Occupational Job Ladders and Displaced Workers

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Abstract

I investigate how movements up and down an occupational job ladder lead to earnings gains and losses for both displaced and non-displaced workers. I find both types of workers exhibit similar rates of upward and downward mobility, and relative occupational wages before mobility strongly predict the direction of mobility. I decompose the difference in wage changes between displaced and non-displaced individuals, and show that occupational mobility can explain about 10% of the gap, indicating that occupational mobility is not the primary source of wage losses for displaced workers.

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1 Introduction

Workers who are involuntarily displaced from their jobs experience substantial earnings losses that persist for decades.[1] However, voluntary mobility is well-known to be associated with wage growth.[2] Why do job changes induced by displacement lead to such different outcomes from voluntary job changes?

Understanding the mechanism responsible for wage losses from displacement is crucial for developing well-designed policy. Losses from displacement can stem from two sources: lower wages for performing similar work, or a change in the type of work the individual performs. If displaced workers accept jobs that are a poor match for their skills, there is a role for policy to support displaced workers in finding new jobs that utilize their skills.

In order to evaluate whether displaced workers make sub-optimal job matches after displacement, I focus on occupational mobility. Occupations provide a description of the tasks an individual performs, and allows measurement of job mobility both within and between firms. Voluntary occupational mobility is common, thus in order to evaluate whether occupational mobility can explain losses from displacement, it is important to construct a benchmark of typical occupational mobility in the absence of displacement.

To do so, I construct an occupational job ladder by ranking occupations using median occupational wages from the Occupational Employment Statistics (OES) survey. I match data from the Current Population Survey (CPS) tenure supplement, displaced worker supplement, and outgoing rotation group files. By combining the tenure and displaced workers supplements, I am able to distinguish firm stayers, non-displaced firm changers, and displaced workers, which allows me to compare mobility outcome by firm mobility. In addition, I use complementary data from the 2008 Survey of Income and Program Participation (SIPP).

I first document the following facts for non-displaced workers: (1) moves down the occupational job ladder are frequent (both within and between firms), (2) these downward occupational moves are associated with wage losses, and (3) downward occupational changers are selected from low within-occupation earners before moving. These patterns of occupational mobility are consistent with models of efficient sorting (such as Gibbons and Waldman (1999)), as the optimal job assignment of the worker changes in response to changes in the individual's (expected) productivity.

I find these patterns of selection and mobility also hold for displaced workers. Over 1/3 of displaced workers move up the occupational job ladder upon re-employment. Pre-displacement occupational earnings strongly predict the direction of occupational mobility

[1] cf. Jacobson, Lalonde, and Sullivan (1993). See Kletzer (1998) for a survey.
[2] cf. Topel and Ward (1992).

after displacement, with low-occupational earners more likely to move to lower-ranked occupations and vice versa.

Decomposing the wage gap between displaced and non-displaced workers, I show the distribution of occupational mobility from displacement can explain less than 10% of the losses from displacement. If displaced workers had the same wage changes from upward and downward mobility as non-displaced movers, the counterfactual average wage change upon displacement would be wage *growth* of 4% after displacement. Instead, displaced workers have average wage losses of 7%.

Thus, although several recent papers have emphasized how earnings losses among displaced workers are correlated with the direction of occupational mobility (e.g. see Huckfeldt (2016) and Robinson (2018)), I show that these patterns are not unique to displaced workers. Further, I find that after controlling for the distance of occupational mobility, displaced workers earn about 9% less per hour than firm-stayers and 11% less per hour than non-displaced firm movers. That is, displaced workers that are able to move up the occupational job ladder still earn 9-11% less than non-displaced workers making similar occupational moves.

I conclude that, while occupational sorting is important for understanding heterogeneity in wage growth, it can only explain a small fraction of the losses associated with displacement. I show that displaced workers are close to median earners for their occupation before displacement, but after displacement they earn about 9% less than median occupational wages. This suggests that losses are not driven by firm-specific human capital. Instead, losses are most likely due to either firm-sorting or bargaining.

Recent evidence from Lachowska, Mas, and Woodbury (2017) investigates the sources of earnings losses for displaced workers, and concludes that time-invariant heterogeneity in firm-pay can only explain about 17% in the reduction in hourly wages. Instead, these workers earn lower wages while working for firms with relatively high firm fixed effects. This could be due to match effects, where wages are lower for individuals that are a poor fit for the firm. However, this is at odds with recent evidence from Bonhomme, Lamadon, and Manresa (2019) who finds a minimal role for match-effects in wages in Sweden. Alternatively, these wage losses could be driven by bargaining power. The fact that displaced workers are forced to find employment under duress likely worsens their bargaining position, which may allow firms to pay these workers lower wages compared with other employees at the firm. This bargaining explanation is consistent with evidence from Fallick, Haltiwanger, and McEntarfer (2012), that finds that jobless spells are an important predictor for earnings losses by individuals leaving distressed establishments. Similarly, I find wage losses from individuals who leave employers under duress are explained by especially low wages after re-employment, rather than high wages before separation. Thus, while it remains an open question the extent to which lower wages are due to firm mismatch, in this paper I show that these losses cannot be explained by mismatch in the type of work the individual performs.

Crucial to this exercise is the ability to disentangle returns to occupational mobility from returns to different types of firm mobility. I take advantage of the fact that the CPS displaced worker supplement and tenure supplement are conducted at the same time. This allows me to separate individuals into three mutually exclusive groups: individuals who have not changed employers in the last year, individuals who have changed employers but report they have not been displaced in the last year, and individuals who report displacement in the last year. However, since these surveys are only administered every two years, this means the sample size restricted. I find very similar results using complementary data from the SIPP.

My findings indicate that careers are substantially more volatile then aggregated wage-growth statistics suggest. Approximately 7% of employed individuals move down the occupational job ladder each year. These downward movers have annual real wage growth that is 3 percentage points slower than occupational stayers, for net real wage losses of about 1 percent. Wage gains for individuals moving up the occupational job ladder are 6 percent within the firm and 15 percent for non-displaced firm changers. These results are consistent with either non-displaced movers sorting to higher-paying firms or muted wage changes for internal movers due to wage compression.

One weakness of using individual survey data to study occupational mobility is that the process of collecting and coding occupations introduces substantial noise into the measurement of occupational mobility. Since most individuals do not change occupations, this will serve to attenuate the wage returns to occupational mobility. However, since this measurement error is not correlated with the type of employer mobility, it should not bias estimates of relative returns by type of firm mobility. In addition, I show that estimates are consistent with the Danish administrative data examined by Groes, Kircher, and Manovskii (2013) and Frederiksen, Halliday, and Koch (2016). Despite these limitations, the CPS provides the best data source in the United States to study displacement and occupational mobility, since there is no administrative data source for occupational mobility.

This paper contributes to the literature on the directionality of returns to mobility. The literatures on promotions within firms (such as Baker, Gibbs, and Holmström (1994a)) and job ladders between firms[3] demonstrate how workers can find higher earnings and better matches by moving between jobs. Recent work has emphasised that the magnitude of these

[3] Moscarini and Postel-Vinay (2016) find worker flows form a job-ladder based on employer size, while Haltiwanger, Hyatt, Kahn, and Mcentarfer (2017) find worker flows form a job-ladder based on establishment wages.

returns depend on whether or not an individual moves to a higher- or lower-ranked job. In two recent papers, Groes et al. (2013) and Frederiksen et al. (2016) document substantial rates of downward occupational mobility using administrative data from Denmark. Within firms, a variety of papers in the personnel literature have found some firms demote individuals within the hierarchy; see Frederiksen, Kriechel, and Lange (2013) for a summary. Finally, Fallick et al. (2012) find individuals leaving distressed and non-distressed establishments experience similar distributions of earnings loss, which is consistent with the heterogeneity in earnings changes I see for both displaced and non-displaced firm-leavers. Thus, across a variety of settings, a substantial flow of workers move to lower-ranked or lower-pay jobs.

Several papers within the displacement literature note heterogeneity in the consequences of displacement. Both Neal (1995) and Poletaev and Robinson (2008) find that individuals who are able to find employment in the same industry or in a job with a similar task-mix are able to partially ameliorate the cost of displacement. More recently, Huckfeldt (2016) finds earnings losses from displacement are concentrated among individuals who make downward occupational changes. Farber (1997) and Farber (2017) find a substantial fraction of respondents to the Displaced Workers Survey indicate wage growth following displacement, which is consistent with evidence from Krueger and Summers (1988) that individuals who move to higher-average-pay industries earn higher wages after displacement. In this paper, I investigate whether these factors that can explain variation in the losses within displaced workers can explain differences in comparative wage changes between displaced and non-displaced job changers.

The most closely related paper is Robinson (2018) who also looks at the distance and direction of occupational mobility after displacement. Robinson finds that the wage losses from displacement are closely related to the distance of occupational change the individual makes, a finding which I show holds for all occupational changers, not just displaced workers. Although Robinson emphasizes that displaced workers make more negative moves than non-displaced individuals, I show that these differences are small can explain little of the wage losses from displacement. In the Appendix, I show that ranking occupations based on the task-composition of jobs does not lead to qualitatively different conclusions. Another related paper is Raposo, Portugal, and Carneiro (2019), who find that job-title fixed effects can explain 46% of the loss in hourly wages for displaced workers in Portugal. This is substantially larger than what I find for occupations in the United States. The discrepancy may be due to the fact that job titles are defined in the Portuguese data by industry-level collective bargaining agreements, thus job title mobility is a combination of firm and occupational mobility.

I next provide an overview the main theoretical explanations of wage losses from displacement and how one can distinguish these mechanisms empirically. In Section 3 I describe the data and the methodology for measuring mobility and ranking occupational moves, as well as the empirical strategy. In Section 4, I present several facts about occupational job ladders. in Section 5, I discuss facts about employer mobility and compared displaced and non-displaced workers. In Section 6, I show occupational sorting cannot explain the losses from displacement. In Section 7 I provide additional empirical tests of alternative theories. In Section 8 I discuss the theoretical implications of my findings, and in Section 9 I conclude.

2 Distinguishing Theories of Losses from Displacement

If labor markets were perfectly competitive and without frictions, we would not expect displacement to be deleterious to workers. Displacement would force workers to change firms, but they would immediately find an equivalent position. Similarly, if there was no heterogeneity in jobs, as soon as the worker found another job his wages would be unchanged from his pre-displacement earnings. Thus, for any model to explain the losses displaced workers experience after re-employment, it must be able to explain the sources of frictions and heterogeneity.

Sources of friction are typically understood to be driven by congestion in the job search process (c.f. Burdett and Mortensen (1998)). Individuals who choose the timing of mobility are able to wait for offers that they prefer to their current job, leading to average wage growth for voluntary movers. Involuntary job loss is associated with wage losses on average, because such individuals do not have the luxury of waiting for a better wage offer. However, by searching on the job, they may be able to recover their previous wage level.

A key source of heterogeneity across jobs is the tasks performed, which can be summarized by the occupation. There are two main frameworks for understanding the wage returns to occupational mobility. The first is the role of occupational specific human capital. If occupations require unique skills and investments, then there will be positive wage returns from specializing in a particular occupation and negative wage consequences from changing occupations, especially after a long tenure in the occupation (c.f. Shaw (1984)).

However, if human capital is more general, individuals may be able to transfer skills across occupations. This is the premise of the the job assignment model (as developed by Gibbons and Waldman (1999)). Further, individuals' (expected) ability can change over time, either due to human capital accumulation or decay, or due to learning about the individuals underlying ability. In this case, as ability crosses the assignment threshold between jobs, individuals will optimally move up or down a job ladder. Observing an individual moves down a job ladder does not mean that the individual has experienced a wage loss due to job assignment, indeed in this framework, the individual would have experienced a larger wage loss in the absence of mobility. Thus, in order to understand whether occupational mobility contributes to the losses from displacement, it will be important to construct an appropriate counterfactual for occupational mobility in the absence of displacement.

In addition, displaced workers may experience wage losses due to mobility between firms. There are several reasons why. First, there may be match-specific productivity, where worker productivity depends on the quality of the match or firm-specific human capital. In this case, a forced separation is likely to lead to wage losses across the board due to productivity losses.

Second, there may be heterogeneity in wages that firms pay to all their employees. For instance, in the classic Burdett and Mortensen (1998) model, firms offer heterogeneous wages to induce search, but there are no productive differences between firms. In this case, individuals who are forced to change employers are more likely to fall down the firm-wage ladder, but not due to productivity losses. Third, if firms and applicants bargain over wages, displaced workers are likely to be disadvantaged due to having worse outside options. This could also lead to lower wages without any productivity differences.

