Recent Patterns of Job-to-Job Transitions in the United States

Joelle Saad-Lessler

Associate Industry Professor and Associate Dean of Undergraduate Studies

Stevens Institute of Technology, School of Business
1 Castle Point Terrace, Hoboken, NJ 07030
Ph: (201) 216-3345
Email: jsaadles@stevens.edu

Florence Neymotin (Corresponding Author)

Professor of Decision Sciences

Huizenga College of Business, Nova Southeastern University
3301 College Ave., Fort Lauderdale, FL, 33498
Ph: 954-262-5339
Email: fneymotin@nova.edu

Recent Patterns of Job-to-Job Transitions in the United States

Abstract: This work examines the phenomenon of job-to-job switching, which, when done quickly, has colloquially been termed 'job-hopping.' Our main analysis employs 2012-2022 U.S. Current Population Survey data and finds temporal impacts of the pandemic and its aftermath on the manner in which individuals switch jobs. We bring empirical evidence to show that our results are due to both changes in coefficients as well as changes in demographic characteristics. Our findings are the first that we know of to examine job-to-job changes and how these patterns have evolved after the onset of, and recovery from, the COVID-19 pandemic.

Keywords: Job-Hopping; Job-Switching; COVID-19; Labor Supply

JEL Code: J21; E24;

Recent Patterns of Job-to-Job Transitions in the United States

INTRODUCTION

The last few years have seen the rise of the "Great Resignation," and many have attributed the recent spikes in the rates of quitting and job-changes to individuals no longer being willing to work, or else lacking interest in what his or her current job has to offer (Sull et al., 2022). Others interpret these downturns in employee retention as a signal of economic improvement and general recovery (Harrison & Morath, 2018; McDonnell, 2022). Reconciling these two views in the face of the COVID-19 pandemic presents an interesting conundrum. It is also difficult to find evidence in the literature on how to view rapid job-switchers, since this is still a nascent - but growing - area of research.

Our goal, in addition to contributing to the sparse research on job-to-job-switching, which we define as changes in employers with no period of unemployment in between, is to determine how these patterns changed from before the pandemic to the present. We employ 2012-2022 U.S. Current Population Survey data to document temporal changes in job switching.[1]

We view our results as a valuable addition to the small current literature on job-switching, and as an initial indication of how this type of employment transition has functioned before, during, and after the COVID-19 period.

[1] While not officially "job-hopping," we do find evidence for the shorter tenure of jobs involved in job-to-job switching. We take this as an indication that job-to-job switching patterns are also indicative of patterns in job-hopping.

BACKGROUND

The recent increase in job-switching should be considered within a longer secular decline in rates of employee retention. Authors in 2003 were already noticing a decrease in employment length, but claimed it was primarily focused in the highly skilled and educated segment of workers (Fleming and Soborg, 2003). By 2011, when nearing the end of the Great Recession that started in 2008, it had become clear that the decrease in retention rates was apparent throughout the economy, and a lasting part of our workplace relations (Levering and Erb, 2011). More recent papers showed that the phenomenon of individuals changing workplaces remains common, but that the primary switchers are now the youngest part of the workforce (Gilbert, 2021; Borg et al., 2021).

The literature on reasons for turnover is, in fact, immense. However, the research on 'job-to-job switching' is much sparser. Consequently, it is within this burgeoning area that we focus our attention. Job-to-job switches often stem from entirely different patterns than job-to-unemployment changes (Royalty, 1998). Many theories have been offered for why individuals switch jobs after only a short period of working at a company, or, colloquially, why they 'job-hop'. Authors can be grouped into those who believe that job-hopping is an optimizing solution given the current economic situation. This is in contrast with those who believe that it is short-sighted on the part of workers, and ultimately hurts both them and possibly their employer, colleagues, and the economy.

On the side that argues that these moves are detrimental overall, the authors generally believe that job-hopping harms lifetime wages by limiting the accrual of capital, position advancement, and networks (Romanov et al., 2016). Sun et al. (2019) used simulation models to find that, for Chinese construction workers, job-hopping ultimately hurts their lifetime salaries and careers. Fan and DeVaro (2020) specify that job-hopping is particularly detrimental to those who are younger and earlier in their careers, and who switch positions after a very short period (less than one year). At least for some countries, such as Belgium and the United States, it is these younger workers who are more likely to be doing the hopping (Baum, 2021; Steenackers & Guerry, 2016). Job-hopping is also seen to be detrimental to the non-hoppers, with Sheehan (1993) using a behavioral experiment to show that when some individuals at a company switched out of working there, the remaining employees were left feeling a sense of "inequity" and, consequently, worked fewer hours at the initial firm. Along this same line of reasoning, Sousa-Poza and Henneberger (2004) argue that even the 'intention to turnover' is important both for those workers, as well as for those they may impact. Finally, most agree that job-hopping is detrimental to firms and increases their costs, with, for example, Balasubramanian et al. (2022) outlining these various costs and empirically examining how non-compete clauses help to curb the effect.

