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 the direction of mobility. I argue these patterns indicate that occupational sorting after displacement is efficient, nonetheless, displaced workers earn 9% less per hour than non-displaced workers who make occupational changes of the same magnitude. After evaluating a variety of alternative mechanisms, I conclude sorting to lower-paying firms is likely the primary driver of these comparative wage losses for displaced workers. Such losses constitute a reallocation of rents rather than a distortion in the assignment process, which has direct policy implications.

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1 Introduction

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

Understanding the mechanism responsible for wage losses from displacement is crucial for developing well-designed policy. Although displacement is individually costly, this may reflect bad luck for displaced workers without constituting an inefficiency. However, if displaced workers are forced to accept jobs that are a poor match for their skills, this may be a source of market failure and destruction of human capital. If post-displacement reallocations are inefficient, there is a role for policy in supporting displaced workers in finding new jobs that utilize their skills.

In order to evaluate whether or not reallocations after displacement are efficient, I focus on mobility up and down an occupational job ladder. Occupations provide a description of the tasks an individual performs, thus distortions in the distribution of moves could indicate an inefficient deployment of talent. 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*

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

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

of 5.5% after displacement. Instead, displaced workers have average wage losses of 7%.

I then turn to alternative explanations for losses in hourly wages following displacement, focusing on specific capital and heterogeneous rents. If workers have invested in specific capital but are unable to find a new job that utilizes their skills, this could lead to wage losses and an inefficient allocation of labor. On the other hand, if employers differ in the rents or wages they offer workers, displaced workers may be forced to accept jobs at firms that offer lower wages than voluntary firm-changers who can wait for a job offer from a high-wage firm. Such relative wage losses are due to a reallocation of rents, but are not inefficient. I find no evidence that specific capital can explain the losses from displacement. In light of complementary evidence from Lachowska, Mas, and Woodbury (2017) that finds about half of the losses in hourly wages after displacement can be attributed to time-invariant heterogeneity in firm-pay[3], I conclude heterogeneous rents are likely the primary source of losses from displacement. Thus, while displacement is individually costly, the evidence indicates it does not lead to an inefficient allocation of workers to jobs.

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.[4] 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[5] 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 Frederiksen, Halliday, and Koch (2016) document substantial rates of downward occu-

[3]With the other half unexplained, but possibly due to differences in displaced workers' bargaining position

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

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

pational 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.

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

I next provide an overview the main theoretical explanations of wage losses from displacement and how one can distinguish these mechanisms empirically. In Section 3 I describe the data and the methodology for measuring mobility and ranking occupational moves, as well as the empirical strategy. In Section 4, I present my main empirical results, in particular, showing that displaced workers suffer substantially larger wage losses than non-displaced, regardless of the direction of occupational mobility. In Section 5, I return to the main question, and show occupational sorting cannot explain the losses from displacement. I then turn to alternative theories, finding no support for specific capital explaining losses. In Section 6 I discuss the theoretical implications of my findings, and in in Section 7 I conclude with policy suggestions.

2 Distinguishing Theories of Losses from Displacement

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

The simplest explanation for losses from displacement is firm-specific human capital, e.g. investment in skills that are only valuable at the current employer.[6] In this case, frictions are infinite, since the worker cannot find another job that utilizes his investment. Less restrictive types of specific capital include industry, occupation, or task-specific capital. If labor market frictions prevent workers from finding employment in the precise type of job for which the worker has accumulated human capital, the worker will be forced to relinquish his investment, leading to waste and inefficient allocations. A natural policy implication is to support displaced workers in finding new employment in a position that utilizes their accumulated human capital.

Although the specific capital framework is useful for understanding heterogeneity in losses for displaced workers, it is unable to explain the fact that non-displaced workers frequently make firm, occupation, and industry moves without experiencing the magnitude of wage losses displaced workers face. In order to explain wage gains from mobility, we need a richer model of mobility.

In contrast to the specific-capital models, the job assignment model (as developed by Gibbons and Waldman (1999)), features general human capital that can be transferred across job categories. Each job is the optimal assignment for different portions of the worker ability distribution, leading workers who accumulate skills to move into a new optimal job assignment bin. Moreover, if a worker's ability is unknown, learning about the worker's talents can also lead to changes in optimal assignment.

Although the model was initially constructed to explain promotion dynamics, negative signals about a workers ability or human capital depreciation could lead to efficient mobility to lower-skill jobs. Thus, observing a worker moves to a lower-skill job does not necessarily imply inefficient job assignment. In this model, if there are no labor market frictions, displaced workers' job assignment should be efficient and indistinguishable from non-displaced workers' voluntary mobility. On the other hand, if frictions forced workers to accept suboptimal matches, we would expect workers to be more likely to match with low-skill jobs they are overqualified for, rather than high-skill jobs they are under-qualified. Thus, frictions in the job market could lead to inefficiencies and wage losses due to occupational assignment.