These different potential explanations of wage losses from displacement have distinct policy implications. If displaced workers' losses are due to some form of mismatch, either in terms of occupation or firm characteristics, then individual wages and aggregate productivity may be improved by encouraging longer or more effective search. On the other hand, if losses are due to a wage ladder as in Burdett and Mortensen (1998), matching with a low-wage firm is individually costly but has no effect on aggregate productivity, since wage heterogeneity is not due to underlying heterogeneity in productivity. Finally, if wage losses are due to bargaining, more generous unemployment insurance could improve workers' bargaining position, but again would have no impact on aggregate productivity. While I will be able to examine in detail the source of losses due to occupational sorting, I will not be able to distinguish between these alternative firm-based explanations for wage losses.

A key contribution of this paper is to investigate the joint distribution of occupation and firm mobility, and compare wage returns for different types of moves. By comparing the distribution of occupational moves for displaced workers with the 'typical' job ladder experienced by non-displaced workers, I am able to determine whether displaced workers experience excessive reallocation or worse reallocations compared to non-displaced individuals. In addition, by isolating individuals who change occupations within firms, I am able to distinguish between wage returns from occupational mobility versus employer mobility. I will show that most occupational mobility occurs within firms, suggesting that occupational job ladders may have different properties than job ladders between firms.

Finally, I will draw on predictions from the job assignment model to determine if occupational change is consistent with efficient sorting. If individuals are moving up and down an effective ability ladder, then individuals are likely to be descending the ladder before a downward move and rising the ladder before an upward move. This means that before a job change, someone who moves down is more likely to have been a low earner for the occupation, while someone who moves up is more likely to have been a high earner for the occupation. On the other hand, after mobility, the relationship flips, with downward movers more likely to be high earners for their new occupation and upward movers more likely to be low earners for their new occupation. I will test these predictions on both non-displaced and displaced individuals.

3 Methodology

In this section, I first introduce the data source in Section 3.1, then discuss the measurement of occupational mobility and construction of the job ladder in Section 3.2. In Section 3.3 I present the econometric specification and in Section 3.4 I discuss measurement error issues.

3.1 Data

The primary data source is monthly CPS survey data from January 1994 through October 2016 and the CPS Tenure and Displaced Worker Supplements (DWS) administered during the same time period. In order to identify the type of firm mobility, I use the tenure and displaced workers supplements, which are administered at the same time in January or February of even years.[4] Wages are collected in the monthly CPS in the outgoing rotation groups (ORG) administered in months 4 and 8. Thus, I match individuals who are in the outgoing rotation group during the months the tenure supplement is administered to their previous outgoing rotation group, which gives me their occupation and wage before a potential mobility event.[5] For individuals who were employed a year ago and are currently employed, reported tenure of greater than a year indicates they did not change firms in the past year. In this way, I can construct measures of annual employer and occupational mobility.

In addition, I use the DWS to classify individuals who changed employers as displaced or non-displaced. In particular, individuals 20 years or older are asked, "During the last 3 calendar years... did you lose a job, or leave one because: your plant or company closed or

[4] In particular, January in the even years between 2002 and 2016 and February in 1998 and 2000.

[5] To match individuals across surveys, I use a procedure developed by Madrian and Lefgren (1999) using administrative IDs and confirm matches using sex, race, and age.

moved, your position or shift was abolished, insufficient work or another similar reason?" If they answer yes, they are asked additional questions, including the reason for job loss and which year they were displaced. In order to continue with the DWS questions, they must report one of the following reasons for displacement: (1) plant or company closed or moved, (2) insufficient work, or (3) position or shift abolished. If an individual reports a displacement event in the previous year for one of the above reasons, I classify them as a displaced worker. This results in three categories: firm-stayers, non-displaced firm-changers, and displaced workers. Table A.2 provides descriptive statistics for this sample.

In addition, I also use a retrospective sample constructed from the Displaced Workers Survey. Although the contemporaneous sample described above allows for comparisons of wage outcomes for displaced and non-displaced workers, the sample of displaced workers is restricted to respondents who were in the 8th month of the sample when answering the DWS supplement. Displaced workers are also asked to report details of the lost job, including occupation and earnings. This retrospective data is what has typically been used by researchers using the CPS DWS data.[6] However, since the previous year's information is collected retrospectively, it is likely less accurate than the contemporaneously collected information in my primary sample. Nonetheless, I use this retrospective sample for individuals who were displaced in the past year as an additional data source. Column 4 of Table A.2 provides descriptive statistics for this sample.

To complement the analysis from the CPS, I also use data from the 2008 Survey of Income and Program Participation (SIPP). The SIPP has several advantages over the CPS. First, the 2008 SIPP is a panel, surveying individuals every 4 month for a span of 5 years (2008-2013). In addition, the SIPP asks more detailed questions about employer mobility, allowing me to disaggregate employer changes into the reasons for employer change. However, the 2008 SIPP does not capture occupational mobility within firms, which is crucial for my research design, so can only be used to supplement the primary CPS results.

The SIPP sample is constructed by matching adjacent 4-month waves. The sample is restricted to individuals who are employed in the first month of each wave. Further, since the SIPP only collects monthly earnings, the sample is restricted to individuals who work 35 or more hours per week and were employed for the whole month for both months. Employer mobility is defined as individuals who report leaving their employer in the second, third or fourth month of the first wave. Individuals who changed employers during the first month of the wave are dropped, due to partial monthly earnings. I am left with a sample of 257 thousand observations, each consisting two four-month waves. In Table A.3 I show summary statistics for key variables.

[6] E.g. Gibbons and Katz (1991), Neal (1995), Farber (1997), and Farber (2017).

3.2 Measuring and Ranking Occupational Mobility

Occupational coding provides a mapping of worker duties and activities to a common classification system across firms. The CPS and SIPP surveys ask individuals open ended questions about their jobs, which are then classified into occupational codes by trained enumerators. It is important to note that this process introduces substantial measurement error into the measurement of occupational mobility, since small differences in how the individual describes their job or how the enumerator classifies the work can lead to changes in occupational codes.

In order to rank occupational changes as positive or negative, I assign each occupation a code based on the median occupational wage from the Occupational Employment Statistics survey (OES). The survey collects occupation and wage data from over a million establishments every three years, providing high-quality employer-reported data on wages. I use 2005 median hourly wages, which were collected between 2002 and 2005 and are reported using the 2000 SOC occupational codes. This avoids changes to the occupational ranking that may occur with small changes in occupational wages each year as in Groes et al. (2013)[7], and also avoids the possibility of temporary changes to the occupational wage structure due to the two most recent recessions (2001 and 2007-2009). I then use Census crosswalks to assign each occupation in the CPS to one of these codes. The OES index ranges from \$6.60 to \$80.25. In the Appendix, I show an alternative ranking method based on occupational tasks yields similar results.

3.3 Econometric Specifications

The main specification is a first-differenced linear regression, in which I regress the change in wages on indicators for whether or not the individual made a negative or positive occupational transition. All reported wages are the log of real hourly wages, deflated to January 1994 values. Since the wage data is collected across a span of 20 years, I include year fixed effects in most specifications. The sample is restricted to individuals who were employed in both outgoing rotation group months, with valid earnings and occupation data in both months, and tenure responses in the second month of the match.

In particular, I run the following basic specification:

$$\ln(w_{it+1}) - \ln(w_{it}) = \alpha_0 + \alpha_1 D_{it}^{down} + \alpha_2 D_{it}^{up} + X_i\beta + \gamma_t + \epsilon_{it}$$

D_{it}^{down} and D_{it}^{up} are indicators for whether or not the individual made a downward or upward

[7]This is likely to be a bigger problem in my sample-based data than it was for Groes et al. (2013) who have nearly universal administrative data.

occupational change. The γ_t represent annual fixed-effects.

The X_i include a variety of controls. The first differenced specification removes any time-invariant worker characteristics, however there may be variation between groups in the growth rate of wages. For instance, wage growth is typically faster for early career workers. Since occupational movers are also younger on average than occupation stayers, this could inflate the returns to occupational mobility. Thus in many specifications I include the following demographic controls: a third-degree polynomial in potential experience (age-education-6), dummy variables for gender and non-white race, and dummy variables for different levels of educational attainment.

In addition, for some specifications I include industry controls which consist of dummy variables for major industries (crosswalked to a consistent 2002 major industry classification across years), or occupation controls, which consist of dummy variables for detailed occupations (crosswalked to consistent 2002 Census codes). All specifications are weighed using CPS sampling weights, and I report robust standard errors.

To evaluate whether or not movers are low or high earners for their occupation before or after moving, I run specifications with the difference between log hourly wages and the log median wage for the detailed occupation-year. To construct the log median wage variable, I use the full monthly CPS survey (1994–2016), and calculate median wages for each detailed occupation each year. This provides a measure for the typical earnings in that occupation in the year of interest.[8] In regressions in which the dependent variable is wages before mobility (or the change in wages), if I include job controls, these are defined for the job before mobility. When the dependent variable is wages after mobility, I instead use job controls defined for the job after mobility has occurred.

In order to evaluate how much of the differences in wage changes between displaced and non-displaced workers may be due to occupational mobility, I perform Oaxaca-Blinder decompositions (c.f. Oaxaca (1973) Blinder (1973)). This methodology is a non-causal statistical decomposition, that separates the gap in an outcome variable between two groups into differences in fixed characteristics, differences in the return to those characteristics, and differences in the interaction between the two. In this case, I decompose the change in wages between displaced workers and non-displaced workers into differences in the types of occupational mobility, differences in the return to the types of mobility, and the interaction. I report the maximal percent of the variation that can be accounted for by differences in the distribution of occupational mobility, which I take to be the sum of the share of the variation due to the distribution of mobility and the share due to the interaction. If this percent is

[8] Results are robust to using median occupational wages from the OES survey, rather than calculated from the CPS.

small, it indicates that most of the gap in wages between displaced and non-displaced is due to displaced individuals earning different wage returns from non-displaced for the same type of occupational mobility.

3.4 Measurement Error

As discussed above, the process of occupational coding introduces substantial errors. Thus it is worth exploring in detail the implications of such measurement error in measuring types of mobility and estimating wages. The most common type of coding error is due to spurious mobility. Most individuals do not change occupations each year. For individuals who remain employed at the same firm, the CPS follows a procedure of dependent coding, in which the interviewer asks whether or not the respondent changed occupations from the previous month. This leads to dramatically lower estimates of annual mobility inside firms, falling from 44% to approximately 5.5% . Occupational mobility for firm-changers is also likely inflated, however there are no dependently coded estimates with which to compare.

For wage change estimates, this measurement error will serve to attenuate estimates of wage changes since individuals who remain in the same job at the same firm typically have modest real wage growth. Thus misclassification of these workers as either upward or downward movers will serve to reduce the average wage gains for upward movers and lessen wage losses for downward movers. However, if all mobility was due to misclassification, earnings growth should not vary based on the type of spurious mobility. Thus the extent to whether or not there is variation in wage changes based on mobility serves as a test for whether there is true mobility underlying the spurious mobility.

A bigger issue arises for the measurement of the distance between earnings and median occupational wages. Consider individuals who are classified as downward occupational movers. Some fraction of these are true movers, however there may be two types of workers misclassified as downward movers. First, an individual could be incorrectly classified in the first month as working in a higher-ranked occupation than his true job. If this error is corrected in the second month of the sample, he would look as if he moved to a lower-ranked occupation. Moreover, if his wages are in line with his true occupation, we would see below-median wages before 'moving' and near median wages after 'moving'. Second, an individual could be correctly classified in the first month, but in the second month be incorrectly classified into a lower-ranked occupation. In this case, he could be expected to have approximately median earnings before 'moving', and above-median earnings after 'moving'. In this case, rather than attenuating the estimated wage outcomes, this misclassification will bias the estimates upward, estimating a larger-than-true value of the wage gap before and after mobility for downward occupational changers.

Although these biases may inflate the estimates for the wage gap with mobility, the extent of this measurement error should not vary by employer mobility. All individuals are asked the same questions about their current occupation and coded by the same enumerators, regardless of what type of mobility they reported. Thus, while the levels of mobility are biased, the relative wage gaps should not be. In addition, when possible I will compare estimates to results from related papers that use administrative data which will serve to corroborate my estimates.

4 Facts about Occupational Job Ladders

In this section, I develop a series of facts about occupational job ladders. I focus on four key facts: (1) most occupational transitions occur within firms, (2) moves down the occupational job ladder are frequent, (3) wage changes reflect the direction and distance of mobility, and (4) downward occupational movers are negatively selected and positive upward movers are positively selected. I show that these facts hold for both firm-stayers, non-displaced firm changers, and displaced workers.

4.1 Fact 1: Most Occupational Transitions Occur within Firms

I begin by investigating the rates and characteristics of occupational mobility for individuals based on whether they change employers or are displaced, which are displayed in Panel A of Table 1. In the first three columns I show the annual occupational mobility rates for individuals in the CPS, while in the final two columns I show the four-month mobility rates for individuals in the SIPP. The CPS data reveals that annual occupational mobility rates are lower for firm-stayers, at 43.4% per year compared with about 75% of individuals who changed employers. Nonetheless, since only 11% of individuals changed employers over the year, 80% of these occupational moves are internal-firm moves.

