Occupational Job Ladders and the Efficient Reallocation of 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 whether or not the individual moves up or down the job ladder. These patterns indicate that occupational sorting after displacement may be efficient, nonetheless, displaced workers earn approximately 9% less than non-displaced workers who make occupational changes of the same magnitude. I conclude sorting to lower-paying firms is likely the primary driver of relative 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?

In this paper, I focus on occupational changes as a source of heterogeneous outcomes for displaced and non-displaced movers. In particular, can displaced workers' wage losses be explained by the distribution of occupational moves they make after displacement? Or do displaced workers' losses exceed those experienced by non-displaced individuals making similar moves?

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. I argue these patterns of occupational mobility are consistent with efficient sorting, as the optimal job assignment of the worker changes in response to changes in his (expected) productivity.

I find these patterns of selection and mobility also hold for displaced workers. Nearly 1/3 of displaced workers move up the occupational job ladder. Pre-displacement occupational earnings strongly predict the direction of occupational mobility after displacement, with low-occupational earners more likely to move to lower-quality occupations and vice versa.

Because of the similarities in occupational sorting for displaced and non-displaced workers, I show the distribution of occupational mobility from displacement cannot explain the differences in wage outcomes between displaced workers and non-displaced movers. If displaced workers had the same wage changes from upward and downward mobility as voluntary movers, the counterfactual average wage change upon displacement would be wage *growth* of 3.3% after displacement. Instead, displaced workers have wage losses of 7%.

In order to understand the sources of these wage losses, I examine wages before and after mobility. I show these losses are not due to differences in earnings between displaced and non-displaced movers before mobility, indicating that lost specific capital is not likely responsible for the wages losses for displaced workers. Instead, I find that after displacement these workers suffer dramatic wage losses, in both absolute terms and relative to their new occupation. This indicates that displaced workers most likely sort to lower-paying firms.[3]

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

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

[3] Although it is also possible that displaced workers accept lower wages at similar firms, due to their worse bargaining position.

Regardless of the distance of the change in occupational quality, wages after mobility are 9% lower than those of non-displaced firm changers who make moves of the same magnitude.

The similarities in occupational mobility after displacement with mobility for non-displaced workers suggests that displacement may speed up the ongoing process of occupational realignment that affects all workers as they move through their careers. This is consistent with models such as Gibbons and Waldman (1999) in which changing worker capabilities leads to changes in optimal assignment. However, the fact that displaced workers exhibit earnings losses across the board suggests that the primary source of losses from displacement is due to firm-sorting. This is supported by new evidence from Lachowska, Mas, and Woodbury (2017), who decompose earnings losses from displacement into firm effects and worker effects and find that half of wage losses are due to sorting to lower-wage firms. This is consistent with job-ladder models in which a deterioration of the outside option leads individuals to accept offers from lower-wage firms, while voluntary movers can wait for an offer that exceeds their current wage.[4]

In addition, 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, which is consistent with voluntary movers sorting to higher-paying firms.

There is a substantial literature in labor economics on the race between returns to job mobility and job stability. Many authors have documented how wages grow with tenure in the same firm, industry, occupation, or task-family.[5] Such returns are typically attributed to specific capital, but could also be due to the selective survival of high-quality matches. However, many other authors have documented wage growth from mobility. The literatures on promotions within firms (such as Baker, Gibbs, and Holmström (1994a)) and job ladders between firms[6] demonstrate how workers can find higher earnings and better matches by moving between jobs.

This paper contributes to a newer literature emphasizing the *directionality* of mobility. That is, the returns to mobility depend on whether or not an individual moves to a higher- or lower-ranked job. In two recent papers Groes, Kircher, and Manovskii (2013) and

[4] E.g. (Burdett & Mortensen, 1998).

[5] See, for instance, Farber (1999) for a survey and Shaw (1984) for early work on mobility and stability between occupations.

[6] Moscarini and Postel-Vinay (2016) find worker flows form a job-ladder based on employer size, while Kahn and Mcentarfer (2014) find worker flows form a job-ladder based on establishment wages.

Frederiksen, Halliday, and Koch (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 voluntary and involuntary firm-leavers. Thus, across a variety of settings, a substantial flow of workers move to lower-quality or lower-pay jobs.

There have been a variety of papers within the displacement literature that note the 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 in individuals who make downward occupational changes. Farber (1997) finds a substantial fraction of respondents to the Displaced Workers Survey indicate wage growth following displacement. Krueger and Summers (1988) observe that individuals who move to higher-average-pay industries earn higher wages after displacement. In addition, Kletzer and Fairlie (2003) investigate the cost of displacement on young workers and find that, although their absolute earnings losses are zero, their *relative* earnings losses are substantial. This is because workers often experience rapid earnings growth at the beginning of their careers. This is consistent with my finding of relative wage losses for individuals who make positive occupational transitions after displacement, despite the fact that their absolute wage changes are approximately zero.

Finally, my findings suggest there are fundamental differences between occupational job ladders and firm job ladders. In the case of occupational job ladders, over 90% of occupational mobility occurs within firms, indicating that the primary driver of occupational reassignment is not likely to be due to search frictions. Moreover, the fact that occupational movements are directional, with previous wage gaps predicting the direction of the move, indicates the process of occupational mobility is not well-explained by models of horizontal differentiation by which each new match is an independent productivity draw. Instead, the facts I uncover are most consistent with models of firm learning, human capital, and efficient job assignment, such as Gibbons and Waldman (1999).

In the case of movements between firms, I find evidence that is suggestive of workers moving up and down a job ladder between firms, specifically, moving up with voluntary moves and falling down after displacement. The fact that this is also directional suggests workers may be aware of the quality of the match before moving. Further, the evidence of firm-sorting uncovered by Lachowska et al. (2017) suggests that workers sort across a common firm-wage ranking rather than an idiosyncratic ranking based on individual fit. Finally, the fact that the process of recovery is slow is consistent with frictions slowing workers' process of recovering their position in the hierarchy between firms.

2 The Theory of Mobility

In order to understand job mobility, it is important to understand why optimal job assignment may change over time. The standard model for understanding promotion dynamics is Gibbons and Waldman (1999). In this model there are multiple possible jobs, each with a different productivity schedule, such that workers of different ability are efficiently assigned to different jobs. As a worker's ability changes (or the firm's belief about the worker's ability changes) the worker may cross the threshold into a new comparative advantage bin, leading his optimal job assignment to change.

In the original Gibbons and Waldman (1999) paper the focus was on explaining upward mobility and, in particular, promotion dynamics within firms. However such a model can be expanded to consider downward mobility, as well as mobility between firms. For instance, Groes et al. (2013) build upon the Gibbons and Waldman (1999) framework to model occupational mobility between firms with endogenous wages. In particular, as a firm learns about a worker's time-invariant ability, we would expect that such learning would lead to both upward and downward revisions of the prior, resulting in both upward and downward mobility. In addition, although human capital is typically considered as something that is accumulated, it is also possible that it could depreciate over time, leading to upward mobility early in worker's career and downward mobility as the worker ages. Similarly, if the technology of production changes over time, the productivity of previously acquired human capital may diminish over the worker's career.

In contrast to these types of directional mobility, there may also be horizontal mobility. An example would be the match-specific capital model of Jovanovic (1979), in which individuals are induced to match with a new firm if they learn their current match is low-quality. Such a model may be better suited for describing movement between firms rather than job mobility inside firms, as it is less likely in internal moves that both parties are uninformed about the quality of new matches within the firm.

These three theoretical explanations for efficient mobility, (human capital, firm-learning, and match-specific capital) produce distinct implications for dynamics after an exogenous displacement event. In the case of human capital and learning, in a frictionless market the worker should be able to instantly find re-employment in a similar job that utilizes his skills.[7] In contrast, an individual who is displaced in a match-specific capital framework will take time to find another high-quality match, since past learning about firm-specific matches will provide no information about productivity at other firms. This could lead to a slow recovery of wages after displacement.

On the other hand, mobility may be due to inefficiencies, mis-match, or congestion, in what are sometimes referred to as job ladder models. In the simplest example (Burdett & Mortensen, 1998) firms offer heterogeneous wages and workers conduct undirected on-the-job search, accepting offers that exceed their outside option and rejecting those that do not. Models of directed-search job ladders effectively rely on congestion (such as Jung and Kuhn (2016)), where workers know the location of the pool of optimal matches but must wait for positions to become available. Finally, if workers invest in firm-specific skills, as in Pissarides (1994), workers weigh the trade off between the benefit of switching to a more-productive match and the cost of lost accumulated human capital.

What dynamics would we expect from models of inefficient mobility after an exogenous displacement event? Since the search process is congested, it will take time for workers to find a similar position. Thus we would expect workers, on average, to experience wage losses after displacement that may persist for some time. Further, we would expect workers recover by moving between jobs.

Although I do not formalize it here, a Gibbons and Waldman-style model could be incorporated into a job ladder model, leading to both efficient sorting between jobs as well as costly and persistent displacement costs. In this case, we would expect the following patterns. First, absent displacement, we would expect low-earners within the job to move down, and high-earners within the job to move up. In addition, if the change in ability underlying the reassignment is not too large, we would expect downward movers to be above-average earners in their new occupations, while we would expect upward movers to be below-average earners. Second, in the case of displacement, we should see similar patterns, in which low-earners are more likely to find re-employment in lower-quality occupations and vice versa for high-earners.

[7] If learning is private, such as in Gibbons and Katz (1991), the market will infer the worker's quality based upon whether or not he was laid-off, which could affect the market's belief about their post-displacement productivity.

3 Methodology

In this section, I first introduce the data source in Section 3.1, then discuss the measurement of occupational mobility in Section 3.2. In Section 3.3 I introduce the procedure for mapping occupational changes into moves up and down a job ladder. In Section 3.4 I present the econometric specification and in Section 3.5 I discuss measurement error issues.

3.1 Data

The data source is monthly CPS survey data from January 1994 through October 2016 and the CPS Tenure and Displaced Worker Supplements administered during the same time period. The CPS is a large national survey of U.S. households, which provides cross-sectional data for measuring national employment statistics. Although its primary purpose is as a cross-sectional dataset, the CPS is in fact designed as a panel, in which each household is surveyed multiple times; thus individuals can be followed across pairs of months.[8]

I construct two matched datasets. First, I match individuals across adjacent months. There are two advantages to this dataset: first, it provides a large sample size of over 11 million observations. Second, since 1994 the CPS has utilized dependent coding within the first four months of the sample and again within the second four months. This allows researchers to measure employer mobility, since respondents are asked whether or not they have changed employers since last month. In addition, dependent coding of occupations reduces spurious mobility, which I discuss this in more detail in Section 3.2. Table A.1 shows summary statistics for key variables.

One major drawback to the paired monthly sample is that the CPS only collects earnings information in the 4th and 8th months of the sample (i.e. outgoing rotation groups). A key research question is how wages change after mobility; thus I construct a second sample that matches individuals from the 4th and 8th months, which gives me earnings data that spans a year. However, between months 4 and 5 of the sample (which covers a gap of 8 calendar months), the survey reverts to independent coding. This means we do not know whether or not the respondent changed employers, which prevents the comparison of returns to mobility for firm stayers and firm changers.

In order to get around this, I turn to the Tenure Supplement. The Tenure Supplement is administered in January or February of even years.[9] I match individuals who are in the outgoing rotation group during the months the tenure supplement is administered to

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

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

their previous outgoing rotation group, using the matching method described above. 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.

The Tenure Supplement is conducted in conjunction with the Displaced Workers Survey (DWS). The DWS asks individuals about whether they were displaced from a job in the last three years. 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. In this way, I have three categories: firm-stayers, voluntary firm-changers, and displaced workers. Table A.2 provides descriptive statistics for this sample.