On the other hand, firms may choose to offer heterogeneous wages that induce workers to move to higher-wage firms independent from any productivity or assignment considerations. A prime example is the classic Burdett and Mortensen (1998) model, in which jobs are

[6] Cf. Becker (1964).

identical however pay different wages. Unemployed (or displaced) workers accept the first job offer that exceeds their outside option, but continue to search on the job for higher wage jobs. In this case, displacement is individually costly but does not lead to an inefficient allocation. To see this, consider a firm that is hit by a productivity shock and forced to close. Free entry will induce another firm enter to fill the open position on the wage-ladder. Other searching workers will find employment at this new firm, and the wage distribution will return to equilibrium. Thus, although the employees of the closed firm are likely to suffer individual losses by accepting job offers from lower-wage firms, these losses reflect a redistribution of rents rather than an inefficient allocation of labor.

Finally, there could be a match-specific component of productivity as in Jovanovic (1979). In this model, workers learn on the job about the match quality, choosing to leave the firm only if they learn that the job is a poor fit. This model shares features with the other specific capital models. If displaced workers are forced to leave a high-quality match, they are more likely to randomly match with a lower-quality match, leading to an inefficient destruction of productive capacity. Thus, reallocations due to specific capital and frictions are likely inefficient, reallocations due to job assignment are likely efficient, and reallocations due to rent heterogeneity are neutral.

Whether or not reallocations following displacement are efficient is closely linked to the mechanism driving the earnings losses. The primary empirical contribution of this paper is to evaluate these various theories of losses from displacement. In particular, the empirical strategy I employ focuses on comparing the wage changes following moves for individuals who are displaced versus those non-displaced. This differs from the two other primary empirical strategies in the literature: first, the event study specifications (such as in Jacobson et al. (1993)) focus on identifying similar workers who differ only in their exposure to an exogenous displacement event. Such papers can identify the causal effect of displacement, but cannot identify the mechanism leading to the losses. Second, papers such as Neal (1995) examine variation in losses between displaced workers. These papers have illuminated the question of what types of job changes following displacement are associated with worse outcomes for displaced workers, however they cannot explain why we see losses for displaced workers in general.

By comparing wage changes for displaced and non-displaced workers making similar moves, I provide new evidence on the underlying mechanism driving wage losses for displaced workers. This in turn allows me to evaluate the efficiency of losses, which has direct policy implications. I return to this question in Section 6.

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 is used to produce 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.[7]

I construct two matched datasets. In the larger dataset, 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.[8] I match individuals who are in the outgoing rotation group during the months the tenure supplement is administered to

[7]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.

[8]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.[9] 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

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

enough information that the coders will be able to classify the worker's occupation.[10]

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 in order to capture wage changes.[11] 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%.

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

[11] 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 focus 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 annual mobility rates of 14.4% within firms, and 35.5% between firms. Thus, although the mobility rates I observe in the annual data indubitably include substantial rates of spurious mobility, there is good reason to believe a substantial fraction of measured occupational mobility is due to true mobility. In Section 3.5 I discuss in detail 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, the most straightforward method to identify movements within firms is to use the the organizational chart to identify the hierarchy of positions within the firm, as in 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, which has the advantage of providing a strict ranking for all jobs.[12]

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 firms to describe unique jobs. Two strategies are employed in the literature. Frederiksen et

[12]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.

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, I primarily use a method similar to Groes et al. (2013), based on median occupational wages and follow 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 Appendix A.

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)[13], 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.

Table 2 reports how the distribution of occupational mobility (same occupation, down-

[13] 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.

ward 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 changers move down.

Thus, although displaced workers have somewhat higher rates of downward occupational mobility, over 45% of non-displaced 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 moves 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, as noted in Dohmen et al. (2004), 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 for early career workers. 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.[14] 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 spurious mobility. From the monthly data, we have that approximately 5.5% of individuals remaining employed by the same firm change occupations over a year, however, due to independent coding, the annual mobility rate inside the firm from the tenure supplement is

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

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 Section 4.1 I show that wage losses for displaced workers is driven by earnings losses after mobility. In Section 4.2 I find that occupational sorting is directional and consistent with efficient reallocations. In Section 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 Section 4.4 I derive additional results, showing occupational sorting for displaced workers appears to be efficient.

4.1 Wage Changes by Employer Mobility

I first examine how wage growth varies by the type of employer move. In Panel A of Table 3, 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.

Table 3: 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.

In Panel B, I separate firm-changers into those who did not report displacement in the last year and those that did.[15] Here we see that non-displaced firm-changers have annual

[15] In Appendix Tables A.11 and A.12 I show the wage patterns are similar if we further separate displaced workers into those displaced by plant closing and non-plant closing.

earnings growth of 6.8%, which falls to 5.7% with the inclusion of worker demographic controls. In contrast, individuals who are displaced 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 4. 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.

Table 4: 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.