As discussed in Section 3.4, self-reported occupational data introduces substantial spurious occupational mobility, thus these estimates are an over-estimates of mobility rates. I can compare these estimates to administrative occupational data from Denmark reported by Groes et al. (2013), which is less likely to suffer from measurement error. Although the authors do not emphasize differences in occupational mobility within firms versus between firms, I calculate the Danish within-firm mobility occupational mobility rate is 14.4% while the between-firm mobility rate is 35.5%, using data reported in their Appendix Tables 1 and 2. Nonetheless, since only 20% of individual change firms a year, 62% of occupational changes in Denmark occur within firms.

The fact that most occupational mobility occurs within firms suggests that the primary driver of occupational mobility is unlikely to be congested search, which is the standard mechanism behind models of firm job ladders. Within firms, workers and employers should be aware of potential alternative matches. Instead, mobility is likely due changing worker capabilities or congestion through capacity constraints.

4.2 Fact 2: Moves Down the Occupational Job Ladder are Frequent

I next turn to the direction of occupational mobility. As discussed in Section 3.2, I rank occupations based on the annual median OES occupational wage. In Panel B of Table 1, I show that over 40% of occupational moves are to lower-ranked occupations. These estimates vary slightly across types of firm mobility within the CPS, with 47.5% of internal movers moving down, 44.6% of non-displaced between firm movers moving down, and 49.5% of displaced workers moving down. Rates of downward mobility are somewhat larger in the SIPP, with 47% of non-displaced and 54% of displaced, respectively.

These estimates are remarkably consistent with Danish administrative mobility analyzed by Groes et al. (2013), who find downward movements by 46% of occupation changers inside the firm, and 45% for occupational changers between firms. Nonetheless, rates of downward mobility are substantially larger than estimates of demotion rates within firms from the personnel literature.[9] This may be due to occupational transitions including lateral moves that would not necessarily be considered a demotion, but implies occupational mobility is somewhat different from firm promotion hierarchies.

In Panels C through E of Table 1, I turn to the distance of occupational moves, measured as the change in the log median occupational wage. Panel C shows that the average distance of occupational moves varies by the type of firm mobility. Internal movers on average gain 1.5% in occupational wage ranks, while non-displaced between firm movers gain between 2.8% (SIPP) and 4.6% (CPS). However, for displaced workers, the average change in rank is negative, with losses between 1.4% (CPS) and 5.3% (SIPP). This is consistent with Robinson (2018), who finds displaced workers are more likely to make a negative occupational moves.

Panels D and E show that the average change in occupational rank obscures large changes

[9] Frederiksen et al. (2013) harmonized a variety of datasets from the literature in order to compare promotion and demotion rates. These authors' analysis revealed demotion rates ranging from less than 1% of all position changes in the case of Baker et al. (1994a) to a high of 29% for white-collar workers during a period of contraction in Dohmen, Kriechel, and Pfann (2004). Thus, while finding substantial rates of downward mobility inside firms is not unheard of, these measured occupational changes occur at substantially higher frequency than demotions in the personnel literature.

in rank, with positive movers gaining about 33 log points in rank, and negative movers losing about 33 log points. These estimates are similar across firm-mobility samples.

Thus, occupational job ladders are extremely dynamic, with many workers moving up and slightly fewer workers moving down each year. Although the frequencies of upward and downward mobility are similar across firm-mobility types, we do see that both higher rates of downward mobility and smaller positive rank gains lead to negative average rank changes for displaced workers, compared to the small positive average rank changes within firms and between firms. This suggests that a factor of losses from displacement may be that displaced workers move down occupational job ladders.

4.3 Fact 3: Wage Growth Reflects the Direction and Distance of Mobility

I next turn to measuring the wage return to occupational mobility. In Table 2, I regress the change in log wages on several different occupational change indicators, following the specification described in Section 3.3. In all specifications, I include controls for potential experience, gender, race, and education. In the first three columns, I focus on the 12-month matched CPS sample, with separate specifications for individuals who do not change firms over the 12 months, those who change firms but do not report being displaced in the last 12 months, and those who report displacement. In the fourth and fifth columns, I report the same specifications for the 4-month SIPP sample, with non-displaced and displaced firm changers, respectively.

I begin by focusing on occupational changers who do not change firms, reported in Column (1). For these workers, the first-difference specification partials out any fixed employer characteristics that contribute to their wages. This allows us to see returns from occupational mobility absent changes in employer characteristics. Panel A shows that wage changes for occupational changers within firms are indistinguishable from those for occupational stayers, with real average wage growth of 2.65%. However, in Panel B, when I separate wage changes for upward and downward occupational changes, we see that individuals who move down the occupational job ladder experience wage growth that is 3.36% slower than occupation-stayers, while those that move up the job ladder experience wage growth that is 3.51% faster than occupation-stayers. Thus, average wage growth can be ranked based on the direction of moves up and down the occupational job ladder: 0.7% wage losses for downward moves, 2.65% wage growth for occupation-stayers and 6.26% wage growth for upward moves.

These results are consistent with evidence from the personnel literature on promotion dynamics within firms. Frederiksen et al. (2016) find that individuals moving up into management experience faster wage growth than those who do not move. Within the personnel literature, a variety of papers find faster wage growth with promotion than for job stayers (cf. Baker, Gibbs, and Holmström (1994b); also see Gibbons and Waldman (1999) for a broader review). Fewer papers focus on demotions; however, Frederiksen et al. (2016) find slower wage growth for those moving out of management compared with for job-stayers.

In Panel C and D, I instead focus on the distance of occupational mobility, measured as the change in the log of the OES occupational score. Panel C shows that each additional log point of distance is associated with a 10% wage increase for occupational changers inside firms. Thus, while the wage changes grow the larger the change in occupational distance, the distance is smaller than the difference in median wages between the two job titles. This is consistent with a variety of papers in the personnel literature that find promoted individuals move from the top of the wage distribution from the previous job and into the bottom of the wage distribution in the new position, leading the average change in wages upon promotion to be smaller than the difference in average wages between the two levels (see Gibbons and Waldman (1999) for a review of this literature reporting this fact).

In Panel D, I investigate whether the returns to occupational distance are symmetric for individuals moving within firms. Point estimates are somewhat larger for upward movers (11.4%) compared with downward movers (8.06%), although these estimates are not statistically distinct. This suggests that wages may be stickier on the downside.

Now we can compare results for firm-changers to these patterns within the firm. As discussed above, individuals changing employers may be sorting to firms with different wage policies. If individuals are moving voluntarily, they are more likely to be sorting to a firm with higher average pay, while displaced workers may be forced to accept positions at employers with lower average pay. On the other hand, there may be wage compression within firms that limits upside and downside wage growth.

Panel B shows that for all samples, individuals moving down the occupational job ladder have wage losses on average, however these losses are substantially larger for displaced workers than non-displaced firm changes, with displaced workers moving down the occupational job ladder losing 17.9% on average in the CPS sample, and 24.8% in the SIPP sample. In contrast, non-displaced workers moving down the occupational job ladder lost 1.07% in the CPS sample and 3.06% in the SIPP sample, both of which are slightly larger losses than that of downward movers within the firm (0.7%).

Similarly, moves up the occupational job ladder are associated with wage gains for non-displaced firm changers, with wage gains of 15.5% (CPS) and 12.04% (SIPP) , dwarfing the wage gains of 6.26% within firms. In contrast, upward moving displaced workers experience wage losses of 1.03% (CPS) and 4.08% (SIPP), but these losses are substantially smaller than those experienced by displaced workers who also move down the occupational job ladder. Panels C and D shows that firm-movers' wages are much more responsive to the change in occupational distance than within firms, with larger point estimates for both positive and negative moves.

Thus, across all samples, wage changes can be ranked based on the type of occupational change, with the largest wage gains for individuals that move up the occupational job ladder, then occupation stayers, and wage losses for moves down the occupational job ladder. Non-displaced individuals moving between firms are best positioned to realize positive wage gains from upward occupational moves, however they also have larger wage losses than individuals moving down the job ladder inside the firm. Displaced workers have more negative wage returns across the board, but they still follow the relative ranking of wage changes by occupational distance and direction.

4.4 Fact 4: Downward Occupational Movers are Negatively Selected and Positive Occupational Movers are Positively Selected

In the Gibbons and Waldman (1999) model of efficient job mobility, firms promote high performers and demote low performers. This means that before mobility, individuals that will be promoted are likely to be above average earners for their job, while individuals who will be demoted are likely to be below average earners for their job. On the other hand, a newly promoted individual is likely to be a low earner for their new position, since they just surpassed the productivity threshold to be promoted. Similarly, if an individual is demoted, they are likely to be a high earner for their new position. These predictions about upward mobility are borne out in personnel data, such as in Baker et al. (1994b).

In this section, I test whether occupational job ladders follow similar patterns. To measure selection, I estimate the gap between an individual's wage and the median log hourly wage for all individuals employed that year in the CPS. This specification is described in detail in section 3.3.

In Table 3, I focus on the selection process for individuals who make these occupational changes without changing employers. In Panel B, I show how this wage gap differs based on the direction of move. Both with and without controls, individuals who will move down the occupational job ladder in the following year are low earners for their occupation, earning 1% below median occupational wages after controlling for demographic and job characteristics. In contrast, individuals who will subsequently move up the occupational job ladder earn about 10% above median occupational wages before moving. Thus, the selection of upward and downward movers is consistent with sorting based on productivity.

In Columns (3) and (4), I consider the wage gap in the second year. This reveals the opposite pattern: individuals who moved down now earn approximately 13% higher wages than median occupational wages for their new position, while individuals who moved up now earn 5% below median occupational wages.

Panels C and D reveal a similar pattern, where the wage gap before moving is positively correlated with the distance of the occupational move, and the wage gap after moving is negatively correlated. This indicates that the larger the positive move, the higher paid the individual was for their previous occupation, and the lower-paid the individual is for their new occupation. Conversely, the larger the negative move, the lower paid the individual was for their previous occupation and the higher paid they are for their new occupation. Thus, occupational mobility with firms is consistent with the Gibbons and Waldman (1999) model of efficient sorting across job categories based on changing worker productivity.

Now we want to examine the selection dynamics for individuals who change firms. In Table 4 I replicate Table 3 for non-displaced and displaced firm changers. Since the SIPP does not collect information on hourly wages, I restrict this test to the CPS sample. All columns include worker and job controls. Panel A shows that firm changers are on average below-median earners both before and after mobility, with occupational changers somewhat more negatively selected than non-changers.

Panel B reveals the familiar pattern for negative occupational movers, who are especially low earners before moving. This is true for both non-displaced and displaced workers, although the point estimate for displaced workers is not statistically significant. This pattern is consistent with what we observed for downward occupational movers inside firms. However, for non-displaced movers that make a positive occupational move between firms, negative and insignificant point estimates, which is inconsistent with the expected positive selection. Displaced workers exhibit imprecise point estimates consistent with positive selection. After mobility, point estimates are consistent with the sorting pattern for internal firm movers, with downward movers earning high-wages for their occupation and upward movers earning low wages for their occupation.

Panels C and D show similar results to Panel B, with a muted relationship between the distance of positive moves and the pre-displacement wage gap. However the negative relationship is stronger for displaced workers, indicating individuals who moving down between firms are more strongly negatively selected than those who move down within firms. Thus, in net, some of the selection patterns are similar for firm changers as we saw within the firm, the evidence of positive selection of upward movers is particularly muted for non-displaced firm changers. However, since we saw in Table 2 that positive occupational movers experience large wage gains when they change firms, this suggests these workers may be choosing to move precisely because they are underpaid for their position.

In order to illustrate the extent of positive and negative selection, in Figure 1, I replicate Figure 3 in Groes et al. (2013), showing how the percentage of occupational switchers who move up or down relates to the individual's position in the occupational wage distribution before moving. Panel A shows mobility for all non-displaced workers, and reveals remarkably similar patterns to the administrative data in Groes et al. (2013), with rates of upward mobility beginning around 30% for the lowest decile and rising to a high of just above 70% for the top decile. Thus, the relationship between a worker's position in the occupational wage distribution and his subsequent mobility is quite robust. This is reassuring, since as discussed in the measurement error section, the gap between wages and median wages may be biased from mismeasurement of occupational mobility. The fact that there are similar patterns in personnel and administrative records (which should have more accurate coding of occupational mobility) supports my findings from the CPS.

