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# Job Displacement and Sectoral Mobility

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**Abstract:**
This paper combines two components of the US Current Population Survey to characterize the relationship between job displacement and sectoral mobility for long-tenured workers over the 1996–2019 period: (1) the cross-sectional Displaced Worker Survey and (2) the 16-month longitudinal design of the Basic Monthly Survey. While displacement negatively correlates with mobility over time, such job loss has a positive causal impact on mobility for displaced workers compared with similar non-displaced workers. Education and industry structure facilitate post-displacement industry switching, and several factors, including business cycles, affect whether the alternative to sectoral mobility is likely to be same-industry employment or nonemployment.

**JEL Classifications:** J63, J24
**Keywords:** job displacement, sectoral mobility, Current Population Survey, Displaced Worker Survey

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# 1 Introduction

Economic shocks can manifest in the labor market with severe harm to the affected population. For instance, an unanticipated fall in labor demand that causes job displacement typically leads to sizable and persistent earnings losses for long-tenured workers who are displaced, as compared with similar workers who are not displaced (Couch and Placzek 2010; Jacobson, LaLonde, and Sullivan 1993; Topel 1990).[1] These earnings losses are generally larger for displaced workers who change industries once reemployed. This result could stem from factors such as relinquishing accumulated industry-specific human capital or forfeiting time-invariant, match-specific productivity acquired through multiple jobs in an industry (Kim 1998; Kletzer 1996; Neal 1995; Ong and Mar 1992). Despite experiencing diminished earnings from sectoral mobility following job loss, displaced workers may still benefit from different-industry employment. The new sector may be a preferred alternative to nonemployment with zero earnings, may offer better long-run prospects for positive earnings, or may have desirable traits not related to earnings, such as improved benefits or job stability. Given such implications of post-displacement sectoral mobility, and since this mobility is not random, it is important to understand the determinants of these industry changes following job loss.

This paper characterizes the relationship between job displacement and sectoral mobility for long-tenured workers in the United States. Displacement is a natural measure to focus on when studying determinants of post-displacement industry changes. I first establish descriptive patterns of industry switching following job loss. I then estimate the causal impact of job displacement on sectoral mobility. To perform both analyses for a broad sample across time and space, I combine two components of the US Current Population Survey from 1996 through 2019: (1) the cross-sectional Displaced Worker Survey (DWS), and (2) the 16-month longitudinal design of the Basic Monthly Survey (BMS). The resulting

[1] Overviews of the displacement literature, including Carrington and Fallick (2017), Fallick (1996), and Kletzer (1998), also document this finding.

DWS-BMS panel data set leverages the BMS over time to ensure data quality, utilizes the DWS and BMS to identify displaced and non-displaced workers, and imposes sample restrictions to help confirm that the DWS reference job is the position held by displaced workers in the BMS first month-in-sample. These panel data also allow for inclusion of worker fixed effects to capture unobserved heterogeneity, which is not feasible with cross-sectional data. In addition to the DWS-BMS panel, I use a pooled DWS cross section with similar sample restrictions for much of the descriptive analysis due to counts of displaced workers that are larger than those in the panel.

Descriptively for the 1996–2019 period, I find that the share of workers who are displaced negatively correlates over time with the share of displaced workers who change industries. However, the share of reemployed displaced workers who change industries is comparatively stable over time, exhibiting a somewhat positive correlation with the displacement rate. These findings at least partly reflect countercyclical increases in the rate of post-displacement nonemployment and concurrent rate decreases in same-sector reemployment following displacement and, to a lesser degree, different-sector reemployment as well. Overall, nearly 75 percent of same-sector reemployment following job loss occurs with limited to no intervening nonemployment, while less than 50 percent of different-sector reemployment likewise occurs immediately. On net, reemployed displaced workers are drawn to the public administration and various services industries, while such workers tend to leave the manufacturing and mining industries. The public sector finding may reflect preferences regarding job stability, while the other sectoral patterns may be consistent with broader market trends.

Turning to causal analysis, I use the 1996–2019 DWS-BMS panel of long-tenured displaced workers and comparable non-displaced workers—namely, continuously employed or voluntarily separated workers. For each worker, the panel spans 16 calendar months, eight of which are survey months-in-sample and include a baseline month of full-time employment. For workers who are employed or reemployed, I find that the sectoral mobility rate increases by 13.2 percentage points following a job separation (on a pre-separation base of

0, expectedly), and displacement increases that rate by an additional 7.9 percentage points (59.8 percent). Dynamic effects also occur, as the probability of industry switching rises with increased months following separation. Displacement's impact on sectoral mobility also falls when never-reemployed workers are included in the estimation. This result suggests that the chance of nonemployment is greater after a job loss than after a voluntary job separation. The higher risk of nonemployment following displacement may contribute to the observed sectoral mobility effect, with different-sector reemployment acting as a preferred alternative. Policy-relevant heterogeneity analysis reveals pre-displacement education and industry structure facilitate post-displacement industry switching. This finding suggests the importance of both individual and market traits, as well as roles for both general and industry-specific skills. Also of policy interest is the finding that several factors affect whether the alternative to sectoral mobility is likely to be same-industry employment or nonemployment. These factors include business cycles, worker age, and the presence of any children in the worker's household.

Within the vast job displacement literature, this study contributes to a small subset of work that examines the determinants of post-displacement sectoral mobility. For instance, Fallick (1993) focuses on supply-side labor market behavior, using search theory to analyze how different factors affect the sectoral mobility of US displaced workers. Work by Neffke, Otto, and Hidalgo (2018), which shares elements of Fallick (1993) and this study, uses a job search model to examine how the local industry mix influences the geographic and sectoral mobility of displaced workers in Germany. The authors find that job displacement increases the probability of industry switching. The current paper contributes to the literature by characterizing the relationship between job displacement and sectoral mobility in the US over a long recent period. Moving forward, in light of shifts in labor demand due to the COVID-19 pandemic, growing automation, and other causes, this paper has implications for understanding post-displacement sectoral mobility in the face of such events.

The remainder of the paper is organized as follows. Section 2 describes the Current

Population Survey and creation of the cross-sectional and panel samples used for analysis. Section 3 outlines the strategy for estimating the impact of job displacement on sectoral mobility, while section 4 explores descriptive patterns. Section 5 presents the main causal findings, and section 6 discusses additional findings. Lastly, section 7 concludes.

## 2 Current Population Survey

The Current Population Survey (CPS), started in 1940 to measure national unemployment, is the main source of labor force statistics for the United States and is sponsored jointly by the US Census Bureau and the US Bureau of Labor Statistics (BLS). The Basic Monthly Survey component of the CPS relies on a rotating sample of 60,000 households, whose responses on numerous topics refer to activities during the preceding week that includes the 12th of the month. Households are in the CPS for four consecutive months, out for eight months, and then return for four months before leaving the sample permanently (United States Census Bureau 2006). With this 4-8-4 design, the BMS has the scope to be used as a longitudinal survey, although it is typically utilized as a pooled cross section. The Minnesota Population Center provides CPS data as part of its online Integrated Public Use Microdata Series (IPUMS) (Flood et al. 2020). The center's website and linking methods greatly facilitate use of the BMS for longitudinal research (Drew, Flood, and Warren 2014).

Additional information to supplement the BMS is collected as part of the CPS on a semi-regular basis. One of these supplements is the Displaced Worker Survey, administered biannually since 1984 in January or February of the given year. The DWS gathers data from workers who lost jobs in any of the preceding five years (from 1984 through 1992) or three years (from 1994 onward) in order to learn more about the causes and consequences of displacement (United States Census Bureau 2006). Widely used in research on job loss, this survey typically offers a broader array of areas, periods, covariates, and details on the cause of job separation as compared with administrative data, which are also frequently used for displacement studies.

In this paper, I develop a joint DWS-BMS panel to leverage the aforementioned benefits of both data sources and address some shortcomings of the DWS cross section. For displaced workers, the DWS-BMS panel focuses on those who are employed full-time in the first month in sample (MIS) and experience a job loss over the remaining 15 months spanning their CPS participation. Using various sample restrictions, I try to ensure that the BMS job in the first month-in-sample is the DWS reference job lost. Regarding DWS shortcomings, a DWS-BMS panel may mitigate potential recall bias from the retrospective DWS by aligning the referenced job separation with contemporaneous BMS responses. Data quality might also be improved with the DWS-BMS data by using the longitudinal aspect of the BMS to drop persons with inconsistent or otherwise erroneous responses. Use of contemporaneous information in the DWS-BMS panel also allows me to determine the timing of reemployment and sectoral mobility without relying on retrospective information regarding weeks of unemployment. Such retrospective information might suffer from inaccuracies, is missing for some respondents in the DWS, and may omit stints out of the labor force. Using contemporaneous information in the DWS-BMS data, combined with focusing on long-tenured workers, also helps reduce concerns about omitted job separations when multiple job loss events occur since DWS responses reflect only one reference job. The DWS-BMS panel also facilitates inclusion of workers who do not participate in the DWS when the survey occurs—namely, continuously employed or voluntarily separated workers. Identifying such non-displaced workers helps determine descriptive displacement rates and is crucial for my identification strategy to estimate the causal impact of displacement on sectoral mobility. Lastly, the DWS-BMS panel also facilitates inclusion of worker fixed effects in regression models to capture unobserved heterogeneity.

Despite these advantages of the DWS-BMS panel, disadvantages remain. First, the 16-month calendar span of the BMS restricts analysis of sectoral mobility to, at most, a five-quarter period given baseline full-time employment in MIS1. Second, methods to align the MIS1 job in the BMS with the reference job in the DWS, while extensive, may still be imperfect. Third, even upon restricting the study to workers with a full eight months-in-sample to minimize unobserved industry changes, the intervening eight months out-of-sample for each worker complicates data construction and analysis. Nevertheless, the advantages of the DWS-BMS panel support its construction for this study, and there is precedence by the BLS for analysis aligning DWS cross-sectional data with BMS longitudinal data (Devens Jr. 1986). In addition to the DWS-BMS panel, I create a pooled DWS cross section with similar sample restrictions, excluding restrictions that require longitudinal data or otherwise do not apply. These pooled DWS cross-sectional data are used for much of the descriptive analysis due to larger counts of displaced workers compared with the DWS-BMS panel.