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

These results indicate that the primary source of losses for displaced workers is the type of match they make after displacement. This lends credence to the hypothesis that occupational sorting after displacement may be able to explain the losses experienced by displaced workers.

4.2 Wage Changes by Occupational Mobility

I next investigate the wage changes associated with positive and negative occupational mobility. 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.

4.2.1 Wage Results

Table 5: 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 5, we see how the change in real log wages relates to the direction of occupational mobility the worker experiences.[16] 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

[16] In Appendix Table A.10, I show consistent results using alternative occupational rankings.

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.[17] 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. Such spurious mobility should bias wage changes with mobility toward zero. Thus, the strong positive relationship between wage growth and positive occupational mobility (and, conversely, negative wage growth and negative mobility) indicates that the relationship between wages and mobility is robust. Nonetheless, since such measurement error will attenuate the estimates, the measured changes in wages with mobility are a conservative estimate.

[17] 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.

4.2.2 Selection Results

Now that I have established that wage changes are consistent with the direction of occupational mobility, I want to further explore the role of selection in explaining wage changes with occupational mobility. 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 6 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.

Table 6: 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.

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.[18] 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 5. This indicates that

[18]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.

future upward movers are employed in comparatively low earning occupations, but are highly 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. 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, while downward movers are low-paid for their occupations before moving, they are well-paid for their new occupations after moving. Conversely, 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 5, 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.

4.2.3 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 pre-promotion earnings and the promotion probability. For instance, Baker et al. (1994b) found that individuals who are promoted are selected from individuals who earn above-average wages in their previous job, but after promotion earn *below*-average wages 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.

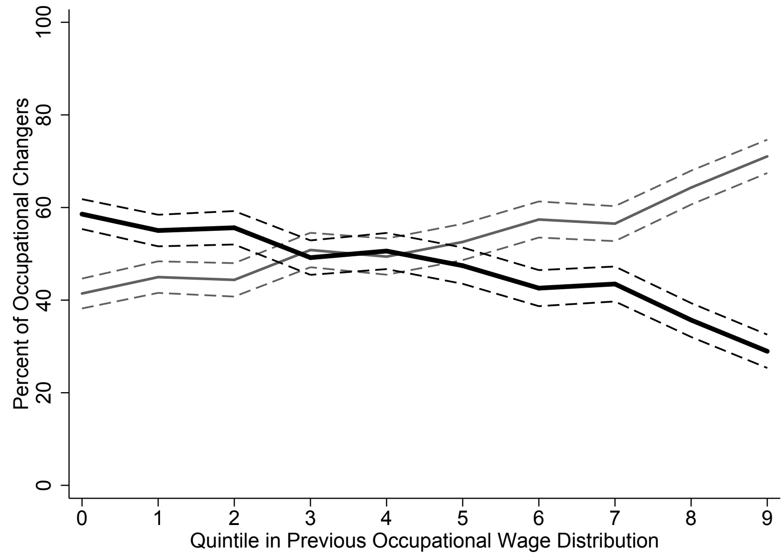

Figure 1: Percent of occupational switchers moving to lower-quality occupations (black) or higher-quality occupations (gray), by decile of the occupational wage distribution. Dashed lines represent 95% confidence intervals.

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 (which should have more accurate coding of occupational mobility) supports my findings from the CPS.

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 Table 7, I disaggregate the specifications from Tables 5 and 6 by separating individuals based on whether they stayed at the same firm, voluntarily changed firms, or were displaced.[19]

Table 7: Wages by Occupation and Firm Mobility

	(1) W. Chg	(2) Prev. W.	(3) Next W.	(4) Prev. Gap	(5) Next Gap
Downward Occ. Change	-0.0339***	0.000807	-0.0331***	-0.0864***	0.0679***
	(0.00811)	(0.00887)	(0.00896)	(0.00808)	(0.00796)
Upward Occ. Change	0.0358***	-0.0244**	0.0114	0.0735***	-0.0799***
	(0.00799)	(0.00891)	(0.00876)	(0.00772)	(0.00787)
No Occ. Chg. X Vol. Firm Chg.	-0.00637	-0.0130	-0.0194	-0.0394+	-0.0435*
	(0.0207)	(0.0265)	(0.0267)	(0.0208)	(0.0210)
Down. Occ. Chg. X Vol. Firm Chg.	-0.0185	-0.127***	-0.146***	-0.0644***	-0.0676***
	(0.0211)	(0.0194)	(0.0217)	(0.0191)	(0.0176)
Up. Occ. Chg. X Vol. Firm Chg.	0.0906***	-0.213***	-0.123***	-0.122***	-0.0959***
	(0.0189)	(0.0175)	(0.0183)	(0.0157)	(0.0169)
No Occ. Chg. X Disp.	-0.0518	-0.0842	-0.136**	-0.0743+	-0.132***
	(0.0341)	(0.0523)	(0.0519)	(0.0383)	(0.0369)
Downward Occ. Chg. X Disp.	-0.160***	-0.100**	-0.260***	-0.0134	-0.152***
	(0.0433)	(0.0381)	(0.0436)	(0.0359)	(0.0365)
Upward Occ. Occ. Chg. X Disp.	-0.0638	-0.0899+	-0.154***	-0.0414	-0.129***
	(0.0500)	(0.0499)	(0.0377)	(0.0447)	(0.0365)
Constant	0.0844***	1.632***	1.717***	-0.228***	-0.208***
	(0.0134)	(0.0158)	(0.0153)	(0.0177)	(0.0172)
N	19459	19459	19459	19459	19459
R-sq	0.014	0.268	0.261	0.117	0.121
Worker Controls	Y	Y	Y	Y	Y
Job Controls				Y	Y
Mean of Omitted	0.0265	2.256	2.283	0.0638	0.0553

