IZA Institute of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 16682

Occupational Job Ladders within and between Firms

Eliza Forsythe

DECEMBER 2023

I Z A Institute of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 16682

Occupational Job Ladders within and between Firms

Eliza Forsythe
University of Illinois at Urbana-Champaign and IZA

DECEMBER 2023

ISSN: 2365-9793

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Occupational Job Ladders within and between Firms*

I present four facts about occupational mobility: (1) most movements occur within firms, (2) downward moves are frequent, (3) wage growth reflects the direction and distance of mobility, and (4) relative occupational wages before mobility predict the direction of mobility, except for non-displaced movers between firms. I show these facts are consistent with models of vertical sorting. I show that non-displaced movements between firms obscure the positive selection of upward occupational movers, likely reflecting moves up a firm-wage job ladder. Displaced workers show similar predisplacement selection to internal movers, with pre-displacement occupational wage rank predicting the direction of occupational mobility.

JEL Classification: J31, J62, J63, M51

Keywords: job mobility, job ladders, displaced workers

Corresponding author:
Eliza Forsythe
University of Illinois at Urbana-Champaign
School of Labor and Employment Relations and Department of Economics
901 West Illinois Street
Urbana
IL 61801
USA

E-mail: eforsyth@illinois.edu

* Thanks to Bart Hobijn, Lisa Kahn, John Haltiwanger, Gueorgui Kambourov, Pawel Krolikowski, Marta Lachowska, Fabian Lange, Kathryn Shaw, and Evan Starr for helpful discussion, seminar participants at the Bureau of Labor Statistics, Brigham Young University, the University of Minnesota, the Saint Louis Fed, the Census Bureau, and Purdue University, as well as audience members at the IZA Junior/Senior Labor Symposium, the NBER Summer Institute, the Wharton People and Organizations Conference, the Society of Labor Economists Meeting, the IZA/SOLE Transatlantic Meeting of Labor Economics, the NBER Organizational Economics Meeting, and the SF Fed Micro Macro Labor Economics Conference. Aibak Hafeez, Juan Muñoz, and Yueyuan Yu provided excellent research assistance. An earlier version of this paper circulated under the title "Occupational Job Ladders and Displaced Workers".

1 Introduction

Job mobility is an important source of wage growth,[1] but involuntary job loss is associated with substantial earnings losses that can persist for decades.[2] Understanding the mechanisms behind voluntary mobility is important for several reasons. First, job mobility factors prominently in modern macroeconomic models to explain how the labor market responds to aggregate and reallocation shocks. Recent papers have employed a variety of mechanisms, including match-specific capital (Krolikowski, 2016) and occupation/industry-specific capital (Jung & Kuhn, 2019; Huckfeldt, 2016). Different modeling choices have different aggregate and individual implications, thus a clearer understanding of the mechanisms provides an important input to this literature. Second, individuals are subject to a variety of reallocation shocks, ranging from economic downturns, trade shocks, and other displacement events. A clear description of how typical careers unfold is a crucial policy input to assist individuals recovering from these adverse events.

In this paper, I focus on measuring occupational mobility and the wage returns in the United States. Occupations provide a description of the tasks an individual performs, and allows for common measurement of job mobility both within and between firms. 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 document the following facts: (1) most occupational movements occur within firms, (2) moves down the occupational job ladder are frequent (both within and between firms), (3) wage growth reflects the direction and distance of mobility, and (4) downward occupational

[1] cf. Topel and Ward (1992).

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

movers are negatively selected (and positive occupational movers are positively selected), except for non-displaced workers who move between firms. Moreover, after mobility, downward occupational movers are high paid for their new positions, while upward occupational movers are low paid for their new positions.

I compare these fact patterns with predictions from three classes of models that are frequently used to explain job mobility: models of congested search or slot-constraints within firms (Burdett & Mortensen, 1998; Demougin & Siow, 1994), models of horizontal sorting across jobs with learning about fit on-the-job (Jovanovic, 1979), and finally models of vertical sorting and learning or human capital accumulation/depreciation (Gibbons & Waldman, 1999). I conclude the fact pattern is uniquely consistent with vertical sorting.

However, I find that the selection patterns for non-displaced between-firm occupational movers reveals that between-firm movers appear to be negatively selected, even for upward occupational movers. In contrast, pre-displacement occupational earnings predict the direction of occupational mobility for displaced workers. This is consistent with high-ability workers at low-wage firms voluntarily leaving to climb a firm-wage or productivity job ladder (J. C. Haltiwanger, Hyatt, Kahn, & McEntarfer, 2018), while involuntary movers exhibit no such selection. Thus, voluntary employer mobility obscures the sorting properties of occupational job ladders.