Initial sample restrictions for data quality and subsequent DWS-BMS sample restrictions to determine worker subsamples are in Appendix Tables A1 and A2. Some restrictions are minimally binding if at all, as expected, but are imposed for assurance purposes. The analogous sample restrictions for the pooled DWS cross section are omitted for brevity. The resulting data sets span job separations (or pseudo-separations in MIS1, for continuously employed workers) from 1996 through 2019. This timespan is limited to 24 years due in part to data availability and consistency—a "same employer" measure to indicate job changes is not available until 1994, and that same year, the DWS recall period changes from five years to three years. The sample period also begins and ends when it does due to linking issues in 1994 and 1995 (Drew, Flood, and Warren 2014) and prohibitively small sample counts after 2019.

I focus on workers with at least three years of tenure in their initial or only job to ensure comparability of DWS participants and non-participants, as the latter do not experience a job loss for at least that length of time, given the DWS three-year recall period. Workers are restricted to their experience with no more than one job separation, as this helps align the BMS MIS1 job and the DWS reference job when applicable. Additionally, given numerous sample restrictions for both the DWS-BMS panel and the pooled DWS cross section, I create descriptive weights for all sample workers. These weights incorporate both a CPS sample design weight and a post-stratification weight, with the latter intended to capture inadvertent sample selection along various dimensions including sex, education, and area (see Appendix). With the weights applied, sample statistics for share measures reasonably reflect the national population of interest.[2] Regarding unweighted counts, the DWS pooled cross section contains 8,212 displaced workers, of which 5,492 are reemployed displaced workers, and a further subset of 2,474 are reemployed displaced workers who change industries. The DWS-BMS panel contains 50,907 workers, including 750 displaced workers, of which 503 are reemployed displaced workers, and a further subset of 154 are reemployed displaced workers who change industries.

# 3 Estimation

I use the DWS-BMS panel to identify the impact of job displacement on sectoral mobility for displaced workers compared with similar non-displaced workers. I estimate the following difference-in-differences specification for worker $i$ and month in sample $t$ using ordinary least squares (OLS):

$$Y_{it} = \omega + \beta Displaced_{it} + \lambda Post_{it} + \delta Displaced_{it} \times Post_{it} + \mathbf{X}'_{it}\theta + \alpha_i + \gamma_t + \varepsilon_{it}. \quad (1)$$

Outcome $Y$ is an indicator for a worker having changed industries as of a given month in sample. *Displaced* is a broad indicator for ever being displaced—namely, if the reason for job loss is that the plant or company closed down or moved, insufficient work, or the position or shift was abolished. Given concerns raised in some studies that job loss due to slack work or position elimination may relate to worker productivity (Farber 1997; Gibbons and Katz 1991), sensitivity analysis will define *Displaced* more narrowly based solely on

[2]In validity checks, the DWS-BMS panel and pooled DWS cross section samples with weights applied closely replicate targeted population statistics such as the share female (0.51 in 2019 according to census estimates, and estimated as 0.52 in the DWS-BMS panel and 0.50 in the DWS cross section).

plant closings. *Post* is an indicator for all post-separation months-in-sample, including the month of separation and always equal to 0 for continuously employed workers. Time-varying and time-invariant controls are reflected by $\mathbf{X}$ and include indicators for sex, being married, presence of children and young children in the household, age, education, period of job separation or pseudo-separation, race/ethnicity, industry, occupation, and region, as well as continuous month-year measures for the log of region-industry employment, the region-industry unemployment rate, and a region-specific industry similarity index (based on the overlap of occupations, which act as proxies for skills).[3] Fixed effects for worker and month-in-sample are given by $\alpha$ and $\gamma$, respectively; $\omega$ is a constant; and $\varepsilon$ is an error term. I cluster standard errors at the worker level in case of serial correlation. The primary coefficient of interest is $\delta$, the post-separation difference in the probability of sectoral mobility between displaced workers and non-displaced workers, relative to the pre-separation difference.

To allow the conditional means estimated by $\beta$, $\lambda$, and $\delta$ to be representative of the population, I apply descriptive weights. Additionally, to improve the comparability of non-displaced workers as a control group for displaced workers, I generate and apply inverse probability weights that adjust for potential selection into displacement. This approach is similar to the matching method used by Neffke, Otto, and Hidalgo (2018). I estimate equation (1) by OLS to allow for straightforward inclusion of fixed effects, acknowledging the caveats of linear probability models. Worker fixed effects partly help address concerns of unobserved worker productivity being correlated with displacement (also partly addressed by the alternative *Displaced* definition noted earlier). Month-in-sample fixed effects help tackle worries that a job separation, which can occur in MIS2 through MIS8, is not random with respect to a given month-in-sample. Also, due to the intervening eight months out-of-sample for each worker, equation (1) focuses on estimating $\delta$ over the entire post-separation period. However, alternative specifications examine dynamics as well, in addition to heterogeneous effects.

[3] I follow the approach outlined by Finger and Kreinin (1979) in their creation of an export similarity index.

To identify additional effects of policy interest in an auxiliary specification, I analyze a cross section of displaced workers from the DWS-BMS panel in the period just before displacement. Workers in this cross section are either those who are later reemployed in the same sector or those who remain nonemployed. I estimate the following OLS specification for worker $i$:

$$Y_i = \omega + \mathbf{X}_i'\theta + \varepsilon_i. \tag{2}$$

Here, outcome $Y$ is an indicator for same-sector reemployment instead of nonemployment. Various factors are reflected by $\mathbf{X}$, $\omega$ is a constant, and $\varepsilon$ is an error term. For this analysis, inclusion of descriptive weights may be warranted to address heteroskedasticity (Solon, Haider, and Wooldridge 2015). However, since such weights might not yield efficient estimates given an unknown error structure, I will estimate equation (2) both with and without weighting, in addition to including heteroskedasticity-robust standard errors.

# 4 Sectoral Mobility Patterns

Figure 1 illustrates the relationship between job displacement and sectoral mobility for six four-year periods from 1996 through 1999 to 2016 through 2019. Data are grouped in these bins to prevent small sample counts. I use the DWS-BMS panel data to examine the displacement rate rather than calculate a cross-sectional analog due to the challenge of imposing the job tenure restriction for workers overall (tenure is available only biannually in a CPS supplement). However, the two sectoral mobility rates shown in the figure are derived from the DWS cross-sectional data. The figure shows that the rate of workers who are displaced is countercyclical as expected, ranging from 1.6 percent (2016 through 2019) to 3.7 percent (2008 through 2011). These estimates closely align with available BLS estimates of job-loss rates for long-tenured workers.[4] The displacement rate also negatively correlates over time with the rate of displaced workers who change industries (correlation: –0.75). This sectoral

[4]For instance, I obtain a job displacement rate of 2.7 percent in the 2000–2003 period. A BLS estimate of the displacement rate for long-tenured workers in the 1999–2000 period is 2.5 percent (Helwig 2004).

mobility rate is procyclical and ranges from 22.8 percent (2008 through 2011) to 37.3 percent (1996 through 1999).[5] However, the share of reemployed displaced workers—that is, now excluding workers remaining nonemployed—who change industries is stable over time, displaying a positive correlation with the job-loss rate (correlation: 0.70) and ranging from 42.2 percent (2012 through 2015) to 46.0 percent (2008 through 2011).

Turning to Figure 2, I observe trends over time in the alternatives to sectoral mobility. This figure relies again on DWS cross-sectional data. Examining the allocation of displaced workers in the 1996–2019 period, I find that 29.6 percent change industries, 37.3 stay in the same industry, 31.3 percent remain unemployed one to two years after job loss, and 1.8 percent are out of the labor force one to two years after job loss.[6] This allocation varies over time, with countercyclical increases in the rate of post-displacement nonemployment and concurrent rate decreases in same-sector reemployment following displacement and, to a lesser degree, different-sector reemployment as well. Such trends at least partly account for the earlier cyclical patterns in Figure 1.

Returning to the DWS-BMS panel, these data provide the opportunity to examine the amount of time that elapses before a worker is reemployed in a new or former industry, as shown in Figure 3. Overall, nearly 75 percent of same-sector reemployment following job displacement occurs with limited to no intervening nonemployment, while less than 50 percent of different-sector reemployment likewise occurs immediately. Accordingly, the share of delayed reemployment in a different sector exceeds analogous same-sector reemployment, most notably for three or more months after separation (28.6 percent compared with 12.1 percent). This pattern may be consistent with different-sector employment as a primary option, with workers perhaps needing time to acquire relevant human capital for the job search or position. Alternatively, the trends depicted in Figure 3 may reflect different-

[5]Kim (1998) finds that 55 percent of workers displaced due to a plant closing switch industries in the DWS across the 1982–1988 surveys. This rate is somewhat comparable to my 1996–1999 estimate, and the disparity in rates may be due to differences in the time period and sample restrictions.

[6]In order to uniquely assign displaced workers to each separation year from 1996 through 2019 given the biannual DWS, the DWS cross section in this study focuses on the subset of respondents with a job loss one or two years before the DWS.

sector employment as a secondary option, with workers resorting to such employment in the absence of a same-sector position in order to avoid nonemployment. Earnings results from the displacement literature suggest the latter narrative may be more likely, but both explanations are feasible.

Finally, continuing to focus on reemployed displaced workers and shifting back to the DWS cross section, Table 1 depicts a matrix of industry transitions for nine industries. Section A of the table presents mobility to each industry as a share of total employment for reemployed displaced workers. As expected, diagonal elements reflecting same-industry reemployment are typically the plurality reallocation of displaced workers in a given industry. The sole exception to this pattern is the public administration sector, where 0.4 percent of all reemployed displaced workers return to the industry, but 0.5 percent of reemployed displaced workers switch to the various services sector. The largest off-diagonal elements, which reflect different-industry reemployment, indicate mobility from manufacturing to various services (5.3 percent of reemployed displaced workers), trade to various services (3.4 percent), and manufacturing to trade (3.3 percent).