Finally, I also use a third 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.[10] Thus, 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.

3.2 Measuring Occupational Mobility

Occupational coding provides a mapping of worker duties and activities to a common classification system across firms. In survey data such as the CPS, the process of assigning individuals to occupations can introduce considerable measurement error. This is of particular issue when measuring occupational mobility. Independent coding of occupations can substantially raise the measured rate of occupational mobility, since the individual has two chances to be mis-coded. Under this coding procedure, individuals are asked open-ended questions (e.g., "What kind of work do you do, that is, what is your occupation?") to solicit

[10] E.g. Farber (1997).

enough information that the coders will be able to classify the worker's occupation.[11] As mentioned in Section 3.1, one reason the CPS introduced dependent coding in 1994 was to reduce spurious occupational mobility. Under this procedure, respondents are read their response from the previous month, and asked if this is an accurate description of their current job. While this can substantially reduce measured occupational mobility, the main sample I use is collected via independent coding.[12]

Finally, it is worth noting that the rate of occupational mobility depends on the mesh of the classification system. Fewer occupational codes leads to lower mobility since some changes will be within group. Thus even in the absence of measurement error, the true rate of occupational mobility will depend on the structure of the classification system.

With these caveats, Table 1 shows occupational mobility rates in the two different data samples, using detailed occupational coding (510 occupations). The first column shows the annual rate of occupational mobility from the tenure sample. Here we see mobility rates are substantially lower for individuals who stay at the firm: 44% of firm stayers over the year, versus 76% of firm changers.

Table 1: Rates of Occupational Mobility

		Annual CPS	Monthly CPS	Monthly CPS Activities Change
Within Firm:		44.03%	1.31%	0.47%
	N	17,520	10,653,565	10,609,695
Between Firm:		76.05%	61.80%	
	N	2,295	254,442	
	Total:	19,815	10,460,134	

Sample restrictions include employed in both months, valid and non-allocated occupation in both months, and non-missing employer change or tenure variables. The Annual CPS figures are also further restricted to individuals with valid earnings in both months, in order to be consistent with wage regressions.

In the second and third columns of Table 1, I turn to mobility measured at the monthly level. The second column shows raw mobility within the firm. This data is collected using dependent coding, leading to a dramatically lower rate of measured mobility compared with the annual rate. If individuals have equal probability of changing occupations each month, a monthly rate of 1.3% corresponds to an annual rate of 14.6% with at least one occupational change within the firm. In the third column, individuals are further restricted to those that positively affirm that their activities have changed. This further reduces the monthly mobility rate to 0.47%, corresponding to an annual mobility rate of 5.5%.

[11] See (*Current Population Survey Design and Methodology, Technical Paper 66*, 2006) for more details on the survey design.

[12] In particular, the CPS only uses dependent coding in months 2 through 4 and 6 through 8 of the sample who did not change employers. Thus matching between months 4 and 8 crosses the 'independent coding chasm', even if the individual did not change employers.

We can compare these mobility estimates to the literature. In a recent paper, Moscarini and Thomsson (2007) use CPS data to estimate firm and occupational mobility. Although this was not the driver of their paper, they do report the co-incidence of occupational mobility and employer mobility, from which we can derive the rate of within-firm and between-firm occupational mobility, for detailed occupational codes. Within firms they find 1.26% change occupations, while between firms they find 64% change occupations. Sample differences include corrections for possible spurious mobility and exclusion of women. Despite these sample differences, these estimates are similar to the less-restrictive monthly estimates reported in Column (2) of Table 1.

These mobility rates can also be compared to the administratively measured occupational mobility reported by Groes et al. (2013). This data contains about half the number of occupations as the CPS. In addition, since the data is administrative, it should be much less likely to suffer from spurious mobility. Accordingly, these authors find a 14.4% annual mobility rate within the firm, and a 35.5% annual mobility rate between firms. Thus, although these results suggest the measured occupational mobility rates from the CPS are inflated, there is good reason to believe a substantial fraction of measured occupational mobility is due to true mobility. Section 3.5 further discusses the implications of this measurement error.

3.3 Ranking Occupational Mobility

Although the concepts of promotion and demotion are intuitive, in practice there are a variety of methods one can use to rank jobs. Within the personnel literature, several methods have been employed to identify movements within individual firms. The most straightforward method is to use the organizational chart to identify the hierarchy of positions within the firm. This method was employed by Dohmen, Kriechel, and Pfann (2004). Alternatively, Baker et al. (1994a) used worker flows to construct a job hierarchy, in part because they did not have access to the organizational chart. While this method worked well for their firm, which rarely used demotions, in organizations that more frequently move individuals up and down between jobs worker flows do not provide sufficient information to sign the direction of the move. Finally, Lazear (1992) used average wages within job title to rank jobs. This is the most straightforward method, since it provides a strict ranking for all jobs.[13]

When examining job changes that span firms, it becomes necessary to derive an externally consistent job ranking. Most authors have used occupational coding, which is meant to provide a consistent classification of job tasks to occupational titles across firms. However, occupational coding is substantially more coarse than the job titles that are used within

[13]Nonetheless, most researchers prefer to use non-wage based rankings if available, to avoid using wages as both the outcome variable and the source of ranking.

firms to describe unique jobs.

Two strategies are employed in the literature. Frederiksen et al. (2016) examine movements in and out of management positions. By simplifying the job structure to two types of jobs, these authors ensure an accurate ranking of jobs, however are limited in the scope of mobility they can examine. In contrast, Groes et al. (2013) use average real hourly wages to rank occupations. This methodology allows a strict ranking between any two pairs of occupations; however, it may lead to spurious re-ranking with small fluctuations in wages. In addition, moves that may be considered lateral moves to employees and employers are forced to be ranked, inflating the rate of upward and downward mobility. This is similar in spirit to the methodology used by Lazear (1992) to categorize promotions within a firm.

In this paper, although I primarily use a method similar to Groes et al. (2013), based on median occupational wages and following the methodology of Acemoglu (1999), I also construct a variety of alternative quality metrics, using data on occupational characteristics collected by O*NET. These alternative measures are described in detail in the Appendix.

In order to construct an occupational wage ranking, I use data from the Occupational Employment Statistics (OES) survey, a representative survey of occupational wages conducted by the Bureau of Labor Statistics. 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)[14], 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.

Table 2: Distribution of Moves

	Monthly Sample		Contemp. Sample			Retrosp. Sample
	Within Firm	Btwn.	Within Firm	Vol. Btwn	Displaced	Displaced
Same Occ.	99.51%	79.18%	56.6%	26.0%	26.8%	33.5%
Down	0.23%	10.07%	20.6%	34.7%	36.3%	35.6%
Up	0.26%	10.76%	22.8%	39.3%	37.0%	30.9%
N	10,601,353	254,442	17,520	1,655	284	2,927
Conditional on Changing Occupation:						
Down	46.90%	48.35%	47.5%	46.9%	49.5%	53.5%

Rates of mobility for each category: within-firm movers, voluntary movers between firms, displaced due to plant closings, and other displaced. The retrospective file only includes displaced workers.

[14]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.

Table 2 reports how the distribution of occupational mobility (same occupation, downward move, or upward move) varies based on the type of employer mobility. Columns (1) and (2) show mobility from the monthly CPS sample, while Columns (3) through (5) use the annual sample and Column (6) reports mobility from the retrospective sample. Since we do not have displacement information in the monthly sample, some portion of the between-firm movers are displaced workers who found new work immediately.

As discussed in Table 1, the rates of staying in the same occupation vary dramatically based on the sample and the type of employer mobility. Part of this is due to true differences in mobility due to a longer time-gap between surveys and the higher coincidence of occupational mobility and employer mobility. However some is due to spurious mobility, which inflates the rate of occupational mobility. I discuss the consequences of such measurement error in Section 3.5.

In order to more easily compare differences in the distribution of occupational moves between these datasets, I compare the share of individuals moving to lower-quality occupations conditional on changing occupations. Here we see that for all types of mobility, the share of downward moves is over 46%, with a high of 53.5% from the retrospective sample. Within firms, both the monthly sample and the annual sample from the tenure supplement show 48% of occupational changers move to lower-quality occupations. For between-firm movers in the monthly sample, we see 48% of occupational movers move down.

Thus, although displaced workers have somewhat higher rates of downward occupational mobility, for both within-firm and voluntary between-firm movers, over 45% of occupation-changers move down the occupational job ladder. Conversely, for all categories of displaced workers, over 45% of occupation-changers move *up* the occupational job ladder. These results indicate that, while displaced workers do have somewhat elevated rates of downward mobility, the differences in the distributions of move are not likely to be the primary driver of wage losses for displaced workers.

Next I compare these estimates to others from the literature. In the most similar exercise, Groes et al. (2013) use Danish administrative data and find remarkably comparable rates of downward mobility: downward movements by 46% of occupation changers inside the firm, and 45% for occupational changers between firms. This is quite similar to the mobility rates reported in Table 2. One small difference is the slightly higher rate of downward mobility they find between firms.

However, comparisons to measures of demotion rates in the personnel literature reveal stark differences. 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 et al. (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.

Why might we see such higher rates of downward mobility? First, Dohmen et al. (2004) noted that most personnel datasets are based on year-end snapshots. Although they had monthly data of flows, when the authors evaluated the rate of downward mobility they would observe if they had annual data, they would miss 27% of demotions, since 12% of demoted leave the firm within the year and 22% of demotions are followed by an offset vertical move within the year. Thus, lower frequency data may miss a substantial fraction of negative transitions.

In addition, the ranking of occupational moves based on median wages forces all transitions to be ranked as up or down, while some of these moves are closer to lateral moves rather than true demotions. Thus, while occupational mobility will capture some moves that would be considered promotions or demotions within the firm, it will also capture some additional moves (such as lateral moves) as well as miss moves between job titles within the same occupation. Nonetheless, the fact that we see similar rates of downward occupational mobility for dependent and independently coded occupational changes in the CPS, as well as similarities to other data sources in the literature, suggests that rates of downward occupational changes of 45-48% of all occupational moves are a reasonable estimate.

3.4 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 dummies that indicate whether or not the individual made a downward or upward occupational change. In some specifications I instead divide individuals by whether or not they voluntarily changed firms or were displaced, with firm-stayers the omitted category. Finally, in the most complex regression I include dummies for the interactions of occupational mobility (up, down, or stay) with firm mobility (voluntary move, displaced, or stay). The omitted category is individuals who remain in the same occupation in the same firm. 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 earlier on one's career. Since occupational movers are also younger on average than occupation stayers, this could over-estimate the returns to occupational mobility. Thus the demographic variables control for as many differences between the mobility groups as available in the CPS. Specifically, in regressions that indicate demographic controls, I include 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.[15] 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.

3.5 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 changes in coding leading to a spurious mobility. From the monthly data, we have that approximately 5.5% of individuals remaining employed by the same firm change occupations

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

over a year, however, due to independent coding, the annual mobility rate inside the firm from the tenure supplement is measured as 44%. 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: 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 we see 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-quality 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. Thus, while the levels may be biased, the relative gaps should not be. In addition, I will compare estimates to results from related papers that use administrative data which will serve to corroborate my estimates.