In addition, I find over 1/3 of displaced workers move up the occupational job ladder upon re-employment. Among displaced workers, wage losses are largest for individuals who move down the occupational job ladder and smallest for those who move up. Nonetheless, wage growth is substantially slower for upward moving displaced movers compared with non-displaced making similar moves. Thus, while the direction of occupational mobility can explain some of the losses for displaced workers, it cannot explain the relative losses for displaced workers that move up the occupational job ladder.

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 is restricted. I find very similar results using complementary data from the SIPP.

My findings indicate that average wage growth masks the fact that downward moves are not rare. 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.

A 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. This is particularly an issue for measuring the level of occupational mobility.[3]. However, for the purposes of this paper, the issue is somewhat less severe. Since most individuals do not change occupations, spurious mobility attenuates estimates of wage returns to occupational mobility. However, since this measurement error is not correlated with the type of employer mobility, it will not bias estimates of relative returns by type of firm mobility. Thus, wage estimates should be taken as a lower-bound of the magnitude of the true return to mobility. In addition, I show that estimates are consistent with the Danish administrative data examined by Groes, Kircher, and Manovskii (2013) and Frederiksen,

[3]See Lehn, Ellsworth, and Kroff (2021) for a detailed treatment and solution for recovering the true level of occupational mobility in the CPS. See also Kambourov and Manovskii (2008) and Kambourov and Manovskii (2009a) who examine similar issues using the PSID

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[4] demonstrate how workers can find higher earnings and better matches by moving between jobs. Recent work has emphasised that the magnitude of these 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, Haltiwanger, and McEntarfer (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.

2 Theories of Occupational Mobility

There are three primary reasons why individuals may change occupations. First, there may be congestion in the search process (Burdett & Mortensen, 1998) or slot-constraints within the firm (Demougin & Siow, 1994). Both processes prevent individuals from immediately transitioning to their most preferred match. Second, there may be horizontal sorting across occupations, and workers may learn on-the-job whether or not they are a good fit. If they get good news, they will continue to invest in occupation and stay put (cf. Shaw

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

(1984)). However, if they learn it is not a good fit, they may choose to try another career path (e.g. Papageorgiou (2014)). Third, there may be general human capital and ability that leads workers to sort between occupations vertically, with the highest ability workers optimally matching with high-ranked occupations (cf. Gibbons and Waldman (1999)). In this case, as workers gain skills or learn about their ability, they will move up or down the occupation ladder.

Each class of models leads to different empirical predictions about the direction of mobility and sorting. In the case of congestion, we would not expect workers to make negative occupational moves and we would expect wages to increase upon mobility. In the case of horizontal learning and sorting, we would expect occupational movers to be negatively selected from their prior occupation, since individuals will only move if they find out the job is not a good fit. Further, they are likely to be low earners in their new occupation, since they are unable to transfer skills and investments across occupations.

Finally, in the case of a vertical job ladder, we may see upward or downward mobility, depending on the learning process and human capital accumulation and decay. 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. This relationship flips after mobility, 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.

All three classes of models lead to different predictions about what may happen after an exogenous job displacement shock. If the labor market is relatively efficient, individuals should quickly be able to return to their optimal match. If there are switching costs that slow down voluntary sorting, the exogenous shock may even induce efficient reallocations. However, if there is congestion and incomplete information in the labor market, job seekers may struggle to match with their optimal occupation, and instead match with a job for which they are less-well suited. In the case of horizontal sorting, this may result in the destruction of specific human capital and long-term earnings losses. On the other hand, in the case of vertical sorting, individuals will be able to use accumulated human capital and again climb the occupational job ladder.

Thus, the observation of occupational mobility after an exogenous job displacement shock is not enough to conclude inefficient occupational reallocations. Instead, it must be compared to mobility for similar non-displaced workers. By measuring the frequency of upward and downward mobility, the prevalence of mobility within versus between firms, and the corresponding wage changes associated with different types of mobility, I will be able to distinguish between these theories of occupational mobility.

3 Methodology

The primary data source is monthly CPS survey data (1994-2016) matched with the CPS Tenure and Displaced Worker Supplements (DWS).[5] 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.[6] 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. To complement the analysis from the CPS, I also use data from the 2008 Survey of Income and Program Participation (SIPP).[7] The data sources are described in detail in the Appendix.

[5](Bureau of Labor Statistics, 2016)

[6]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.

[7](U.S. Census Bureau, 2008)

3.1 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)[8], 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.

3.2 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 and with the lowest 1% of earnings winsorized. In addition, I inflate top-coded

[8]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.

earnings by a factor of 1.4 ((Lemieux, 2006)). It is important to note that this is the hourly wage, so does not include overtime, bonus payments, or severance pay. 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 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.[9] In regressions in which the dependent variable is wages before mobility (or the change in wages), job controls 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.

3.3 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 43% 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.[10] Thus the extent

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

[10]This is consistent with Kambourov and Manovskii (2009b) who find robust results of wage returns to occupational tenure when varying the definition of mobility to either exclude more spurious mobility (but also excluding more valid changes) or to include more valid changes (but also including more spurious mobility).