However, the aforementioned patterns are partly due to the size of the industries. Various services, manufacturing, and trade are the three largest sectors based on former-industry employment (30.9 percent, 22.2 percent, and 17.9 percent of reemployed displaced workers). Section B of Table 1 thus depicts mobility to each industry as a share of former-industry employment, effectively adjusting for industry scale. Persistence in industry employment is greatest for various services, as 69.7 percent of these displaced workers remain in the industry once reemployed. Such industry persistence is lowest for public administration, where only 28.9 percent of displaced workers stay in the sector. Accordingly, the largest off-diagonal element corresponds to flows from public administration to various services, which reflect 40.6 percent of pre-displacement public administration employment.

Lastly, Section C of Table 1 denotes net mobility to each industry. On net, displaced workers are attracted to the public administration and various services sectors. In terms of reemployed displaced workers, post-displacement employment growth in those two industries is 64.8 percent and 17.5 percent, respectively. In contrast, displaced workers tend to exit the manufacturing and mining sectors. Based solely on reemployed displaced workers, those industries exhibit very similar post-displacement employment declines of 31.5 percent and 31.4 percent, respectively. The public administration employment finding may reflect displaced-worker preferences regarding job stability. However, the relatively large gross outflows from that industry following job loss—again, primarily to various services—suggest that these workers may also update their beliefs about public sector job security following displacement from the industry and seek other sectors. The net mobility findings regarding various services, manufacturing, and trade may reflect broader market trends in those industries from 1996 through 2019.

# 5 Impact of Job Displacement on Sectoral Mobility

## 5.1 Overall

Table 2 assesses the inverse probability weights used to align displaced and non-displaced workers in order to credibly estimate equation (1). As the table shows, applying these weights (multiplied by the descriptive weights) substantially improves the comparability of the aforementioned treatment and control group workers. Mean differences between the groups for examined indicator measures are all less than 3 percentage points when inverse probability weights are applied, and only one such difference is statistically significant.

Table 3 presents the results of estimating equation (1) for workers continuously employed or reemployed following a job separation. In the most basic specification with no controls, worker or month-in-sample fixed effects, or inverse probability weights, I find that a job separation increases the probability of sectoral mobility ($\hat{\lambda}$) by 16.4 percentage points on a pre-separation base of 0. The additional treatment effect for a displacement compared with a voluntary separation ($\hat{\delta}$) is 8.9 percentage points, or 54.3 percent ($8.9/16.4 \times 100$).

Effect magnitudes are slightly reduced with the application of inverse probability weights and additional regressors but remain quite stable. The displacement-mobility treatment effect ranges from 6.5 percentage points to the aforementioned 8.9 percentage points. In the most stringent, preferred specification with inverse probability weights, controls, and both worker and month-in-sample fixed effects, sectoral mobility increases by 13.2 percentage points following a job separation, and displacement further raises the sectoral mobility rate by 7.9 percentage points (59.8 percent).

## 5.2 Dynamics

Table 4 explores effect dynamics, with all specifications now including controls along with worker and month-in-sample fixed effects. Due to the eight-month out-of-sample period and job separations occurring in MIS2 through MIS8, dynamic effects can be identified only for the month of separation and subsequent three months ($k = 0$ to $k = 3$), as well as 9 to 14 months following separation ($k = 9$ to $k = 14$). Note that the dynamic effects for three months after a job separation are identified solely from separations in MIS5 and the eight-month out-of-sample period, combined with MIS8 outcomes. Similarly, effects for ninth months after a job separation are identified solely from separations in MIS4 combined with outcomes in MIS5 and the intervening eight-month period. Thus, these two dynamic effects are subject to greater measurement error and should be interpreted with caution given their reliance on the out-of-sample period with unobserved worker activity.

The table shows that the dynamic impact of job displacement on sectoral mobility differs significantly from zero and generally grows with increased time following separation, as dynamic coefficients also differ significantly from each other. Once again, the displacement-mobility treatment effect is reduced with inverse probability weighting but remains similar. The observed dynamics could be due to post-separation differences over time in the probability of reemployment, the preference for industry switching, or both. The third specification of Table 4 confirms that effectively holding these factors fixed—accomplished by excluding separated workers unless they are immediately reemployed—results in dynamic displacement-mobility treatment effects that are stably 7 to 8 percentage points when significant ($k = 0$ to $k = 2$). And despite being less precise when assessed across all dynamic periods, the displacement-mobility effects remain fairly stable—typically 7 to 10 percentage points.

# 6 Additional Findings

## 6.1 Sensitivity

Table 5 examines the sensitivity of the displacement-mobility effect. The first specification of the table estimates the preferred model (7) from Table 3 but now includes separated workers who are never reemployed, aligning with the sample in the Table 2 balance assessment. In this broader sample, sectoral mobility increases by 11.3 percentage points following a job separation, and displacement increases the sectoral mobility rate by an additional 3.1 percentage points (27.4 percent). This decrease in the displacement-mobility effect suggests a higher probability of nonemployment after a job loss compared with after a voluntary job separation. The greater risk of nonemployment following displacement may contribute to the sectoral mobility effect, with different-sector reemployment acting as a preferred alternative to zero earnings.

The second specification of Table 5 drops continuously employed workers from the control group, in case the preferred counterfactual is limited to workers who could potentially change industries because they experience a job separation. Since the displacement-mobility effect is not identified from continuously employed workers, the absolute estimate (7.7 percentage points) is expectedly similar to the one in Table 3 (7.9 percentage points). However, given the resulting change in the *Post* coefficient, $\hat{\lambda}$ (8.7 percentage points compared with 13.2 percentage points in Table 3), the relative estimate of the displacement-mobility effect is now higher (88.5 percent compared with 59.8 percent in Table 3).

The third specification of Table 5 restricts the definition of a displaced worker to one who experiences a job loss due to a plant closing to address potential concerns that slack work and shift elimination may be related to worker productivity. At the expected cost of some estimate precision, this sample restriction actually strengthens the findings by raising the displacement-mobility effect. Sectoral mobility now increases by 14.2 percentage points following a job separation, and displacement further increases this sectoral mobility rate by 9.8 percentage points (69 percent).

Lastly, Table 5 includes a specification where separations in MIS5 or the intervening eight-month period are dropped from the sample. Such a restriction might help alleviate some measurement-error concerns related to the uncertainties of the out-of-sample period, partly highlighted by Table 4. Although expectedly less precise, the estimates resulting from this sample restriction are similar to those in Table 3. Sectoral mobility increases by 13.5 percentage points following a job separation, and displacement increases the sectoral mobility rate by an additional 7.1 percentage points (52.6 percent).

## 6.2 Heterogeneity

Table 6 explores heterogeneity in the impact of job displacement on sectoral mobility. I focus on select individual and market characteristics, all measured in the month-in-sample before job separation (or in MIS1 for continuously employed workers). Specifically, the individual-level controls of interest are pre-displacement indicators of having at least a high school diploma or equivalent, being at least 55 years old, and having any children in the household. The market-level controls of interest are pre-displacement continuous measures of the market industry similarity index, the log of market-industry employment, and the market-industry unemployment rate (where a market is a region). These pre-displacement controls replace their analogs in estimation. Such heterogeneity may be of policy interest, especially given a focus on pre-displacement information, even if sectoral mobility might be only a second-best option for workers.

Across specifications, the findings in the table suggest that the displacement-mobility effect is strongly and positively related to a worker having at least a high school diploma before displacement.[7] There is also limited evidence that having any children in the household decreases the displacement-mobility effect, and that the industry similarity index increases the displacement-mobility effect. Regarding the latter, the maximum value of the similarity index for displaced workers in the estimation sample is 0.175. Focusing on specification (9) in the table where all heterogeneous effects are included, a rescaled coefficient for the similarity index interaction term that is analogous to the 0.190 coefficient on the high-school-or-more education interaction term is $1.136 \times 0.175 = 0.199$. If the industry similarity index is interpreted as broadly reflecting industry-specific skills, then this result suggests there may be comparable effects on sectoral mobility of both general and industry training. Additionally, the log of market-industry employment and the market-industry unemployment rate may reflect market information newly conveyed to a displaced worker when job loss occurs. If so, then the absence of significant effect heterogeneity for those measures further supports sectoral mobility as the second-best option rather than the best one.

## 6.3 Sectoral Mobility Alternatives

A remaining question of both methodological and policy interest is this: Which counterfactual is more likely for a displaced worker who changes sectors—same-sector reemployment or nonemployment? Following up on the descriptive analysis in Figure 2, Table 7 examines the impact of various factors on such sectoral mobility alternatives by estimating equation (2). Several effects are statistically significant and robust to either weighting scheme, although efficiency favors the unweighted specification given smaller standard errors. For instance, the presence of any children in a worker's household increases the probability of same-industry reemployment rather than nonemployment. This effect may be due to such dependents in-

[7]No significant effect occurs when substituting the indicator for having at least a high school diploma with either of the following alternative indicators: (i) having at least some college education, or (ii) having at least a bachelors degree.

creasing the cost of nonemployment for a worker. In contrast, being age 55 or older has a negative effect on the probability of same-industry reemployment. Given such workers' likely experience and commensurate compensation, they may be costly to employers.

Market factors matter as well. For instance, relative to the omitted 1996–1999 separation period, being displaced during the period that includes most of the Great Recession (2008 through 2011) or the subsequent period (2012 through 2015) significantly and substantively decreases the probability of same-sector reemployment. Thus, as alluded to by Figure 2, business cycles play a notable role in the likely alternative to sectoral mobility. Such cyclicality may therefore warrant consideration in policies related to the reemployment of displaced workers.

# 7 Conclusion

This paper uses two features of the US Current Population Survey to examine the relationship between job displacement and sectoral mobility for long-tenured workers over the 1996–2019 period: (1) the cross-sectional Displaced Worker Survey and (2) the 16-month longitudinal framework of the Basic Monthly Survey. I find that job displacement negatively correlates with sectoral mobility over time. However, such job loss has a positive causal effect on sectoral mobility for displaced workers compared with similar non-displaced workers. A high school or higher education (general training) and industry similarity (industry training) increase the probability of post-displacement sectoral mobility, and several factors, including business cycles, affect whether the alternative to sectoral mobility is more likely to be same-industry reemployment or nonemployment.

