.

LACHOWSKA, M., A. MAS, AND S. A. WOODBURY (2018): "Sources of Displaced Workers' Long-Term Earnings Losses," Working Paper 24217, National Bureau of Economic Research.

NEAL, D. (1995): "Industry-specific human capital: Evidence from displaced workers," *Journal of labor Economics*, 653–677.

OREOPOULOS, P., T. VON WACHTER, AND A. HEISZ (2012): "The short-and long-term career effects of graduating in a recession," *American Economic Journal: Applied Economics*, 4, 1–29.

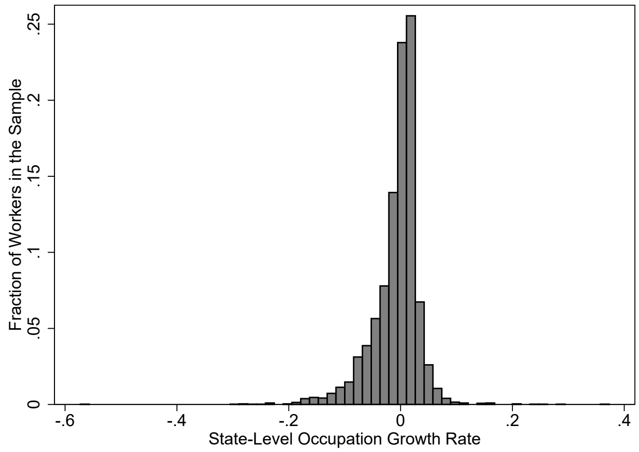
OYER, P. (2006): "Initial Labor Market Conditions and Long-Term Outcomes for Economists," *The Journal of Economic Perspectives*, 20, 143–160.

POLETAEV, M. AND C. ROBINSON (2008): "Human capital specificity: evidence from the Dictionary of Occupational Titles and Displaced Worker Surveys, 1984–2000," *Journal of Labor Economics*, 26, 387–420.

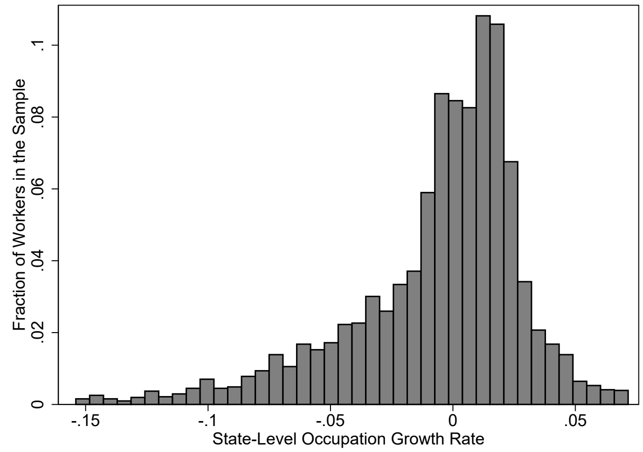
TSCHOPP, J. (2017): "Wage Formation: Towards Isolating Search and Bargaining Effects from the Marginal Product," *The Economic Journal*, 127, 1693–1729.

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

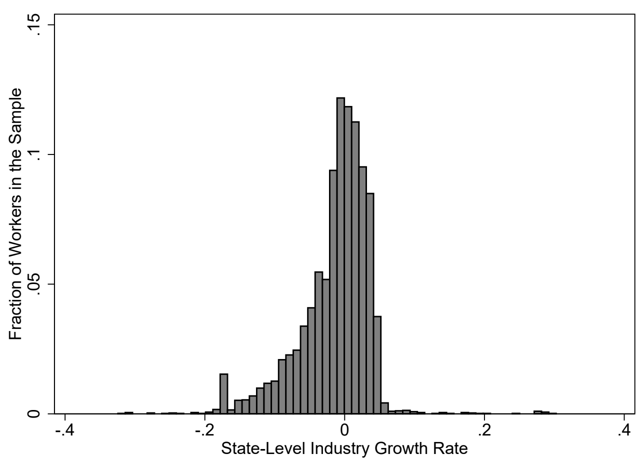
(a) Distribution of Occupation Growth Rates



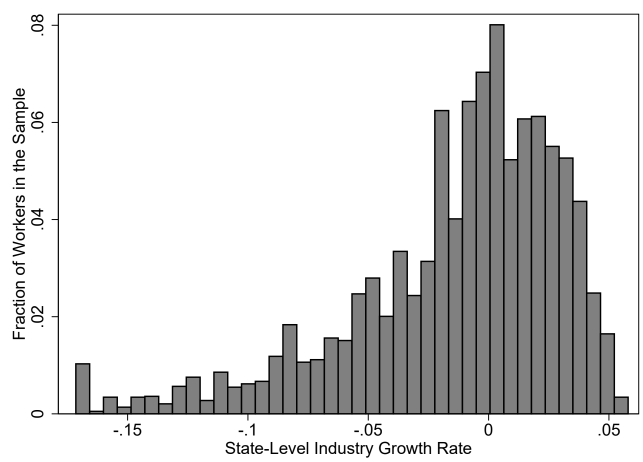
(b) Distribution of Occupation Growth Rates - Excluding growth rates below the 1st percentile and above the 99th percentile