Coefficients from regressions based on the CPS Tenure supplement. Robust standard errors in parentheses: $^{+}$ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. The dependent variables for columns (4) and (5) are the gap between the individual's wage and median occupational wages, before and after mobility respectively. See Section 3.4 for more details. Omitted category is workers who were employed at the same firm in both months without changing occupations.

4.3.1 Occupation Changers Within the Firm

I first focus on occupational mobility inside the firm. These individuals allow for the isolation of wage changes from occupational mobility from wage changes that may be due to sorting between employers. Moreover, mobility is unlikely to be driven by search fric-

[19] In Appendix Table A.10 I compare these estimates with those based on alternative occupational rankings.

tions, since it should be relatively costless for an individual to learn about vacancies and opportunities within the firm.

Wage estimates for within-the-firm movers are very similar to estimates from Tables 5 and 6. This is not surprising, since fewer than 10% of individuals in the sample change employers. Briefly, downward movers have substantially slower wage growth than occupational stayers, however the net effect cannot be statistically distinguished from zero. Upward movers have wage growth that is substantially faster than downward movers and occupational stayers, for net growth of 6%. In Column (4), we see that downward movers are below median earners for their occupation before moving, while upward movers are above median earners. After mobility, we see the pattern reversed, with downward movers above median for the new occupation, and upward movers below median. As discussed in Section 4.2, these patterns are consistent with efficient sorting across an occupational quality ladder.

4.3.2 Non-Displaced Firm-Changers

I next 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 percentage points larger than those who move up inside the firm. 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 3 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 (2) and (3) 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 3, 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 Columns (4) and (5) of Table 7 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 with non-displaced workers. Non-displaced between-firm movers may have some control over the timing of their move, allowing them to select higher-quality firms. In contrast, displaced workers are forced to leave their previous employer under duress, which may result in them accepting lower-quality job offers. However if we compare displaced workers and voluntary firm changers, both will give up any firm-specific capital they have accumulated.

I first consider wage changes for displaced workers who manage to find employment in the same narrowly defined occupation. By remaining in the same occupation they are able to preserve any occupation-specific capital, despite the loss of firm-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 distinguish statistically. 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 Columns (4) and (5) of Table 7. 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.

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

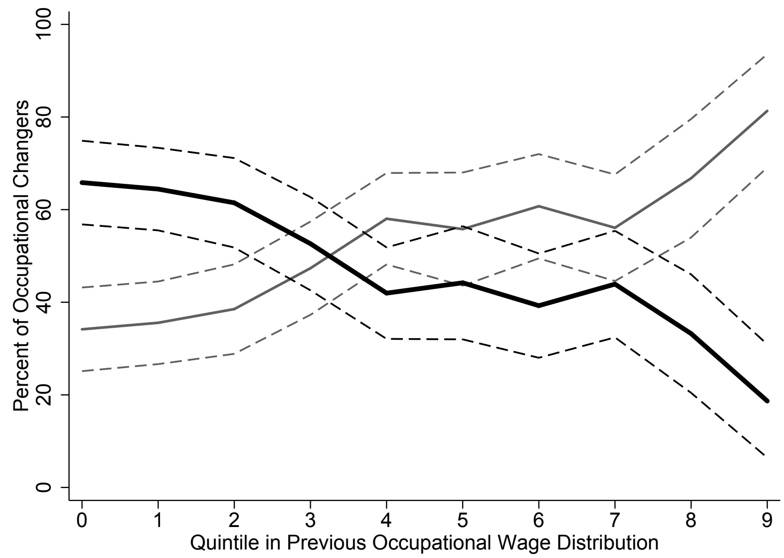

Figure 2: Percent of occupational switchers among displaced workers moving to lower-quality occupations (black) or higher-quality occupations (gray), by decile of the occupational wage distribution, retrospective occupations from the Displaced Worker Survey. Dashed lines represent 95% confidence intervals.

occupational changers. In particular, individuals who are in the bottom portion of the occupational 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, conditional on displacement, patterns of occupational reallocation mirror 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.

5 Explaining Displaced Workers' Wage Losses

Now I return to the original question: why does displacement lead to wage losses? Recall from Table 4.1 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 5.5% 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.