This research has important implications for understanding sectoral mobility in the face of shifts in labor demand even after 2019. Such recent shifts of interest include those prompted by the COVID-19 pandemic (including related childcare concerns of workers) and the rise of automation. Once additional data become available, future research exploring those phenomena and their effects on sectoral mobility would be of definite interest and policy relevance.

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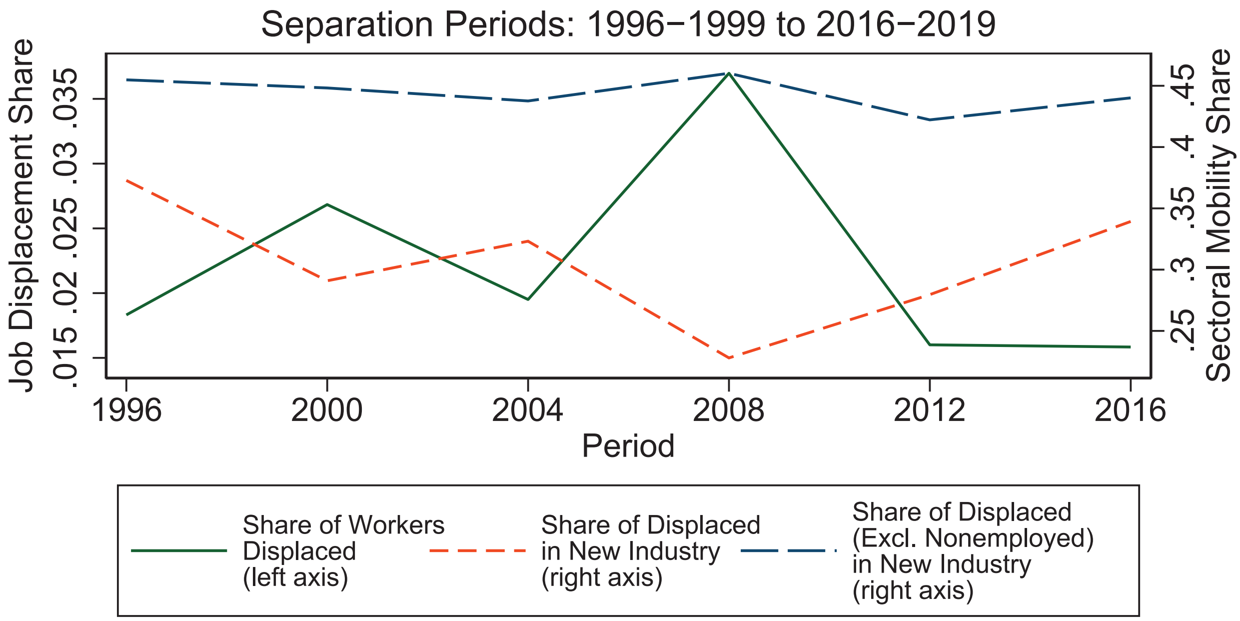


Figure 1: Job Displacement and Sectoral Mobility over Time
*Source(s)*: 1996–2019 Current Population Survey data and author's calculations.

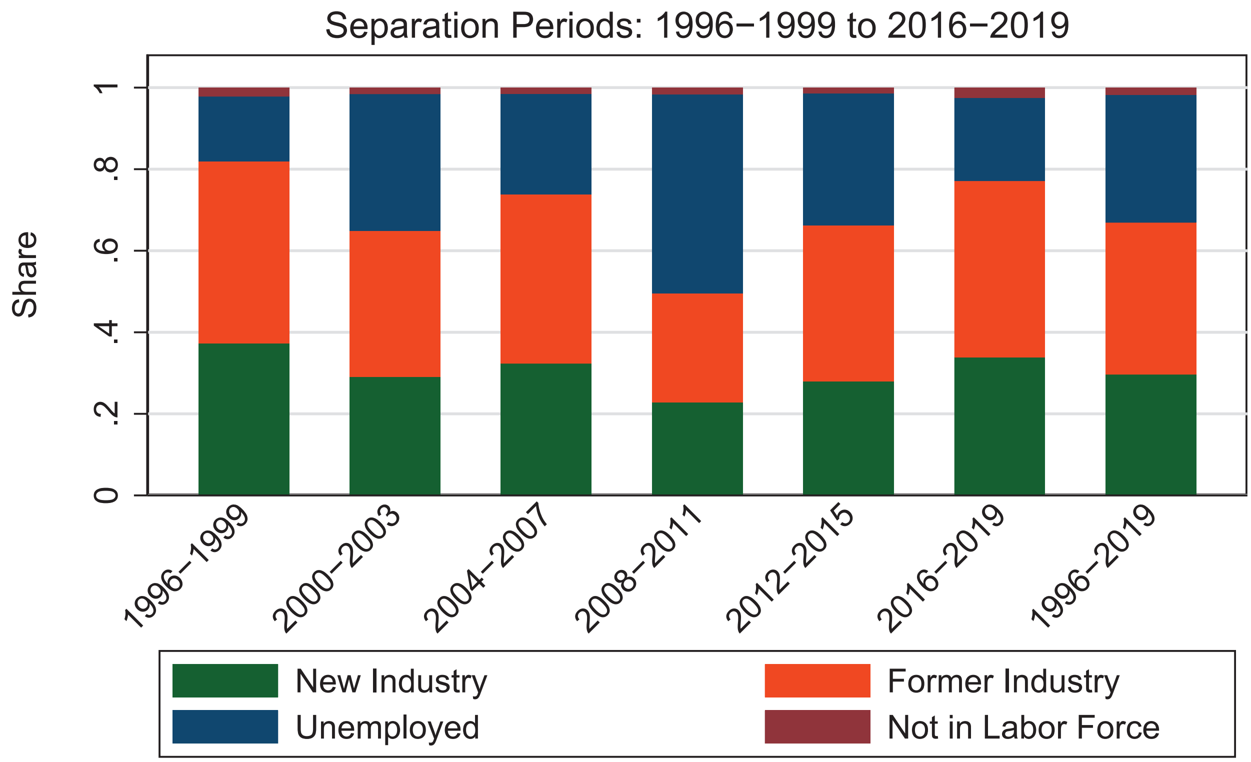


Figure 2: Alternatives to Sectoral Mobility over Time for Displaced Workers
*Source(s)*: 1996–2019 Current Population Survey data and author's calculations.

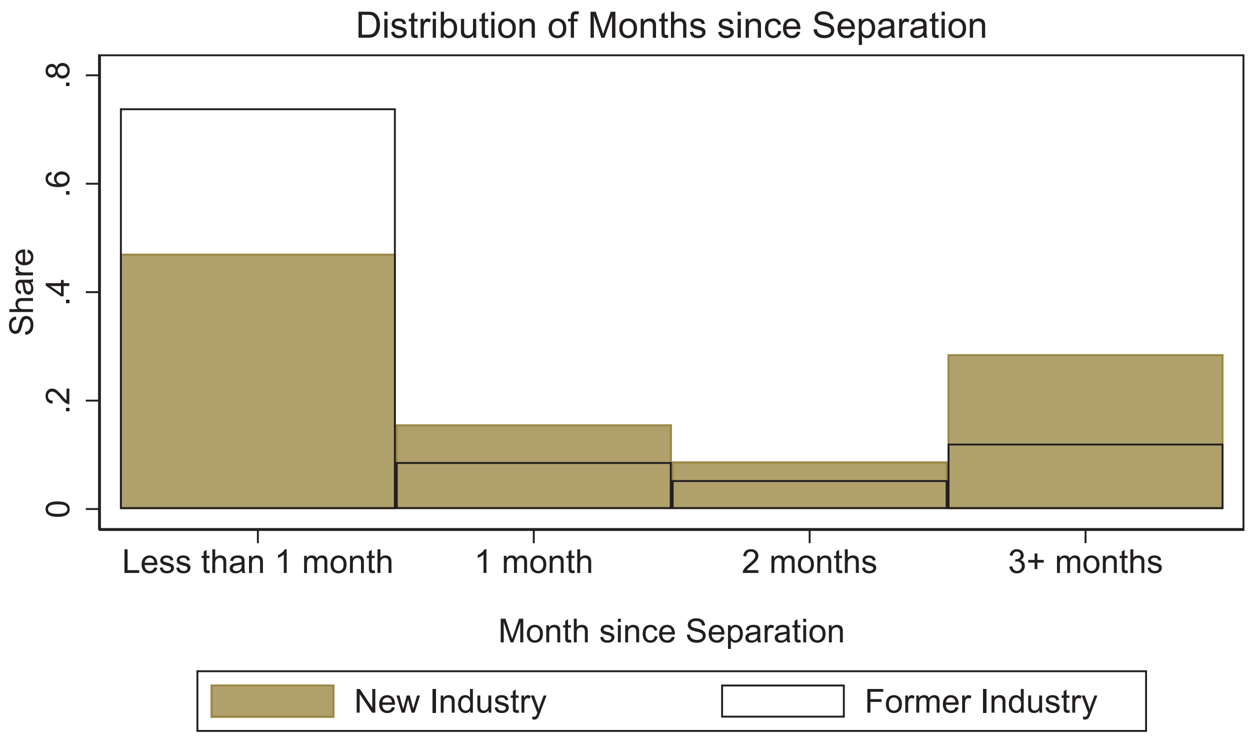


Figure 3: Time until Reemployment, New Industry vs. Former Industry
*Source(s)*: 1996–2019 Current Population Survey data and author's calculations.