On the side of beneficial effects, the seminal paper by Jovanovic (1979) documents that turnover will happen when workers and employers are not a good match. As Dreher and Dougherty (1980) demonstrate, having outside options is a primary determinant of whether such turnover can happen. To be more precise, Fan and Devaro (2020) document that taking a job during an economic downturn—such as the COVID-19 pandemic in our case—means that it is beneficial to job-hop as soon as the economy moves into recovery, and outside options become available.

Following this line of reasoning, authors on this side of the argument would say that the current increases in the job-hopping rate, particularly on the part of younger and less educated workers, may not be a sign of economic difficulty and the impact of the "Great Resignation."

Rather, it may demonstrate that the economy is on its way to recovery (Hobijn, 2022). In this context, our analysis helps to determine whether job-hopping patterns have changed after these events.

Furthermore, differences in resignation versus reallocation/recovery in employment may vary by industry (Parker and Clark, 2022), with authors claiming that current job-hopping trends in retail shows signs of recovery, but those of construction and manufacturing display patterns of resignation (Birinci, 2022). The case of retirees is also more complicated, with 'resignation' often correlating with involuntary retirements (Schuster et al., 2020). Clearly, the question of the benefit versus detriment of job-hopping is complex.

Education and other determinants of whether individuals job-hop have also recently been investigated. As Parker and Clark (2022) demonstrate, job attributes strongly affect the tendency to job hop. Specifically, workers in Oregon cited their main reason for job-hopping as, in order of importance: (1) money, (2) benefits, (3) flexibility, (4) remote options, (5) feeling valued, (6) having independence, (7) having time off, (8) seeing the chance for upward mobility, and (9) other factors. As a specific community subset, Nzukuma and Bussin (2011) asked Black African managers, who are thought to have very high job-hopping rates, for their motivations, and were told that they job-hop to 'take control of their career development.'

In terms of demographics, the most relevant area of literature concerns the effects of education. Specifically, there is a strong debate about the relationship between education and job-hopping. Steenackers & Guerry (2016) find no effect of education on the tendency to job-hop in their Belgian study. Royalty (1998) instead finds that education does matter for job-hopping, with young uneducated women looking quite different in their hopping patterns when compared with either young, educated women, or young men regardless of education status.

Taken together, job-hopping should be seen as different from regular turnover, and is potentially correlated with age and education. In addition, it can be associated with both the path to economic recovery, as well as a depression of salaries and outcomes for certain groups. To this end, the present analysis examines changes in rates of job-switching before, during, and in the aftermath of the COVID-19 pandemic.[2] We pay particular attention to effects of both age and education, along with multiple other demographic factors. We consider this to be a crucial piece of evidence in understanding how job-hopping impacts the lives of workers and the economy.

MATERIALS AND METHODS

Data and Sample

Our analysis employed January 2012-November 2022 Current Population Survey (CPS) data.[3] We felt that the CPS was well suited to questions of job-switching, since it includes recent and large samples. We restricted our initial sample of 16,001,150 individuals to those aged 18-75. We further employed a validation structure to ensure that the same

[2] While we cannot definitively say that these were "rapid" switches, the CPS job tenure supplement indicates that job-to-job switchers tend to have shorter tenure at their place of employment. These calculations are available upon request.

[3] In related and ongoing work, we are examining shorter sub-periods including 1994-2012 and 2012-2019 in order to isolate long-term job-switching trends. Due to the nature of the questions, 1994 is the earliest point for which consistent questions on job-switching are available in the CPS data. Our results indicate that COVID-19 presents a unique and important part of this story. The focus of the present analysis on post-2012 data was motivated by our desire to disentangle pre- and post-Great-Recessionary results from those occurring due to the COVID-19 pandemic. Results from the longer timeframe are available upon request.

individuals were followed, rather than the population being refreshed due to sample attrition.[4] After these restrictions, our sample was limited to 10,704,125 individuals.

Measures

We considered individuals to be "job-switchers" if they were employed in each of two consecutive months, and, simultaneously, said that they were no longer with the same employer. That is, the individual had switched to another job without ever entering the pool of unemployed or out of the labor force. Similarly, non-switchers for comparison were those who had been employed during two consecutive periods but had not changed jobs. Limiting our analysis to workers in the wage and salary sector who were employed for two consecutive months, our final dataset contained 71,531 (2.2%) job-switchers and 3,191,231 (97.8%) non-switchers.

In addition to controls for demographic variables, we also controlled for job characteristics, geographic, and labor market indicators, as well as time effects. We coded observations as belonging to the period labeled "After Pandemic Occurrence" if they were surveyed after March 2020.