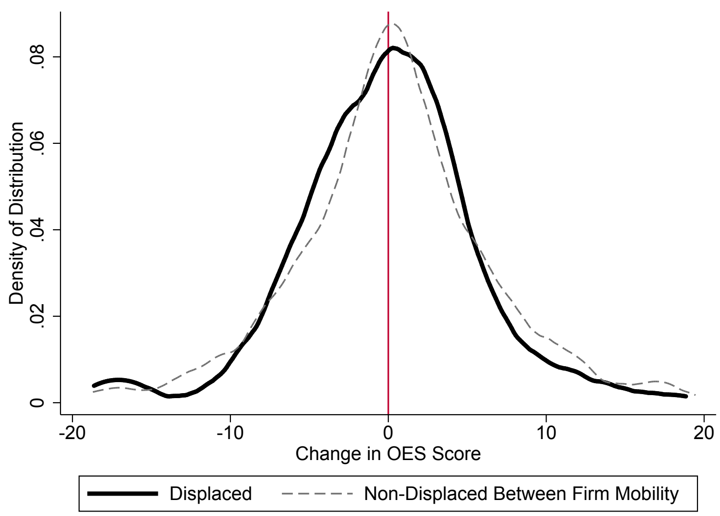

Figure 3: Kernel density plots for different types of mobility, conditional on changing occupations.

As a first step, Figure 3 illustrates kernel-density plots for the change in the OES wage score for displaced workers and non-displaced between firm movers, conditional on changing occupations. If displaced workers were making substantially worse 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 substantive difference in the distribution of moves for displaced workers.

Table 8 allows us to examine analytically the pattern from Figure 3, by measuring the

Table 8: 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.

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.

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 gray plus signs show non-displaced

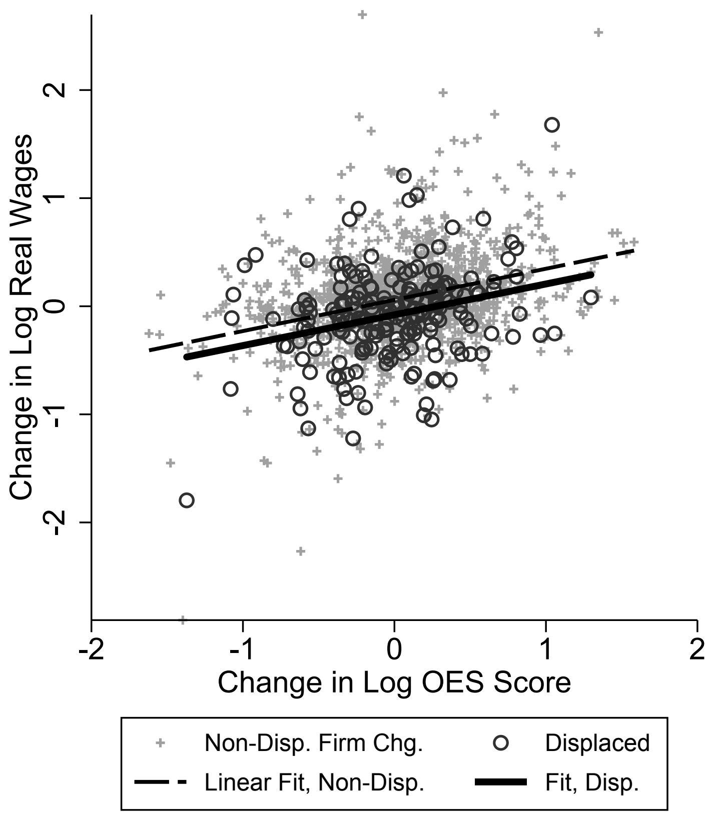

Figure 4: Scatter plot of change in log OES score by change in log real wage for non-displaced firm changers and displaced workers, conditional on changing occupation.

firm changers while the black circles show displaced workers. I also create fitted lines for non-displaced movers (dashed) and displaced workers (solid). 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 9 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 9: 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.

5.1 Distinguishing Between Alternative Theories of Displacement

If occupational sorting cannot explain the wage losses from displacement, what can? In this section, I return to the alternative explanations discussed in Section 2: specific capital (firm, occupation, or industry), job assignment, job ladders, and match-specific capital. In the previous sections, I have shown that occupational sorting appears to be efficient, indicating that inefficient job assignment cannot explain the losses from displacement. In this section, I focus on other sources of losses from reallocation.

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

I first examine occupation- and industry-specific capital, by including an indicator for whether or not the individual changed occupations or industries, reported in Columns (2) and (3) of Panel (A), respectively. Here we see very little changes in the magnitude of the displacement indicator, continuing to represent about a 10 percentage point decrease in wages compared to firm-stayers. Thus, there is no evidence that changing occupation or industry is responsible for the relative losses experienced by displaced workers.