4 Results

In this section, I first establish results about wage changes with occupational mobility and with employer mobility (both non-displaced and displaced), to establish a set of facts about mobility. In particular, in Subsection 4.1 I find that occupational sorting is directional and consistent with efficient reallocations. In Subsection 4.2 I show that wage losses for displaced workers is driven by earnings losses after mobility. In Subsection 4.3, I compare wage changes with upward and downward occupational mobility for displaced workers with wage changes for within-firm movers and non-displaced between-firm movers. This approach allows me to distinguish between occupational sorting from firm sorting and other costs of displacement. Finally, in Subsections 4.4 and 4.5 I derive additional results, showing occupational sorting for displaced workers appears to be efficient, and, rather, displaced workers' wage losses occur within occupation.

4.1 Occupational Mobility: Wages and Efficient Sorting

I first answer the question: how do wage changes after mobility relate to the direction of occupational change? I then investigate the source of the wage changes, focusing on relative wages before and after the mobility event. I then show estimates are consistent with results from the literature. Finally, I investigate the theoretical implications of the wage patterns, and I show that the results are consistent with efficient occupational sorting.

4.1.1 Wage Results

Table 3: Wages by Type of Occupational Mobility

	(1) W. Chg.	(2) W. Chg.	(3) Prev. W.	(4) Next W.	(5) Next W.
Downward Occ. Change	-0.0384***	-0.0402***	-0.0168*	-0.0568***	-0.106***
	(0.00768)	(0.00769)	(0.00826)	(0.00854)	(0.00512)
Upward Occ. Change	0.0510***	0.0475***	-0.0528***	-0.00624	-0.0294***
	(0.00758)	(0.00753)	(0.00831)	(0.00824)	(0.00454)
N	19459	19459	19459	19459	1971139
R-sq	0.007	0.011	0.260	0.255	0.281
Worker Controls		Y	Y	Y	Y
Mean of Omitted	0.0261	0.0261	2.253	2.276	2.279

Coefficients from regressions based on the CPS Tenure supplement (Columns (1) through (4)) and Matched Monthly File (Column (5)). Robust standard errors in parentheses: $^{+}$ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. See Section 3.4 for more details. Omitted category is workers who were employed in both months without changing occupations.

I first examine wage changes associated with occupational mobility. In Columns (1) and (2) of Table 3, we see how the change in real log wages relates to the type of mobility the worker experiences. In Column (1), we see that the annual change in wages is 3.8 percentage points smaller for workers who move to lower-quality occupations than for workers who make no occupational change at all, who experience an average real wage growth of 2.6% over the year. Although the net change in log wages is -1.2%, I cannot statistically reject that the change in real wages is zero for these downward movers. In contrast, for workers who make positive occupational changes, the annual change in real wages is 5.1 percentage points larger than for occupation-stayers, for a total of 7.7% wage growth. Column (2) adds in demographic controls, as discussed in Section 3.4, which slightly decrease the wage growth for upward movers and slightly increase the wage losses for downward movers.

Columns (3) and (4) look at wages before and after the mobility event, respectively. To conserve space I only include the specifications with worker controls.[16] Here we see that both downward and upward occupational changers earned lower hourly wages than occupation stayers before moving, 1.7 log points less for downward movers and 5.3 log points less for upward movers. After the mobility event, downward occupational changers' positions become comparatively worse; they earn 5.7 log points less per hour than individuals who did not change occupations during the previous year. In contrast, upward occupational changers improve their wages and are statistically indistinguishable from occupational stayers. Thus the wage losses experienced by downward occupational changers are partially dampened by the fact that they are comparatively low earners before moving. In contrast, the wage gains experienced by upward occupational movers are entirely driven by the reversal of comparatively low earnings before moving.

Column (5) uses the full matched monthly CPS sample. This increases the sample size to 1.9 million observations; however, it can only be used to examine wages after mobility due to the structure of the survey design. Here we see similar patterns as in the tenure supplement sample: individuals who move to lower-quality occupations have substantially lower wages after moving compared with occupational stayers, however the magnitude of the difference is now larger, at -10.6 log points. For upward movers we now see that wages are lower than for occupational stayers by 2.9 log points. Nonetheless, the basic pattern that wages are lower after mobility for downward occupational changers versus upward occupational changers is robust to the larger sample.

As discussed in the measurement error section, misclassification of occupations can lead to spurious mobility. However, if measured occupational mobility was primarily due to this measurement error, we would expect to see no relationship between wage changes and the sign of mobility. The fact that we see a strong positive relationship between wage growth and positive occupational mobility (and, conversely, negative wage growth and negative mobility) indicates that there is sufficient true mobility to cut through the noise. Nonetheless, such measurement error will attenuate the estimates, so the measured changes in wages with mobility are a conservative estimate.

[16]Estimates are similar without controls, however since occupational changers tend to be a bit younger and hence lower earning, we do see the point estimates are more negative without controls.

4.1.2 Selection Results

Table 4: Distance from Median Occupational Wages

	(1) Prev. W.	(2) Prev. W.	(3) Next W.	(4) Next W.	(5) Next W.	(6) Next W.
Downward Occ. Change	-0.108***	-0.0839***	0.0426***	0.0603***	0.0356***	0.0249***
	(0.00791)	(0.00787)	(0.00778)	(0.00780)	(0.00447)	(0.00431)
Upward Occ. Change	0.0360***	0.0255***	-0.114***	-0.118***	-0.104***	-0.106***
	(0.00762)	(0.00750)	(0.00767)	(0.00767)	(0.00433)	(0.00413)
N	19459	19459	19459	19459	1971139	1971139
R-sq	0.020	0.191	0.025	0.165	0.001	0.095
Worker Controls		Y		Y		Y
Job Controls		Y		Y		Y
Mean of Omitted	0.057	0.057	0.0483	0.0483	0.0300	0.0300

Coefficients from regressions based on the CPS Tenure supplement (Columns (1) through (4)) and Matched Monthly File (Columns (5) and (6)). Robust standard errors in parentheses: $^{+}$ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. See Section 3.4 for more details. Omitted category is workers who were employed in both months without changing occupations.

Now that I have established that wage changes are consistent with the direction of occupational mobility, I want to further explore how selection may explain this result. In particular, I now consider the distance between the worker's log hourly wage and median log hourly wages for all individuals employed in the same occupation in that year. Table 4 shows how this distance measure varies depending on the type of occupational change the worker makes. This specification is described in detail in Section 3.4.

In Columns (1) and (2), I consider the wage gap before mobility. Individuals who do not change occupations earn on average 5.7 percentage points above real median occupational wages.[17] Individuals who will make a negative occupational change in the subsequent year earn 10.8 percentage points less than occupational stayers, which results in a net wage gap of 5.1 percentage points below median occupational wages. Even after including controls for worker demographic characteristics, industry, and occupation, these individuals still earn 2.7% below median occupational wages for their occupation. Thus, individuals who will subsequently move to a lower-quality occupation are negatively selected from their previous occupations.

In contrast, individuals who will subsequently make a positive occupational change earn between 8.3 and 9.3 percentage points above median earners for their occupation, depending on fixed effects. This is despite the fact that upward movers earn wages that are 5.3 log points less than occupational stayers before moving, as shown in Table 3. This indicates that future upward movers are employed in comparatively low earning occupations, but are highly

[17]This is because individuals who have remained employed for a year are already positively selected from the set of all individuals employed in a particular occupation-year cell.

paid for these occupations. Thus, individuals who will subsequently move to a higher-quality occupation are positively selected from their previous occupations.

In Columns (3) and (4), I instead consider wages after the mobility event. This allows me to investigate how these occupational movers compare to other workers who are employed in their new occupation. In this case, real wages for occupational stayers are now on average 4.8% above median occupational wages. Compared to the wages in their new occupations, downward occupational movers are now comparatively well-paid, with earnings of 9.1% to 10.9% above those of median earners. Thus, while downward movers are low-paid for their occupations before moving, they are well-paid for their new occupations after moving.

In contrast, upward occupational changers are now low-paid for their new occupations, earning between 5.6% and 7.0% below median wages for their new occupations. Thus, upward occupational changers go from being well-paid in their previous occupations to low-paid in their new occupations. Despite these patterns of comparative wages within occupation, as we saw in Table 3, in net, downward occupational changers have earnings losses, while upward occupations have earnings gains.

In Columns (5) and (6), I again turn to the full matched monthly sample. Here we see a similar pattern, however the wage gaps are somewhat attenuated: downward movers in this sample earn 5.5% above median wages in their new occupations after controlling for fixed effects, while upward movers earn 7.6% below median wages. Thus we can conclude that these patterns about wages after mobility are consistent in both samples.

4.1.3 Comparing with Literature

The result that wage growth is faster for individuals who move to higher-ranked occupations is consistent with evidence in the literature. 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) do find slower wage growth for those moving out of management compared with for job-stayers. In addition, Groes et al. (2013) report consistent wage evidence from administrative data from Denmark, finding wage growth is faster for individuals who move up the occupational job ladder compared with for occupational stayers, while downward occupational movers experience the slowest growth of all. Moreover, due to the administrative nature of their data, these authors are able to show these patterns persist after 5 years.

Another robust result from the personnel literature is the relationship between prepromotion earnings and the promotion probability. For instance, Baker et al. (1994b) found that individuals who are promoted are selected from individuals who make above-average earnings in their previous job, but after promotion make *below*-average earnings in their new job. Although occupational categories are broader than the job levels used in Baker et al. (1994b), I find a consistent pattern with occupational sorting. However, as discussed in Section 3.3, the firm they study rarely demotes individuals, so they do not observe the negative sorting pattern I report above.

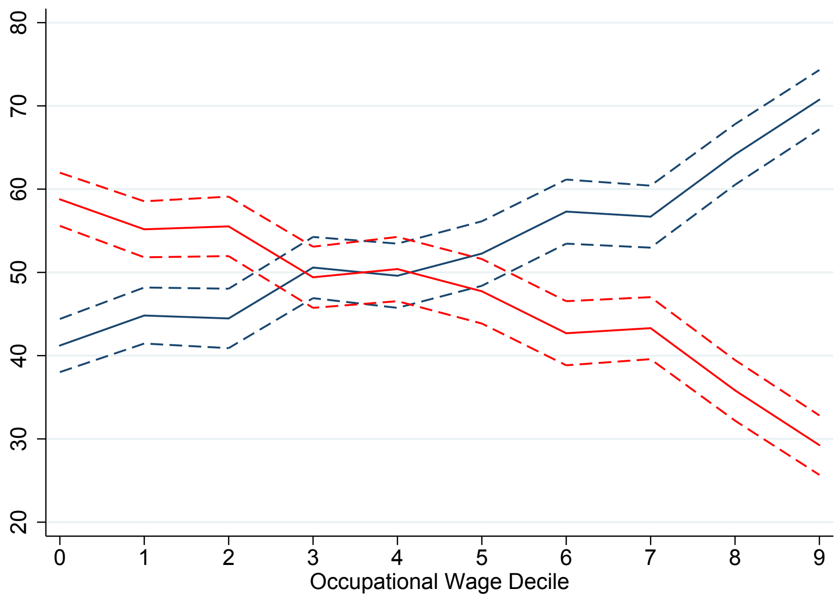

Figure 1: Percent of occupational switchers moving to lower-quality occupations (red) or higher-quality occupations (blue), by decile of the occupational wage distribution.

In order to more directly derive the extent of positive and negative selection, in Figure 1 I show how the percentage of occupational switchers who move up or down relates to the individual's position in the occupational wage distribution before moving. This is similar to Figure 3 in Groes et al. (2013), and shows remarkably similar patterns, 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 we see similar patterns in personnel and administrative records that should have accurate coding of occupational mobility supports my findings from the CPS.