## Table 1: Industry Transition Matrix

*Section A: Mobility to each industry as a share of total employment (reemployed displaced workers)*

| | New Industry | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Former Industry** | **AgForFish** | **Mining** | **Construction** | **Manufacturing** | **TranCommOth** | **Trade** | **FIRE** | **VarServ** | **PubAdm** | **TOTAL** |
| **AgForFish** | **0.0069** | 0 | 0.0017 | 0.0011 | 0.0003 | 0.0031 | 0 | 0.0012 | 0.0010 | 0.015 |
| **Mining** | 0.0007 | **0.0034** | 0.0011 | 0.0009 | 0.0006 | 0.0015 | 0.0001 | 0.0022 | 0 | 0.011 |
| **Construction** | 0.0017 | 0.0005 | **0.0535** | 0.0073 | 0.0047 | 0.0079 | 0.0014 | 0.0100 | 0.0004 | 0.087 |
| **Manufacturing** | 0.0028 | 0.0020 | 0.0093 | **0.1019** | 0.0110 | 0.0329 | 0.0057 | 0.0533 | 0.0033 | 0.222 |
| **TranCommOth** | 0.0011 | 0.0003 | 0.0030 | 0.0051 | **0.0272** | 0.0094 | 0.0044 | 0.0204 | 0.0017 | 0.073 |
| **Trade** | 0.0014 | 0 | 0.0073 | 0.0159 | 0.0150 | **0.0944** | 0.0081 | 0.0338 | 0.0026 | 0.179 |
| **FIRE** | 0 | 0.0007 | 0.0022 | 0.0031 | 0.0040 | 0.0070 | **0.0504** | 0.0217 | 0.0023 | 0.091 |
| **VarServ** | 0.0005 | 0.0003 | 0.0087 | 0.0162 | 0.0122 | 0.0320 | 0.0180 | **0.2155** | 0.0059 | 0.309 |
| **PubAdm** | 0 | 0 | 0.0006 | 0.0006 | 0.0002 | 0.0021 | 0.0004 | 0.0052 | **0.0037** | 0.013 |
| **TOTAL** | 0.015 | 0.007 | 0.087 | 0.152 | 0.075 | 0.190 | 0.088 | 0.363 | 0.021 | **1.000** |

*Section B: Mobility to each industry as a share of former industry employment (reemployed displaced workers)*

| | New Industry | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Former Industry** | **AgForFish** | **Mining** | **Construction** | **Manufacturing** | **TranCommOth** | **Trade** | **FIRE** | **VarServ** | **PubAdm** | **TOTAL** |
| **AgForFish** | **0.4481** | 0 | 0.1104 | 0.0714 | 0.0195 | 0.2013 | 0 | 0.0779 | 0.0649 | 1.000 |
| **Mining** | 0.0667 | **0.3238** | 0.1048 | 0.0857 | 0.0571 | 0.1429 | 0.0095 | 0.2095 | 0 | 1.000 |
| **Construction** | 0.0195 | 0.0057 | **0.6121** | 0.0835 | 0.0538 | 0.0904 | 0.0160 | 0.1144 | 0.0046 | 1.000 |
| **Manufacturing** | 0.0126 | 0.0090 | 0.0419 | **0.4586** | 0.0495 | 0.1481 | 0.0257 | 0.2399 | 0.0149 | 1.000 |
| **TranCommOth** | 0.0152 | 0.0041 | 0.0414 | 0.0703 | **0.3752** | 0.1297 | 0.0607 | 0.2814 | 0.0234 | 1.000 |
| **Trade** | 0.0078 | 0 | 0.0409 | 0.0890 | 0.0840 | **0.5286** | 0.0454 | 0.1892 | 0.0146 | 1.000 |
| **FIRE** | 0 | 0.0077 | 0.0241 | 0.0339 | 0.0438 | 0.0766 | **0.5514** | 0.2374 | 0.0252 | 1.000 |
| **VarServ** | 0.0016 | 0.0010 | 0.0281 | 0.0524 | 0.0395 | 0.1035 | 0.0582 | **0.6970** | 0.0191 | 1.000 |
| **PubAdm** | 0 | 0 | 0.0469 | 0.0469 | 0.0156 | 0.1641 | 0.0313 | 0.4063 | **0.2891** | 1.000 |
| **TOTAL** | 0.015 | 0.007 | 0.087 | 0.152 | 0.075 | 0.190 | 0.088 | 0.363 | 0.021 | **1.000** |

*Section C: Net mobility to each industry, change in share of total employment (reemployed displaced workers)*

| | Industry | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **AgForFish** | **Mining** | **Construction** | **Manufacturing** | **TranCommOth** | **Trade** | **FIRE** | **VarServ** | **PubAdm** | **TOTAL** |
| **Net Mobility to Industry** | -0.0004 | -0.0033 | 0 | -0.0700 | 0.0028 | 0.0116 | -0.0030 | 0.0540 | 0.0083 | 0 |
| **Net Mobility to Industry as a Share of Former Industry Employment** | -0.0260 | -0.3143 | 0 | -0.3150 | 0.0386 | 0.0649 | -0.0328 | 0.1746 | 0.6484 | 0 |

*Source(s)* : 1996–2019 Current Population Survey data and author's calculations.

*Note(s)* : AgForFish is Agriculture, Forestry, and Fishing; TranCommOth is Transportation, Communication, and Other Utilities; Trade is Wholesale and Retail Trade; FIRE is Finance, Insurance, and Real Estate; VarServ is Various Services; and PubAdm is Public Administration.

Table 2: Balance of Reweighted Sample

| Measure | Weights: Descriptive Treatment Mean (Displaced) | Weights: Descriptive Control Mean (Non-Displaced) | Weights: Descriptive Difference | Weights: Descriptive x Inverse Probability Treatment Mean (Displaced) | Weights: Descriptive x Inverse Probability Control Mean (Non-Displaced) | Weights: Descriptive x Inverse Probability Difference |
|---|---|---|---|---|---|---|
| Female | 0.5541 | 0.5421 | 0.012 | 0.5389 | 0.5421 | -0.003 |
| Married | 0.6322 | 0.6548 | -0.023 | 0.6397 | 0.6544 | -0.015 |
| Any children | 0.5288 | 0.5348 | -0.006 | 0.5389 | 0.5346 | 0.004 |
| Any children < age 5 | 0.1237 | 0.1304 | -0.007 | 0.1247 | 0.1303 | -0.006 |
| Age (35–54) | 0.6608 | 0.6188 | 0.042 | 0.6422 | 0.6195 | 0.023 |
| Age (55+) | 0.1907 | 0.1872 | 0.003 | 0.1860 | 0.1872 | -0.001 |
| Edu (HS) | 0.3792 | 0.3451 | 0.034 | 0.3417 | 0.3457 | -0.004 |
| Edu (Some Col) | 0.2751 | 0.2768 | -0.002 | 0.2711 | 0.2767 | -0.006 |
| Edu (Col+) | 0.2084 | 0.2429 | -0.034** | 0.2466 | 0.2422 | 0.004 |
| Separated (00–03) | 0.2472 | 0.2244 | 0.023 | 0.2215 | 0.2247 | -0.003 |
| Separated (04–07) | 0.1558 | 0.1902 | -0.034 | 0.1703 | 0.1895 | -0.019 |
| Separated (08–11) | 0.2922 | 0.2092 | 0.083*** | 0.2149 | 0.2113 | 0.004 |
| Separated (12–15) | 0.0987 | 0.1270 | -0.028* | 0.1254 | 0.1263 | -0.001 |
| Separated (16–19) | 0.0873 | 0.1124 | -0.025* | 0.1144 | 0.1118 | 0.003 |
| Race (Black non-Hisp) | 0.0845 | 0.0932 | -0.009 | 0.1058 | 0.0930 | 0.013 |
| Race (Hisp) | 0.1410 | 0.1435 | -0.003 | 0.1376 | 0.1434 | -0.006 |
| Race (Asian non-Hisp) | 0.0223 | 0.0328 | -0.010** | 0.0220 | 0.0326 | -0.011 |
| Race (Other non-Hisp) | 0.0161 | 0.0145 | 0.002 | 0.0232 | 0.0146 | 0.009 |
| Ind (Mining) | 0.0115 | 0.0072 | 0.004 | 0.0079 | 0.0073 | 0.001 |
| Ind (Construction) | 0.0608 | 0.0660 | -0.005 | 0.0637 | 0.0658 | -0.002 |
| Ind (Manufacturing) | 0.3411 | 0.2080 | 0.133*** | 0.2097 | 0.2114 | -0.002 |
| Ind (TranCommOth) | 0.0493 | 0.0636 | -0.014 | 0.0644 | 0.0632 | 0.001 |
| Ind (Trade) | 0.2025 | 0.2087 | -0.006 | 0.2215 | 0.2084 | 0.013 |
| Ind (FIRE) | 0.0870 | 0.0903 | -0.003 | 0.0919 | 0.0902 | 0.002 |
| Ind (VarServ) | 0.2415 | 0.3294 | -0.088** | 0.3317 | 0.3272 | 0.005 |
| Ind (PubAdm) | 0.0004 | 0.0135 | -0.013*** | 0.0007 | 0.0134 | -0.013*** |
| Occ (TechSalesAdm) | 0.3480 | 0.3321 | 0.016 | 0.3489 | 0.3323 | 0.017 |
| Occ (Serv) | 0.0687 | 0.0958 | -0.027* | 0.0955 | 0.0952 | 0 |
| Occ (FarmForFish) | 0.0044 | 0.0112 | -0.007* | 0.0060 | 0.0111 | -0.005 |
| Occ (ProdCraftRep) | 0.1172 | 0.1124 | 0.005 | 0.1038 | 0.1126 | -0.009 |
| Occ (OperFabLabor) | 0.1888 | 0.1456 | 0.043 | 0.1436 | 0.1465 | -0.003 |
| Reg (Middle Atlantic) | 0.1686 | 0.1566 | 0.012 | 0.1703 | 0.1569 | 0.013 |
| Reg (East N. Central) | 0.1827 | 0.1648 | 0.018 | 0.1704 | 0.1651 | 0.005 |
| Reg (West N. Central) | 0.0583 | 0.0642 | -0.006 | 0.0693 | 0.0641 | 0.005 |
| Reg (South Atlantic) | 0.1553 | 0.1808 | -0.026 | 0.1707 | 0.1802 | -0.009 |
| Reg (East S. Central) | 0.0387 | 0.0447 | -0.006 | 0.0385 | 0.0446 | -0.006 |
| Reg (West S. Central) | 0.0635 | 0.0846 | -0.021 | 0.0766 | 0.0843 | -0.008 |
| Reg (Mountain) | 0.0561 | 0.0665 | -0.01 | 0.0646 | 0.0663 | -0.002 |
| Reg (Pacific) | 0.2143 | 0.1820 | 0.032 | 0.1830 | 0.1827 | 0 |
| Number of workers | 693 | 38,722 | | 693 | 38,722 | |

* $p$ < 0.10, ** $p$ < 0.05, *** $p$ < 0.01

*Source(s)* : 1996–2019 Current Population Survey data and author's calculations.