I next examine the role of selection: in columns (4), (5), and (6) of Panel (A), I include demographic controls, previous occupation fixed effects, and previous industry fixed effects, respectively. This tests whether or not observable characteristics of workers can explain the losses experienced by displaced workers. Here we again see little variation in the coefficient on displacement. Similarly, in columns (7) and (8) I include indicators for whether or not the worker moved to a higher- or lower-wage occupation or a higher- or lower-wage industry,[20] respectively, which also reveal no impact on the displacement indicator.

In Column (9) I include all the previous controls, and in Column (10) I add in fixed effects for the industry and occupation of the new job. Although these 'kitchen sink' regressions are able to reduce the explanatory power of the non-displaced firm-change indicator, falling from a 4 percentage point wage premium in the specification without controls in Column (1) to a non-significant 1 percentage point premium in Column (10), we continue to see little

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

Table 10: Understanding Sources of Losses from Displacement

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

Coefficients from regressions based on the CPS Tenure supplement. Robust standard errors in parentheses: $^{+}$ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. See Section 3.4 for more details. Omitted category is workers who were employed at the same firm in both months.

movement on the displacement coefficient, falling slightly from a 9.8 percentage points wage loss to 9.5 percentage points. Thus, neither specific-capital, nor observable industry and occupational sorting can explain the losses we see for displaced workers.

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

Thus, although papers such as Neal (1995) and Gibbons and Katz (1991) have found that specific capital or selection can explain variation in the losses from displacement *between* displaced workers, in this section I have demonstrated that such theories cannot explain the relative losses from displacement compared with non-displaced workers making observationally similar movements.

What about the match-specific capital hypothesis? In this model, individuals will choose to remain with their match unless they receive information that it is not a productive match. Thus the model predicts that, while voluntary movers should be lower paid than displaced workers before mobility, both should be sampling from the same new wage distribution after mobility. From Tables 3 and 4, we saw that, while it is true that non-displaced firm changers are lower paid than displaced workers before mobility, after mobility displaced workers are substantially lower paid, both on average (in Table 3) and compared to their occupation's median wages (Table 4). Thus the evidence is not consistent with match-specific capital explaining the losses from displacement.

6 Discussion

In the above analysis, I have demonstrated that the survey data available in the Current Population Survey is unable to explain the losses in hourly wages experienced by re-employed displaced workers within one year of displacement, compared to non-displaced individuals. What other explanations could be driving the relative earnings losses we observe for displaced workers compared to non-displaced workers in observational identical employment?

One possibility is that displaced workers match with firms that pay less to all individuals. Although industry information could not explain the losses from displacement in this sample, recent evidence from Abowd, Kramarz, and Margolis (1999) and others has shown that there is substantial variation in pay between firms within industry, even after controlling for worker characteristics. Alternatively, it could be the case that displaced workers are paid less in observationally identical jobs and firms. Under standard wage bargaining assumptions, unemployed individuals can be expected to receive lower-wages than currently employed individuals given their weaker outside position. Thus, it would not be surprising if displaced individuals are willing to accept lower-wages than a hire that moves directly between employers.

These two explanations are consistent with a recent paper, Lachowska et al. (2017), which uses matched employer-employee data from Washington State's unemployment insurance system to decompose the earnings losses of displaced workers. The authors find that, 5 years after displacement, about half of the reduction in hourly wages can be attributed to working for a lower-paying employer. The other half, which remains unexplained, could be due to bargaining.

In conclusion, I do not find evidence that supports the theory that wage losses from displacement are due to inefficient reallocations. Neither occupational sorting, industry sorting, firm-specific capital, industry-specific capital, or occupation-specific capital can explain the losses we observe for displaced workers. Further, even the 'kitchen sink' specification that includes all of the possible variables can explain the losses. Instead, in light of other evidence, the most likely source of losses for displaced workers is sorting to lower-paying firms and accepting lower wages at similar firms. Although I measure a robust relative earnings loss of about 9% in hourly wages, the evidence indicates this is due to inequality in firm-rents rather than an efficiency loss. This indicates that, although these wage losses are individually costly, it does not constitute a market failure.

My results have implications for a growing macro literature seeking to explain the duration of earnings losses for displaced workers. Beginning with a puzzle raised by Davis and von Wachter (2011), that the workhorse Diamond-Mortensen-Pissardes search model was unable to match the empirical wage loss distribution, several recent papers (including Krolikowski (2016), Jung and Kuhn (2016) and Huckfeldt (2016)) have sought to use frictional job ladder models to explain this puzzle. However, in order to match the slow recovery in wages after displacement, all these papers introduce some source of mismatch: either destruction of match-specific capital (Krolikowski (2016)), or occupation/industry-specific capital (Jung and Kuhn (2016) and Huckfeldt (2016)). However I have shown that none of these sources of mismatch can explain the relative losses experienced by displaced workers, and instead, it appears the losses from displacement are due to sorting to lower-wage firms. It remains a puzzle as to why, if there is no additional destruction of human capital (compared with non-displaced movers), displaced workers cannot recover more quickly.