(c) Distribution of Industry Growth Rates

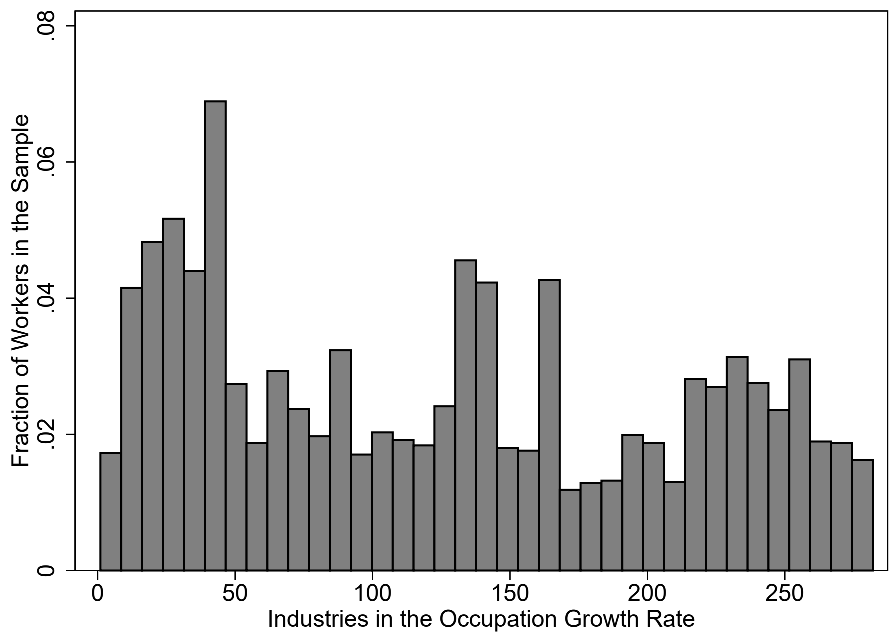


(d) Distribution of Industry Growth Rates - Excluding growth rates below the 1st percentile and above the 99th percentile



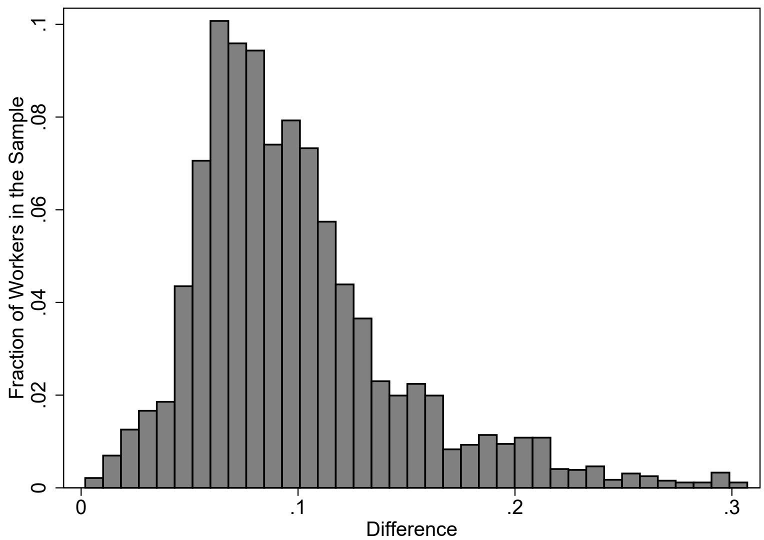
Notes: The sample is limited to workers responding to the Current Population Survey Displaced Workers Survey Supplement between 2004 and 2014. Workers have been displaced because their plant or firm closed or moved, and be displaced from a full-time occupation. Workers in this sample must report pre-displacement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

Figure 2: Distribution of the Number of Industries Used to Estimate Each Worker's Occupation Growth Rate



Notes: This figure displays the number of 4-digit NAICS industries affecting each worker's occupation's employment. The observation is at the worker level, 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.