In Panel B of Figure 1, I repeat the exercise for displaced workers. Since the sample of displaced workers in the contemporaneous sample is too small to separate by decile, I instead use the retrospective sample. The retrospective sample asks the individual to recall their occupation and wage before the displacement event. This gives me a sample of 1076 displaced workers. Here the pattern is very similar to Figure 1 for all occupational changers. Thus, displaced workers' occupational mobility is also closely tied to their initial position in the occupational wage distribution.

4.5 Discussion

In this section, I have documented four facts about occupational mobility. I find that internal occupational job ladders are very similar to promotion hierarchies in two ways: first, that wage gains are largest for upward movers and second, upward moves are high-earners for their previous job and low-earners for their subsequent jobs. However, internal occupational job ladders differ from promotion hierarchies by the fact that downward moves are quite common. Nonetheless, wages and selection are consistent with theories of job assignment, with downward movers experiencing wage losses and negative selection.

In addition, I show that internal occupational job ladders are an important source of occupational mobility for workers, with the majority of occupational changes occurring within firms. Nonetheless, moves between firms have different dynamics, with non-displaced upward movers appearing to be less negatively selected yet garnering large wage premiums from moving. This may reflect sorting to higher pay firms on top of the positive occupational mobility.

Finally, I show that displaced workers do not have dramatically different occupational mobility patterns from non-displaced workers, with somewhat higher rates of downward mobility, but similar distances of positive and negative moves. Nonetheless, these workers have wage losses on average, while internal movers and non-displaced workers have average wage gains, a fact that I explore in more detail in the next section.

5 Wage Changes by Firm-Mobility

Next I want to establish how displaced worker's wage growth differs from non-displaced individuals. I begin by tabulating the distribution of employer mobility by the reason for mobility, displaced in Table 5. In the CPS sample, 15% of individuals changing employers over a year report being displaced from their previous job, while in the SIPP, 6% can be classified as displaced. The SIPP allows for further disaggregation of the reason for firm mobility, which shows over half of individuals quit to take another job. Other categories include on layoff (11%), fired (3%), and personal issues such as illness or childcare problems (2%).

In Table 6, I measure how wage growth varies by type of firm mobility. In Panel A, I aggregate all firm-changers together in the CPS sample. Average wage growth for firm stayers is 2.81%, while firm movers have wage growth that is 1-2% higher, but not statistically distinct from firm-stayers after including demographic controls. Panel B reveals that this small positive wage growth mask substantial heterogeneity by mobility type, with non-displaced individuals experiencing wage growth of 6.8% and displaced individuals experiencing wage losses of 7.1%. In Columns (3)-(6), I consider wages before and after mobility for each group. Both non-displaced and displaced individuals earn lower wages before mobility than firm stayers, even after controlling for worker demographics. After mobility, non-displaced individuals are still lower paid than firm stayers, but have improved their standing, while displaced individuals lose ground.

In Panels C and D of Table 6, I repeat the exercise for individuals from the 2008 SIPP. Here we find somewhat larger relative gains from mobility for non-displaced over firm-stayers compared to the CPS (6.8%), but the total wage gains are similar (6.9%). I separate displaced workers into two groups: displaced due to slack business conditions and displaced due to other reasons (e.g. employer sold business or employer bankrupt). Individuals who are displaced due to slack conditions have wage losses of 2.1%, while individuals displaced for all other reasons have losses of 10.4%. Columns (3) through (6) show why: individuals who are displaced due to slack conditions already have substantially lower earnings than other displaced groups before displacement, while after displacement they have similar point estimates. This suggests that these individuals are already experiencing earnings losses due to slack conditions before the final separation. This could be due to a drop in working hours before displacement, however I am unable to measure working hours in the SIPP. In Appendix Table A.4, I show that individuals in the CPS who are displaced due to insufficient work have similar hourly wages before displacement to other displaced individuals. Finally, for non-slack displaced workers, relative wages before and after mobility are similar to estimates from the CPS sample.

In Figure 2, I disaggregate employer movers from the SIPP by the detailed reason for leaving the previous employer. I show wage changes relative to wage growth for firm-stayers and after controlling for demographic characteristics and years. Relative wage changes from displacement range from 13% growth for individuals who quit to accept another job, to 34% losses for individuals who retire but are employed full-time 4 months later. Average wage gains for non-displaced individuals are driven by just three categories: quits (13% growth), temporary positions that ended (11% growth), and 'other' (5% growth). On the other hand, several categories of non-displaced individuals have wage losses: layoffs (-7%), fired (-8%), family or personal issues (-17%), school (-25%), and retired (-34%). As we saw in Table 5, these positive categories comprise 70% of all firm mobility, hence the robustly positive average wage growth.

Finally, we can compare workers who are displaced due to employer sale or bankruptcy to other categories of firm movers. Individuals on layoff have very similar patterns to displaced workers. Although individuals who are fired have a similar wage change to displaced workers (-8%), their wages before displacement are 10 percentage points lower, consistent with negative selection leading to job loss. Nonetheless, some individuals who would be classified as 'position or shift abolished' in the CPS may fall into this category in the SIPP. The fact that most groups that could be classified as involuntary mobility have below average wages after mobility is consistent with either falling down a job ladder or worse bargaining position leading to lower wages.

In Table 6, we saw that displaced workers are earn 9.5 log points less than firm-stayers before displacement, which could indicate that these individuals are negatively selected. In order to better understand this wage gap, In Table 7 I return to the methodology from Table 3, and calculate the gap between the individual's wages and median occupational wages, using hourly wage data from the CPS. Before mobility, non-displaced firm changers earn wages that are below median wages, while displaced and firm-stayers both earn above-median occupational wages. However, after displacement, displaced workers now earn wages that are substantially below median wages. Thus, displaced workers' relative position is similar to non-displaced firm stayers before displacement, but their fortunes worsen dramatically thereafter.

These number can be compared with estimates from the literature. Farber (1997)'s analysis of the Displaced Workers Survey from 1983 to 1995 found average losses in weekly earnings for displaced workers to range from 10 to 16%, depending on the year. These rates are somewhat larger than the 7% I find using hourly wages. One difference is Farber (1997) uses retrospectively reported wages as well as displacements that occurred as many as 3 years in the past, which could lead to recall-bias in wages before mobility. More recently, Farber (2017) found a loss of 6.17% when he extended his analysis through 2014, which is closer to my estimate. In addition, Farber (1997) constructed a synthetic control group, using CPS data from non-displaced workers. For these individuals he found average real weekly earnings growth of 3.1%. This estimate falls in between the wage growth estimates I find of 2.8% for firm-stayers and 4.7% for non-displaced firm changers.

These results indicate that the primary source of losses for displaced workers is the type of match or wage offer they receive after displacement, rather than lost specific capital. This lends credence to the hypothesis that occupational sorting after displacement may explain the losses experienced by displaced workers.

6 Explaining Displaced Workers' Wage Losses

Now I return to the original question: why does displacement lead to wage losses? In Table 6 we saw that displaced workers who are re-employed within a year of displacement have average real wage losses of 7%, while non-displaced firm-changers have wage gains of about 6%. Can differences in the distribution of occupational moves explain these different outcomes?

As a first pass, I use the distribution of occupational changes from Table 1 and the estimates of average wage changes by occupational mobility for non-displaced firm changers from Table 2 to estimate counterfactual wage changes. If displaced workers had the same magnitude of wage changes upon mobility as non-displaced firm-changers, they would have average wage *gains* of 4.4% after displacement. This discrepancy is driven by the fact that, for both positive and negative occupational moves, displaced workers have substantially worse wage outcomes than non-displaced individuals.

In order to more formally decompose the difference in wage changes into differences in the distribution of occupational changes versus differences in the returns to occupational moves, I perform an Oaxaca-Blinder decomposition. In Table 8, I perform the decomposition on three samples: all non-displaced versus displaced in the CPS, just firm movers in the CPS, and firm movers from the SIPP sample.[10] The top panel shows displaced workers have average wage gains between 10% and 13% less than non-displaced workers, depending on the sample.

I then decompose this gap into three pieces: differences in the types of occupational moves these individuals make, differences in returns to those moves, and differences in the interaction between the types of moves and the returns. In Table 8 I report the portion of the difference in wage gains attributable to the returns to mobility, as well as the maximum percent of the wage gains that can be attributed to changes in the distribution of moves, which I define as the sum of the fraction that can be attributed to the types of moves, and the interaction between the types of moves and the returns.

The first column reports my preferred specification, which compares the wage returns for displaced workers within individuals that do not change firms. This avoids conflating changes in employer characteristics with occupational mobility and also affords the largest sample sizes. However for completeness I also report results restricting to individuals who change employers in the CPS (Column 2) and the SIPP (Column 3).

The first decomposition shows that at most 3 to 6% of the losses from displacement can be attributed to differences in the distance of occupational moves that displaced workers make, while the vast majority is attributed to differences in the returns to these moves. In the second decomposition, instead of using the distance of occupational moves, I include detailed fixed effects for the occupations before and after mobility. Occupational fixed effects could account for as much as 10% of the losses in the full CPS sample and 6% in the SIPP sample. The CPS firm movers estimate is somewhat larger, at 22%, but still indicates at most 1/4 of the losses from displacement can be attributed to displaced workers making more negative occupational moves.

In decompositions 3 through 6, I add in successive additional controls, to see if other differences in characteristics between displaced and non-displaced workers can account for the losses from displacement. The addition of demographic controls can account for up to 28% of the gap, however when I add in detailed industry controls, the controls can account for at most 20% of the losses. Thus, differences in occupational changes, industry changes, and demographics cannot account for the vast majority of the losses experienced by displaced workers relative to non-displaced.

To more directly see how changes in wages relate to the distance of occupational moves, Figure 3 shows a scatter plot of the change in log real wages after mobility plotted against the change in log OES score for occupational changers. The gray plus signs show non-displaced firm changers while the black circles show displaced workers. I also create fitted lines for

[10] The SIPP does not measure occupational mobility for individuals who do not change firms.

non-displaced movers (dashed) and displaced workers (solid). The pattern of mobility is very similar for the two groups. Both groups show a robust positive slope. Individuals who make more negative OES changes are more likely to have negative changes in log real wages, while individuals who make more positive moves are more likely to have positive wage growth. The fitted lines show that displaced workers have a negative shift in the relationship between wages and the distance of the OES change, but the slope does not appear to be substantially different.

To quantify this, in Table 9 I regress wages on the interaction between distance of occupational change with indicators for different types of mobility: non-displaced firm changers, displaced firm changers, with firm stayers as the omitted category. As before, I use the log of the change in the OES score. This specification allows the slope of the relationship between the change in the OES score and the change in log real wages to vary based on the type of firm mobility. It also allows the average change in log real wages to differ based on the type of firm mobility. Non-displaced firm changers have steeper slopes, that is, for the same change in OES score, an individual who moves between firms has a bigger change in wages than someone who moves inside the firm. Displaced workers may have steeper slopes, but their point estimates are too noisy to distinguish from internal occupational movers.

Most dramatically we can see displaced workers have a 9% wage loss across the board, regardless of the direction of mobility or the distance of the move. For individuals who make upward moves, the positive return to the change in OES lessens the negative shift, as we saw in Figure 3. For individuals who make negative moves, the change in OES score worsens the losses. Thus, while the sign and magnitude of occupational mobility can explain variation in wage losses within displaced workers, when we compare displaced to non-displaced firm-changers and within-firm occupational changers, there is a robust wage penalty from displacement that is distinct from changes that are associated with occupational sorting.

I conclude that occupational mobility cannot explain the bulk of the losses experienced by displaced workers. While the direction and magnitude of occupation are strongly correlated with the relative magnitude of wage returns to displacement, this pattern is no different from what occurs for non-displaced occupational changers, and while displaced workers are slightly more likely to make negative occupational moves, this can only explain a small fraction of their losses. In the Appendix, I show that this result is robust to propensity re-weighting to account for non-random selection into displacement.

7 Alternative Explanations for Displacement Losses

If occupational sorting cannot explain the wage losses from displacement, what can? In this section, I return to several of the alternative explanations discussed in Section 2. In particular, I will focus on specific capital (firm, occupation, or industry), selection, and job ladders.

I begin with the basic wage change specification from Table 6. In this table, we saw that individuals who were displaced during the last year have wage losses of about 7 percent, compared with wage growth for firm-stayers and non-displaced firm-changers of about 3 percent and 5 percent, respectively. In Table 10 I test the hypothesis that the magnitude of the losses from displacement are due to some omitted characteristic of mobility. If this is the case, including a direct measure of the omitted characteristic should reduce the explanatory power of the displacement indicator. That is, this specification tests the hypothesis that common features of job mobility can explain the losses that displaced workers face compared with non-displaced workers.

I begin by considering various sources of specific capital. If displaced workers have invested in their occupation, firm, or industry, they may be high earners in their position before displacement, but suffer losses after displacement because they cannot find employment in a position that uses their accumulated skills. Although I cannot measure firm, industry, or occupational tenure, I proxy for these moves by constructing indicators for industry and occupational mobility.