4.1.4 Theoretical Implications

What does the relationship between the direction of mobility and workers' wages tell us about the underlying process governing mobility? First, it is difficult to rationalize downward occupational reallocations and (relative) wage losses with job-ladder models that rely on congestion to slow down sorting to optimal matches. In these models, worker and firm characteristics are fixed, but the matching process leads some individuals to be sub-optimally matched at any point in time. These models are well suited for explaining reallocations up a job ladder, as workers have strong incentive to wait for high-quality matches or jobs; but for downward movers, it is unlikely that congestion prevented them from making the move earlier, especially since it is accompanied by wage losses.[18]

Second, consider horizontally differentiated jobs, such as models of match-specific capital. In this case, we would expect low-quality matches to be more likely to dissolve. Depending on assumptions about how earnings evolve, workers may be willing to take a lower-paying job with more upside potential, leading to the pattern we see with low-wage individuals moving down to lower-paying occupations. However, such models cannot match the patterns for upwardly mobile individuals: if occupational-productivity is an independent draw, high-earning individuals should be less likely to change occupations and should not improve their wages by doing so.

The fact that we see relative wages predicting the direction of mobility and relating to wage growth or losses strongly suggests workers' productivity is correlated across occupations. Further, the fact that we see reallocations both up and down the occupational job-ladder strongly suggests information about the worker's optimal assignment is changing over time. As discussed in Section 2, such changes can be driven by changing human capital stocks or learning about worker ability.

This is consistent with Gibbons and Waldman (1999), who derive predictions about the wage patterns associated with mobility. As firms learn about a worker's ability and he accumulates human capital, his wages will rise within his position, until he crosses the promotion threshold to the new job. Thus, before moving, individuals who move up will earn more on average than the typical occupational stayer. After moving up to a new job, a worker is likely to be less-skilled than the average individual in the job, since he recently crossed the threshold. Thus he will earn less than the average occupational stayer in the new position. On the other hand, for downward movers, such a model would predict that pre-displacement wages should be lower than the average stayer in the occupation, while post-displacement wages should on average be higher. All four of these wage predictions are

[18] Moreover, as we saw in Table 2, 90% of occupational changes occur *within* the firm, where we would expect informational frictions to be relatively low.

supported by the results in Table 4.

4.2 Wages by Employer Mobility

Next, I compare wage changes by firm mobility. In Panel A of Table 5, I combine all firm-changers together, regardless of the reason for mobility. Here we see firm changers have wage growth that is almost double that of firm stayers (4.7% versus 2.8%, respectively), however the magnitude falls with the inclusion of worker controls. In Columns (3) through (6) we see that this wage growth is driven by the fact that firm changers are lower paid before moving compared with individuals who will not change firms. After moving, the gap between the wages for firm-changers and firm-stayers shrinks, however, these mobile workers still earn substantially less than firm stayers.

In Panel B, I separate firm changers based on the reason for mobility. In particular, I separate individuals into those who did not report displacement in the last year and those that did.[19] Here we see that voluntary firm-changers have annual earnings growth of 6.8%, which falls to 5.7% with the inclusion of worker demographic controls. In contrast, individuals who are affected by a plant closing have wage losses of 6.7%, which rises to 7.1% with controls. Before mobility, voluntary firm-changers do have a somewhat larger wage gap with firm-stayers than do displaced workers, though these differences are not statistically significant. However, after mobility, we see substantial variation in outcomes: voluntary firm changers on average narrow their wage gap with firm-stayers (falling from 13.7 log points to 10.7 log points), while displaced workers see their wage gap widen: rising from 9.5 log points to 19.4 log points after mobility.

We can see this dynamic more explicitly by examining the gap between wages and median occupational wages in Table 6. Here we see that, 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 not unusual before displacement, but their fortunes worsen dramatically after.

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 lower reported wages before mobility. In addition,

[19]In Appendix Tables A.10 and A.11 I show the wage patterns are similar if we further separate displaced workers into those displaced by plant closing and non-plant closing.

Table 5: Wages Within and Between Firms

	(1) W. Chg.	(2) W. Chg	(3) Prev. W.	(4) Prev. W.	(5) Next W.	(6) Next W.
	Panel A: All Firm-Changers					
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-Changers					
Non-Displaced Firm Change	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 Firm Change	-0.0955***	-0.0992***	-0.0953**	-0.0951***	-0.191***	-0.194***
	(0.0265)	(0.0263)	(0.0306)	(0.0267)	(0.0278)	(0.0259)
N	19459	19459	19459	19459	19459	19459
R-sq	0.002	0.006	0.017	0.264	0.014	0.259
Worker Controls		Y		Y		Y
Mean of Omitted	0.0281	0.0281	2.239	2.239	2.267	2.267

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 3.4 for more details. Omitted category is workers who were employed at the same firm in both months.

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 they make after displacement. Before mobility, displaced workers earn higher wages than non-displaced movers, and earn lower wages than individuals who will not change firms. However, after mobility their relative earnings fall dramatically. This is in contrast to non-displaced movers, who manage to improve their position relative to firm stayers, leading to wage growth. Thus, individuals who have more control over their mobility are able to find new jobs that pay higher hourly wages than their previous job. This suggests that firm-specific capital or rents are not the primary reason for wage losses after mobility, since non-displaced individuals also lose any firm-specific rents they have accrued in the previous position.

4.3 Occupation and Firm Mobility Interacted

Now that I have established the patterns of wage changes with occupational mobility and employer mobility separately, I want to focus on how these two types of mobility interact. In Tables 7 and 8, I disaggregate the specifications from Tables 3 and 4 by separating individuals based on whether they stay at the same firm, voluntarily change firms, or are displaced. Table 7 shows how the change in log real wages and log real wages before and

Table 6: 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: $^{+}$ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. See Section 3.4 for more details. Omitted category is workers who were employed at the same firm in both months.

after mobility vary based on the firm and occupational mobility. Table 8 shows how the gap between wages and median real occupational wages varies with worker mobility.

4.3.1 Occupation Changers Within the Firm

I first focus on occupational mobility inside the firm. These individuals allow us to isolate wage changes from occupational mobility from any wage changes that may be due to sorting between employers. Moreover, mobility is unlikely to be driven by search frictions, since it should be relatively costless for an individual to learn about vacancies and opportunities within the firm.

Columns (1) and (2) of Table 7 reveal that wage changes are closely linked to the direction of mobility. Individuals who remain employed at the firm across the year but do not change occupations have average earnings growth of 2.7%. Downward occupational changers inside the firm have earnings growth that is 3.4 percentage points smaller, with a net earnings loss of 0.7%, however this is not statistically distinct from zero. In contrast, upward occupational changers inside the firm have positive earnings growth which is 3.6 percentage points higher than occupational stayers, for a net earnings growth of over 6%. These estimates are unchanged with the inclusion of worker controls.

Next I turn to wages before and after mobility. In columns (3) and (4) of Table 7 we see that downward occupational changers are not especially low paid (after controlling for worker and job characteristics), but after the negative mobility event, they do appear to be substantially lower paid than the average occupational-stayer inside the firm. In contrast, upward occupational changers are low paid before mobility, but improve their wages after mobility to become indistinguishable from firm-stayers. In Table 8, we see that individuals

Table 7: Displaced Workers

	(1) W. Chg.	(2) W. Chg	(3) Prev. W.	(4) Next W.
Downward Occ. Change	-0.0335***	-0.0339***	0.000807	-0.0331***
	(0.00810)	(0.00811)	(0.00887)	(0.00896)
Upward Occ. Change	0.0376***	0.0358***	-0.0244**	0.0114
	(0.00805)	(0.00799)	(0.00891)	(0.00876)
No Occ. Chg. X Vol. Firm Chg.	-0.000746	-0.00637	-0.0130	-0.0194
	(0.0208)	(0.0207)	(0.0265)	(0.0267)
Downward Occ. Chg. X Vol. Firm Chg.	-0.00822	-0.0185	-0.127***	-0.146***
	(0.0209)	(0.0211)	(0.0194)	(0.0217)
Upward Occ. Chg. X Vol. Firm Chg.	0.100***	0.0906***	-0.213***	-0.123***
	(0.0187)	(0.0189)	(0.0175)	(0.0183)
No Occ. Chg. X Disp.	-0.0484	-0.0518	-0.0842	-0.136**
	(0.0341)	(0.0341)	(0.0523)	(0.0519)
Downward Occ. Chg. X Disp.	-0.158***	-0.160***	-0.100**	-0.260***
	(0.0433)	(0.0433)	(0.0381)	(0.0436)
Upward Occ. Occ. Chg. X Disp.	-0.0590	-0.0638	-0.0899+	-0.154***
	(0.0508)	(0.0500)	(0.0499)	(0.0377)
N	19459	19459	19459	19459
R-sq	0.011	0.014	0.268	0.261
Worker Controls		Y	Y	Y
Mean of Omitted	0.0265	0.0265	2.256	2.283

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 3.4 for more details. Omitted category is workers who were employed at the same firm in both months without changing occupations.

Table 8: Distance from Median Occupational Wages

	(1) Prev. W.	(2) Prev. W.	(3) Next W.	(4) Next W.
Downward Occ. Change	-0.0960***	-0.0864***	0.0578***	0.0679***
	(0.00847)	(0.00808)	(0.00839)	(0.00796)
Upward Occ. Change	0.0595***	0.0735***	-0.0937***	-0.0799***
	(0.00818)	(0.00772)	(0.00825)	(0.00787)
No Occ. Chg. X Vol. Firm Chg.	-0.0726***	-0.0394+	-0.0737***	-0.0435*
	(0.0212)	(0.0208)	(0.0213)	(0.0210)
Downward Occ. Chg. X Vol. Firm Chg.	-0.115***	-0.0644***	-0.115***	-0.0676***
	(0.0193)	(0.0191)	(0.0182)	(0.0176)
Upward Occ. Chg. X Vol. Firm Chg.	-0.182***	-0.122***	-0.152***	-0.0959***
	(0.0159)	(0.0157)	(0.0171)	(0.0169)
No Occ. Chg. X Disp.	-0.0809*	-0.0743+	-0.138***	-0.132***
	(0.0407)	(0.0383)	(0.0385)	(0.0369)
Downward Occ. Chg. X Disp.	-0.0132	-0.0134	-0.151***	-0.152***
	(0.0374)	(0.0359)	(0.0350)	(0.0365)
Upward Occ. Occ. Chg. X Disp.	-0.0606	-0.0414	-0.146***	-0.129***
	(0.0475)	(0.0447)	(0.0368)	(0.0365)
N	19459	19459	19459	19459
R-sq	0.029	0.117	0.035	0.121
Worker Controls		Y		Y
Job Controls		Y		Y
Mean of Omitted	0.0638	0.0638	0.0553	0.0553

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 3.4 for more details. Omitted category is workers who were employed at the same firm in both months without changing occupations.

who will subsequently move to a lower-quality occupation within the firm are particularly low paid for their occupation, earning below median pay. In contrast, after moving, they are now high-paid for their new occupation. For individuals who will move to higher-quality occupations, this pattern is reversed: these individuals are high paid for their previous occupation, but are low paid at their new occupation.

Thus, in sum we see that the patterns of wages and occupational mobility for individuals inside the firm are very similar to those we saw for all occupational movers in Tables 3 and 4. This is not surprising, since over 90% of the observations in the sample are individuals who remain in the firm. As discussed in Section 4.1, these patterns are consistent with efficient sorting across an occupational quality ladder.

4.3.2 Non-Displaced Firm-Changers

I next want to compare these results for occupational mobility inside the firm with occupational mobility for non-displaced between-firm-movers. In this case, workers may still move between occupations based on efficient sorting, however the fact that they are changing employers means that search frictions, firm-specific human capital, and firm-heterogeneity may affect the returns to different types of mobility. Non-displaced individuals who move between firms will lose any firm-specific rents they have accrued, but should have more choice over the timing of exit than displaced workers, allowing them a better chance of sorting to a higher-paying firm.