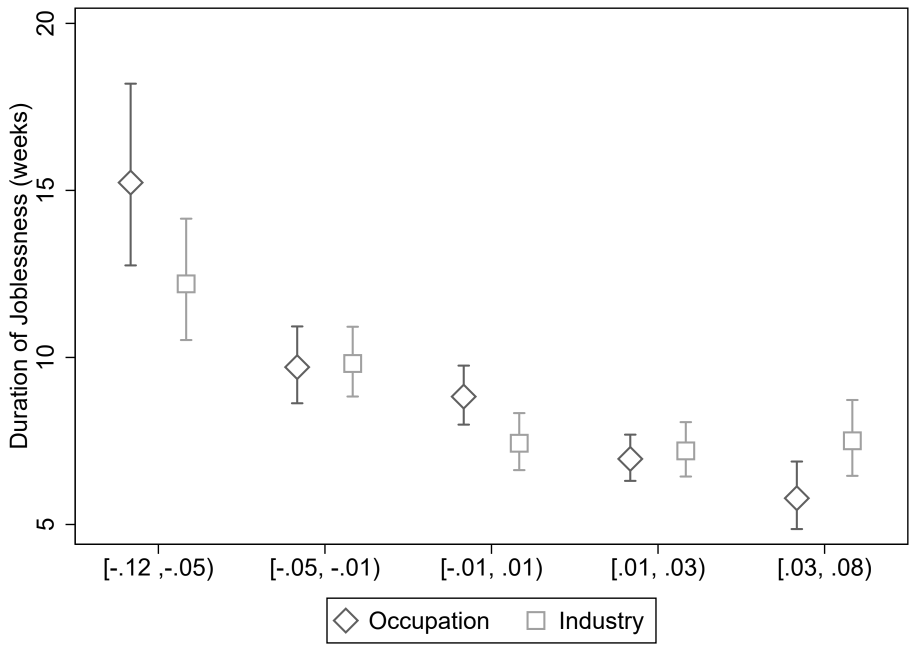
Figure 3: Distribution of Differences between Highest and Lowest Growth Rate within Occupation-State Cells



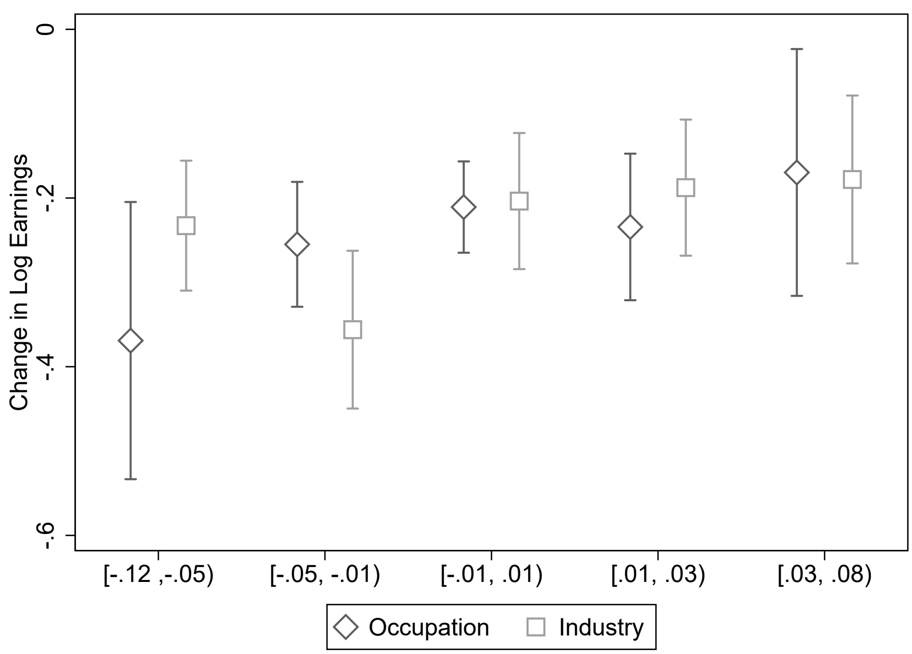
Notes: The sample is limited to occupation-state combinations that correspond to workers responding to the Current Population Survey Displaced Workers Survey Supplement between 2004 and 2014. Workers have been displaced because their plant or firm closed or moved, and be displaced from a full-time occupation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