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.

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% 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 3.3, self-reported occupational data introduces substantial spurious occupational mobility, thus these estimates are 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 report differences in occupational mobility within firms versus between firms, I derive rates using data reported in their Appendix Tables 1 and 2. I calculate the Danish within-firm mobility occupational mobility rate is 14% while the between-firm mobility rate is 36%. Nonetheless, since only 20% of individual change firms a year, 62% of occupational changes in Denmark occur within firms.

Fact 2: Moves Down the Occupational Job Ladder are Frequent

I next turn to the direction of occupational mobility. As discussed in Section 3.1, 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 48% of internal movers moving down, 40% of non-displaced between firm movers moving down, and 50% 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 (which includes displaced and non-displaced individuals). Nonetheless, rates of downward mobility are substantially larger than estimates of demotion rates within firms from the personnel literature.[11] This may be due to occupational transitions including lateral moves that would not necessarily be considered a demotion, but implies occupational mobility is a broader measure than firm promotion hierarchies.[12]

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 in rank, with positive movers gaining about 33 log points in rank, and negative movers losing

[11] 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.

[12] Further, employers may label movements promotions if they are accompanied with a wage increase, even if the job duties of the job are unchanged (Van der Klaauw & Da Silva, 2011). Occupation-based measures should avoid this issue.

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.

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 3.2. 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 3.1% slower than occupation-stayers, while those that move up the job ladder experience wage growth that is 3.7% faster than occupation-stayers. Thus, average wage growth can be ranked based on the direction of moves up and down the occupational job ladder: 0.4% wage losses for downward moves, 2.7% wage growth for occupation-stayers and 6.3% 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 9.4% wage increase for occupational changers inside firms. Thus, while the wage changes grow with 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.[13]

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 (11.2%) compared with downward movers (7.4%), although these estimates are not statistically distinct. This suggests that wages may be stickier on the downside. In addition, the fact that we see that the magnitude of wage changes grow with the magnitude of the occupational distance change provides further evidence that there is content to these occupational

[13]See Gibbons and Waldman (1999) for a review of this literature reporting this fact.

changes, despite the noise from measurement error.

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. Alternatively, it could be that moving employers is costly, so employers have to compensate external hires for them to be willing to move.

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 17.5% 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 0.4% in the CPS sample and 3.1% in the SIPP sample, which are equal or slightly larger losses than that of downward movers within the firm (0.4%).

Similarly, moves up the occupational job ladder are associated with wage gains for non-displaced firm changers, with wage gains of 14.7% (CPS) and 12.0% (SIPP), dwarfing the wage gains of 6.3% within firms. In contrast, upward moving displaced workers experience wage losses of 2.0% (CPS) and 4.1% (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.

Fact 4: The Direction of Occupational Mobility Reflects Pre-Mobility Wage Rank for Internal and Displaced Movers, But Not for Non-Displaced Firm-Changers

In this section, I test how *ex ante* and *ex post* selection varies with mobility. To measure selection, I estimate the gap between an individual's wage and the median log hourly wage for all individuals employed in the same occupation that year in the CPS. This specification is described in detail in section 3.2.

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 1.3% 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 10.0% above median occupational wages before moving. Thus, the selection of upward and downward movers is consistent with sorting based on *ex ante* 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 12.9% higher wages than median occupational wages for their new position, while individuals who moved up now earn 5.7% 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. These patterns for upward mobility are consistent with promotion evidence from personnel data, such as in Baker et al. (1994b). 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.

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, non-displaced movers that make a positive occupational move between firms have negative and insignificant point estimates, which is inconsistent with the positive selection we saw within firms. 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 move down between firms are more strongly negatively selected than those who move down within firms. Thus, in net, while many 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. However, unlike Groes et al. (2013), I am able to separate firm-changers into displaced and non-displaced, to illustrate how selection patterns differ.

Panel A shows mobility for occupational movers within the firm, and reveals remarkably similar patterns to the administrative data in Groes et al. (2013), with rates of upward mobility beginning around 40% for the lowest decile and rising to a high of over 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, described in Appendix A.1. 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.

Finally, in Panel C, I restrict the sample to individuals who changed firms but do not report being displaced. Here we see a very different pattern. Individuals in the bottom 3 deciles are roughly equally likely to make positive or negative occupational moves, however for all higher deciles individuals are more likely to move to higher ranked occupations than lower ranked occupations. Thus, consistent with Table 4, the relationship between pre-mobility wage rank and the direction of mobility is weaker for non-displaced firm-changers.

Discussion

Now that I have documented these four facts about occupational mobility, I return to the three candidate theories from Section 2: congestion/slot-constraints, horizontal learning and sorting, and vertical job assignment.