*Note(s)* : Omitted categories are Age (20–34), Edu (< HS), Separated (96–99), Race (White non-Hisp), Ind (AgForFish), Occ (MgrProf), and Reg (New England). Industry abbreviations: AgForFish is Agriculture, Forestry, and Fishing; TranCommOth is Transportation, Communication, and Other Utilities; Trade is Wholesale and Retail Trade; FIRE is Finance, Insurance, and Real Estate; VarServ is Various Services; and PubAdm is Public Administration. Occupation abbrevations: MgrProf is Managerial and Professional Specialty; TechSalesAdm is Technical, Sales, and Administrative Support; Serv is Service; FarmForFish is Farming, Forestry, and Fishing; ProdCraftRep is Precision Production, Craft, and Repair; OperFabLabor is Operators, Fabricators, and Laborers. Non-displaced workers are either voluntarily separated or continuously employed.

Table 3: The Impact of Job Displacement on Sectoral Mobility

| | Dependent Variable: Industry Change from Baseline as of Given Month-in-Sample (0/1) | | | | | | |
|---|---|---|---|---|---|---|---|
| | Desc. Weight | Desc. Weight x Inv. Prob. Weight | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Displaced | 0.000*** | 0.000*** | 0.005 | | 0.011*** | | |
| | (0.000) | (0.000) | (0.005) | | (0.002) | | |
| Post | 0.164*** | 0.164*** | 0.162*** | 0.165*** | 0.155*** | 0.142*** | 0.132*** |
| | (0.007) | (0.007) | (0.008) | (0.007) | (0.008) | (0.008) | (0.008) |
| Displaced x Post | 0.089*** | 0.079*** | 0.078*** | 0.083*** | 0.065** | 0.083*** | 0.079*** |
| | (0.025) | (0.026) | (0.026) | (0.028) | (0.026) | (0.028) | (0.024) |
| Controls | no | no | yes | no | no | no | yes |
| Worker FEs | no | no | no | yes | no | yes | yes |
| MIS FEs | no | no | no | no | yes | yes | yes |
| Pre-disp Treatment Mean of Outcome | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| R-squared | 0.176 | 0.231 | 0.214 | 0.562 | 0.184 | 0.566 | 0.611 |
| Number of Observations | 307,480 | 307,480 | 307,480 | 307,480 | 307,480 | 307,480 | 307,480 |
| Number of Displaced Workers | 455 | 455 | 455 | 455 | 455 | 455 | 455 |
| Number of Non-Displaced Workers | 37,980 | 37,980 | 37,980 | 37,980 | 37,980 | 37,980 | 37,980 |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

*Source(s)* : 1996–2019 Current Population Survey data and author's calculations.

*Note(s)* : Robust standard errors clustered at the worker level in parentheses. Control group is continuously employed workers and voluntarily separated workers. Separated workers excluded unless reemployed.

Table 4: The Dynamic Impact of Job Displacement on Sectoral Mobility

| | Dependent Variable: Industry Change from Baseline as of Given Month-in-Sample (0/1) | | |
|---|---|---|---|
| | Desc. Weight | Desc. Weight x Inv. Prob. Weight | |
| | (1) | (2) | (3) |
| Post, k=0 | 0.106*** | 0.107*** | 0.136*** |
| | (0.006) | (0.007) | (0.009) |
| Post, k=1 | 0.137*** | 0.138*** | 0.131*** |
| | (0.008) | (0.009) | (0.010) |
| Post, k=2 | 0.155*** | 0.158*** | 0.131*** |
| | (0.010) | (0.011) | (0.011) |
| Post, k=3 | 0.342*** | 0.353*** | 0.215*** |
| | (0.038) | (0.043) | (0.034) |
| Post, k=9 | 0.190*** | 0.183*** | 0.142*** |
| | (0.014) | (0.016) | (0.016) |
| Post, k=10 | 0.185*** | 0.184*** | 0.142*** |
| | (0.011) | (0.013) | (0.013) |
| Post, k=11 | 0.182*** | 0.181*** | 0.139*** |
| | (0.010) | (0.011) | (0.011) |
| Post, k=12 | 0.182*** | 0.180*** | 0.139*** |
| | (0.010) | (0.010) | (0.011) |
| Post, k=13 | 0.175*** | 0.172*** | 0.135*** |
| | (0.009) | (0.010) | (0.010) |
| Post, k=14 | 0.175*** | 0.172*** | 0.135*** |
| | (0.010) | (0.012) | (0.011) |
| Displaced x Post, k=0 | 0.041** | 0.039* | 0.073** |
| | (0.021) | (0.021) | (0.032) |
| Displaced x Post, k=1 | 0.076*** | 0.074*** | 0.084** |
| | (0.026) | (0.027) | (0.033) |
| Displaced x Post, k=2 | 0.098*** | 0.087*** | 0.083** |
| | (0.030) | (0.029) | (0.033) |
| Displaced x Post, k=3 | -0.053 | -0.072 | |
| | (0.049) | (0.052) | |
| Displaced x Post, k=9 | 0.041 | 0.039 | 0.014 |
| | (0.066) | (0.056) | (0.048) |
| Displaced x Post, k=10 | 0.183*** | 0.153*** | 0.087 |
| | (0.059) | (0.050) | (0.071) |
| Displaced x Post, k=11 | 0.189*** | 0.157*** | 0.075 |
| | (0.052) | (0.046) | (0.058) |
| Displaced x Post, k=12 | 0.196*** | 0.161*** | 0.072 |
| | (0.052) | (0.046) | (0.057) |
| Displaced x Post, k=13 | 0.203*** | 0.174*** | 0.098 |
| | (0.049) | (0.048) | (0.062) |
| Displaced x Post, k=14 | 0.160*** | 0.123** | 0.051 |
| | (0.053) | (0.052) | (0.036) |
| R-squared | 0.670 | 0.623 | 0.675 |
| Number of Observations | 307,480 | 307,480 | 298,056 |
| Number of Displaced Workers | 455 | 455 | 301 |
| Number of Non-Displaced Workers | 37,980 | 37,980 | 36,956 |
| P-value: Displaced x Post Jointly Zero | 0.000 | 0.000 | 0.084 |
| P-value: Displaced x Post Jointly Equal | 0.000 | 0.000 | 0.060 |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

*Source(s)* : 1996–2019 Current Population Survey data and author's calculations.

*Note(s)* : Robust standard errors clustered at the worker level in parentheses. Control group is continuously employed workers and voluntarily separated workers. Separated workers excluded unless reemployed (models 1 and 2) or immediately reemployed (model 3). All models include controls, worker fixed effects, and month-in-sample fixed effects. Months since separation indexed by k. Displaced x Post, k=3 coefficient missing in model 3 since identified solely from separations in month-in-sample 5 and the out-of-sample period.

Table 5: The Robustness of the Impact of Job Displacement on Sectoral Mobility

| | Dependent Variable: Industry Change from Baseline as of Given Month-in-Sample (0/1) | | | |
|---|---|---|---|---|
| | Include Never Reemployed (1) | Drop Cont. Employed (2) | Displaced = Plant Closings (3) | Drop MIS5 Separations (4) |
| Post | 0.113*** | 0.087*** | 0.142*** | 0.135*** |
| | (0.007) | (0.008) | (0.008) | (0.008) |
| Displaced x Post | 0.031* | 0.077*** | 0.098** | 0.071* |
| | (0.018) | (0.024) | (0.042) | (0.037) |
| R-squared | 0.587 | 0.611 | 0.656 | 0.680 |
| Number of Observations | 315,320 | 41,192 | 305,344 | 303,400 |
| Number of Displaced Workers | 693 | 472 | 188 | 149 |
| Number of Non-Displaced Workers | 38,722 | 4,677 | 37,980 | 37,776 |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

*Source(s)* : 1996–2019 Current Population Survey data and author's calculations.

*Note(s)* : Robust standard errors clustered at the worker level in parentheses. Control group is continuously employed workers and voluntarily separated workers, except in model (2) where continuously employed workers are dropped. Separated workers excluded unless reemployed, except in model (1) where all separated workers are included. All models are weighted using descriptive weights x inverse probability weights and include controls, worker fixed effects, and month-in-sample fixed effects. Inverse probability weights are estimated separately for model (3) given the notable change in the control group.