In Columns (2) and (3) of Panel (A) in Table 10, I show these measures have no effect on the magnitude of the displacement indicator, continuing to represent about a 10 percentage point decrease in wages compared to firm-stayers. Further, in Table 6 and Table 7 we saw that displaced workers are not particularly high paid before displacement, compared with firm stayers or compared with the median occupational earner. Instead, their losses are due to being exceptionally low paid after displacement. This is inconsistent with displaced workers' losses being driven by lost specific capital.

I next examine the role of selection. In columns (4), (5), and (6) of Panel (A), I include demographic controls, previous occupation fixed effects, and previous industry fixed effects, respectively. This tests whether or not observable characteristics of workers can explain the losses experienced by displaced workers. Here we again see little variation in the coefficient on displacement.

In Columns (7) and (8), I include indicators for whether or not the worker moved to a higher- or lower-wage occupation or a higher- or lower-wage industry.[11] The first measure

[11]This measure is constructed using median industrial wages from the full CPS monthly file.

captures moves up and down the occupational job ladder, which, not surprisingly, has little effect on the displacement indicator. The second measure constructs a job ladder between industries. This serves as a crude measure for job ladders between firms. Nonetheless, this also has no impact on the displacement indicator. Interestingly, the industry job ladder measures do attenuate the magnitude of non-displaced firm changers, suggesting some of the gains from employer change are due to sorting to higher-average pay industries.

In Column (9) I include all the previous controls at once, and in Column (10) I add in fixed effects for the industry and occupation of the new job. Although these 'kitchen sink' regressions are able to reduce the explanatory power of the non-displaced firm-change indicator from a 3.7 percentage point wage premium in the specification without controls in Column (1) to a non-significant 1.4 percentage point premium in Column (10), we continue to see little movement on the displacement coefficient. Thus, I do not find any evidence in the CPS that specific-capital or observable industry and occupational sorting can explain the losses experienced displaced workers, with the caveat that I am unable to measure firm or occupation-specific tenure.

In Panel (B) of Table 10, I turn to an alternative explanation for losses from displacement proposed by Gibbons and Katz (1991) that firms choose to layoff their least productive workers. In this case, other employers will update their beliefs about displaced workers' productivity, leading to lower wage offers for individuals displaced from a partial downsizing versus a complete plant closing. To investigate this mechanism, in each column of Panel (B) I repeat the specification from Panel (A), but now report separate estimates based on whether or not the worker was displaced due to a plant closing or any other reason. Consistent with Gibbons and Katz (1991), we do see a slightly smaller estimate for wage losses for individuals subject to plant closing versus other displacement, with losses ranging from 7 to 8 percentage points for plant closings and ranging from 10 to 11 percentage points for other displacement, however these differences are not statistically distinct. When I add in additional controls, we continue to see a negative displacement effect for both groups that is robust to the battery of controls.

Thus, although papers such as Neal (1995) and Gibbons and Katz (1991) have found that specific capital or selection can explain variation in the losses from displacement between displaced workers, in this section I have demonstrated that the available evidence from the CPS does not support these mechanisms explaining the relative losses from displacement compared with non-displaced workers making observationally similar movements.

8 Discussion

In this paper, I have demonstrated that occupational mobility is only able to explain a small fraction of the losses in hourly wages experienced by re-employed displaced workers within one year of displacement, compared to non-displaced individuals. Nonetheless, I find that occupational mobility is important for understanding wage growth and losses for both displaced and non-displaced workers. Importantly, I show that displaced workers that move up the occupational job ladder appear not to sustain wage losses, however when compared with the average wage gains experienced by non-displaced workers, these workers also experience a 9-11% relative wage loss from displacement.

My findings uncover fundamental differences between occupational job ladders and employer job ladders. First, since as much as 80% of occupational changes occur within firms, it is unlikely that search frictions are the primary driver of aggregate occupational movements. Second, occupational mobility is clearly ranked, with low-earners moving to lower-skill occupations and high-earners moving to higher-skill occupations. This is inconsistent with models based on horizontal differentiation or idiosyncratic match quality. I conclude that occupational mobility is best described by job assignment models, such as Gibbons and Waldman (1999). On the other hand, firm mobility appears to be much better described by frictions such as in the Burdett and Mortensen (1998) model, with slow-recovery from displacement consistent with frictional search. These results indicate the mechanisms driving occupational mobility and employer mobility are distinct and should be modeled accordingly.

These results have implications for a growing macro literature seeking to explain the duration of earnings losses for displaced workers. Beginning with a puzzle raised by Davis and von Wachter (2011) that the workhorse Diamond-Mortensen-Pissardes search model was unable to match the empirical wage loss distribution, several recent papers (including Krolikowski (2016), Jung and Kuhn (2016) and Huckfeldt (2016)) have sought to use frictional job ladder models to explain this puzzle. In order to match the slow recovery in wages after displacement, each paper introduces some source of mismatch: either destruction of match-specific capital (Krolikowski (2016)), or occupation/industry-specific capital (Huckfeldt (2016) and Jung and Kuhn (2016), respectively).

As I have shown that occupational mismatch can only explain a small fraction of the losses experienced by displaced workers, these frictional job ladders are much more likely to be driven by mobility between firms rather than occupations. Nonetheless, the source of this heterogeneity between firms remains an open question, with conflicting results about the role of match or other factors in the literature. In Tables 8 and 10, I show that industry mobility is unable to explain the losses from displacement in the CPS and SIPP sample, suggesting match factors or other unobserved firm characteristics are the most likely culprit.

9 Conclusions

In this paper, I have examined earnings losses for displaced workers in the context of employer and occupational mobility. I find evidence that occupational mobility patterns sort individuals up and down the job ladder, with low-occupational earners more likely to move down the job ladder and high-occupational earners more likely to move up the job ladder. This pattern applies to non-displaced and displaced workers. Further, wage changes after mobility are consistent with the direction of the movement, with individuals who move down the job ladder experiencing relative wage losses and individuals who move up experiencing wage gains. The magnitude of wage change grows with the magnitude of the change in job quality.

For displaced workers, wage changes are shifted down by about 9%, leading displaced workers who move down the job ladder to experience substantial losses and those who move up the job ladder to have diminished wage growth compared with non-displaced workers who make similar changes. I perform a series of Oaxaca-Blinder decompositions, and show occupational mobility can account for about 10% of the losses from displacement.

My findings can inform policy for assisting displaced workers. Since I show that occupational mobility can only explain a small fraction of the losses from displacement, this suggests that focusing on finding re-employment in the same occupation should not be the primary focus of job search assistance, and indeed, many displaced workers are able to make pro-career occupational movements. Instead, search assistance should focus on the two other sources of potential losses: matching with low-wage (or poor match) firms or bargaining. This suggests displaced workers may be helped by additional job search assistance to improve the quality of the match. Further, access to this assistance should continue for some time after accepting post-displacement job to help individuals continue to climb the firm job ladder.

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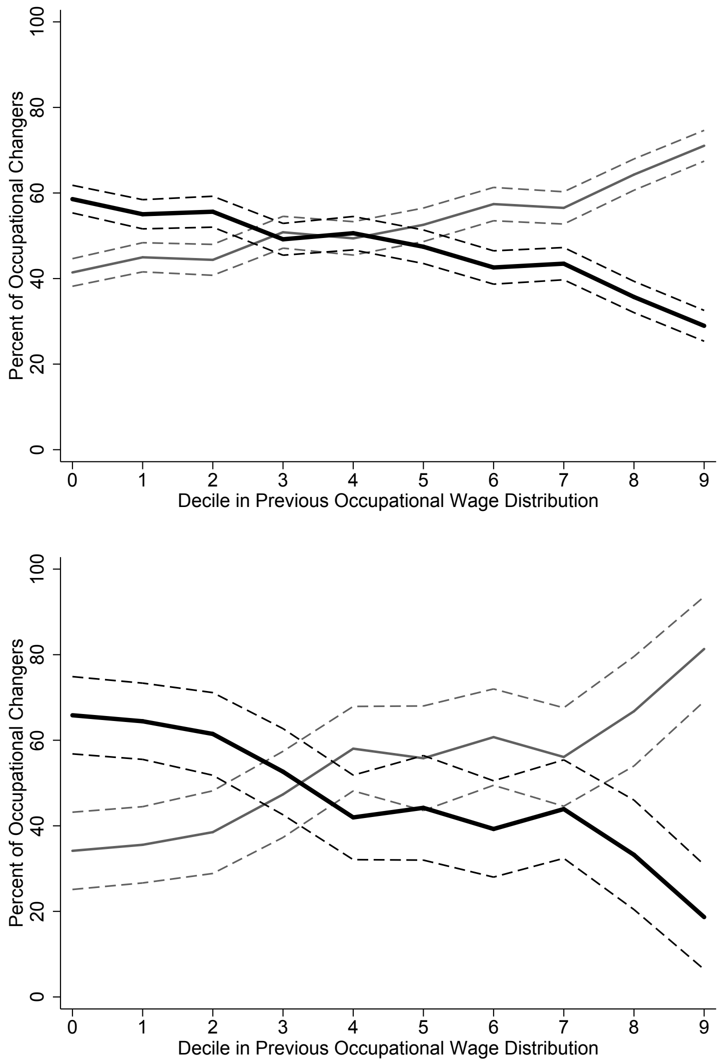

Figure 1: Percent of occupational switchers moving to lower-ranked occupations (black) or higher-ranked occupations (gray), by decile of the occupational wage distribution, for non-displaced (top) and displaced workers (bottom). Displaced estimates uses retrospective occupations from the Displaced Worker Survey. Dashed lines represent 95% confidence intervals.

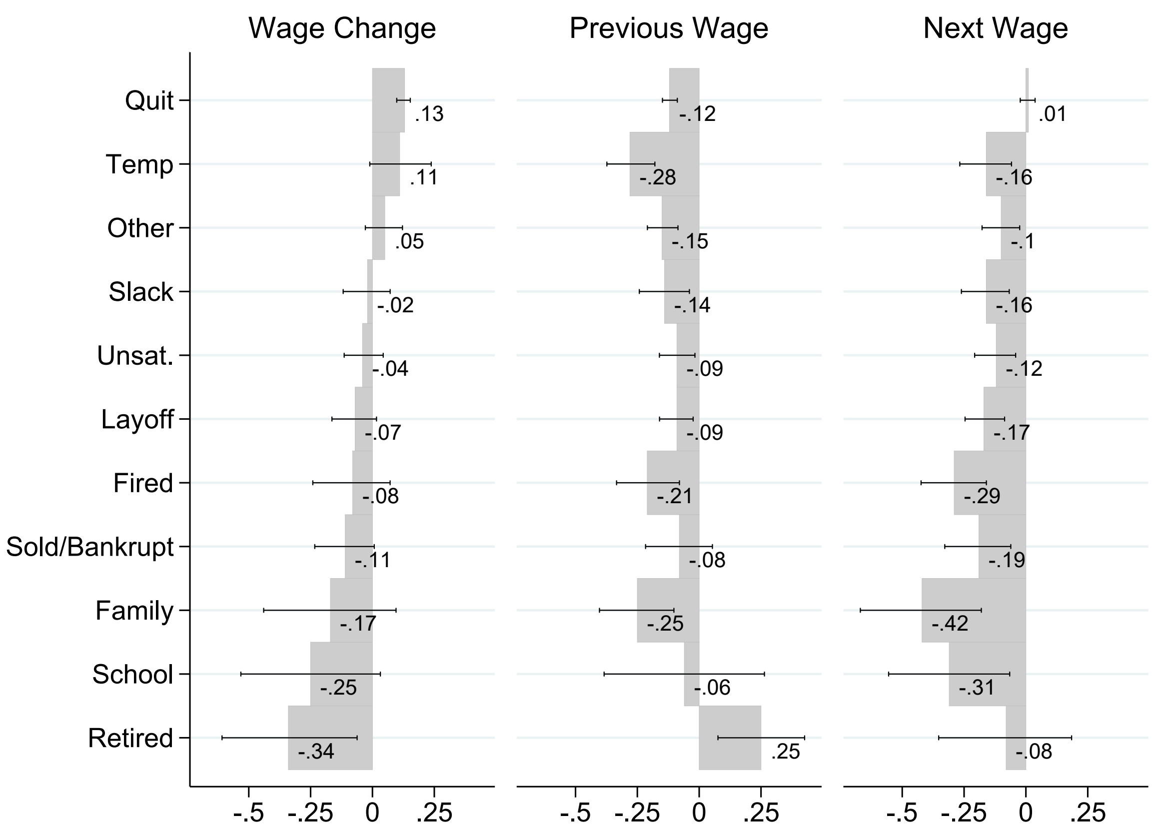

Figure 2: Average wage changes (left), wages in pre-period (middle), and wages in post-period (right) for individuals in the 2008 SIPP, separated by reason for firm change.