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. While it could be the case that slot-constraints within the firm slows down occupational assignment, slot-constraints are unlikely to be driving downward occupational mobility.[14]

If horizontal learning was the primary driver of occupational mobility, we would expect to see occupational movers to be negatively selected from both their previous and subsequent occupations. While we do see *ex ante* negative selection for downward movers, these individuals are positively selected *ex post*, and vice versa for upward movers. This is inconsistent with the idea that mobility is driven by individuals learning they are a poor fit for an occupation and leaving specific investments behind.

The model that is most consistent with the series of facts is a model of vertical job assignment, with a combination of learning about the workers' ability as well as human capital accumulation and depreciation. This is best described by the Gibbons and Waldman (1999) model, which is consistent with all four facts from Section 4. This suggests that individuals are able to transfer skills and investments across occupations, even in the case of downward moves. Of course, while this model can explain all four of the facts, it does not mean that congestion and horizontal sorting do not play a role in careers.

These mobility facts also reveal an important new fact: displaced workers follow similar

[14]One exception to this would be if lower-ranked occupations had higher non-pecuniary benefits, which led workers to queue for these jobs.

occupational mobility patterns as non-displaced workers. Almost half of displaced workers are able to move up the occupational job ladder after displacement and experience wage losses that are smaller compared with other displaced workers. However, when compared with other non-displaced workers that climb the occupational job ladder, displaced upward movers experience wage growth that is 2 to 8 percentage points slower than upward movers inside the firm (and 12 to 18 percentage points slower than voluntary between firm movers).

Thus, while falling down an occupational job ladder may contribute to wage losses after displacement, it cannot explain the missing wage growth for displaced workers who move up the occupational job ladder.[15] Explanations for these losses may include sorting to lower-average-pay employers, receiving lower pay due to a worse bargaining position, or being forced to accept a poor firm match. Consistent with this, Lachowska, Mas, and Woodbury (2020) estimate 17% of wage losses are due to moving to lower-wage firms, while half of losses are due to match-specific factors.

Finally, these results provide an important distinction between occupational mobility and employer mobility. Workers who move between firms have wage growth on average, which is especially pronounced for upward occupational movers (wage growth of 12-15% vs. 6% internally). Unlike upward movers inside firms, non-displaced upward movers between firms are not high earners for their pre-mobility occupation, suggesting that they may be moving in part because they are receiving low wages in their prior position. Consistent with this is the fact that displaced workers, who move employers involuntarily, exhibit similar positive selection to internal occupational movers. This fact pattern is consistent with a frictional job ladder model, in which workers search on-the-job for a higher-paying match. Thus, while search frictions are not the primary driver of occupational mobility, they may play a role in mobility between firms.[16]

[15] In a previous working paper version of this paper, I show that displaced workers earn about 10% less than non-displaced movers conditional on the distance of the occupational change. See http://publish.illinois.edu/elizaforsythe/files/2020/03/Forsythe_OccLadders_3_4_2020.pdf for more details.

[16] Papageorgiou (2018) finds that larger employers both pay higher wages and employ a wider diversity of occupations, thus workers may sort to these employers precisely for these additional opportunities for internal reallocation.

5 Conclusions

In this paper, I have examined the characteristics and frequency of occupational mobility, within and between firms. 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 learning and sorting. 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, as voluntary movers appear to be sorting to higher-paying firms. These results indicate the mechanisms driving occupational mobility and employer mobility are distinct and should be modeled accordingly.

This has important implications for understanding how to help individuals that suffer career displacements or other negative shocks. If careers were best described by horizontal sorting, it would be especially important for individuals to return to their previous occupation. This is because if the individual has sufficient tenure in the occupation, it indicates that they are well-suited for the job and likely have accumulated specific human capital. Instead, since normal careers are best characterized by vertical sorting, it implies that individuals can transfer skills across related occupations, thus can likely be successful in a wider range of jobs. However, the relative wage loss patterns of displaced workers suggests that firm-matching may be just as important as occupations for recovering wages.

References

Baker, G., Gibbs, M., & Holmström, B. (1994a). The Internal Economics of the Firm: Evidence from Personnel Data. *Quarterly Journal of Economics*, *109*(4), 881–919.

Baker, G., Gibbs, M., & Holmström, B. (1994b). The Wage Policy of a Firm. *The Quarterly Journal of Economics*, *109*(4), 921–955.

Burdett, K., & Mortensen, D. T. (1998). Wage differentials, employer size, and unemployment. *International Economic Review*, *39*(2), 257-273.

Bureau of Labor Statistics. (2016). *Current Population Survey.* https://www.census.gov/programs-surveys/cps/data/datasets.html. (Accessed Jan 1, 2021)

Demougin, D., & Siow, A. (1994). Careers in ongoing hierarchies. *The American Economic Review*, 1261–1277.

Dohmen, T. J., Kriechel, B., & Pfann, G. a. (2004, jun). Monkey bars and ladders: The importance of lateral and vertical job mobility in internal labor market careers. *Journal of Population Economics*, *17*(2), 193–228.