Figure 4: Estimates by Bins of Occupation and Industry Growth Rates

(a) Duration by Bins of Occupation and Industry Growth Rates

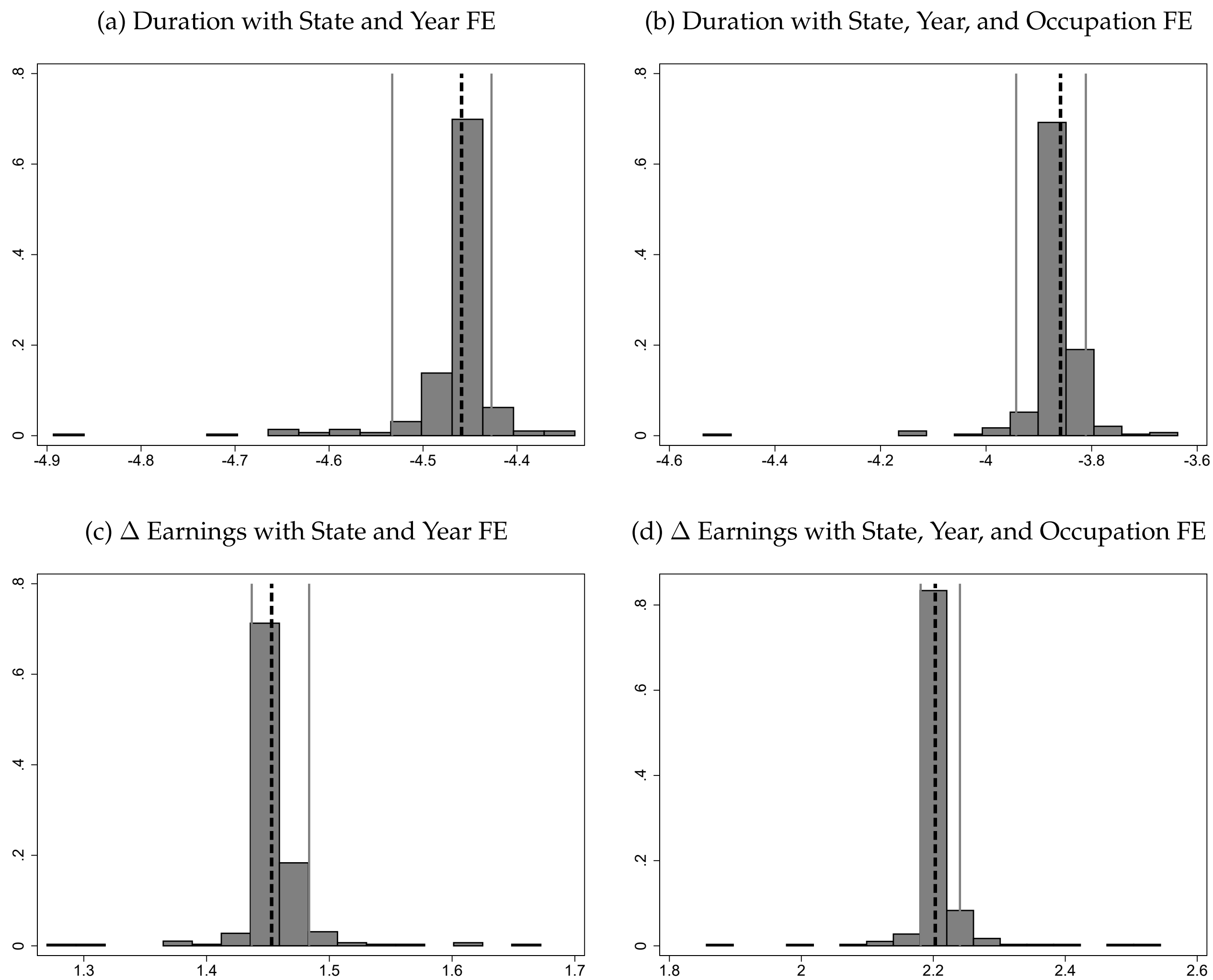


(b) Earnings Changes by Bins of Occupation and Industry Growth Rates



Notes: This figure displays coefficients and 95 percent confidence intervals by bin of the occupation growth rate and industry growth rate from the regressions on log duration of joblessness (on the top) and change in log earnings (on the bottom). Workers outside of this range of industry or occupation growth rates are excluded. Workers have been displaced because their plant or firm closed or moved, and be displaced from a full-time occupation and report their occupation and industry and have a corresponding occupation and industry growth rate.

Figure 5: Leave One Out Estimates of the Effect of Occupation Growth Rate



Notes: This figure displays regression estimates based on an occupation growth rate leaving one industry out from the construction of the occupation growth rate. Sample restrictions are the same as Tables 5 and 7. Subfigures (a) and (b) plot the effect of these "leave-one-out" occupation growth rates on log duration of joblessness, and subfigures (c) and (d) plot the effect of these "leave-one-out" occupation growth rates on change in log earnings. Subfigures (a) and (c) include state and year fixed effects, and (b) and (d) include state, year, and occupation fixed effects. The solid lines correspond to the 95 percent confidence interval of these estimates. The dashed line corresponds to the estimate including all industries, displayed in Tables 5 and 7.

Table 1: Summary Statistics

Less Than HS	0.128
	(0.335)
HS Diploma	0.357
	(0.479)
Some College	0.292
	(0.455)
BA/BS	0.167
	(0.373)
Graduate Degree	0.0552
	(0.228)
White	0.794
	(0.405)
Black	0.136
	(0.342)
Asian	0.00952
	(0.0971)
Other Race	0.0612
	(0.240)
Age	42.82
	(12.18)
Tenure	6.750
	(7.758)
Female	0.419
	(0.493)
Displaced 3 Years Ago	0.325
	(0.468)
Displaced 2 Years Ago	0.305
	(0.460)
Displaced Last Year	0.371
	(0.483)
Change in Weekly Earnings	-108.1
	(465.7)
Change in Log Earnings	-0.253
	(0.909)
Worked for Pay Since Displacement	0.704
	(0.457)
Duration of Joblessness in Weeks	15.73
	(21.75)
Year Displaced	2006.6
	(3.508)
Occupation Growth Rate	-0.00792
	(0.0430)
Observations	5975

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, full-time status before displacement, and whether they moved after displacement. 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