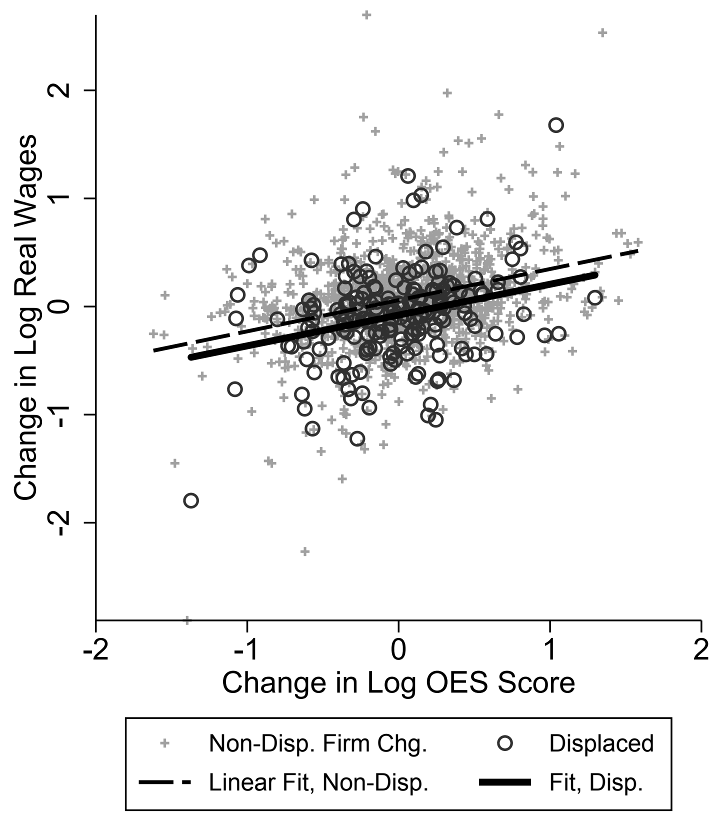

Figure 3: Scatter plot of change in log OES score by change in log real wage for non-displaced firm changers and displaced workers, conditional on changing occupation.

Table 1: Measuring Occupational Mobility

	CPS (12 month)			SIPP (4 Month)	
	Within Firm	Non-Disp. Between	Disp. Between	Non-Disp. Between	Disp. Between
Panel A: Rate of Occupational Change					
Mean	0.434018	0.75634	0.732394	0.678121	0.586364
SD	0.495641	0.429397	0.443492	0.467271	0.493608
N	17,520	2,011	284	3,172	220
Panel B: Share of Occ. Moves that are Negative					
Mean	0.475145	0.446417	0.495192	0.470014	0.542636
SD	0.499415	0.497284	0.501183	0.499216	0.500121
N	7,604	1,521	208	2,151	129
Panel C: Distance of Occupational Change					
Mean	0.01512	0.045892	-0.01366	0.028384	-0.05299
SD	0.442971	0.451256	0.415862	0.516513	0.480865
N	7,604	1,521	208	2,132	129
Panel D: Distance if Positive Move					
Mean	0.33708	0.352381	0.30541	0.409728	0.34275
SD	0.286003	0.303778	0.260064	0.331333	0.29525
N	3,991	842	105	1,121	59
Panel E: Distance if Negative Move					
Mean	-0.34052	-0.33417	-0.33893	-0.39445	-0.38654
SD	0.285699	0.284136	0.265278	0.31746	0.329987
N	3,613	679	103	1,011	70

Summary statistics for occupational mobility measures for employed individuals matched across twelve months (CPS) or four months (SIPP).

Table 2: Wage Returns to Occupational Mobility

	(1)	(2)	(3)	(4)	(5)
		CPS (12 month)		SIPP (4 Month)	
Panel A: Occupational Change					
Occ. Change	0.00268	0.0595	-0.0774	-0.0430	-0.160
	(0.00643)	(0.0223)	(0.0463)	(0.0249)	(0.0745)
Mean of Omitted	0.0265	0.0200	-0.021	0.0924	0.0043
R-sq	0.003	0.022	0.059	0.020	0.126
Panel B: Positive versus Negative Occupational Change					
Neg. Occ. Chg	-0.0336	-0.0307	-0.158	-0.123	-0.252
	(0.00810)	(0.0260)	(0.0582)	(0.0297)	(0.0912)
Pos. Occ. Chg	0.0361	0.135	0.0107	0.0280	-0.0451
	(0.00799)	(0.0244)	(0.0602)	(0.0290)	(0.0947)
Mean of Omitted	0.0265	0.0200	-0.021	0.0924	0.0043
R-sq	0.007	0.054	0.091	0.030	0.143
Panel C: Distance of Occupational Change (Chg. In Log OES score)					
Chg. In Occ. Distance	0.0980	0.242	0.293	0.145	0.275
	(0.0116)	(0.0277)	(0.126)	(0.0329)	(0.113)
Mean of Omitted	0.0275	0.0641	-0.059	0.0684	-0.045
R-sq	0.010	0.074	0.120	0.029	0.137
Panel D: Distance of Occ. Change, Positive vs. Negative					
Chg in Distance if Positive	0.114	0.277	0.315	0.148	0.369
	(0.0177)	(0.0434)	(0.211)	(0.0539)	(0.209)
Chg. In Distance if Negative	0.0806	0.197	0.273	0.141	0.220
	(0.0175)	(0.0454)	(0.157)	(0.0544)	(0.141)
Mean of Omitted	0.0248	0.0541	-0.063	0.0642	-0.055
R-sq	0.010	0.075	0.120	0.029	0.138
N	17520	2011	284	3152	220
Sample	Within Firm	Non-Disp. Between	Disp. Between	Non-Disp. Between	Disp. Between

Coefficients from regressions based on the CPS Tenure supplement and the 2008 SIPP. Robust standard errors in parentheses. See Section 3.3 for more details. Omitted category is workers who were employed at the same firm in both months.

Table 3: Distance from Median Occupational Wages, within Firm

	(1)	(2)	(3)	(4)
	Selection Before Mobility		Selection After Mobility	
Panel A: Occupational Change				
Occ. Change	-0.0147	-0.0122	-0.0213	-0.0221
	(0.00677)	(0.00668)	(0.00670)	(0.00669)
Mean of Omitted	0.0657	0.0657	0.0501	0.0501
R-sq	0.002	0.189	0.003	0.151
Panel B: Positive versus Negative Occupational Change				
Neg. Occ. Chg	-0.0960	-0.0737	0.0579	0.0737
	(0.00847)	(0.00848)	(0.00839)	(0.00843)
Pos. Occ. Chg	0.0596	0.0414	-0.0937	-0.106
	(0.00817)	(0.00798)	(0.00825)	(0.00818)
Mean of Omitted	0.0620	0.0620	0.0538	0.0538
R-sq	0.020	0.197	0.021	0.171
Panel C: Distance of Occupational Change (Chg. In Log OES score)				
Chg. In Occ. Distance	0.204	0.154	-0.219	-0.284
	(0.0120)	(0.0123)	(0.0120)	(0.0126)
Mean of Omitted	0.0551	0.0551	0.0456	0.0456
R-sq	0.026	0.199	0.031	0.186
Panel D: Distance of Occ. Change, Positive vs. Negative				
Chg in Distance if Positive	0.150	0.102	-0.260	-0.302
	(0.0171)	(0.0162)	(0.0176)	(0.0172)
Chg. In Distance if Negative	0.263	0.227	-0.175	-0.259
	(0.0197)	(0.0208)	(0.0190)	(0.0207)
Mean of Omitted	0.0628	0.0628	0.0514	0.0514
R-sq	0.027	0.200	0.032	0.186
Controls	No	Yes	No	Yes
N	17520	17520	17520	17520

Coefficients from regressions based on the CPS Tenure supplement. Robust standard errors in parentheses. See Section 3.3 for more details. Omitted category is workers who were employed at the same firm in both months. The dependent variable is the difference between the individual's wage and the median occupational wage, either before or after the potential mobility event.

Table 4: Distance from Median Occupational Wages, Firm Changers

	(1)	(2)	(3)	(4)
	Selection Before Mobility		Selection After Mobility	
	Panel A: Occupational Change			
Occ. Change	-0.0696	-0.0109	-0.0633	-0.0483
	(0.0256)	(0.0793)	(0.0247)	(0.0679)
Mean of Omitted	-0.023	-0.060	-0.032	-0.131
R-sq	0.326	0.616	0.267	0.634
	Panel B: Positive versus Negative Occupational Change			
Neg. Occ. Chg	-0.106	-0.0756	0.0445	0.0320
	(0.0280)	(0.0940)	(0.0269)	(0.0783)
Pos. Occ. Chg	-0.0422	0.0511	-0.143	-0.125
	(0.0273)	(0.0926)	(0.0278)	(0.0828)
Mean of Omitted	-0.021	-0.064	-0.035	-0.126
R-sq	0.330	0.622	0.301	0.648
	Panel C: Distance of Occupational Change (Chg. In Log OES score)			
Chg. In Occ. Distance	0.114	0.196	-0.262	-0.180
	(0.0278)	(0.148)	(0.0311)	(0.109)
Mean of Omitted	-0.106	-0.035	-0.081	-0.152
R-sq	0.331	0.624	0.311	0.642
	Panel D: Distance of Occ. Change, Positive vs. Negative			
Chg in Distance if Positive	0.0171	0.00718	-0.333	-0.218
	(0.0363)	(0.217)	(0.0408)	(0.136)
Chg. In Distance if Negative	0.322	0.458	-0.110	-0.128
	(0.0628)	(0.223)	(0.0645)	(0.196)
Mean of Omitted	-0.070	-0.050	-0.052	-0.164
R-sq	0.340	0.631	0.316	0.643
Controls	Yes	Yes	Yes	Yes
N	2011	284	2011	284
Sample	Non-Disp. Between	Disp. Between	Non-Disp. Between	Disp. Between

Coefficients from regressions based on the CPS Tenure supplement. Robust standard errors in parentheses. See Section 3.3 for more details. Omitted category is workers who were employed at the same firm in both months. The dependent variable is the difference between the individual's wage and the median occupational wage, either before or after the potential mobility event.

Table 5: Reasons for Firm Mobility

	Total	Share of Firm Movers
CPS:		
Displaced	284	0.15
Non-Displaced	1,655	0.85
Total:	1,939	
SIPP:		
Displaced	233	0.06
Non-Displaced	3317	0.94
Total:	3464	
SIPP Disaggregated:		
Quit to take Another Job	1,827	0.53
Other	409	0.12
On Layoff	385	0.11
Temp Job Ended	172	0.05
Unsatisfactory Work	150	0.04
Slack Conditions$^+$	128	0.04
Fired	115	0.03
Family and Personal Issues	71	0.02
Employer Sold$^+$	68	0.02
Retirement	34	0.01
School	26	0.01
Employer Bankrupt$^+$	24	0.01

Tabulation of reasons for mobility among individuals in the CPS and SIPP samples.
$^+$ indicates categorized as displacement.

Table 6: Wage Returns to Firm Mobility

	(1) W. Chg	(2) W. Chg	(3) Prev. W.	(4) Prev. W.	(5) Next W.	(6) Next W.
Panel A: Aggregated Firm Mobility (CPS)						
Firm Change	0.0190	0.00940	-0.208	-0.130	-0.189	-0.120
	(0.0109)	(0.0111)	(0.0123)	(0.0112)	(0.0124)	(0.0116)
R-sq	0.000	0.004	0.017	0.264	0.014	0.258
Panel B: Disaggregated Firm Mobility (CPS)						
Non-Displaced	0.0395	0.0293	-0.228	-0.136	-0.189	-0.107
	(0.0117)	(0.0119)	(0.0131)	(0.0121)	(0.0135)	(0.0126)
Displaced	-0.0955	-0.0992	-0.0953	-0.0951	-0.191	-0.194
	(0.0265)	(0.0263)	(0.0306)	(0.0267)	(0.0278)	(0.0259)
R-sq	0.002	0.006	0.017	0.264	0.014	0.259
N (CPS)	19459	19459	19459	19459	19459	19459
Mean of Omitted	0.0281	0.0281	2.239	2.239	2.267	2.267
Panel C: Aggregated Firm Mobility (SIPP)						
Firm Change	0.0600	0.0576	-0.194	-0.124	-0.134	-0.0666
	(0.0119)	(0.0119)	(0.0138)	(0.0112)	(0.0143)	(0.0120)
R-sq	0.001	0.001	0.001	0.308	0.001	0.304
Panel D: Disaggregated Firm Mobility (SIPP)						
Non-Displaced	0.0676	0.0652	-0.194	-0.126	-0.126	-0.0609
	(0.0124)	(0.0124)	(0.0143)	(0.0116)	(0.0149)	(0.0125)
Displaced (Non-Slack)	-0.105	-0.106	-0.0322	-0.0321	-0.137	-0.138
	(0.0624)	(0.0624)	(0.0794)	(0.0668)	(0.0837)	(0.0724)
Displaced (Slack)	-0.0217	-0.0232	-0.305	-0.141	-0.326	-0.164
	(0.0485)	(0.0485)	(0.0651)	(0.0516)	(0.0613)	(0.0494)
R-sq	0.001	0.001	0.001	0.308	0.001	0.304
N (SIPP)	257748	257748	257748	257748	257748	257748
Mean of Omitted	0.00198	0.00198	8.125	8.125	8.127	8.127
Controls	No	Yes	No	Yes	No	Yes

Coefficients from regressions based on the CPS Tenure supplement and the 2008 SIPP. Robust standard errors in parentheses. See Section 3.3 for more details. Omitted category is workers who were employed at the same firm in both months.