Fallick, B. C., Haltiwanger, J., & McEntarfer, E. (2012). Job-to-job flows and the consequences of job separations. *Finance and Economics Discussion Series*.

Farber, H. S. (1997). The changing face of job loss in the United States, 1981-1995. *Brookings Papers on Economic Activity*(June 1997), 55–142.

Farber, H. S. (2017). Employment, hours, and earnings consequences of job loss: Us evidence from the displaced workers survey. *Journal of Labor Economics*, *35*(S1), S235–S272.

Forsythe, E. (2019). Careers within firms: Occupational mobility over the lifecycle. *LABOUR*, *33*(3), 241–277.

Frederiksen, A., Halliday, T., & Koch, A. K. (2016). Within-and cross-firm mobility and earnings growth. *Industrial and Labor Relations Review*, *69*(2), 320–353.

Frederiksen, A., Kriechel, B., & Lange, F. (2013). Performance Evaluations and Careers: Similarities and Differences across Firms. *Working Paper*.

Gibbons, R., & Katz, L. F. (1991). Layoffs and Lemons. *Journal of Labor Economics*, *9*(4), 351–380.

Gibbons, R., & Waldman, M. (1999). A theory of wage and promotion dynamics inside firms. *Quarterly Journal of Economics*, *114*(4), 1321–1358.

Groes, F., Kircher, P., & Manovskii, I. (2013). The U-shapes of occupational mobility. *Review of Economic Studies*, *82*(2), 659–692.

Haltiwanger, J., Hyatt, H., Kahn, L. B., & Mcentarfer, E. (2017). *Cyclical Job Ladders by Firm Size and Firm Wage.*

Haltiwanger, J. C., Hyatt, H. R., Kahn, L. B., & McEntarfer, E. (2018). Cyclical job ladders by firm size and firm wage. *American Economic Journal: Macroeconomics*, *10*(2), 52–85.

Huckfeldt, C. (2016). Understanding the Scarring Effect of Recessions. *Working Paper*.

Jacobson, L. S., Lalonde, R. J., & Sullivan, D. G. (1993). Earnings losses of displaced workers. *American Economic Review*, *83*(4), 685–709.

Jovanovic, B. (1979). Job Matching and the Theory of Turnover. *Journal of Political Economy*, *87*(5), 972.

Jung, P., & Kuhn, M. (2019). Earnings losses and labor mobility over the life cycle. *Journal of the European Economic Association*, *17*(3), 678–724.

Kambourov, G., & Manovskii, I. (2008, February). Rising Occupational and Industry Mobility in the United States: 1968–97. *International Economic Review*, *49*(1), 41–79.

Kambourov, G., & Manovskii, I. (2009a, April). Occupational Mobility and Wage Inequality. *Review of Economic Studies*, *76*(2), 731–759.

Kambourov, G., & Manovskii, I. (2009b). Occupational specificity of human capital*. *International Economic Review*, *50*(1), 63–115.

Kletzer, L. G. (1998). Job Displacement. *Journal of Economic Perspectives*, *12*(1), 115–136.

Krolikowski, P. (2016). Job Ladders and Earnings of Displaced Workers. *American Economic Journal: Macroeconomics*.

Lachowska, M., Mas, A., & Woodbury, S. A. (2020). Sources of displaced workers' long-term earnings losses. *American Economic Review*, *110*(10), 3231–66.

Lehn, C. v., Ellsworth, C., & Kroff, Z. (2021). Reconciling occupational mobility in the current population survey.

Lemieux, T. (2006). Increasing residual wage inequality: Composition effects, noisy data, or rising demand for skill? *The American Economic Review*, *96*(3), 461–498.

Madrian, B. C., & Lefgren, L. J. (1999). A Note on Longitudinally Matching Current Population Survey (CPS) Respondents. *NBER Working Paper No. t0247.*.

Moscarini, G., & Postel-Vinay, F. (2016). Did the Job Ladder Fail After the Great Recession? *Journal of Labor Economics*, *34*(1).

Neal, D. (1995). Industry-specific human capital: Evidence from displaced workers. *Journal of Labor Economics*, *13*(4), 653–677.

Papageorgiou, T. (2014). Learning your comparative advantages. *Review of Economic Studies*, *81*(3), 1263–1295.

Papageorgiou, T. (2018). Large firms and within firm occupational reallocation. *Journal of Economic Theory*, *174*, 184–223.

Poletaev, M., & Robinson, C. (2008). Human Capital Specificity: Evidence from the Dictionary of Occupational Titles and Displaced Worker Surveys, 1984- 2000. *Journal of Labor Economics*, *26*(3), 387–420.

Robinson, C. (2018). Occupational Mobility , Occupation Distance and Specific Human Capital. *Journal of Human Resources*. doi: 10.3368/jhr.53.2.0814.6556R2

Shaw, K. L. (1984). A Formulation of the Earnings Function Using the Concept of Occupational Investment. *The Journal of Human Resources*, *19*(3), 319–340.