	Analysis Sample	Missing Data	Difference
	(1)	(2)	(3)
Less Than HS	0.128	0.166	-0.038
	(0.335)	(0.372)	(0.013)
HS Diploma	0.357	0.358	-0.000
	(0.479)	(0.480)	(0.016)
Some College	0.292	0.279	0.013
	(0.455)	(0.448)	(0.015)
BA/BS	0.167	0.157	0.011
	(0.373)	(0.364)	(0.012)
Graduate Degree	0.055	0.040	0.015
	(0.228)	(0.197)	(0.007)
White	0.794	0.759	0.035
	(0.405)	(0.428)	(0.015)
Black	0.136	0.175	-0.040
	(0.342)	(0.381)	(0.014)
Asian	0.010	0.012	-0.002
	(0.097)	(0.108)	(0.004)
Other Race	0.061	0.054	0.007
	(0.240)	(0.226)	(0.008)
Age	42.817	42.783	0.034
	(12.179)	(13.516)	(0.451)
Tenure	6.750	4.604	2.146
	(7.758)	(5.590)	(0.305)
Female	0.419	0.414	0.005
	(0.493)	(0.493)	(0.017)
Displaced 3 Years Ago	0.325	0.253	0.072
	(0.468)	(0.435)	(0.018)
Displaced 2 Years Ago	0.305	0.305	0.000
	(0.460)	(0.460)	(0.019)
Displaced Last Year	0.371	0.443	-0.072
	(0.483)	(0.497)	(0.021)
Change in Weekly Earnings	-108.134	80.517	-188.651
	(465.743)	(403.863)	(40.803)
Change in Log Earnings	-0.253	0.067	-0.320
	(0.909)	(1.007)	(0.098)
Worked for Pay Since Displacement	0.704	0.804	-0.100
	(0.457)	(0.397)	(0.015)
Duration of Joblessness in Weeks	15.733	10.213	5.520
	(21.751)	(14.420)	(1.083)
Year Displaced	2006.622	2007.471	-0.849
	(3.508)	(3.454)	(0.142)
Observations	5975	1128	7103

Notes: This table compares workers who have been displaced from a firm or plant closing who do report (Column 1) and do not report (Column 2) key variables – pre-displacement occupation, year of displacement, full-time status at pre-displacement occupation, and whether the worker moved after displacement. 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

SOC Major	SOC Minor	SOC Broad	SOC Detailed	Census Code	
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	5800	Computer Operators
		43-9020			Data Entry and Information Processing Workers
			43-9021	5810	Data Entry Keyers
			43-9022	5820	Word Processors and Typists
		43-9030			Desktop Publishers
			43-9031	5830	Desktop Publishers
		43-9040			Insurance Claims and Policy Processing Clerks
			43-9041	5840	Insurance Claims and Policy Processing Clerks
		43-9050			Mail Clerks and Mail Machine Operators, Except Postal Service
			43-9051	5850	Mail Clerks and Mail Machine Operators, Except Postal Service
		43-9060			Office Clerks, General
			43-9061	5860	Office Clerks, General
		43-9070			Office Machine Operators, Except Computer
			43-9071	5900	Office Machine Operators, Except Computer
		43-9080			Proofreaders and Copy Markers
			43-9081	5910	Proofreaders and Copy Markers
		43-9110			Statistical Assistants
			43-9111	5920	Statistical Assistants
		43-9190			Miscellaneous Office and Administrative Support Workers
			43-9199	5930	Office and Administrative Support Workers, All Other

Notes: This table is an example of the occupation categorization from the 2000 Standard Occupation Classification (SOC) for illustrative purposes, with SOC major, SOC minor, SOC broad, SOC detailed and Census (2002) occupation codes displayed.

Table 4: Ever Worked For Pay Since Displacement

	(1)	(2)
Occupation	0.274	-0.122
Growth Rate	(0.199)	(0.273)
HS Diploma	0.0621***	0.0585***
	(0.0181)	(0.0179)
Some College	0.0798***	0.0629***
	(0.0169)	(0.0176)
BA/BS	0.143***	0.105***
	(0.0200)	(0.0204)
Graduate Degree	0.176***	0.110***
	(0.0330)	(0.0338)
Displaced 3	0.274***	0.282***
Years Ago	(0.0210)	(0.0198)
Displaced 2	0.0942*	0.0895*
Years Ago	(0.0526)	(0.0510)
Black	-0.0726***	-0.0601**
	(0.0245)	(0.0254)
Asian	-0.0467	-0.0431
	(0.0537)	(0.0526)
Other Race	-0.0611**	-0.0411
	(0.0287)	(0.0266)
Age 20-29	-0.00870	-0.00802
	(0.0197)	(0.0192)
Age 40-49	-0.0243	-0.0258
	(0.0223)	(0.0202)
Age 50 Plus	-0.153***	-0.155***
	(0.0201)	(0.0170)
Female	-0.0346	-0.0242
	(0.0220)	(0.0214)
Tenure	-0.000471	0.000288
	(0.00195)	(0.00186)
Tenure Squared	-0.000157**	-0.000174***
	(0.0000672)	(0.0000616)
State and Year FE	Yes	Yes
Occupation FE	No	Yes
Dept. var mean	0.707	0.707
Observations	5090	5090
Adjusted R2	0.134	0.153