In Table 7, we see that downward occupational changers who voluntarily change firms have wage losses that have a smaller point estimate than those who move down inside the firm but are statistically indistinguishable. On the other hand, upward occupational changers who voluntarily change firms have wage increases that are 9 to 10 percentage points larger than those who move up inside the firm, depending on worker controls. In net, voluntary firm changers who move to lower-quality occupations have earnings losses of 2.6% while those who move to higher-quality occupations have earnings gains of 15.1%, after controlling for worker characteristics. Voluntary firm changers who stay in the same occupation have net earnings gains of 2.3%, which is not statistically distinguishable from occupation stayers within the firm. Thus the average wage gains of 5.7% for voluntary firm-changers that we saw in Table 5 masks substantial heterogeneity in the returns to voluntary employer mobility based on the type of concurrent occupational change.

Next consider wages before mobility and after mobility for voluntary firm changers. In Columns (3) and (4) of Table 7, we see that voluntary firm changers are lower-earning before and after mobility than their internal firm comparisons, although the difference is not statistically significant for occupation stayers. Similar to the results of Table 5, we see the large wage growth for positive movers is due to reducing the distance between their earnings and within-firm stayers, despite remaining substantially lower paid than firm stayers after mobility. In contrast, downward occupational movers are low paid before moving and become even lower paid after mobility.

In Table 8 the gap between wages and median occupational wages shows a similar pattern. Similar to downward occupational movers inside the firm, voluntary movers between firms who will subsequently move to a lower-quality occupation also earn wages that are below median occupational wages. In net, they earn wages that are 8.7% below median occupational wages which are substantially lower wages before mobility than any other group. In contrast to upward occupational changers inside the firm, who are selected from relatively high-earning workers within the occupation, voluntary firm changers who will move to a higher-quality occupation barely show positive selection with wages that are 12.2 log points less than upward occupational changers inside the firm, and in net wages are just barely above median occupational wages.

Similar to downward movers inside the firm, after the mobility event downward occupational changers who move voluntarily between firms are above-median earners in their new occupation, with net earnings that are close to the wages of firm and occupational stayers. Nonetheless, they remain less well paid for their new occupation than downward occupational changers inside the firm. After mobility, similar to upward occupational movers inside the firm, upward occupational movers who move voluntarily between firms are low earners in their new position; however, the gap is substantially larger for these between-firm movers, with net wages that are 12.1% below median occupational wages (compared with 2.5% below median for upward movers inside the firm).

Thus, although the general patterns of selection for these voluntary between-firm movers are roughly consistent with within-firm movers, the patterns are muted for upward occupational changers before mobility and downward occupational changers after mobility. This suggests between-firm movers may be sorting to firms of different qualities or pay scales. In particular, the fact that upward movers who change firms are not particularly well-paid for their occupations, even after controlling for demographic differences, could indicate that these workers were initially matched with lower-paying firms. Alternatively, the smaller wage gains for upward movers inside the firm could be due to wage-compression within the firm.

The fact that we see larger wage gains for upward movers who change firms is consistent with evidence from Frederiksen et al. (2016) and Groes et al. (2013), who find larger wage gains for upward movers between firms versus within firms. However, there is less agreement about wage changes for downward movers. Frederiksen et al. (2016) finds no difference in wage growth for individuals moving down out of management compared with occupation stayers, for either within-firm or between-firm movers. On the other hand, Groes et al. (2013) find relative losses for downward movers, which are larger for between-firm movers than for internal movers. In contrast, in my sample, while I do find relative losses for downward movers, and a smaller point estimate for downward movers, this is at most a 2 percentage point difference and it is not statistically significant.

4.3.3 Displaced Workers

Now we can compare wage changes for displaced workers. Non-displaced between-firm movers may have some control over the timing of their move, allowing them to select higher-quality firms. However displaced workers are forced to leave their previous employer under duress, which may result in them accepting lower-quality job offers and receiving lower wages compared with non-displaced individuals. However if we compare displaced workers and voluntary firm changers, both will give up any firm-specific capital they have accumulated.

I first want to compare wage changes for individuals who manage to find employment in the same narrowly defined occupation. These individuals will suffer from any lost firm-specific capital, however, by remaining in the same occupation they are able to preserve any occupation-specific capital. Here we see that these individuals have earnings losses of approximately 2.5%, compared with earnings gains of 2.0% for voluntary firm changers; however, both point estimates are too imprecise to distinguish statistically from each other or the average earnings gains for occupation-stayers within firms (2.7%). If we examine wages before mobility, we see that displaced workers do have a smaller point estimate than voluntary movers, but this is again too noisy to be able to statistically distinguish. However, after mobility displaced workers who stay in the same occupation earn 13.5 log points less than occupational stayers within the firm, compared with wages for voluntary firm changers that are 1.9 log points below the comparison group and not statistically significant. Thus, these results are broadly consistent with the perspective that displaced workers accept jobs at lower-paying firms compared with voluntary-movers who make a similar move.

I see even stronger evidence of firm-sorting for individuals who make upward or downward occupational changes upon moving between firms. For downward occupational changers, we see that wage losses are substantially larger for displaced workers, with a net change of 16.5% real earnings losses, which is 14.9 percentage points smaller than estimates for voluntary firm changers who move down. Similarly, displaced workers who make upward occupational changes have earnings changes of between -0.15% and .5%, which is 15.3 percentage points smaller than the wage growth experienced by voluntary firm changers who move up. Further, these estimates are not due to substantially different pre-displacement earnings: downward occupational movers who move firms voluntarily and involuntarily have similar earnings before moving; however, after moving displaced workers earn substantially less. For upward occupational movers, while voluntary firm-changers are lower paid before moving, they surpass the displaced workers after mobility. Thus in both cases, the displaced workers are unable to match the successes of voluntary movers in earnings post-mobility.

Finally consider the wage gap in Table 8. Downward occupational changers are slightly less negatively selected before moving than voluntary movers, with downward displaced workers earning 3.6% below median occupational earnings, compared with 8.7% for voluntary movers and 2.3% for downward movers inside the firm. However, after moving these displaced workers are less well-paid in their new position compared to voluntary movers and firm-stayers, earning below-median wages (2.9%), while downward occupational changing voluntary movers and firm-stayers both earn above-median wages in their new occupations.

Upward occupational changing displaced workers are relatively high earners before displacement, earning 9.6% above median occupational wages, compared with 1.5% above median for voluntary firm changers and 13.7% for upward movers inside the firm. After mobility, all types of upward occupational changers are below-median earners in their new occupations; however, displaced workers are especially so, earning in net 15.4% below median occupational wages, compared with 2.6% for within-firm movers and 12.1% for voluntary firm changers. Thus, in net, displaced workers are low paid after mobility, which persists even when we look within occupations.

4.4 Efficient Occupational Sorting of Displaced Workers

In the last section, I documented that displaced workers follow a similar pattern of selection to non-displaced workers, with downward occupational changers earning below-median wages for their occupation before moving, and upward occupational changers earning above-median wages for their occupation before moving. In this section, I replicate Figure 1 for displaced workers, in order to more directly test whether displaced workers follow a similar selection process as other occupational changers.

Since the sample of displaced workers in the contemporaneous sample is small, I instead use the retrospective sample. This gives me a sample of 1076 displaced workers. However, now the data on wages and occupation before mobility is collected retrospectively, and so may be less precise.

Figure 2 shows how the share of occupational changers moving up or down among displaced workers varies based on the individual's place in the occupational wage distribution before the displacement event. Here we see a pattern that is very similar to Figure 1 for all occupational changers. In particular, individuals who are in the bottom portion of the occu-

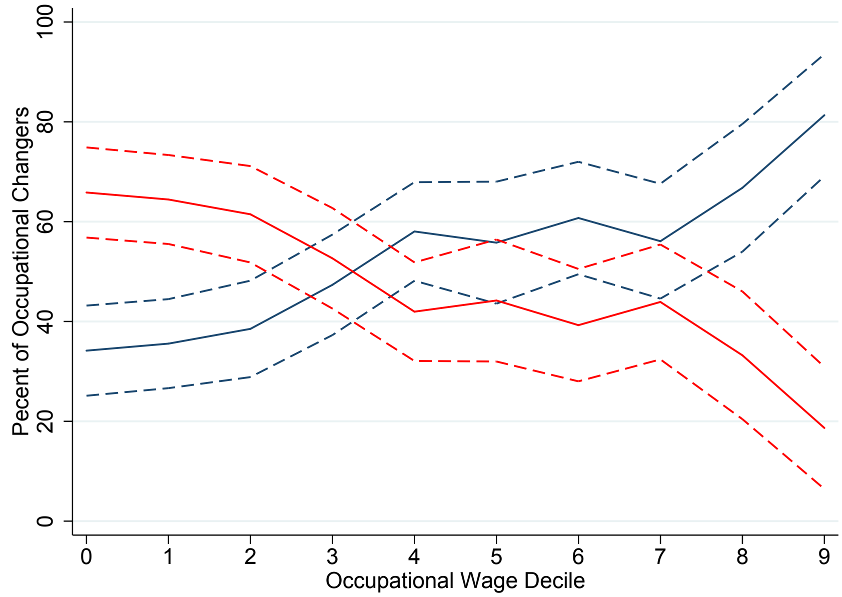

Figure 2: Percent of occupational switchers among displaced workers moving to lower-quality occupations (red) or higher-quality occupations (blue), by decile of the occupational wage distribution, retrospective occupations from the Displaced Worker Survey.

pational wage distribution are substantially more likely to move to a lower-quality occupation upon displacement. For individuals in the middle, the transition rates roughly equalize, but for individuals in the top 20 percent of the wage distribution for their occupation the rates of upward mobility dwarf those of downward mobility.

Thus, although I do not find evidence of selection in terms of the individuals who are displaced, I do see that, conditional on displacement, patterns of occupational reallocation are consistent with the patterns we see for voluntary mobility. These patterns of sorting, by which low occupational earners are more likely to move down and high occupational earners are more likely to move up, are consistent with models of efficient reallocation based on changing worker capabilities or firm learning about worker ability.

4.5 Can Occupational Mobility Explain Displaced Workers' Wage Losses?

Now I return to the original question: why does displacement lead to wage losses? Recall from Table 4.2 we saw that, on average, displaced workers who are re-employed within a year of displacement have real wage losses of 7%, while voluntary firm-changers have wage gains of about 6%. Can differences in the distribution of occupational moves explain these different outcomes? To do so, I use the distribution of occupational changes from Table 2 and the estimates of average wage changes by occupational mobility for non-displaced firm changers from Table 7 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 3.3% after displacement. This discrepancy is driven by the fact that, for each type of occupational move, displaced workers have substantially worse wage outcomes. For both downward and upward occupational changes, displaced workers have wage changes that are about 15 percentage points lower than voluntary movers. These results indicate that, although the direction of occupational mobility can explain variation in wage losses within displaced workers, it cannot explain differences in wage changes between displaced and non-displaced firm-changers.

However, an alternative explanation is that the extent of upward and downward mobility are different for displaced workers: if displaced workers move to lower-quality occupations, we would expect them to have larger wage losses than voluntary movers who make similar moves. Thus, in this section I use the distance of occupational changes to evaluate whether there is substantial heterogeneity in occupational outcomes.