Topel, R. H., & Ward, M. P. (1992). Job Mobility and the Careers of Young Men. *The Quarterly Journal of Economics*, *107*(2), 439-479.

U.S. Census Bureau. (2008). *Survey of Income and Program Participation.* https://www.census.gov/programs-surveys/sipp/data.html. (Accessed Jan 1, 2021)

Van der Klaauw, B., & Da Silva, A. D. (2011). Wage dynamics and promotions inside and between firms. *Journal of Population Economics*, *24*(4), 1513–1548.

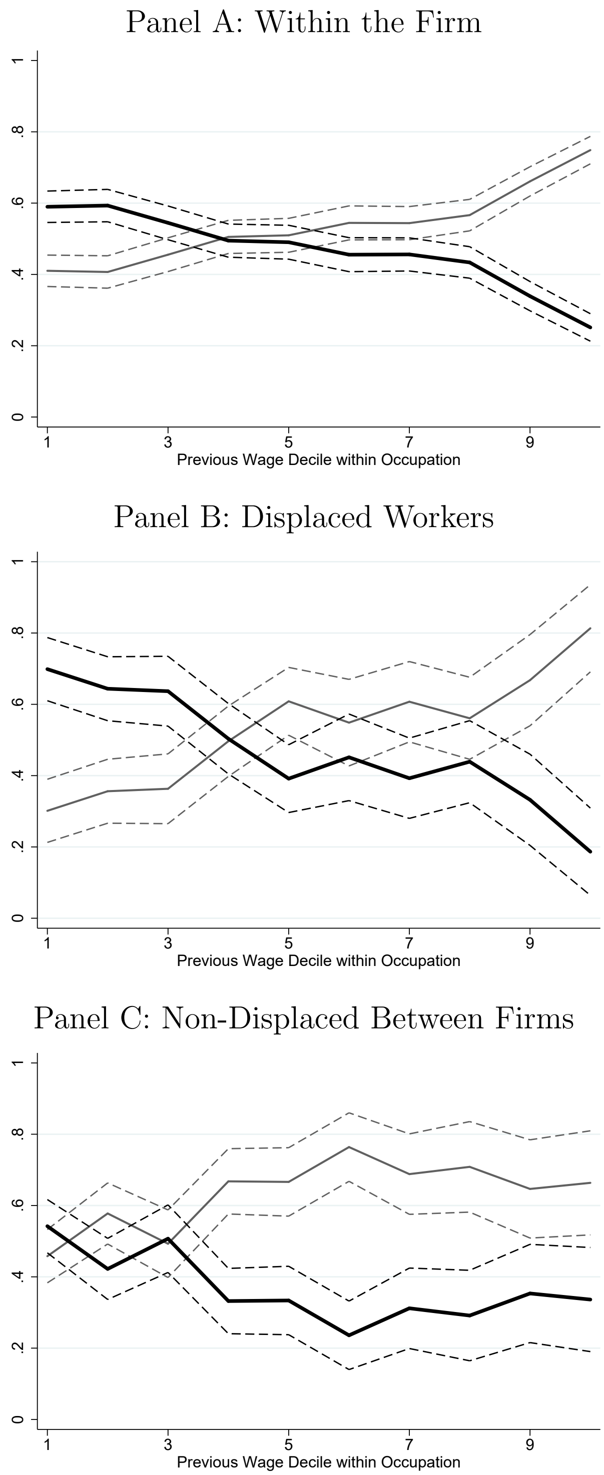

Figure 1: Share of occupational switchers moving to lower-ranked occupations (black) or higher-ranked occupations (gray), by decile of the occupational wage distribution, conditional on the type of employer move. Displaced estimates uses retrospective occupations from the Displaced Worker Survey. Dashed lines represent 95% confidence intervals.

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	0.43	0.76	0.73	0.68	0.59
SD	0.50	0.43	0.44	0.47	0.49
N	17,520	2,011	284	3,172	220
Panel B: Share of Occ. Moves that are Negative					
Mean	0.48	0.45	0.50	0.47	0.54
SD	0.50	0.50	0.50	0.50	0.50
N	7,604	1,521	208	2,151	129
Panel C: Distance of Occupational Change					
Mean	0.02	0.05	-0.01	0.03	-0.05
SD	0.44	0.45	0.42	0.52	0.48
N	7,604	1,521	208	2,132	129
Panel D: Distance if Positive Move					
Mean	0.34	0.35	0.31	0.41	0.34
SD	0.29	0.30	0.26	0.33	0.30
N	3,991	842	105	1,121	59
Panel E: Distance if Negative Move					
Mean	-0.34	-0.33	-0.34	-0.39	-0.39
SD	0.29	0.28	0.27	0.32	0.33
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). The column headings indicate the sample restriction. 'Within Firm' refers to individuals who did not change firms, 'Non-Disp. Between' are firm-changers who were not displaced, and 'Disp. Between' is displaced workers.