Notes: Sample is limited to workers displaced because their plant or firm closed or moved, have a non-missing pre-displacement occupation state growth rate, were displaced from a full-time job, and did not move after displacement. 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 Growth Rate	-4.459***	-3.859***
	(0.722)	(0.959)
HS Diploma	-0.0148	-0.0238
	(0.107)	(0.102)
Some College	0.195	0.220*
	(0.126)	(0.111)
BA/BS	0.0955	0.0786
	(0.110)	(0.118)
Graduate Degree	0.0827	0.00314
	(0.194)	(0.182)
Displaced 3 Years Ago	0.614***	0.596***
	(0.0625)	(0.0634)
Displaced 2 Years Ago	0.572***	0.567***
	(0.179)	(0.181)
Black	0.414***	0.390***
	(0.0664)	(0.0779)
Asian	0.0937	0.174
	(0.373)	(0.377)
Other Race	0.251*	0.254*
	(0.128)	(0.148)
Age 20-29	-0.118	-0.115
	(0.0799)	(0.0786)
Age 40-49	0.0869	0.0651
	(0.0707)	(0.0660)
Age 50 Plus	0.183**	0.162**
	(0.0781)	(0.0727)
Female	0.111	0.112
	(0.0715)	(0.0881)
Tenure	0.0216**	0.0217*
	(0.0103)	(0.0121)
Tenure Squared	-0.000339	-0.000388
	(0.000423)	(0.000469)
State and Year FE	Yes	Yes
Occupation FE	No	Yes
Dept. var mean	2.133	2.133
Observations	2902	2902
Adjusted R2	0.105	0.118

Notes: Sample is limited to workers displaced because their plant or firm closed or moved, have a non-missing pre-displacement occupation state growth rate, were displaced from a full-time job, and did not move after displacement. 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. All regressions use Displaced Workers Survey sample weights and have state and year of displacement fixed effects. Column (2) adds minor group occupation fixed effects. Standard errors are clustered by state. * $p<0.1$ ** $p<0.05$ *** $p<0.01$

Table 6: Occupation Change

	(1)	(2)
Occupation Growth Rate	-0.949***	-0.865***
	(0.211)	(0.209)
HS Diploma	0.0369	0.0228
	(0.0234)	(0.0201)
Some College	0.0700***	0.0442***
	(0.0233)	(0.0161)
BA/BS	0.0762*	0.0532
	(0.0390)	(0.0340)
Graduate Degree	0.0426	0.0743*
	(0.0392)	(0.0426)
Displaced 3 Years Ago	0.127***	0.121***
	(0.0183)	(0.0171)
Displaced 2 Years Ago	0.0837*	0.0962**
	(0.0441)	(0.0428)
Black	0.0342	0.0474*
	(0.0267)	(0.0252)
Asian	0.117***	0.111**
	(0.0432)	(0.0524)
Other Race	-0.0391	-0.0344
	(0.0260)	(0.0277)
Age 20-29	0.0459**	0.0537**
	(0.0191)	(0.0202)
Age 40-49	-0.00878	-0.0121
	(0.0178)	(0.0192)
Age 50 Plus	-0.00379	-0.00454
	(0.0207)	(0.0181)
Female	0.0350*	0.0102
	(0.0181)	(0.0196)
Tenure	0.00208	0.000906
	(0.00286)	(0.00313)
Tenure Squared	-0.000128	-0.000144
	(0.000105)	(0.000109)
State and Year FE	Yes	Yes
Occupation FE	No	Yes
Dept. var mean	0.640	0.640
Observations	4455	4455
Adjusted R2	0.0197	0.0833

Notes: Sample is limited to workers displaced because their plant or firm closed or moved, have a non-missing pre-displacement occupation state growth rate, were displaced from a full-time job, and did not move after displacement. 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. All regressions use Displaced Workers Survey sample weights and have state and year of displacement fixed effects. Column (2) adds minor group occupation 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	1.453**	2.203***
Growth Rate	(0.623)	(0.704)
HS Diploma	-0.0376	-0.0307
	(0.0414)	(0.0424)
Some College	-0.0555	-0.0305
	(0.0586)	(0.0576)
BA/BS	-0.120*	-0.0359
	(0.0668)	(0.0653)
Graduate Degree	-0.113	0.01000
	(0.101)	(0.117)
Displaced 3	-0.0115	-0.00320
Years Ago	(0.0553)	(0.0555)
Displaced 2	-0.0699	-0.0757
Years Ago	(0.122)	(0.129)
Black	-0.0937*	-0.150**
	(0.0551)	(0.0696)
Asian	0.0869	0.108
	(0.159)	(0.161)
Other Race	0.0109	0.00516
	(0.158)	(0.153)
Age 20-29	0.0635	0.0483
	(0.0645)	(0.0765)
Age 40-49	-0.0515	-0.0319
	(0.0565)	(0.0664)
Age 50 Plus	-0.120***	-0.127***
	(0.0414)	(0.0405)
Female	-0.0260	-0.0320
	(0.0411)	(0.0554)
Tenure	-0.00384	-0.00356
	(0.00695)	(0.00667)
Tenure Squared	-0.000118	-0.000150
	(0.000219)	(0.000213)
State and Year FE	Yes	Yes
Occupation FE	No	Yes
Dept. var mean	-0.237	-0.237
Observations	2737	2737
Adjusted R2	0.0161	0.0250