Table 6: The Heterogeneous Impact of Job Displacement on Sectoral Mobility

| | Dependent Variable: Industry Change from Baseline as of Given Month-in-Sample (0/1) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Post | 0.114*** | 0.149*** | 0.133*** | 0.143*** | 0.123*** | 0.432*** | 0.149*** | 0.513*** | 0.513*** |
| | (0.022) | (0.009) | (0.010) | (0.024) | (0.018) | (0.165) | (0.014) | (0.179) | (0.180) |
| Displaced x Post | -0.067 | 0.060** | 0.132*** | -0.033 | 0.011 | -0.137 | 0.096** | -0.019 | -0.325 |
| | (0.045) | (0.029) | (0.038) | (0.058) | (0.057) | (0.438) | (0.043) | (0.471) | (0.448) |
| Displaced x Post x Edu (HS+) Pre-disp | 0.171*** | | | 0.164*** | | | | | 0.190*** |
| | (0.052) | | | (0.052) | | | | | (0.062) |
| Displaced x Post x Age (55+) Pre-disp | | 0.095 | | 0.058 | | | | | 0.067 |
| | | (0.062) | | (0.063) | | | | | (0.061) |
| Displaced x Post x Any children Pre-disp | | | -0.096* | -0.067 | | | | | -0.056 |
| | | | (0.051) | (0.050) | | | | | (0.050) |
| Displaced x Post x Market Industry Similarity Pre-disp | | | | | 0.779 | | | 0.720 | 1.136* |
| | | | | | (0.783) | | | (0.734) | (0.689) |
| Displaced x Post x Log(Market-Ind Emp) Pre-disp | | | | | | 0.015 | | 0.003 | 0.012 |
| | | | | | | (0.031) | | (0.031) | (0.029) |
| Displaced x Post x Market-Ind Unemp Rate Pre-disp | | | | | | | -0.843 | -0.485 | -0.037 |
| | | | | | | | (1.079) | (1.041) | (1.009) |
| R-squared | 0.609 | 0.601 | 0.604 | 0.611 | 0.603 | 0.601 | 0.602 | 0.604 | 0.615 |
| Number of Observations | 307,480 | 307,480 | 307,480 | 307,480 | 307,480 | 307,480 | 307,480 | 307,480 | 307,480 |
| Number of Displaced Workers | 455 | 455 | 455 | 455 | 455 | 455 | 455 | 455 | 455 |
| Number of Non-Displaced Workers | 37,980 | 37,980 | 37,980 | 37,980 | 37,980 | 37,980 | 37,980 | 37,980 | 37,980 |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

*Source(s)* : 1996–2019 Current Population Survey data and author's calculations.

*Note(s)* : Robust standard errors clustered at the worker level in parentheses. Control group is continuously employed workers and voluntarily separated workers. Separated workers excluded unless reemployed. All models are weighted using descriptive weights x inverse probability weights and include controls, worker fixed effects, and month-in-sample fixed effects. Listed controls are measured in the month-in-sample before job separation (or in MIS1 for continuously employed workers) and are also interacted with Displaced and Post indicators.

Table 7: The Impact of Various Factors on Sectoral Mobility Alternatives

| | Dependent Variable: Same-Industry Reemployment instead of Nonemployment (0/1) | |
|---|---|---|
| | No Weight | Desc. Weight |
| | (1) | (2) |
| Female | 0.012 | 0.009 |
| | (0.047) | (0.054) |
| Married | -0.041 | -0.040 |
| | (0.045) | (0.053) |
| Any children | 0.140*** | 0.124** |
| | (0.049) | (0.059) |
| Any children < age 5 | 0.081 | 0.119* |
| | (0.068) | (0.069) |
| Age (35–54) | -0.047 | 0.010 |
| | (0.061) | (0.070) |
| Age (55+) | -0.136* | -0.137* |
| | (0.070) | (0.083) |
| Edu (HS+) | -0.012 | -0.047 |
| | (0.080) | (0.086) |
| Separated (00–03) | -0.134** | -0.067 |
| | (0.067) | (0.092) |
| Separated (04–07) | -0.168** | -0.078 |
| | (0.076) | (0.097) |
| Separated (08–11) | -0.435*** | -0.369*** |
| | (0.069) | (0.094) |
| Separated (12–15) | -0.306*** | -0.225** |
| | (0.088) | (0.108) |
| Separated (16–19) | -0.045 | 0.088 |
| | (0.097) | (0.113) |
| Race (Black non-Hisp) | -0.201** | -0.190** |
| | (0.088) | (0.091) |
| Race (Hisp) | -0.082 | 0.064 |
| | (0.078) | (0.081) |
| Race (Asian non-Hisp) | -0.244* | -0.220* |
| | (0.130) | (0.132) |
| Race (Other non-Hisp) | -0.537*** | -0.575*** |
| | (0.190) | (0.219) |
| Reg (Middle Atlantic) | -0.133 | -0.034 |
| | (0.111) | (0.140) |
| Reg (East N. Central) | 0.003 | 0.074 |
| | (0.135) | (0.168) |
| Reg (West N. Central) | -0.025 | -0.006 |
| | (0.089) | (0.113) |
| Reg (South Atlantic) | -0.033 | 0.051 |
| | (0.136) | (0.169) |
| Reg (East S. Central) | 0.047 | 0.115 |
| | (0.127) | (0.137) |
| Reg (West S. Central) | -0.093 | -0.123 |
| | (0.147) | (0.166) |
| Reg (Mountain) | -0.040 | 0.110 |
| | (0.101) | (0.124) |
| Reg (Pacific) | -0.153 | -0.155 |
| | (0.122) | (0.155) |
| Ind (Mining) | -0.967*** | -1.088*** |
| | (0.215) | (0.205) |
| Ind (Construction) | -0.689*** | -0.760*** |
| | (0.203) | (0.217) |
| Ind (Manufacturing) | -0.810*** | -0.927*** |
| | (0.225) | (0.254) |
| Ind (TranCommOth) | -0.708*** | -0.816*** |
| | (0.195) | (0.202) |
| Ind (Trade) | -0.661*** | -0.780*** |
| | (0.232) | (0.272) |
| Ind (FIRE) | -0.534*** | -0.584*** |
| | (0.187) | (0.197) |
| Ind (VarServ) | -0.540* | -0.575 |
| | (0.291) | (0.353) |
| Ind (PubAdm) | 0.156 | -0.100 |
| | (0.182) | (0.190) |
| Occ (TechSalesAdm) | -0.025 | -0.089 |
| | (0.056) | (0.065) |
| Occ (Serv) | 0.090 | 0.001 |
| | (0.097) | (0.102) |
| Occ (FarmForFish) | 0.105 | 0.068 |
| | (0.226) | (0.222) |
| Occ (ProdCraftRep) | 0.111 | 0.078 |
| | (0.077) | (0.089) |
| Occ (OperFabLabor) | -0.010 | -0.041 |
| | (0.072) | (0.081) |
| Market Industry Similarity | 0.202 | -0.438 |
| | (0.716) | (0.844) |
| Log(Market-Ind Emp) | 0.071 | 0.049 |
| | (0.087) | (0.113) |
| Market-Ind Unemp Rate | 4.727*** | 2.912 |
| | (1.498) | (1.880) |
| Mean of Outcome | 0.566 | 0.566 |
| R-squared | 0.195 | 0.250 |
| Number of Observations (Displaced Workers) | 549 | 549 |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

*Source(s)* : 1996–2019 Current Population Survey data and author's calculations.

*Note(s)* : Heteroskedasticity-robust standard errors in parentheses. Workers dropped unless displaced and not reemployed in a new sector. Cross-sectional sample reflecting the month-in-sample before displacement.

# A Appendix

## A.1 Descriptive Weight Construction

### A.1.1 DWS-BMS

As noted in the main text, given numerous sample restrictions for the DWS-BMS panel, I create a descriptive weight for all DWS-BMS workers to reflect their nationally representative count. These weights incorporate both a "sample design" component and a "post-stratification" component. The two components are multiplied to generate the descriptive weight, $WTALL$, which is used for both descriptive and causal analysis, as noted in the main text and displays.

For the sample design weight component, I adjust the $WTFINL$ measure provided by IPUMS-CPS. $WTFINL$ is described as "the final person-level weight that should be used in analyses of basic monthly data" and "is based on the inverse probability of selection into the sample" with additional adjustments for various factors (Flood et al. 2020). Further adjustments to $WTFINL$ are needed in this paper due to multiple observations (eight) for each worker and assignment of each worker to a unique calendar year based on the date of job separation (or pseudo-separation in MIS1, for continuously employed workers). For each worker and calendar year, I calculate the sum of $WTFINL$ across all months surveyed and then divide that worker-year sum by 12 (call this the "weight mean"). For each worker and calendar year, I also create a binary indicator that equals 1 in the one job-separation calendar year out of two or three calendar years reflected by a worker's survey participation (which spans 16 continuous calendar months; call this the "year indicator"). Finally, for each calendar year, I also calculate a factor to account for the unique assignment of each worker to one calendar year rather than the two or three calendar years in which they appear in the CPS. This factor is the sum across all workers of the weight mean, divided by the sum across all workers of the weight mean multiplied by the year indicator (call this the "scaling factor"). Thus, for each worker-year, the adjusted $WTFINL$ measure, $WTFINLADJ$, equals the product of the year indicator, the scaling factor, and the weight mean. Note that $WTFINLADJ$ is non-zero only in the unique separation year.

For the post-stratification weight component, the goal is to further adjust the descriptive weight for any differential sample selection across a set of key individual traits. Such selection is determined by comparing the baseline sample of individuals with person-level IDs noted in Appendix Table A1 (call this the "raw" sample) and the combined DWS-BMS sample noted in Appendix Table A2 (call this the "final" sample). Since some people have multiple observations, I focus on MIS1 values for each individual trait. Both the raw and final samples reflect the resulting calendar years spanned by workers in the final sample given separation years from 1996 through 2019. Both samples are also restricted to persons age 20 and older since the DWS is constrained to such individuals. I focus on five categories for individual traits, with the corresponding number of values for each measure indicated in parentheses: sex (2), race/ethnicity (2), age (2), education (4), and area (9).[8] Every person is uniquely

[8] Regarding category values: sex is male or female; race/ethnicity is white non-Hispanic or not white non-Hispanic; age is 20 to 44 or 45 and older; education is less than high school (diploma or equivalent, including persons "not in universe" or with missing responses), high school (diploma or equivalent), some

assigned to one bin among all 288 possible bin combinations from those five traits. For each bin and the corresponding workers assigned to those bins, the post-stratification weight, $WTPOST$, is the count of persons in the raw sample divided by the count of persons in the final sample.

The final descriptive weight for each worker in the DWS-BMS sample, $WTALL$, is thus $WTFINLADJ \times WTPOST$. As noted in the main text, I run validity checks to compare various population statistics (shares) with those generated by the DWS-BMS sample with the $WTALL$ descriptive weight applied. In these validity checks, I am able to closely replicate the chosen population statistics.

### A.1.2 Pooled DWS

The equivalent descriptive weight for the pooled DWS sample is constructed using an approach similar to the one used to construct the DWS-BMS descriptive weight. Since the calculated statistics using the pooled DWS always involve a BMS response, I rely on $WTFINL$ for the sample design weight component rather than the DWS weight, $DWSUPPWT$. However, results are similar when $DWSUPPWT$ is used instead.[9] Additionally, since the pooled DWS is a cross section, the sample design weight is simply $WTFINL$.