Table 2: Wage Returns to Occupational Mobility

	(1)	(2)	(3)	(4)	(5)
	CPS (12 month)			SIPP (4 Month)	
Sample	Within Firm	Non-Disp. Between	Disp. Between	Non-Disp. Between	Disp. Between
Panel A: Occupational Change					
Occ. Change	0.00443	0.0581**	-0.0793+	-0.0430+	-0.160*
	(0.00614)	(0.0204)	(0.0462)	(0.0249)	(0.0745)
Mean of Omitted	0.0265	0.0200	-0.021	0.0924	0.0043
R-sq	0.004	0.022	0.061		
Panel B: Positive versus Negative Occupational Change					
Neg. Occ. Chg	-0.0309***	-0.0238	-0.154**	-0.123***	-0.252**
	(0.00779)	(0.0236)	(0.0571)	(0.0297)	(0.0912)
Pos. Occ. Chg	0.0369***	0.127***	0.00149	0.0280	-0.0451
	(0.00761)	(0.0225)	(0.0569)	(0.0290)	(0.0947)
Mean of Omitted	0.0265	0.0200	-0.021	0.0924	0.0043
R-sq	0.008	0.054	0.090	0.030	0.143
Panel C: Distance of Occupational Change (Chg. In Log OES score)					
Chg. In Occ. Distance	0.0942***	0.215***	0.258*	0.145***	0.275*
	(0.0111)	(0.0254)	(0.105)	(0.0329)	(0.113)
Mean of Omitted	0.0275	0.0641	-0.059	0.0684	-0.045
R-sq	0.010	0.070	0.109	0.029	0.137
Panel D: Distance of Occ. Change, Positive vs. Negative					
Chg in Distance if Positive	0.112***	0.259***	0.246	0.148**	0.369+
	(0.0170)	(0.0402)	(0.163)	(0.0539)	(0.209)
Chg. In Distance if Negative	0.0744***	0.158***	0.268+	0.141**	0.220
	(0.0168)	(0.0409)	(0.156)	(0.0544)	(0.141)
Mean of Omitted	0.0248	0.0541	-0.063	0.0642	-0.055
R-sq	0.010	0.072	0.109	0.029	0.138
N	17533	2011	284	3152	220

Coefficients from regressions based on the CPS Tenure supplement and the 2008 SIPP. Robust standard errors in parentheses: $^{+}$ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. See Section 3.2 for more details. Omitted category is workers who did not change occupations. The column headings indicate the sample restriction. 'Within Firm' refers to individuals who did not change firms, 'Non-Disp. Between' are firm-changers who were not displaced, and 'Disp. Between' is displaced workers.

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	-0.00456	-0.0151*	-0.00967	-0.0241***
	(0.00620)	(0.00643)	(0.00613)	(0.00651)
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	-0.0888***	-0.0746***	0.0676***	0.0752***
	(0.00780)	(0.00823)	(0.00766)	(0.00823)
Pos. Occ. Chg	0.0729***	0.0368***	-0.0807***	-0.111***
	(0.00742)	(0.00767)	(0.00753)	(0.00787)
Mean of Omitted	0.0620	0.0620	0.0538	0.0538
R-sq	0.113	0.199	0.108	0.168
	Panel C: Distance of Occupational Change (Chg. In Log OES score)			
Chg. In Occ. Distance	0.214***	0.151***	-0.213***	-0.293***
	(0.0107)	(0.0120)	(0.0108)	(0.0122)
Mean of Omitted	0.0551	0.0551	0.0456	0.0456
R-sq	0.121	0.201	0.119	0.185
	Panel D: Distance of Occ. Change, Positive vs. Negative			
Chg in Distance if Positive	0.164***	0.0967***	-0.249***	-0.311***
	(0.0152)	(0.0156)	(0.0161)	(0.0165)
Chg. In Distance if Negative	0.269***	0.225***	-0.175***	-0.268***
	(0.0175)	(0.0203)	(0.0170)	(0.0202)
Mean of Omitted	0.0628	0.0628	0.0514	0.0514
R-sq	0.122	0.203	0.120	0.185
Controls	No	Yes	No	Yes
N	17533	17533	17533	17533