Notes: Sample is limited to workers displaced because their plant or firm closed or moved, have a non-missing pre-displacement occupation state growth rate, were displaced from a full-time job, and did not move after displacement. 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. Column (2) adds minor group occupation fixed effects. Standard errors are clustered by state. 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)
Panel A: Log Duration of Joblessness						
Occupation	-4.465***		-4.206***	-3.887***		-3.818***
Growth Rate	(0.725)		(0.675)	(0.962)		(0.853)
Industry		-2.113**	-0.409		-1.243	-0.130
Growth Rate		(0.808)	(0.769)		(0.871)	(0.806)
State and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE	No	No	No	Yes	Yes	Yes
Dept. var mean	2.133	2.133	2.133	2.133	2.133	2.133
Observations	2881	2881	2881	2881	2881	2881
Adjusted R2	0.105	0.0985	0.105	0.118	0.114	0.118
Test of Equality	0.0001		0.00183	0.0002		0.00260
Panel B: Change in Log Earnings						
Occupation	1.509**		1.220	2.263***		2.121**
Growth Rate	(0.629)		(0.862)	(0.700)		(0.972)
Industry		0.936***	0.470		0.848*	0.269
Growth Rate		(0.314)	(0.498)		(0.472)	(0.655)
State and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE	No	No	No	Yes	Yes	Yes
Dept. var mean	-0.237	-0.237	-0.237	-0.237	-0.237	-0.237
Observations	2723	2723	2723	2723	2723	2723
Adjusted R2	0.0162	0.0151	0.0161	0.0255	0.0222	0.0252
Test of Equality	0.4028		0.564	0.1378		0.242

Notes: Sample is limited to workers displaced because their plant or firm closed or moved, have a non-missing pre-displacement occupation state growth rate, were displaced from a full-time job, and did not move after displacement. Additionally, they must have a non-missing 3 digit NAICS state industry 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 log 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. Columns (4)-(6) adds minor group occupation fixed effects. The test of equality row displays the p-value associated with the t-tests conducted comparing the occupation growth rate and industry growth rate. The p-value between Column (1) and (2) results from a test of equality of the occupation growth rate and industry growth rate coefficients in Columns (1) and (2). The p-value in Column (3) tests the hypothesis that the coefficients on occupation growth rate and industry growth rate in Column (3) are equal. Columns (4) - (6) follow the same pattern. 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)
Panel A: Log Duration of Joblessness								
Contemporaneous	-4.061***				-3.714***			
	(0.881)				(1.125)			
Prior Year		-2.254**				-1.608		
		(1.023)				(1.123)		
Two Years Ago			-0.589				0.333	
			(1.255)				(1.224)	
Mean				-3.334***				-2.985**
				(1.208)				(1.412)
State and Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE	No	No	No	No	Yes	Yes	Yes	Yes
Dept. var mean	2.073	2.073	2.073	2.073	2.073	2.073	2.073	2.073
Observations	2405	2405	2405	2405	2405	2405	2405	2405
Adjusted R2	0.0996	0.0935	0.0917	0.0950	0.116	0.111	0.110	0.112
Panel B: Change in Log Earnings								
Contemporaneous	1.579**				2.929***			
	(0.726)				(1.040)			
Prior Year		0.479				-1.206		
		(0.768)				(1.518)		
Two Years Ago			0.210				-2.254	
			(0.541)				(1.782)	
Mean				1.088				-0.710
				(0.954)				(2.018)
State and Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE	No	No	No	No	Yes	Yes	Yes	Yes
Dept. var mean	-0.235	-0.235	-0.235	-0.235	-0.235	-0.235	-0.235	-0.235
Observations	2284	2284	2284	2284	2284	2284	2284	2284
Adjusted R2	0.0179	0.0155	0.0154	0.0162	0.0330	0.0271	0.0319	0.0264

Notes: Sample is limited to workers displaced from a full-time job because their plant or firm closed or moved, were displaced from a full-time job, and did not move after displacement. They must 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. Mean occupation growth rate is the mean of the occupation growth rates of the contemporaneous year, the prior year, and two years ago. 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	-4.422***		-3.207***	
Growth Rate	(0.814)		(1.004)	
Four Years		-2.297**		-0.425
Later		(1.003)		(1.183)
State and Year FE	Yes	Yes	Yes	Yes
Occupation FE	No	No	Yes	Yes
Dept. var mean	2.130	2.130	2.130	2.130
Observations	2354	2354	2354	2354
Adjusted R2	0.103	0.0934	0.118	0.114
Test of Equality	0.0688		0.1026	