Table 7: Distance from Median Occupational Wages by Firm Mobility

	(1) Prev. W.	(2) Prev. W.	(3) Next W.	(4) Next W.
Non-Displaced Firm Change	-0.134	-0.0816	-0.128	-0.0758
	(0.0106)	(0.0106)	(0.0109)	(0.0108)
Displaced	-0.0604	-0.0313	-0.147	-0.136
	(0.0420)	(0.0391)	(0.0215)	(0.0216)
N	19459	19459	19459	19459
R-sq	0.011	0.099	0.013	0.102
Worker Controls		Y		Y
Job controls		Y		Y
Mean of Omitted	0.0603	0.0603	0.0427	0.0427

Coefficients from regressions based on the CPS Tenure supplement. Robust standard errors in parentheses. See Section 3.3 for more details. Omitted category is workers who were employed at the same firm in both months.

Table 8: Decompostion of Wage Changes

	CPS: all		CPS: firm movers		SIPP: firm movers	
Non-Displaced	0.028116	(0.003)	0.0375212	(0.007)	0.074317	(0.011)
Displaced	-0.06994	(0.023)	-0.0699354	(0.023)	-0.05947	(0.042)
Difference	0.098051	(0.024)	0.1074567	(0.024)	0.133783	(0.044)
N	22,219		4,648		3,372	
Decomposition 1: Occupational Distance						
Coefficients	0.095543	(0.023)	0.1009995	(0.024)	0.126062	(0.044)
Max % Controls	2.56		6.01		5.77	
Decomposition 2: Before and After Detailed Occupation Fixed Effects						
Coefficients	0.087954	(0.029)	0.0834253	(0.048)	0.130349	(0.044)
Max % Controls	10.3		22.36		2.57	
Decomposition 3: Occ. Distance + Demographic Controls						
Coefficients	0.097472	(0.024)	0.0981167	(0.025)	0.108909	(0.046)
Max % Controls	0.59		8.69		18.59	
Decomposition 4: Occ. FE + Demo Controls						
Coefficients	0.09213	(0.029)	0.0778949	(0.049)	0.111498	(0.046)
Max % Controls	6.04		27.51		16.66	
Decomposition 5: Occ. Distance + Demo Controls + Detailed Industry FE						
Coefficients	0.095472	(0.030)	0.1040116	(0.036)	0.10657	(0.062)
Max % Controls	2.63		3.21		20.34	
Decomposition 6: Occ. FE + Demo Controls + Industry FE						
Coefficients	0.091654	(0.024)	0.1396576	(0.051)	0.106767	(0.062)
Max % Controls	6.52		-29.97		20.19	

Coefficients from Oaxaca-Blinder decompositions based on the CPS Tenure supplement and the 2008 SIPP.

Table 9: Wage Return by Distance of OES Change and Firm Mobility

	(1) Wage Chg.	(2) Wage Chg.	(3) Prev. Wage	(4) Next Wage
Log OES Change	0.0997	0.0980	-0.0464	0.0517
	(0.0116)	(0.0116)	(0.0117)	(0.0119)
Log OES Chg. X Non.Disp.	0.153	0.152	-0.0651	0.0869
	(0.0317)	(0.0317)	(0.0307)	(0.0330)
Log OES Chg. X Displaced	0.197	0.192	-0.0682	0.124
	(0.121)	(0.119)	(0.118)	(0.0765)
Non-Disp. Firm Change	0.0325	0.0237	-0.134	-0.110
	(0.0114)	(0.0116)	(0.0120)	(0.0126)
Displaced	-0.0869	-0.0908	-0.0985	-0.189
	(0.0260)	(0.0257)	(0.0277)	(0.0252)
N	19459	19459	19459	19459
R-sq	0.016	0.019	0.266	0.261
Mean of Omitted	0.0275	0.0275	2.239	2.267

Coefficients from regressions based on the CPS Tenure supplement. Robust standard errors in parentheses. See Section 3.3 for more details. Omitted category is workers who were employed at the same firm in both months.

Table 10: Understanding Sources of Losses from Displacement

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A.: Aggregated Displaced Workers										
Displaced	-0.0961	-0.0981	-0.101	-0.0992	-0.0894	-0.0991	-0.0952	-0.0963	-0.0957	-0.0946
	(0.0263)	(0.0264)	(0.0265)	(0.0263)	(0.0267)	(0.0265)	(0.0260)	(0.0258)	(0.0263)	(0.0240)
Non. Disp. New Firm	0.0372	0.0352	0.0326	0.0293	0.0341	0.0353	0.0342	0.0292	0.0193	0.0139
	(0.0117)	(0.0118)	(0.0122)	(0.0119)	(0.0119)	(0.0119)	(0.0117)	(0.0121)	(0.0126)	(0.0126)
R-sq	0.004	0.004	0.004	0.006	0.039	0.021	0.010	0.008	0.064	0.125
Panel B.: Disaggregated Displaced Workers										
Plant Closing	-0.0761	-0.0777	-0.0799	-0.0795	-0.0748	-0.0719	-0.0696	-0.0781	-0.0687	-0.0860
	(0.0402)	(0.0402)	(0.0403)	(0.0398)	(0.0407)	(0.0405)	(0.0399)	(0.0393)	(0.0398)	(0.0395)
Other. Disp	-0.105	-0.107	-0.110	-0.108	-0.0961	-0.111	-0.107	-0.105	-0.108	-0.0986
	(0.0335)	(0.0335)	(0.0336)	(0.0335)	(0.0339)	(0.0336)	(0.0329)	(0.0327)	(0.0331)	(0.0295)
Non. Disp. New Firm	0.0372	0.0352	0.0325	0.0293	0.0341	0.0353	0.0341	0.0292	0.0193	0.0139
	(0.0117)	(0.0118)	(0.0122)	(0.0119)	(0.0119)	(0.0119)	(0.0117)	(0.0121)	(0.0126)	(0.0126)
R-sq	0.004	0.004	0.004	0.006	0.039	0.021	0.011	0.008	0.064	0.125
N	19459	19459	19459	19459	19459	19459	19459	19459	19459	19459
Mean of Omit.	0.0281	0.0281	0.0281	0.0281	0.0281	0.0281	0.0281	0.0281	0.0281	0.0281
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Occ. Mob.		Y							Y	Y
Ind. Mob.			Y						Y	Y
Demographic				Y					Y	Y
Prev. Occ.					Y				Y	Y
Prev. Ind.						Y			Y	Y
Dir. Occ.							Y		Y	Y
Dir. Ind.								Y	Y	Y
New Occ.										Y
New Ind.										Y

Coefficients from regressions based on the CPS Tenure supplement. Robust standard errors in parentheses. See Section 3.3 for more details. Omitted category is workers who were employed at the same firm in both months.

10 Appendix

A.1 Summary Statistics

Table A.1: Data Description, Monthly CPS Sample

	Firm Stayers	Btwn.
	Mean	Mean
Age	41.61	37.07
	(13.41)	(14.14)
Years Sch.	13.70	13.36
	(2.76)	(2.70)
Experience	21.91	17.71
	(13.40)	(13.86)
Share Female	0.48	0.47
	(0.50)	(0.50)
Share Non-white	0.15	0.14
	(0.35)	(0.35)
OES Index (month 1)	19.58	17.17
	(11.16)	(10.07)
Log Real Hourly Wage (month 2)	2.19	2.04
	(0.49)	(0.50)
N	10,863,076	254,359
N, wages	1,922,178	49,040

Standard deviations in parenthesis.

Table A.2: Data Description, CPS Tenure Supplement Sample

	Firm Stayers	Non-Disp. Btwn	Displaced	Retro., Displaced
Age	41.91	34.72	37.05	37.47
	(13.20)	(12.62)	(11.52)	(12.40)
Years Sch	12.75	12.81	12.62	12.62
	(2.15)	(1.84)	(1.96)	(2.07)
Experience	23.16	15.91	18.42	18.86
	(13.31)	(12.73)	(11.66)	(12.49)
Share Female	0.53	0.55	0.44	0.43
	(0.50)	(0.50)	(0.50)	(0.50)
Share Non-white	0.15	0.15	0.14	0.15
	(0.36)	(0.36)	(0.34)	(0.36)
OES Index	15.45	13.88	14.14	14.71
	(7.18)	(6.10)	(6.06)	(6.22)
Log Real Hourly Wages	2.25	2.03	2.17	3.26
	(0.48)	(0.45)	(0.45)	(2.01)
N	17,520	1,655	284	2,930

Standard deviations in parenthesis. The first three columns use the contemporaneous matched sample, while the third column uses the Displaced Workers Supplement data with retrospective occupation and wage data.

Table A.3: Data Description, 2008 SIPP

	Firm Stayers	Non-Disp. Between	Displaced
Age	43.95	37.21	41.11
	(11.96)	(11.52)	(12.22)
Yrs School	14.21	14.26	13.2
	(2.68)	(2.67)	(2.68)
Potential Experience	23.74	16.95	21.91
	(12.18)	(11.69)	(11.87)
Share Female	0.46	0.41	0.25
	(0.5)	(0.49)	(0.43)
Share Non-White	0.18	0.17	0.16
	(0.39)	(0.37)	(0.37)
OES Index	20.81	19.91	19.18
	(11.27)	(11.3)	(9.91)
Log Real Wages	8.13	7.93	7.94
	(0.66)	(0.71)	(0.71)
N	254,356	3,172	220

Standard deviations in parenthesis.

A.2 Additional Tables

Table A.4: Wage Returns by Reason for Firm Mobility

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Detailed Firm Mobility (CPS)					
	W. Chg	Prev. W.	Prev. W.	Next W.	Next W.	
Non-displaced	0.0395	0.0293	-0.228	-0.136	-0.189	-0.107
	(0.0117)	(0.0119)	(0.0131)	(0.0121)	(0.0135)	(0.0126)
Plant closed	-0.0741	-0.0795	-0.112	-0.0838	-0.186	-0.163
	(0.0401)	(0.0398)	(0.0525)	(0.0444)	(0.0483)	(0.0456)
Insufficient Work	-0.0997	-0.103	-0.112	-0.111	-0.212	-0.214
	(0.0420)	(0.0416)	(0.0449)	(0.0414)	(0.0383)	(0.0372)
Position/Shift Abolished	-0.119	-0.122	-0.0259	-0.0718	-0.145	-0.193
	(0.0535)	(0.0535)	(0.0653)	(0.0490)	(0.0681)	(0.0557)
N	19459	19459	19459	19459	19459	19459
R-sq	0.002	0.006	0.018	0.264	0.014	0.259
Mean of Omitted	0.0281	0.0281	2.239	2.239	2.267	2.267
	Panel B: Detailed Firm Mobility (SIPP)					
On Layoff	-0.0712	-0.0737	-0.237	-0.0924	-0.308	-0.166
	(0.0460)	(0.0460)	(0.0381)	(0.0347)	(0.0432)	(0.0408)
Retirement	-0.335	-0.335	0.357	0.251	0.0217	-0.0839
	(0.139)	(0.139)	(0.130)	(0.0894)	(0.167)	(0.137)
Family and Personal Issues	-0.172	-0.172	-0.311	-0.253	-0.482	-0.425
	(0.136)	(0.137)	(0.0918)	(0.0768)	(0.122)	(0.125)
School	-0.243	-0.250	-0.254	-0.0602	-0.497	-0.310
	(0.144)	(0.144)	(0.188)	(0.165)	(0.159)	(0.125)
Fired	-0.0830	-0.0848	-0.365	-0.207	-0.448	-0.292
	(0.0799)	(0.0798)	(0.0787)	(0.0649)	(0.0787)	(0.0674)
Firm Sold/Bankrupt	-0.111	-0.113	-0.120	-0.0816	-0.231	-0.195
	(0.0614)	(0.0613)	(0.0805)	(0.0689)	(0.0793)	(0.0681)
Temp Job Ended	0.117	0.113	-0.392	-0.276	-0.275	-0.163
	(0.0634)	(0.0633)	(0.0601)	(0.0495)	(0.0589)	(0.0533)
Quit to take Another Job	0.128	0.126	-0.160	-0.118	-0.0319	0.00714
	(0.0140)	(0.0140)	(0.0192)	(0.0154)	(0.0191)	(0.0153)
Slack Conditions	-0.0217	-0.0234	-0.305	-0.141	-0.327	-0.164
	(0.0485)	(0.0485)	(0.0651)	(0.0516)	(0.0613)	(0.0494)
Unsatisfactory Work	-0.0330	-0.0354	-0.198	-0.0889	-0.231	-0.124
	(0.0403)	(0.0403)	(0.0496)	(0.0366)	(0.0532)	(0.0423)
Other	0.0482	0.0464	-0.209	-0.148	-0.160	-0.101
	(0.0383)	(0.0383)	(0.0386)	(0.0315)	(0.0443)	(0.0388)
N	257748	257748	257748	257748	257748	257748
R-sq	0.002	0.003	0.001	0.308	0.001	0.304
Mean of Omitted	0.00198	0.00198	8.125	8.125	8.127	8.127

A.3 Selection into Displacement

In this Appendix, I more thoroughly investigate the counterfactual wages for displaced workers. I begin by evaluating the rate of upward and downward occupational mobility for displaced workers compared with non-displaced workers. In the absence of displacement, most displaced workers would have remained at the same employer while some would have changed employers. Thus, in contrast to the specifications in the main body of the text, I now combine firm stayers and non-displaced firm-changers to create a single comparison group for displaced workers.