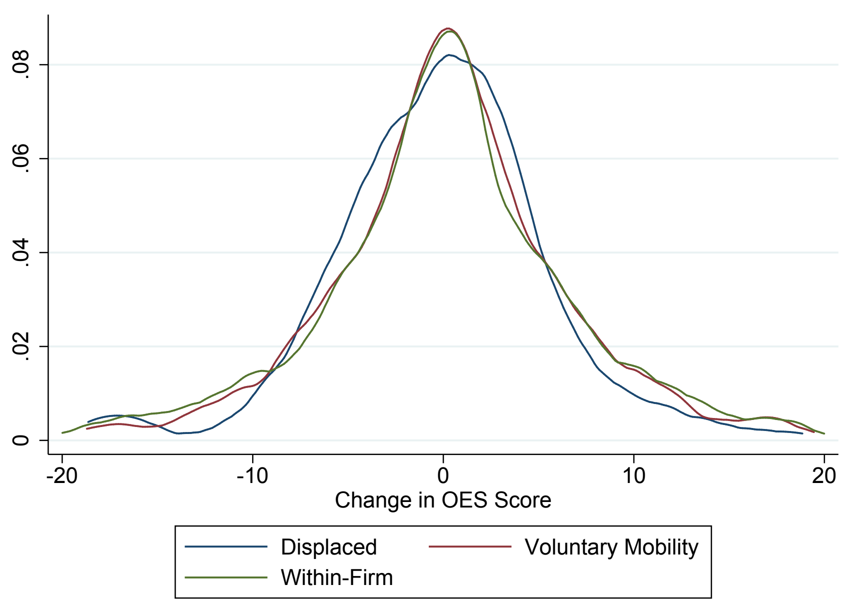

Figure 3: Kernel density plots for different types of mobility, conditional on changing occupations.

As a first step, Figure 3 illustrates kernel-density plots for the change in the OES wage score for each of the three types of movers (Displaced, Voluntary Firm Changers, and Within-Firm), conditional on changing occupations. If displaced workers were making substantially different moves, we would expect to see weight shifted to the left in the distribution. However the graph shows the distribution is not obviously skewed. Thus it does not appear that there is a big difference in the distribution of moves for displaced workers.

Table 9: Change in Occupational Quality by Mobility

	(1)	(2)
Negative Occ. Chg.	-5.715***	-5.350***
	(0.118)	(0.335)
Positive Occ. Chg	5.755***	6.129***
	(0.111)	(0.330)
Downward Occ. Chg. X Vol. Firm Chg.	0.624*	0.554+
	(0.291)	(0.292)
Upward Occ. Chg. X Vol. Firm Chg.	-0.0716	-0.143
	(0.295)	(0.298)
Downward Occ. Chg. X Disp.	0.573	0.632
	(0.599)	(0.597)
Upward Occ. Chg. X Disp.	-1.488**	-1.450**
	(0.540)	(0.544)
N	8936	8936
R-sq	0.464	0.465
Worker Controls		Y

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 3.4 for more details.

Table 9 allows us to examine analytically the pattern from Figure 3, by measuring the change in OES wage score based on the type of move an individual makes. I again restrict the sample to individuals that change occupations. Here we see that displaced workers who move to lower-quality occupations make moves that are statistically indistinguishable from downward movers inside the firm and non-displaced between-firm movers. If anything, the magnitude of the change in occupation quality is smaller for displaced workers. Thus, the distance of the change in occupation quality cannot explain the large wage losses for displaced workers who move to lower-quality occupations.

In contrast, for upward occupational changers, we see that displaced workers do have smaller gains in occupational quality: on average they move to occupations with \$1.50 lower median occupational wages compared with non-displaced individuals. Thus, part of the smaller gain in wages for these workers compared to non-displaced workers may be due to a smaller positive change.

In addition, we can evaluate a result from Table 7: the fact that upward occupational changers who move voluntarily between firms experience larger wage gains compared with positive movers inside the firm. Here we see that upward occupational movers between firms have a smaller magnitude of change in occupational quality compared with those within the firm, thus differences in the distance of moves cannot explain these larger wage gains we see for between-firm voluntary movers.

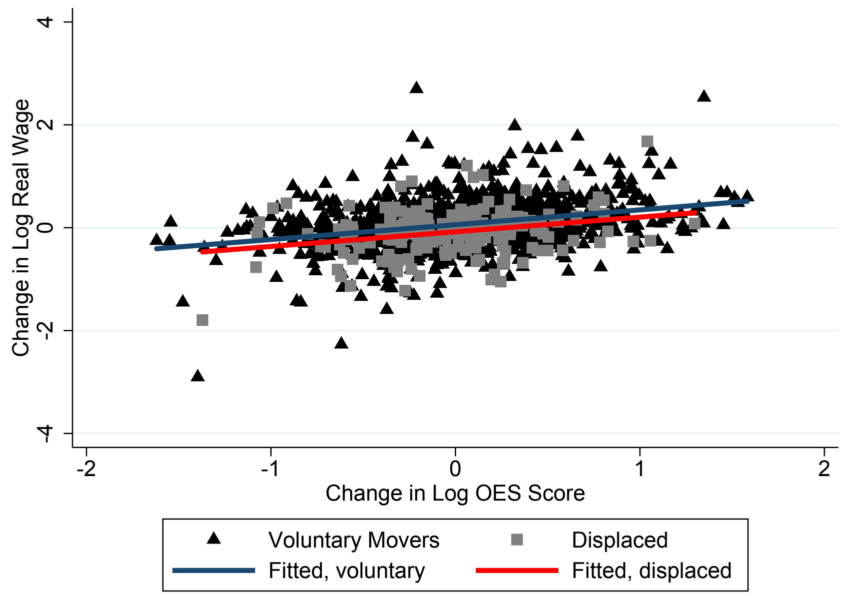

Figure 4: Scatter plot of change in log OES score by change in log real wage for voluntary firm changers and displaced workers, conditional on changing occupation.

To more directly see how changes in wages relate to the distance of occupational moves, Figure 4 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 black triangles show voluntary firm changers, while the gray squares show displaced workers. I also create fitted lines for voluntary movers (blue) and displaced workers (red). Here we see 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 see this analytically, in Table 10 I replicate Table 7; however, now I interact the type of mobility with the distance of the change in OES score and include shifter variables for voluntary firm changers and displaced workers. 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 and whether the change in OES score is positive or negative. It also allows the average change in log real wages to differ based on the type of firm mobility. Here we see voluntary 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 zero.

Table 10: Change in Wages and Change in Occupational Quality

	(1) W. Chg.	(2) W. Chg	(3) Prev. W.	(4) Next W.
Log OES Chg. If Downward Occ. Chg.	0.0811***	0.0809***	-0.0561**	0.0249
	(0.0175)	(0.0175)	(0.0184)	(0.0189)
Log OES Chg. If Upward Occ. Chg.	0.117***	0.114***	-0.0375*	0.0763***
	(0.0178)	(0.0177)	(0.0182)	(0.0182)
Log OES Chg. If Downward Occ. Chg. X Vol. Firm Chg.	0.108*	0.112*	0.0772	0.189**
	(0.0506)	(0.0507)	(0.0536)	(0.0609)
Log OES Chg. If Upward Occ. Chg. X Vol. Firm Chg.	0.188***	0.183***	-0.183***	0.000122
	(0.0513)	(0.0513)	(0.0514)	(0.0520)
Log OES Chg. If Downward Occ. Chg. X Disp.	0.198	0.191	-0.0514	0.140
	(0.163)	(0.163)	(0.115)	(0.136)
Log OES Chg. If Upward Occ. Chg. X Disp.	0.200	0.199	-0.0855	0.113
	(0.242)	(0.237)	(0.273)	(0.121)
Vol. Firm Change	0.0198	0.0124	-0.100***	-0.0879***
	(0.0145)	(0.0146)	(0.0168)	(0.0174)
Displaced Firm Change	-0.0887**	-0.0930**	-0.0954**	-0.188***
	(0.0341)	(0.0339)	(0.0363)	(0.0352)
Worker Controls		Y	Y	Y
N	19459	19459	19459	19459
R-sq	0.016	0.019	0.266	0.261
Mean of Omitted	0.0248	0.0248	2.239	2.264

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 3.4 for more details. Omitted category is workers who were employed at the same firm in both months without changing occupations.

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 4 and the negligible average change in wages for displaced movers who move up from Table 7. For individuals who make negative moves, the change in OES score worsens the losses, leading to the average wage losses of 16.5% we saw in Table 7. 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, we see a robust wage penalty from displacement that is distinct from changes that are associated with occupational sorting.

5 Discussion and 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 is efficient, 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. These differences are most likely due to displaced workers matching with lower-paying employers; however, it could also be due to displaced workers accepting lower wages from similar employers. Although the bulk of losses are experienced by displaced workers who move down the occupational ladder, I find similar relative losses for all displaced workers.

These results can be used to evaluate three recent papers that use job-ladder models to explain the dynamics of job mobility and displacement. As I find in this paper, occupation and firm job ladders likely play an important role in explaining job mobility, the costs of displacement, and the process of recovering from displacement. First, Krolikowski (2016) develops a random-search model in which worker and firm matches each have a match-specific quality. This leads to the construction of a job-ladder, as non-employed individuals are willing to accept lower-quality matches, but search on-the-job to find improved matches. Second, Jung and Kuhn (2016) construct a directed search model with human capital accumulation over the lifecycle and imperfect human capital transmittance across jobs, which helps drive the large losses upon displacement and slow wage recovery as the worker attempts to regain employment in a job that can use his accumulated capital. Third, Huckfeldt (2016) develops a model of occupational mobility in which workers have an endowment of human capital and slowly progress via directed on-the-job search to the occupation in which they will be most productive. All three papers show via calibration that they are able to capture a substantial fraction of the empirical losses due to displacement as well as the persistence of losses.

My results indicate that losses from displacement are not due to sorting between occupations as in Huckfeldt (2016), but rather, due to workers accepting jobs especially low-paying firms conditional on the occupation. The fact that I find a similar pattern of occupational mobility for voluntary movers and displaced workers indicates that wage loses are not due to skill-depreciation after displacement as in Jung and Kuhn (2016). Moreover, in light of recent evidence from Lachowska et al. (2017), these losses from between-firm mobility appear to be largely driven by variation in firm pay, that is, a universal ranking rather than an idiosyncratic match-specific ranking as in Krolikowski (2016) and Jung and Kuhn (2016).

Instead, the process by which workers sort between different types of jobs appears to be distinct from the process by which workers sort between firms. Displacement induces a tumble down the employer-wage job ladder, but does not appear to lead to inefficiencies in the reallocation of workers between occupations.

References

Acemoglu, D. (1999). Changes in Unemployment and Wage Inequality: an Alternative Theory and Some Evidence. *The American Economic Review*.

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.

Current population survey design and methodology, technical paper 66 (Tech. Rep.). (2006, October). U.S. Census Bureau.

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. (1999). Mobility and stability: The dynamics of job change in labor markets. *Handbook of Labor Economics*, *3*(2), 2439–2483. doi: 10.1016/S1573-4463(99)30023-7

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.

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

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. (2016). *Earnings Losses and Labor Mobility over the Lifecycle Earnings Losses and Labor Mobility over the Lifecycle.*

Kahn, L. B., & Mcentarfer, E. (2014). *Worker Flows Over the Business Cycle : the Role of Firm Quality.*

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

Kletzer, L. G., & Fairlie, R. W. (2003). The Long-Term Costs of Job Displacement for Young Adult Workers. *Industrial and Labor Relations Review*, *56*(4), 682–698.

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

Krueger, A. B., & Summers, L. (1988). Efficiency Wages and the Inter-Industry Wage Structure. *Econometrica*, *56*(2), 259–293.