These results also have implications for understanding the sources of wage changes with mobility for non-displaced workers. 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 or higher-rent matches. 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.[21]

The fact that relative wages predict the direction of mobility and wage growth or losses strongly suggests workers' productivity is correlated across occupations. Further, the fact that reallocation occur 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). As firms learn about a worker's ability and the worker accumulates human capital, wages will rise within the position, until the worker 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 the worker 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 supported by the results in Table 6.

In addition, my findings uncover fundamental differences between occupational job ladders and employer job ladders. First, since as much as 90% of occupational changes occur within-the-firm, it is unlikely that search frictions are the primary driver of occupational movements. Second, occupational mobility is clearly ranked, with low-earners moving to lower-skill occupations and high-earners moving to higher-skill occupations, which is inconsistent with models based on horizontal differentiation or idiosyncratic match quality. I conclude that occupational mobility is best described by job assignment models, such as

[21]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.

Gibbons and Waldman (1999). On the other hand, firm-mobility appears to be much better described by frictions such as in the Burdett and Mortensen (1998) model, with slow-recovery from displacement consistent with frictional search. These results indicate the mechanisms driving occupational mobility and employer mobility are distinct and should be modeled accordingly.

7 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. Examining wages before and after displacement, I find little support for theories of inefficient reallocations, including specific capital, match-specific capital, and job assignment. Instead, the evidence supports efficient occupational reallocation for displaced workers, with earnings losses driven by movements down an employer job ladder.

My findings have direct policy implications for displaced workers. If reallocations after displacement were inefficient, that would suggest a role for search assistance or extended unemployment insurance to help displaced workers hold out for jobs that will use their human capital. However, since I do not find evidence of this mismatch (given the current policy regime), this suggests that additional assistance would encourage longer wasteful search. Nonetheless, I do see strong distributional effects of displacement, since for any type of move, displaced workers have earnings losses of about 9%. This suggests a role for insurance to mitigate the individual risk of these exogenous displacement events.

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Appendix

A.1 Summary Statistics

Table A.1: Data Description, Monthly CPS Sample

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

Standard deviations in parenthesis.

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

	Firm Stayers	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.

A.2 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 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. 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 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. 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

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

and occupations.

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

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

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.

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.

In Table A.10, I show broadly consistent results with Tables 5 and 7 in the main text.

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	-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	-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.

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	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	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	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	-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.

In Panel A, I show across a variety of occupational ranking measures, individuals who make downward occupational moves experience relative earnings losses of over 2 percentage points, while those who make upward occupational moves have earnings gains of at least three percentage points, relative to occupational stayers.

In Panel B, I show these results carry over to moves within and between firms. For all measures, non-displaced upward movers between firms have greater earnings growth than upward movers within the firm, and non-displaced downward movers between firms have similar losses to downward movers inside the firm. One difference from the OES-based measure used in the main text is there appears to be less precision in the ranking of moves. In particular, the two O*NET measures (Q1 and Mgmt) both rank some moves as positive that are ranked as downward moves by the OES measure and are associated with slower wage growth than other positive moves. This attenuates wage gains for upward moves within and between firms. For displaced workers, given the large wage losses we see after displacement for those moving to lower ranked occupations by the OES occupational ranking, this leads to much more negative wage changes for displaced workers who move 'up'. Given the small sample sizes for displaced workers, these differences in ranking are common enough to drive to counter-intuitive wage changes upon mobility.