In Table 1, I showed that displaced workers have only modestly higher rates of downward occupational mobility. In Table A.5, I investigate whether this is due to differences between the samples of displaced and non-displaced workers. I accomplish this in two ways. In the first column, I regress an indicator for upward occupational mobility on whether or not the worker was displaced. In the second column, I include the standard demographic controls I include in other specifications, using age, gender, race, education and year fixed effects. In the third column, I instead use inverse probability weighting methodology to adjust for differences in the propensity to be displaced across demographic characteristics. In this two step procedure, I first estimate the probability of displacement using the same demographic controls under a logit model, and then regress the rate of upward mobility on this reweighted specification. In Columns 4 through 6 I repeat the exercise for downward occupational mobility.

Across specifications, even after adjusting for demographic differences between displaced and non-displaced individuals, the estimates for increased upward and downward occupational mobility are similar across specifications. This is consistent with the raw results in Table 1. The probability re-weighting leads to modestly smaller estimates for upward mobility and modestly larger estimates for downward mobility. Displacement does lead to an increase in occupational mobility compared to non-displaced individuals, although the magnitude of downward mobility is larger than that of upward mobility. Thus, there is evidence of a modest increase in negative reallocations for displaced workers.

Since most non-displaced individuals do not change employers, in Panel B of Table A.5, I restrict the sample to individuals who change employers. Since displacement by definition leads individuals to change employers, this panel answers the question of whether displaced individuals experience excessive occupational reallocations compared with individuals who change employers but are not displaced. Displaced individuals are slightly less likely to move to higher-ranked occupations compared with non-displaced firm-changers, and slightly more likely to move to lower-ranked occupations, however none of the estimates are statistically significant. Moreover, adjusting for demographic differences between the samples results in little change in the estimates. Thus, again there is modest evidence that displaced workers are somewhat more likely to make downward occupational moves. Nonetheless, we still see large fractions of displaced workers make upward occupational moves.

Table A.5: Estimated Rates of Occupational Mobility

	(1)	(2)	(3)	(4)	(5)	(6)
	Upward Occ. Move			Downward Occ. Move		
			Panel A: All Workers			
Displaced Workers	0.107	0.0994	0.0835	0.161	0.158	0.178
	(0.0323)	(0.0319)	(0.0331)	(0.0332)	(0.0333)	(0.0350)
Constant	0.245	0.370	0.246	0.222	0.226	0.222
	(0.00357)	(0.0182)	(0.00357)	(0.00345)	(0.0172)	(0.00345)
N	19435	19435	19435	19435	19435	19435
			Panel B: Firm-Changers			
Displaced Workers	-0.0512	-0.0215	-0.0359	0.0379	0.0373	0.0378
	(0.0349)	(0.0351)	(0.0385)	(0.0356)	(0.0362)	(0.0391)
Constant	0.404	0.556	0.398	0.345	0.388	0.345
	(0.0138)	(0.0619)	(0.0137)	(0.0133)	(0.0616)	(0.0133)
N	1939	1939	1939	1939	1939	1939
Controls?		Yes			Yes	
Propensity Re-weighting?			Yes			Yes

Coefficients from regressions based on the CPS Tenure supplement. The omitted category is individuals who were not displaced. Robust standard errors in parentheses.

In Table A.6, I compare the estimated rates of upward and downward occupational mobility for displaced workers with the raw data from Table 1, using the propensity score re-weighted estimates. Adjusting for demographic differences between samples leads to a somewhat larger rate of downward mobility and a somewhat smaller rate of upward mobility for displaced workers than the raw data, but the estimates are quite similar, indicating that differences in observable characteristics are not leading to spuriously similar rates of occupational mobility for displaced and non-displaced individuals.

Table A.6: Comparing Rates of Occupational Mobility for Displaced

	Raw Data	Estimated Using All Employed	Estimated Using Firm Changers
Same Occ.	0.268	0.271	0.255
Down	0.363	0.400	0.383
Up	0.370	0.330	0.362

Next, I want to estimate the real wage changes associated with displacement for upward and downward occupational movers, again comparing between displaced individuals and the aggregated measure of non-displaced. In Table A.7, I regress change in real log wages for individuals based on the type of occupational move they made and whether or not they were displaced. Adjusting for demographic differences between groups and propensity reweighting makes little different in the point estimates.

Table A.7: Wage Returns Occupational Mobility, Displaced and Non-Displaced

	(1)	(2)	(3)
Panel A: All Workers			
Down Non-Displaced	-0.0346	-0.0364	-0.0348
	(0.00774)	(0.00774)	(0.00771)
Up, Non-Displaced	0.0521	0.0488	0.0463
	(0.00764)	(0.00758)	(0.00757)
Same Occ, Displaced	-0.0486	-0.0515	-0.0358
	(0.0341)	(0.0341)	(0.0232)
Down, Displaced	-0.192	-0.194	-0.220
	(0.0430)	(0.0429)	(0.0535)
Up, Displaced	-0.0218	-0.0281	-0.0640
	(0.0509)	(0.0500)	(0.0408)
Constant	0.0267	0.0869	0.0274
	(0.00415)	(0.0134)	(0.00413)
N	19389	19389	19389
Panel B: Firm-Changers			
Down Non-Displaced	-0.0399	-0.0481	-0.0508
	(0.0284)	(0.0287)	(0.0270)
Up, Non-Displaced	0.139	0.132	0.129
	(0.0268)	(0.0268)	(0.0255)
Same Occ, Displaced	-0.0477	-0.0445	-0.0441
	(0.0395)	(0.0403)	(0.0293)
Down, Displaced	-0.191	-0.183	-0.195
	(0.0474)	(0.0476)	(0.0641)
Up, Displaced	-0.0209	-0.0194	-0.0325
	(0.0548)	(0.0546)	(0.0501)
Constant	0.0258	0.0938	0.0325
	(0.0204)	(0.0513)	(0.0184)
N	1937	1937	1937
Controls?		Yes	
Propensity Weighting?			Yes

Coefficients from regressions based on the CPS Tenure supplement. The omitted category is individuals who were not displaced and did not change occupations. Robust standard errors in parentheses.

I can now use these estimates to calculate the counterfactual wage change for displaced individuals. In particular, I use the estimated rates of upward and downward mobility for displaced workers from Table A.5 along with estimates of the wage return from occupational mobility from Table A.7. First, using the estimated mobility rates for displaced workers and the estimated wage changes for each type of occupational mobility for displaced workers, the predicted change in real log wages is a 9 percent loss compared with non-displaced individuals. If instead displaced individuals had the same wage returns from occupational mobility as non-displaced individuals, holding the distribution of occupational moves fixed, they would have real wage gains of 3 percent on average. These results are similar to the estimates in the main text, and indicate that even after adjusting for observable differences between displaced and non-displaced workers, occupational mobility cannot account for the wage losses experienced by displaced workers.

A.4 Replicating Robinson 2018

In this Appendix, I show that task-based measures of the distance of occupational mobility are also unable to account for the losses from displacement. I use a methodology similar to Poletaev and Robinson (2008) and Robinson (2018), to collapse high-dimensional task-based characteristics of occupations into a few factors, using principal component analysis (PCA). However, instead of using the Dictionary of Occupational Titles, which was discontinued in 1999, I update the analysis using the successor program, O NET. This methodology is described in detail in Forsythe (2019). Briefly, I use 277 occupational descriptors coded by O NET for over 900 occupations. Using PCA, I construct two variables that explain the most variation. $ONET_Q1$, explains the largest share of the variation in occupational characteristics, and is equivalent to Robinson (2018) largest index, which he calls 'Analytic'. Variables that are highly weighted in this index include written expression, reading comprehension, judgement, and decision-making. Occupations with high scores include CEOs, neurologists, and judges. The second largest factor, $ONET_V2$ is equivalent to Robinson (2018) second index, which he calls 'Fine Motor'. Variables with a high weight in this index include visualization ability, operation monitoring, and quality control analysis. Occupations that receive high scores include pilots, surgeons, and forest firefighters.

In order to compare these two variables with the main ranking I have used in this paper, the median OES occupational wage, I normalize each variable have a mean of zero and a standard deviation of one. In Table A.8, I show how the average change in each of these three scores varies by firm mobility. On average, firm-stayers make positive moves across all three scores, with magnitudes of 0.017 for OES, 0.023 for ONET Q1, and 0.016 for ONET Q2.

Between firm movers have somewhat larger estimates across the three measures. Finally, for both the OES distance and the ONET Q1 distance, the average change for displaced workers is negative. This is consistent with Robinson (2018), who also finds a negative change in the analytic factor for displaced workers. However, Robinson (2018) also finds a negative change on his second index, while I find no effect. In addition, I find smaller magnitudes of changes, which could be due to differences in normalizing and weighting.

Table A.8: Summary of Occupational Distance Measures

	Within Firm	Non-Disp. Between	Disp. Between
OES Distance	0.017	0.055	-0.012
SD	0.50	0.58	0.53
ONET Q1 Distance	0.023	0.037	-0.030
SD	0.56	0.79	0.81
ONET Q2 Distance	0.016	0.064	0.0032
SD	0.74	0.99	0.94
N	17,520	2,011	284

In order to understand if these measures have a different relationship with wages than the OES distance measure I have focused on, I next replicate Table 2, to see the relationship between the change in these quality scores and wage growth. Column 1 shows that a 1 standard deviation increase in the ONET Q1 score is correlated with a 4% real wage growth, while for the ONET Q2 score it is correlated with a 3% real wage growth. There is a somewhat stronger association for the OES score, of about 6% wage growth. Finally, when I include all three measures, most of the variation loads on the OES score. This suggests that the ONET Q1 score and the OES score are highly co-linear.

Table A.9: Wage Returns Across Occupational Distance Measures

	(1)	(2)	(3)	(4)
Change in ONET Q1	0.0409			0.0123
	(0.00560)			(0.00724)
Change in ONET Q2		0.0334		0.0193
		(0.00426)		(0.00457)
Change in OES			0.0625	0.0405
			(0.00646)	(0.00873)
Constant	0.0292	0.0294	0.0288	0.0286
	(0.00306)	(0.00306)	(0.00305)	(0.00305)
N	19459	19459	19451	19451
R-sq	0.004	0.005	0.007	0.009

Finally, in Table A.10, I replicate the decomposition from Table 8, but perform a new decomposition, where I control for the two task-based occupational distances. These measures explain slightly less than the OES wage based metrics, and can explain at most 5% of the wage gap between displaced and non-displaced individuals. Thus, although it is true that displaced workers are somewhat more likely to make negative occupational changes across measures, it is not enough to explain more than a small fraction of the losses from displacement.

Table A.10: Wage Decomposition Using Task-Based Distance

	CPS: all		CPS: firm movers	
Non-Displaced	0.028116	(0.003)	0.0375212	(0.007)
Displaced	-0.06994	(0.023)	-0.0699354	(0.023)
Difference	0.098051	(0.024)	0.1074567	(0.024)
N	22,219		4,648	
Decomposition 1: Occupational Distance				
Coefficients	0.095543	(0.0229546)	0.101	(0.0236568)
Max. % Attributable to Controls	2.56		6.01	
New Decomposition: Task-Based Distance				
Coefficients	0.095759	(0.023417)	0.102498	(0.024344)
Max.% Attributable to Controls	2.34		4.62	