Lachowska, M., Mas, A., & Woodbury, S. (2017). *Sources of Displaced Workers ' Long-Term Earnings Losses* (Vol. 1).

Lazear, E. (1992). The job as a concept. In J. William J. Bruns (Ed.), *Performance measurement, evaluation, and incentives* (p. 183-215). Boston, MA: Harvard Business School Press.

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).

Moscarini, G., & Thomsson, K. (2007, December). Occupational and Job Mobility in the US. *Scandinavian Journal of Economics*, *109*(4), 807–836.

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

Pissarides, C. A. (1994). Search Unemployment with On-the-job Search. *The Review of Economic Studies*, *61*(208), 457–476.

Poletaev, M., & Robinson, C. (2008). Human Capital Specificity: Evidence from the Dictionary of Occupational Titles and Displaced Worker Surveys, 19842000. *Journal of Labor Economics*, *26*(3), 387–420.

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.

Appendix A

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.

A.1 Alternative Quality Indices

In this section, I construct a variety of alternative quality indices to complement the specifications in the text based on median OES wages. First, I construct a more restrictive definition ('Big OES'), that creates a third, unclassifiable type of move, for changes in OES scores that are less than \$2. This is 1/4 of a standard deviation in the OES score, and represents movements between jobs that may be too similar to assign a strict ranking.

For the second set of quality metrics, I use occupational characteristics from O*NET. O*NET is a database developed by the U.S. Department of Labor to provide detailed information on over 900 occupations. The occupational data is provided by skilled human-resources professionals and includes information on the abilities and skills needed to succeed, tasks performed, required education, experience, and training, among other information. In total there are 277 of these occupational descriptors. These are summarized in Appendix Table A.3.

Since each occupation has hundreds of scores, I use principal component analysis (PCA) to condense these variables into quality indices. This methodology takes advantage of the fact that many of the variables are correlated: for instance, occupations that require workers to have a high level of written expression also require a high level of written comprehension.

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

	Firm Stayers	Vol. 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.

PCA is a procedure to construct linear combinations of variables that explain the most variation in the data.

The first index I construct I call the O*NET Quality Index. To create it, I include variables classified as worker ability and worker skills in the database. These include variables ranging from oral comprehension to stamina to memorization. The variables that are weighted highest in this index are written expression, reading comprehension, judgment and decision-making. Occupations that receive high scores include physicists, CEOs, neurologists, and judges. Occupations that receive low scores include fallers, mine shuttle car operators, dishwashers, and meatpackers. I normalize the index to range from zero to one hundred. See Appendix Table A.4 for more details on the variables and occupations.

For the second index, I explicitly construct a variable using management-related variables in the O*NET database. I include such variables as leadership, resource management skills, decision-making skills, and so forth. Appendix Table A.5 shows a list of all variables included in the index. I again use PCA to create a single index. The variables that are most important to this index include coaching and developing others, motivating subordinates, and management of personnel resources. CEOs receive the highest management score; other high-scoring occupations include education administrators and front-line supervisors. Occupations that receive low management scores include farmworkers, telemarketers, and food preparation workers. I call this index the O*NET Management Index, and again normalize it to be between zero and one hundred. See Appendix Table A.6 for more details on the variables and occupations.

Table A.3: O*NET Variables in Quality Index (Summary)

1.A.1.a.1-4	Verbal Abilities
1.A.1.b.1-7	Idea Generation and Reasoning Abilities
1.A.1.c.1-2	Quantitative Abilities
1.A.1.d.1	Memorization
1.A.1.e.1-3	Perceptual Abilities
1.A.1.f.1-2	Spatial Abilities
1.A.1.g.1-2	Attentiveness
1.A.2.a.1-3	Fine Manipulative Abilities
1.A.2.b.1-4	Control Movement Abilities
1.A.2.c.1-3	Reaction Time and Speed Abilities
1.A.3.a.1-4	Physical Strength Abilities
1.A.3.b.1	Endurance: Stamina
1.A.3.c.1-4	Flexibility, Balance, and Coordination
1.A.4.a.1-7	Visual Abilities
1.A.4.b.1-5	Auditory and Speech Abilities
2.A.1.a-f	Skills: Content (Reading Comprehension, Mathematics, etc)
2.A.2.a-d	Skills: Process (Critical Thinking, Active Learning, etc)
2.B.1.a-i	Social Skills
2.B.3.a-m	Technical Skills
2.B.4.e-h	Systems Skills
2.B.5.a-d	Resource Management Skills

Table A.4: O*NET Quality Index

Largest Positive Weighted Variables:	Written Expression, Speaking Skills, Reading Comprehension, Critical Thinking, Judgment and Decision-Making
Largest Negative Weighted Variables:	Static Strength, Speed of Limb Movement, Stamina, Gross Body Coordination, Reaction Time
Occupations with Highest Score:	Physicists, CEOs, Preventative Medicine Physicians, Neurologists, Judges
Occupations with Lowest Score:	Fallers, Cleaners of Vehicles and Equipment, Mine Shuttle Car Operators, Dishwashers, Meat Packers

Table A.5: O*NET Variables in Management Index

1.B.1.e	Enterprising	Enterprising occupations frequently involve starting up and carrying out projects. These occupations can involve leading people and making many decisions. Sometimes they require risk taking and often deal with business.
1.B.2.a	Achievement	Occupations that satisfy this work value are results oriented and allow employees to use their strongest abilities, giving them a feeling of accomplishment. Corresponding needs are Ability Utilization and Achievement.
1.B.2.c	Recognition	Occupations that satisfy this work value offer advancement, potential for leadership, and are often considered prestigious. Corresponding needs are Advancement, Authority, Recognition and Social Status
1.C.2.b	Leadership	Job requires a willingness to lead, take charge, and offer opinions and direction.
2.B.4.e	Judgment and Decision-Making	Considering the relative costs and benefits of potential actions to choose the most appropriate one.
2.B.4.g	Systems Analysis	Determining how a system should work and how changes in conditions, operations, and the environment will affect outcomes.
2.B.4.h	Systems Evaluation	Identifying measures or indicators of system performance and the actions needed to improve or correct performance, relative to the goals of the system.
2.B.5.a	Time Management	Managing one's own time and the time of others.
2.B.5.b	Management of Financial Resources	Determining how money will be spent to get the work done, and accounting for these expenditures.
2.B.5.c	Management of Material Resources	Obtaining and seeing to the appropriate use of equipment, facilities, and materials needed to do certain work.
2.B.5.d	Management of Personnel Resources	Motivating, developing, and directing people as they work, identifying the best people for the job.
2.C.1.a	Administration and Management	Knowledge of business and management principles involved in strategic planning, resource allocation, human resources modeling, leadership technique, production methods, and coordination of people and resources.
2.C.1.f	Personnel and Human Resources	Knowledge of principles and procedures for personnel recruitment, selection, training, compensation and benefits, labor relations and negotiation, and personnel information systems.
4.A.2.b.1	Making Decisions and Solving Problems	Analyzing information and evaluating results to choose the best solution and solve problems.
4.A.2.b.2	Thinking Creatively	Developing, designing, or creating new applications, ideas, relationships, systems, or products, including artistic contributions.
4.A.2.b.3	Updating and Using Relevant Knowledge	Keeping up-to-date technically and applying new knowledge to your job.
4.A.2.b.4	Developing Objectives and Strategies	Establishing long-range objectives and specifying the strategies and actions to achieve them.
4.A.2.b.5	Scheduling Work and Activities	Scheduling events, programs, and activities, as well as the work of others.
4.A.2.b.6	Organizing, Planning, and Prioritizing Work	Developing specific goals and plans to prioritize, organize, and accomplish your work.
4.A.4.b.1	Coordinating the Work and Activities of Others	Getting members of a group to work together to accomplish tasks
4.A.4.b.2	Developing and Building Teams	Encouraging and building mutual trust, respect, and cooperation among team members.
4.A.4.b.3	Training and Teaching Others	Identifying the educational needs of others, developing formal educational or training programs or classes, and teaching or instructing others.
4.A.4.b.4	Guiding, Directing, and Motivating Subordinates	Providing guidance and direction to subordinates, including setting performance standards and monitoring performance.
4.A.4.b.5	Coaching and Developing Others	Identifying the developmental needs of others and coaching, mentoring, or otherwise helping others to improve their knowledge or skills.
4.A.4.b.6	Provide Consultation and Advice to Others	Providing guidance and expert advice to management or other groups on technical, systems-, or process-related topics.
4.A.4.c.1	Performing Administrative Activities	Performing day-to-day administrative tasks such as maintaining information files and processing paperwork.
4.A.4.c.2	Staffing Organizational Units	Recruiting, interviewing, selecting, hiring, and promoting employees in an organization.
4.A.4.c.3	Monitoring and Controlling Resources	Monitoring and controlling resources and overseeing the spending of money.

Table A.6: O*NET Management Index

Largest (Positive) Weighted Variables:	Provide Consultation and Advice to Others; Scheduling Work and Activities; Guiding, Directing, and Motivating Subordinates; Systems Evaluation; Developing Objectives and Strategies
Smallest (Positive) Weighted Variables:	Occupational Interests: Enterprising; Training and Teaching Others; Performing Administrative Activities; Management of Material Resources; Knowledge of Personnel and Human Resources
Occupations with Highest Score:	CEOs, Education Administrators, Social and Community Service Managers, Medical and Health Services Managers, Program Directors
Occupations with Lowest Score:	Models, Graders and Sorters of Agricultural Products, Telemarketers, Dressing Room Attendants, Farmworkers

Now I can examine the frequency of mobility using these constructed occupational rankings. In Panel A of Table A.7, I report the percent of individuals who report activities changes within the firm from the monthly CPS sample who move to lower-ranked occupations based on different measures. As discussed in Section 3.1, this measure of occupational mobility within the firm provides the most reliable measures in the CPS, although it may still be subject to measurement error in the coding procedure. Column (1) shows the preferred ranking, change in OES score, which shows 46% of occupational changes inside the firm are to occupations with a lower OES score. Similar rates are obtained using the two O*NET quality indices, with 47% for the Quality Index and 46% for the Management Index. Appendix Table A.8 presents the corresponding rates of upward mobility. Here we see that for each occupational mobility definition, individuals are more likely to move up than down, at rates of between 53 and 54% for the simple definitions.

In Panel B of Table A.7, I again use the monthly CPS data, but use the less restrictive occupational change measure in order to compare occupational changes both within and between firms. Here we see similar but slightly higher point estimates for downward mobility within firms, with about 1 additional percentage point for each of the measures. We see a somewhat mixed story in terms of the differences in downward mobility within versus between firms: occupational changers moving between firms are slightly less likely to move lower-quality jobs in terms of the OES ranking, but slightly more likely to move to lower-quality occupations in terms of the O*NET Quality and Management Indices.

In Panel C of Table A.7, I change to the CPS Tenure sample, which measures mobility over the year. Here we see a more consistent story of lower rates of downward mobility across all six rankings for individuals who change employers, although again not significant for the

O*NET derived indices. In addition, the point estimates for rates of downward mobility are somewhat smaller than the monthly estimates from Panel B.