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). The test of equality displays the p-value associated with the t-test conducted comparing the (contemporaneous) occupation growth rate and the occupation growth rate four years later. 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 Growth Nat'l Occ-Ind Dist		Nat'l Ind Growth State Occ-Ind Dist		State Ind Growth Nat'l Occ-Ind Dist		State Ind Growth State Occ-Ind Dist	
Panel A: Log Duration of Joblessness								
Occupation	-4.462***	-3.862***	-2.795***	-2.537***	-1.947**	-1.416*	-1.263**	-0.986*
Growth Rate	(0.724)	(0.961)	(0.901)	(0.733)	(0.754)	(0.763)	(0.570)	(0.548)
State and Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE	No	Yes	No	Yes	No	Yes	No	Yes
Dept. var mean	2.134	2.134	2.130	2.130	2.134	2.134	2.130	2.130
Observations	2890	2890	2871	2871	2890	2890	2871	2871
Adjusted R2	0.105	0.119	0.101	0.116	0.0992	0.115	0.0974	0.114
Panel B: Change in Log Earnings								
Occupation	1.457**	2.201***	0.911**	0.823**	0.422	0.626	0.266	0.122
Growth Rate	(0.624)	(0.705)	(0.401)	(0.359)	(0.358)	(0.475)	(0.256)	(0.212)
State and Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE	No	Yes	No	Yes	No	Yes	No	Yes
Dept. var mean	-0.237	-0.237	-0.236	-0.236	-0.237	-0.237	-0.236	-0.236
Observations	2728	2728	2713	2713	2728	2728	2713	2713
Adjusted R2	0.0160	0.0249	0.0144	0.0214	0.0139	0.0215	0.0134	0.0205

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. The occupation growth rate is 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 at the beginning 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 in Panel (A) is log duration of joblessness and the outcome variable in Panel (B) is change in log 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. The even columns add minor group occupation fixed effects. Standard errors are clustered by state. * $p<0.1$ ** $p<0.05$ *** $p<0.01$

Table 12: Log Duration of Joblessness - Censored Regression

	(1)	(2)
Occupation Growth Rate	-3.878***	-1.998
	(1.037)	(1.261)
Dept. var mean	2.133	2.133
Observations	4530	4530
State and Year FE	Yes	Yes
Occupation FE	No	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. 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. For workers who are not reemployed, the minimum jobless duration is 26 weeks if they were displaced the year prior to the survey, 78 weeks if they were displaced two years prior to the survey, and 130 weeks if they were displaced three years prior to the survey. Columns (1) and (2) are specifications with and without minor group occupation fixed effects. 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 13: Sensitivity to Functional Forms

	(1)	(2)	(3)	(4)	(5)	(6)
	Duration of Joblessness (in weeks)		Exhausted Unemployment Benefits		More Than 26 Weeks of Joblessness	
Occupation Growth Rate	-73.53*** (13.57)	-63.71*** (17.77)	-0.440 (0.266)	-0.748* (0.399)	-0.777** (0.319)	-1.245*** (0.232)
State and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE	No	Yes	No	Yes	Yes	No
Dept. var mean	15.15	15.15	0.387	0.387	0.330	0.330
Observations	3439	3439	2550	2550	4093	4093
Adjusted R2	0.106	0.120	0.0883	0.106	0.183	0.170
	Δ Weekly Earnings		Δ Weekly Earnings Inc Not Re-Employed		Δ Weekly Earnings Inc Not Re-Employed Excluding Outliers	
Occupation Growth Rate	623.6** (292.1)	1153.2*** (387.4)	590.9** (268.9)	598.5 (359.0)	614.3*** (220.5)	555.5** (256.9)
State and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE	No	Yes	No	Yes	No	Yes
Dept. var mean	-98.48	-98.48	-286.3	-286.3	-280.6	-280.6
Observations	2737	2737	3956	3956	3878	3878
Adjusted R2	0.0384	0.0557	0.107	0.124	0.129	0.149

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 be reemployed after displacement. Workers with fewer than $40 of earnings per week prior to displacement are excluded. In the top panel, Columns (1) and (2) are levels of duration of joblessness (in weeks). Columns (3) and (4) are a binary indicator for having exhausted formal unemployment benefits. Columns (5) and (6) are an indicator for more than 26 weeks of joblessness. In the bottom panel, Columns (1) and (2) the outcome is change in weekly earnings (in levels). Columns (3) and (4) include the workers who have not been re-employed since displacement, and consider their entire lost job earnings as the change in weekly earnings. Columns (5) and (6) add to this Column (3) and (4) a restriction of excluding workers at the bottom 1st percentile or top 99th percentile of the change in weekly earnings distribution. All regressions include controls: 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