For the post-stratification weight component, the raw data correspond to every individual in the 1998–2020 DWS who has a person-level ID. The final sample reflects those data with all of the pooled DWS sample restrictions applied. Additionally, the bin categories are the same as the DWS-BMS analogs, except for a coarser, binary education category, which allows for the addition of a sixth category with three values reflecting periods.[10] Every person is uniquely assigned to one bin among all 432 possible bin combinations from those six traits, with the relatively larger pooled DWS sample allowing for more bins than the DWS-BMS sample. For each bin and the corresponding workers assigned to those bins, the cross-sectional post-stratification weight, $WTPOSTCS$, is the count of persons in the raw sample divided by the count of persons in the final sample.

The final descriptive weight for each worker in the pooled DWS sample, $WTALLCS$, is thus $WTFINL \times WTPOSTCS$. And once again, as mentioned in the main text, I run validity checks to compare various population statistics (shares) with those generated by the pooled DWS sample with the $WTALLCS$ descriptive weight applied. As with the DWS-BMS validity checks, I am able to closely replicate the chosen population statistics.

college (including associate degree), and college (bachelor's degree) or more; and area is New England, Middle Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain, and Pacific, reflecting census divisions and the associated states (Flood et al. 2020).

[9] Such similarity is not surprising since $DWSUPPWT$ is identical to $WTFINL$ from 1984 through 1994 and comparable thereafter (Flood et al. 2020).

[10] Regarding category values that differ from those applied to the DWS-BMS: education is high school or less (diploma or equivalent, including persons "not in universe" or with missing responses), or some college or more (including associate degree); and period is 1996 through 2003, 2004 through 2011, or 2012 through 2019, reflecting the year of job separation.

## Table A1: Initial Sample Selection

| Sample Restriction | Count | | | Percentage of Baseline | | |
|---|---|---|---|---|---|---|
| | Household | Individual | Observation | Household | Individual | Observation |
| Baseline w/ CPSIDP (person ID) | 5,476,410 | 14,285,329 | 72,481,982 | 100.00 | 100.00 | 100.00 |
| Drop if CPSIDP only appears once | 4,850,290 | 12,386,498 | 70,583,151 | 88.57 | 86.71 | 97.38 |
| Drop if under age 16 | 4,849,440 | 9,644,849 | 55,275,663 | 88.55 | 67.52 | 76.26 |
| Drop if not in BMS for 8 months-in-sample | 2,061,769 | 3,885,199 | 31,081,592 | 37.65 | 27.20 | 42.88 |
| Drop if race varies across time | 2,051,051 | 3,857,775 | 30,862,200 | 37.45 | 27.01 | 42.58 |
| Drop if Hispanic varies across time | 2,036,151 | 3,821,210 | 30,569,680 | 37.18 | 26.75 | 42.18 |
| Drop if sex varies across time | 2,024,422 | 3,788,284 | 30,306,272 | 36.97 | 26.52 | 41.81 |
| Drop if age varies incorrectly across time | 1,843,409 | 3,211,347 | 25,690,776 | 33.66 | 22.48 | 35.44 |
| Drop if not full-time employed in MIS1 | 1,124,263 | 1,495,536 | 11,964,288 | 20.53 | 10.47 | 16.51 |
| Drop if industry unknown or military or NIU | 1,062,062 | 1,380,122 | 11,040,976 | 19.39 | 9.66 | 15.23 |
| Drop if occupation unknown/NIU or military | 1,062,013 | 1,379,993 | 11,039,944 | 19.39 | 9.66 | 15.23 |
| Drop if state unavailable for any month-in-sample | 1,062,013 | 1,379,993 | 11,039,944 | 19.39 | 9.66 | 15.23 |
| Drop if state varies across time | 1,062,013 | 1,379,993 | 11,039,944 | 19.39 | 9.66 | 15.23 |
| Drop if MIS1 is before January 1994 | 624,114 | 808,841 | 6,470,728 | 11.40 | 5.66 | 8.93 |
| Drop if MIS2 is in June 2015 | 622,315 | 806,616 | 6,452,928 | 11.36 | 5.65 | 8.90 |
| Drop if individual is unexplainably NIU for same employer measure | 578,171 | 745,938 | 5,967,504 | 10.56 | 5.22 | 8.23 |
| Drop if individual is unexplainably IU for same employer measure | 577,903 | 745,499 | 5,963,992 | 10.55 | 5.22 | 8.23 |
| Drop if industry changes without employer change | 570,364 | 733,231 | 5,865,848 | 10.41 | 5.13 | 8.09 |
| Drop if working multiple jobs in any MIS | 501,687 | 624,862 | 4,998,896 | 9.16 | 4.37 | 6.90 |
| Drop if ever NIU or military for employment status | 501,687 | 624,862 | 4,998,896 | 9.16 | 4.37 | 6.90 |
| Drop if same employer measure is refused or unknown | 501,487 | 624,584 | 4,996,672 | 9.16 | 4.37 | 6.89 |

*Source(s)* : January 1976–March 2021 Current Population Survey data and author's calculations.
*Note(s)* : NIU is not in universe and IU is in universe.

Table A2: DWS-BMS Sample Selection

*Subsample A: Displaced Worker Survey Participants (Displacements and Remaining Job Separations)*

| | Count | | | Percentage of Baseline | | |
|---|---|---|---|---|---|---|
| **Sample Restriction** | **Household** | **Individual** | **Observation** | **Household** | **Individual** | **Observation** |
| Baseline w/ initial restrictions | 501,487 | 624,584 | 4,996,672 | 100.00 | 100.00 | 100.00 |
| Drop if no DWS survey response in MIS2–MIS8 | 10,619 | 10,964 | 87,712 | 2.12 | 1.76 | 1.76 |
| Drop if observed unemployment spell exists with likely recall | 10,551 | 10,891 | 87,128 | 2.10 | 1.74 | 1.74 |
| Drop if unobserved unemployment spell exists with likely/existent recall | 10,537 | 10,876 | 87,008 | 2.10 | 1.74 | 1.74 |
| Drop if last worked at previous job more than 2 calendar years ago | 6,929 | 7,149 | 57,192 | 1.38 | 1.14 | 1.14 |
| Drop if having 2 or more jobs since previous job | 6,320 | 6,510 | 52,080 | 1.26 | 1.04 | 1.04 |
| Drop if likely did not experience one job separation since MIS1 | 2,208 | 2,239 | 17,912 | 0.44 | 0.36 | 0.36 |
| Drop if traits of previous job do not match across DWS and MIS1 | 1,754 | 1,777 | 14,216 | 0.35 | 0.28 | 0.28 |
| Drop if tenure at previous job is less than 3 years | 1,256 | 1,270 | 10,160 | 0.25 | 0.20 | 0.20 |
| Drop if age ever under 20 | 1,254 | 1,268 | 10,144 | 0.25 | 0.20 | 0.20 |
| Drop if MIS of separation occurs in 1994, 1995, or 2020 | 1,239 | 1,252 | 10,016 | 0.25 | 0.20 | 0.20 |
| Drop if any error diagnostics apply | 1,157 | 1,170 | 9,360 | 0.23 | 0.19 | 0.19 |

*Subsample B: Voluntarily Separated Workers*

| | Count | | | Percentage of Baseline | | |
|---|---|---|---|---|---|---|
| **Sample Restriction** | **Household** | **Individual** | **Observation** | **Household** | **Individual** | **Observation** |
| Baseline w/ initial restrictions | 501,487 | 624,584 | 4,996,672 | 100.00 | 100.00 | 100.00 |
| Drop if likely did not experience one separation since MIS1 | 61,442 | 63,621 | 508,968 | 12.25 | 10.19 | 10.19 |
| Drop unless MIS5, MIS6, MIS7, or MIS8 occur when DWS administered | 9,997 | 10,310 | 82,480 | 1.99 | 1.65 | 1.65 |
| Drop unless reason for job loss is NIU | 8,030 | 8,270 | 66,160 | 1.60 | 1.32 | 1.32 |
| Drop if age ever under 20 | 7,924 | 8,159 | 65,272 | 1.58 | 1.31 | 1.31 |
| Drop if separation is in 1994, 1995, or 2020 | 7,641 | 7,863 | 62,904 | 1.52 | 1.26 | 1.26 |
| Drop if any error diagnostics apply | 6,522 | 6,682 | 53,456 | 1.30 | 1.07 | 1.07 |

*Subsample C: Continuously Employed Workers*

| | Count | | | Percentage of Baseline | | |
|---|---|---|---|---|---|---|
| **Sample Restriction** | **Household** | **Individual** | **Observation** | **Household** | **Individual** | **Observation** |
| Baseline w/ initial restrictions | 501,487 | 624,584 | 4,996,672 | 100.00 | 100.00 | 100.00 |
| Drop if not full-time employed in MIS2-MIS8 | 269,034 | 308,561 | 2,468,488 | 53.65 | 49.40 | 49.40 |
| Drop if change of employer in MIS2-MIS4 or MIS6-MIS8 | 252,610 | 287,600 | 2,300,800 | 50.37 | 46.05 | 46.05 |
| Drop unless MIS5, MIS6, MIS7, or MIS8 occur when DWS administered | 44,542 | 50,931 | 407,448 | 8.88 | 8.15 | 8.15 |
| Drop unless reason for job loss is NIU | 43,081 | 49,112 | 392,896 | 8.59 | 7.86 | 7.86 |
| Drop if age ever under 20 | 43,007 | 48,978 | 391,824 | 8.58 | 7.84 | 7.84 |
| Drop if MIS1 is in 1994, 1995, or 2020 | 43,007 | 48,978 | 391,824 | 8.58 | 7.84 | 7.84 |
| Drop if any error diagnostics apply | 38,300 | 43,055 | 344,440 | 7.64 | 6.89 | 6.89 |

*Source(s)* : January 1994–March 2021 Current Population Survey data and author's calculations.
*Note(s)* : NIU is not in universe.