Table A.7: Rate of Downward Occupational Mobility

% Down:	(1) OES	(2) Big OES	(3) ONET Q1	(4) ONET Mgmt	(5) All 3	(6) Big All 3
Panel A.: Internal Monthly Occ. Changers (Reporting Activities Changes)						
Average (Firm Stayers)	45.97***	33.77***	46.72***	46.42***	29.01***	20.42***
	(0.255)	(0.242)	(0.255)	(0.255)	(0.232)	(0.205)
N	50600	50600	50600	50600	50600	50600
Panel B.: All Monthly Occ. Changers (New Occupational Code)						
Emp. Change (Dif. from Stayers)	-0.555**	-2.044***	0.564**	0.821***	-1.522***	-1.651***
	(0.187)	(0.178)	(0.188)	(0.188)	(0.171)	(0.152)
Average (Firm Stayers)	47.99***	35.81***	48.53***	48.27***	30.57***	21.75***
	(0.119)	(0.115)	(0.119)	(0.119)	(0.110)	(0.0985)
N	383673	383673	383673	383673	383673	383673
Panel C.: All Annual Occ. Changers (New Occupational Code)						
Emp. Change (Dif. from Stayers)	-2.782+	-4.387**	-0.267	-1.190	-2.945*	-3.001**
	(1.511)	(1.374)	(1.515)	(1.515)	(1.342)	(1.140)
Average (Firm Stayers)	47.79***	32.52***	47.86***	48.55***	29.08***	19.59***
	(0.654)	(0.612)	(0.654)	(0.654)	(0.595)	(0.519)
N	9333	9333	9333	9333	9333	9333

Robust standard errors in parentheses: $^{+}$ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. See Section 3.4 for more details.

In Table A.8 I replicate Table A.7 however now examine the share of individuals moving up. In Table A.9 I examine changes based on average experience requirements, average training requirements, and average educational requirements for the occupation. Here we see similar rates to the OES measure: 46 to 48% of the occupational changers move to lower ranked occupations in terms of experience and training. We see smaller rates of change for education, since it is a courser measure and accordingly has a larger share of occupational movers who move to occupations with the same education requirement.

Table A.8: Rate of Upward Occupational Mobility

% Down:	(1) OES	(2) Big OES	(3) ONET Q1	(4) ONET Mgmt	(5) All 3	(6) Big All 3
Panel A.: Internal Monthly Occ. Changers (Reporting Activities Changes)						
Average (Firm Stayers)	54.03***	39.95***	53.14***	53.44***	35.55***	26.23***
	(0.255)	(0.251)	(0.255)	(0.255)	(0.245)	(0.225)
N	50600	50600	50600	50600	50600	50600
Panel B.: All Monthly Occ. Changers (New Occupational Code)						
Emp. Change (Dif. from Stayers)	0.555**	-1.640***	-0.554**	-0.811***	-2.109***	-2.494***
	(0.187)	(0.182)	(0.188)	(0.188)	(0.175)	(0.157)
Average (Firm Stayers)	52.01***	38.58***	51.29***	51.55***	33.53***	24.24***
	(0.119)	(0.116)	(0.119)	(0.119)	(0.113)	(0.102)
N	383673	383673	383673	383673	383673	383673
Panel C.: All Annual Occ. Changers (New Occupational Code)						
Emp. Change (Dif. from Stayers)	2.782+	-0.554	0.306	1.228	-0.0681	-1.682
	(1.511)	(1.437)	(1.515)	(1.515)	(1.421)	(1.229)
Average (Firm Stayers)	52.21***	34.63***	52.00***	51.31***	32.20***	21.76***
	(0.654)	(0.622)	(0.654)	(0.654)	(0.610)	(0.538)
N	9333	9333	9333	9333	9333	9333

Robust standard errors in parentheses: $^{+}$ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. See Section 3.4 for more details.

Table A.9: Additional Measures of Occupational Mobility

	(1) Neg. Exp.	(2) Neg. Train.	(3) Neg. Edu.	(4) Pos. Exp.	(5) Pos. Train.	(6) Pos. Edu.
Panel A.: Internal Monthly Occ. Changers (Reporting Activities Changes)						
Average (Firm Stayers)	46.71***	47.74***	26.72***	53.15***	52.12***	29.31***
	(0.255)	(0.255)	(0.226)	(0.255)	(0.255)	(0.232)
N	50600	50600	50600	50600	50600	50600
Panel B.: All Monthly Occ. Changers (New Occupational Code)						
Emp. Change (Dif. from Stayers)	0.648***	0.0166	-0.238	-0.638***	-0.00662	0.453**
	(0.188)	(0.188)	(0.168)	(0.188)	(0.188)	(0.170)
Average (Firm Stayers)	48.34***	49.02***	27.78***	51.48***	50.80***	28.86***
	(0.119)	(0.119)	(0.107)	(0.119)	(0.119)	(0.108)
N	383673	383673	383673	383673	383673	383673
Panel C.: All Annual Occ. Changers (New Occupational Code)						
Emp. Change (Dif. from Stayers)	-1.017	-2.718+	-1.647	1.056	2.756+	2.635+
	(1.515)	(1.514)	(1.234)	(1.515)	(1.514)	(1.348)
Average (Firm Stayers)	48.42***	49.51***	22.29***	51.44***	50.35***	24.41***
	(0.654)	(0.654)	(0.544)	(0.654)	(0.654)	(0.562)
N	9333	9333	9333	9333	9333	9333

Robust standard errors in parentheses: $^{+}$ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. See Section 3.4 for more details.

Appendix B

In this Appendix, I disaggregate several tables from the text based on whether or not the displacement was due to a plant closing or other reasons.

Table A.10: Wages Within and Between Firms

	(1) W. Chg.	(2) W. Chg	(3) Prev. W.	(4) Prev. W.	(5) Next W.	(6) Next W.
Panel A: All Firm-Changers						
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-Changers						
Vol. Firm Chg.	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 Closing	-0.0741+	-0.0795*	-0.112*	-0.0838+	-0.186***	-0.163***
	(0.0401)	(0.0398)	(0.0525)	(0.0444)	(0.0483)	(0.0456)
Other Displ.	-0.105**	-0.108**	-0.0877*	-0.100**	-0.193***	-0.208***
	(0.0338)	(0.0335)	(0.0374)	(0.0329)	(0.0338)	(0.0311)
R-sq	0.002	0.006	0.017	0.264	0.014	0.259
Worker Controls		Y		Y		Y
Mean of Omitted	0.0281	0.0281	2.239	2.239	2.267	2.267
N	19459	19459	19459	19459	19459	19459

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 3.4 for more details. Omitted category is workers who were employed at the same firm in both months.

Table A.11: Wages Within and Between Firms

	(1) Prev. W.	(2) Prev. W.	(3) Next W.	(4) Next W.
Vol. Firm Chg.	-0.134***	-0.0816***	-0.128***	-0.0758***
	(0.0106)	(0.0106)	(0.0109)	(0.0108)
Plant Closing	-0.0604	-0.0313	-0.104**	-0.0755*
	(0.0420)	(0.0391)	(0.0329)	(0.0330)
Other Displ.	-0.0558+	-0.0521+	-0.167***	-0.163***
	(0.0302)	(0.0290)	(0.0270)	(0.0269)
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	0.0426	0.0426
N	19459	19459	19459	19459

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 3.4 for more details. Omitted category is workers who were employed at the same firm in both months.

Table A.12: Displaced Workers

	(1) W. Chg.	(2) W. Chg	(3) Prev. W.	(4) Next W.
Downward Occ. Change	-0.0335***	-0.0339***	0.000629	-0.0333***
	(0.00810)	(0.00811)	(0.00887)	(0.00896)
Upward Occ. Change	0.0376***	0.0357***	-0.0248**	0.0109
	(0.00805)	(0.00799)	(0.00892)	(0.00876)
No Occ. Chg. X Vol. Firm Chg.	-0.00653	-0.0155	-0.0106	-0.0261
	(0.0192)	(0.0193)	(0.0238)	(0.0244)
Downward Occ. Chg. X Vol. Firm Chg.	-0.0296	-0.0445*	-0.115***	-0.159***
	(0.0186)	(0.0189)	(0.0171)	(0.0193)
Upward Occ. Occ. Chg. X Vol. Firm Chg.	0.138***	0.120***	-0.198***	-0.0779***
	(0.0160)	(0.0164)	(0.0157)	(0.0155)
No Occ. Chg. X Plant Closing	-0.0763*	-0.0816*	-0.118	-0.200*
	(0.0378)	(0.0386)	(0.0898)	(0.0871)
Downward Occ. Chg. X Plant Closing	-0.0984	-0.0979	-0.0938	-0.192**
	(0.0691)	(0.0702)	(0.0654)	(0.0734)
Upward Occ. Occ. Chg. X Plant Closing	-0.0280	-0.0429	-0.0505	-0.0935
	(0.0914)	(0.0884)	(0.0757)	(0.0668)
No Occ. Chg. X Other Displ.	-0.0322	-0.0341	-0.0637	-0.0978
	(0.0490)	(0.0488)	(0.0638)	(0.0638)
Downward Occ. Chg. X Other Displ.	-0.240***	-0.243***	-0.102*	-0.345***
	(0.0530)	(0.0526)	(0.0461)	(0.0511)
Upward Occ. Chg. X Other Disp.	-0.0193	-0.0232	-0.135*	-0.158***
	(0.0598)	(0.0591)	(0.0603)	(0.0436)
Constant	0.0265***	0.0844***	1.654***	1.738***
	(0.00424)	(0.0130)	(0.0150)	(0.0147)
	19815	19815	19815	19815
	0.012	0.015	0.283	0.273

Robust standard errors in parentheses: $^{+}$ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. See Section 3.4 for more details.

Table A.13: Distance from Median Occupational Wages

	(1) Prev. W.	(2) Prev. W.	(3) Next W.	(4) Next W.
Downward Occ. Change	-0.0960***	-0.0865***	0.0578***	0.0677***
	(0.00847)	(0.00808)	(0.00840)	(0.00797)
Upward Occ. Change	0.0596***	0.0731***	-0.0938***	-0.0803***
	(0.00818)	(0.00773)	(0.00825)	(0.00788)
No Occ. Chg. X Vol. Firm Chg.	-0.0883***	-0.0267	-0.0965***	-0.0401*
	(0.0193)	(0.0190)	(0.0198)	(0.0193)
Downward Occ. Chg. X Vol. Firm Chg.	-0.236***	-0.144***	-0.0719***	0.0139
	(0.0168)	(0.0168)	(0.0159)	(0.0157)
Upward Occ. Occ. Chg. X Vol. Firm Chg.	-0.139***	-0.0190	-0.262***	-0.150***
	(0.0136)	(0.0139)	(0.0137)	(0.0144)
No Occ. Chg. X Plant Closing	-0.0778	-0.0460	-0.157**	-0.121*
	(0.0568)	(0.0562)	(0.0589)	(0.0573)
Downward Occ. Chg. X Plant Closing	-0.104	-0.110+	-0.0381	-0.0411
	(0.0643)	(0.0571)	(0.0525)	(0.0549)
Upward Occ. Occ. Chg. X Plant Closing	0.00659	0.103	-0.180***	-0.0956+
	(0.101)	(0.0908)	(0.0516)	(0.0547)
No Occ. Chg. X Other Displ.	-0.0828	-0.0902+	-0.128*	-0.137**
	(0.0550)	(0.0506)	(0.0503)	(0.0476)
Downward Occ. Chg. X Other Displ.	-0.111*	-0.0937*	-0.121**	-0.104*
	(0.0451)	(0.0448)	(0.0436)	(0.0461)
Upward Occ. Chg. X Other Disp.	-0.00320	0.00913	-0.258***	-0.244***
	(0.0533)	(0.0509)	(0.0444)	(0.0428)
Constant	0.0623***	-0.213***	0.0544***	-0.191***
	(0.00977)	(0.0170)	(0.00903)	(0.0167)
	19815	19815	19815	19815
	0.034	0.121	0.040	0.125

Robust standard errors in parentheses: $^{+}$ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. See Section 3.4 for more details.