Table A.10: Wage Changes with Mobility: Alternative Rankings

	(1) OES	(2) Big OES	(3) Q1	(4) Mgmt	(5) All 3	(6) Big all 3
Panel A.: Occupational Mobility						
Downward Occ. Change	-0.0402***	-0.0467***	-0.0234**	-0.0248**	-0.0442***	-0.0478***
	(0.00769)	(0.00905)	(0.00770)	(0.00771)	(0.00960)	(0.0112)
Indeterm. Occ. Change		-0.0130			-0.00325	-0.00292
		(0.00881)			(0.00802)	(0.00712)
Upward Occ. Change	0.0475***	0.0723***	0.0326***	0.0340***	0.0615***	0.0775***
	(0.00753)	(0.00873)	(0.00756)	(0.00754)	(0.00922)	(0.0108)
Mean of Omitted	0.0261	0.0261	0.0261	0.0261	0.0261	0.0261
R-sq	0.011	0.013	0.007	0.007	0.010	0.010
Panel B.: Occupational by Firm Mobility						
Downward Occ. Change	-0.0339***	-0.0394***	-0.0255**	-0.0265**	-0.0420***	-0.0447***
	(0.00811)	(0.00958)	(0.00817)	(0.00807)	(0.0101)	(0.0120)
Indeterm Occ. Change		-0.0142			-0.00931	-0.00839
		(0.00944)			(0.00850)	(0.00749)
Upward Occ. Change	0.0358***	0.0574***	0.0235**	0.0247**	0.0491***	0.0627***
	(0.00799)	(0.00922)	(0.00790)	(0.00799)	(0.00975)	(0.0114)
No Occ. Chg. X Vol. Firm	-0.00637	-0.00637	-0.00612	-0.00627	-0.00607	-0.00598
	(0.0207)	(0.0207)	(0.0207)	(0.0207)	(0.0207)	(0.0207)
Down Occ. Chg. X Vol. Firm	-0.0185	-0.0322	0.00916	0.0115	-0.0230	-0.0337
	(0.0211)	(0.0258)	(0.0198)	(0.0213)	(0.0288)	(0.0324)
Indeterm X Vol. Firm		0.0307			0.0457*	0.0438*
		(0.0230)			(0.0205)	(0.0181)
Up Occ. Chg. X Vol. Firm	0.0906***	0.109***	0.0762***	0.0712***	0.0978***	0.112***
	(0.0189)	(0.0239)	(0.0203)	(0.0190)	(0.0254)	(0.0311)
No Occ. Chg. X Disp.	-0.0518	-0.0519	-0.0813*	-0.0814*	-0.0814*	-0.0812*
	(0.0341)	(0.0341)	(0.0387)	(0.0387)	(0.0387)	(0.0386)
Down Occ. Chg. X Disp.	-0.160***	-0.140*	0.0791	-0.0141	0.0663	0.0805
	(0.0433)	(0.0569)	(0.0657)	(0.0862)	(0.0902)	(0.0984)
Indeterm X Disp.		-0.133**			-0.0925	-0.146+
		(0.0495)			(0.0813)	(0.0749)
Up Occ. Chg. X Disp.	-0.0638	-0.0507	-0.230**	-0.133+	-0.214+	-0.0795
	(0.0500)	(0.0659)	(0.0774)	(0.0708)	(0.117)	(0.110)
N	19459	19459	19459	19459	19459	19459
R-sq	0.014	0.016	0.009	0.009	0.013	0.012
Mean of Omitted	0.0265	0.0265	0.0263	0.0263	0.0263	0.0263

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.

A.3 Robustness Checks

In this section I include several robustness check to tables from the text. First, I disaggregate several tables from the text based on whether or not the displacement was due to a plant closing or other reasons. Results are broadly consistent with the tables in the main text, however estimates are less precise.

Second, I reproduce the main Table 7 showing wage changes by occupation and employer mobility. In Columns (1) and (2) I reproduce the first columns form Table 7, while in Columns (3) and (4) I restrict the sample to individuals who work at least 35 hours in both periods. This restricts the sample substantially, but I find results are similar. One difference is that displaced individuals who remain in the same occupation have a surprisingly large drop in wages (14 percent). This may be noise due to the sample size of displaced occupation-stayers falling to only 32 observations. Second, we see a smaller and non-significant wage loss for downward occupational changers within the firm. This is not surprising, as part-time workers are more likely to have less stable employment and accordingly larger swings in job quality.

Table A.11: 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.12: 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.13: 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.14: 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.

Table A.15: Wage Changes for Full-Time Workers

	(1)	(2)	(3)	(4)
Downward Occ. Change	-0.0335***	-0.0339***	-0.0156	-0.0146
	(0.00810)	(0.00811)	(0.0116)	(0.0116)
Upward Occ. Change	0.0376***	0.0358***	0.0326**	0.0318**
	(0.00805)	(0.00799)	(0.0110)	(0.0109)
No Occ. Chg. X Vol. Firm Chg.	-0.000746	-0.00637	0.00407	-0.00193
	(0.0208)	(0.0207)	(0.0290)	(0.0290)
Downward Occ. Chg. X Vol. Firm Chg.	-0.00822	-0.0185	-0.0128	-0.0202
	(0.0209)	(0.0211)	(0.0275)	(0.0281)
Upward Occ. Occ. Chg. X Vol. Firm Chg.	0.100***	0.0906***	0.0956**	0.0883**
	(0.0187)	(0.0189)	(0.0316)	(0.0317)
No Occ. Chg. X Disp.	-0.0484	-0.0518	-0.140**	-0.144**
	(0.0341)	(0.0341)	(0.0535)	(0.0556)
Downward Occ. Chg. X Disp.	-0.158***	-0.160***	-0.115*	-0.113*
	(0.0433)	(0.0433)	(0.0485)	(0.0478)
Upward Occ. Chg. X Disp.	-0.0590	-0.0638	-0.0666	-0.0710
	(0.0508)	(0.0500)	(0.0506)	(0.0519)
N	19459	19459	7685	7685
R-sq	0.011	0.014	0.008	0.014
Mean of Omitted	0.0265	0.0265	0.0259	0.0259
Worker Controls		Y		Y
Full Time?			Y	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. Omitted category is workers who were employed at the same firm in both months without changing occupations.