Coefficients from regressions based on the CPS Tenure supplement. Robust standard errors in parentheses: $^{+}$ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. See Section 3.2 for more details. Omitted category is workers who did not change occupations. 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	-0.0745**	-0.00982	-0.0712**	-0.0493
	(0.0228)	(0.0786)	(0.0227)	(0.0676)
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	-0.108***	-0.0815	0.0483+	0.0314
	(0.0261)	(0.0929)	(0.0256)	(0.0782)
Pos. Occ. Chg	-0.0496*	0.0589	-0.160***	-0.127
	(0.0237)	(0.0907)	(0.0250)	(0.0824)
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	0.106***	0.227+	-0.299***	-0.181+
	(0.0246)	(0.135)	(0.0289)	(0.109)
Mean of Omitted	-0.106	-0.035	-0.081	-0.152
R-sq	0.354	0.625	0.322	0.643
Panel D: Distance of Occ. Change, Positive vs. Negative				
Chg in Distance if Positive	0.0102	0.0715	-0.351***	-0.219
	(0.0305)	(0.187)	(0.0381)	(0.135)
Chg. In Distance if Negative	0.311***	0.443*	-0.186**	-0.129
	(0.0585)	(0.222)	(0.0586)	(0.196)
Mean of Omitted	-0.070	-0.050	-0.052	-0.164
R-sq	0.365	0.630	0.325	0.643
Controls	Yes	Yes	Yes	Yes
N	2011	284	2011	284
Sample	Non-Disp.	Disp.	Non-Disp.	Disp.
Sample	Between	Between	Between	. Between

Coefficients from regressions based on the CPS Tenure supplement. Robust standard errors in parentheses: $^{+}$ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. See Section 3.2 for more details. Omitted category is workers who did not change occupations. The dependent variable is the difference between the individual's wage and the median occupational wage, either before or after the potential mobility event.

Appendix

A.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.[17] 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.[18] 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 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.

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

[18] 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.

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.[19] 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. Retrospective wages are winsorized at the 1% and restricted to a wage of under $140.[20]

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

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

[20]This corresponds to the inflated topcoded value in the regular CPS wages that I use in the main text. However, the retrospective wages are not topcoded and have many extremely large hourly wage responses, which may reflect individuals reporting weekly wages rather than hourly wages. Since it is unclear where these misreported wages should fall in the wage distribution, I truncate the distribution at $140.

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.4 I show summary statistics for key variables.

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

	Within Firm	Non-Disp. Btwn	Disp. Between	Disp. Between, Retro
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. The column headings indicate the sample restriction. 'Within Firm' refers to individuals who did not change firms, 'Non-Disp. Btwn' are firm-changers who were not displaced, 'Disp. Between' is displaced workers using contemporaneous data, and 'Disp. Between, Retro' is displaced workers using retrospective data.

Table A.3: Wage Changes by Firm and Occupational Mobility

	Obs	Mean	SD	Skew
No Firm Change				
Occ. Change	7604	0.030	0.365	-0.273
No Change	9916	0.027	0.363	0.428
Neg Change	3613	-0.007	0.360	-0.354
Positive Change	3991	0.064	0.366	-0.216
Change Firm				
Occ. Change	1521	0.091	0.410	0.307
No Change	490	0.020	0.351	0.291
Neg Change	679	-0.003	0.419	0.268
Positive Change	842	0.164	0.388	0.484
Displaced				
Occ. Change	208	-0.084	0.417	0.273
No Change	76	-0.022	0.275	-0.239
Neg Change	103	-0.165	0.397	-0.749
Positive Change	105	0.005	0.423	1.149

Summary statistics for the wage changes by firm and occupational mobility, weighted using CPS sampling weights.

Table A.4: Data Description, 2008 SIPP

	Within Firm	Non-Disp. Between	Disp. Between
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. 'Within Firm' refers to individuals who did not change firms, 'Non-Disp. Btwn' are firm-changers who were not displaced, and 'Disp. Between' is displaced workers.

A.2 Additional Tables

Table A.5: Wage Returns by Reason for Firm Mobility

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Detailed Firm Mobility (CPS)					
	W. Chg	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
Controls	No	Yes	No	Yes	No	Yes

Coefficients from regressions based on the CPS Tenure supplement (Panel A) and the SIPP (Panel B). Robust standard errors in parentheses: $^{+}$ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. See Section 3.2 for more details and list of demographic controls. Omitted category is workers who were employed at the same firm in both months. The dependent variable is the change in wages (W. Chg), or the difference between the individual's wage and the median occupational wage, the previous wage (Prev. W.) or the wage in the new job (Next W.)

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.6, 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.6, 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.6: 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: $^{+}$ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

In Table A.7, 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.7: 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

Estimates of the rate of occupational mobility for displaced workers, based on whether they were re-employed in the same occupation, moved to a lower-ranked occupation, or moved to a higher-ranked occupation, CPS data.

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.8, 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.

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.6 along with estimates of the wage return from occupational mobility from Table A.8. 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.

Table A.8: 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: $^{+}$ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

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 Q2 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.9, 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.9: 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

Estimates of distance of occupational change measured using OES wage rank, ONET Factor 1 Score, and ONET Factor 2 Score. 'Within Firm' refers to individuals who did not change firms, 'Non-Disp. Between' are firm-changers who were not displaced, and 'Disp. Between' is displaced workers.

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.10: 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

Regression of change in wages on change in occupational rank scores among all employed workers, CPS data. Robust standard errors in parentheses: $^{+}$ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.