Expected Findings

We anticipate finding that job-switching has generally increased during the post-COVID-19 period. We expect that this increase has been moderated by a variety of demographic factors including, most importantly, age and education. For the sake of brevity,

---

[4] In addition to ID number, we matched individual observations by gender, race, and age within a year. This is in keeping with suggested procedures in linking CPS data. See: https://cps.ipums.org/cps/cps_workshop2021_materials.shtml

we focus our present analysis on age and education, however, additional stratifications are available upon request.

Empirical Specification

We consider, for individual *I* in location j:

$$JobSwitch_i = f(Demog_i, Month_i, StateFIPS_j, JobInfo_i, TightLaborMkt_{i,j})$$

Where *JobSwitch* = 0 if an individual was employed with the same employer over two periods, and 1 if an individual remained employed over two consecutive periods, but with a different employer between the two periods.[5]

For the remaining variables in the equation, *Demog* represents all demographic variables including gender, race, age, education, marital status, real family income (2012 dollars) and professional certification.[6]

StateFIPS represents Booleans for the U.S. state where the individual was located. Month picks up seasonal effects that recurred in specific months of the year. *JobInfo* includes information on the individual's occupation and industry of employment, whether they were employed fulltime (>34 hours per week) or parttime, whether they recently (in the last week) worked more than their typical weekly work hours, and whether they were simultaneously

[5] We included clustering at the individual level, since the same individual will be included in the sample several times if they remain continuously employed. Our results do not hinge on this parametrization.

[6] The specific breakdowns of these variables was as follows: Education is split into either less than high school, high school graduate, some college or associate degree, B.S./B.A. degree or higher-level degree (MA, PHD, Professional Degree); Marital status is divided into married, never married, or divorced/widowed/separated; Age is further grouped as 18-25, 26-55, 56-61, and 62+; Race is defined as White, Black, Asian, or Hispanic; Family income is recoded to grouped mean values of $2,500, $6,250, $8,750, $11,250, $13,750, $17,500, $22,500, $27,500, $32,500, $37,500, $45,000, $55,000, $67,500, $87,500, $125,000, and $150,000; Industry is split into Agriculture/forestry/fisheries, Construction, Mining, Manufacturing, Wholesale trade, Retail trade, Transportation and utilities, Information, Finance/Insurance/Real estate, Professional services, Education, Healthcare, Social assistance, Leisure and hospitality and other services (based on 2017 NAICS); Within industries, twenty-two occupations (two-digit SOC) were employed.

employed at more than one job. Finally, *TightLaborMkt* is an indicator for respondents being in a state where the unemployment was below 3.58% and labor force participation did not exceed 66%.[7]

We run both a Linear Probability Model (OLS), as well as a (non-linear) Probit model—since the likelihood of the outcome variable (job switching) is coded in a binary fashion. We separately examine the periods before and after the onset of the pandemic in March of 2020. In comparing Probit results before versus after the pandemic, we use predicted probabilities and test for statistical significance in differences in the predicted probabilities.[8]

For brevity of presentation, we only present the Probit results. We further examine stratifications based upon age and education. Our argument is that examining stratifications allows us to disentangle changes in the coefficients (that is, changes in job switching behavior) from changes in the demographic makeup of the labor force toward groups that exhibit more job changing.[9] In other words, we focus on differences over time in job switching within a particular demographic group.

---

[7] These are the 25th percentile thresholds for labor force participation and unemployment over the sample period.
[8] As pointed out in Allison (1999) and Long (2009), comparing results for groups with binary outcomes is complicated by unaccounted for residual variation. In other words, a simple comparison of coefficients from linear probability models using two different populations will lead to incorrect conclusions. Comparisons of predicted probabilities from two separate models is the suggested and preferred alternative. In other words, we first run a Probit model of job switching on pre-COVID data and find predicted probabilities. We next repeat this method for post-COVID data, and finally test for the equality of predicted probabilities using the Delta method (Xu and Long 2005). Specifically, using P_{x_i} as the predicted probability for group *i* (where *i*=1,2). The z-statistic for a test of Ho: $P_{x_1} = P_{x_2}$ has an asymptotic normal distribution and is computed as: $z = \frac{P_{x_1} - P_{x_2}}{\sqrt{Var(P_{x_1}) + Var(P_{x_2})}}$. See Long and Mustillo (2021) for a full description of this procedure.
[9] We initially attempted a Heckman-selection regression, however, due to the nature of our endogeneity, we could not find an instrument that was both relevant and exogenous. Some possible instruments we tried were the number of children in the home and labor force participation in the past in the same city/gender/age grouping.

RESULTS AND DISCUSSION

Summary Statistics

Figure 1 demonstrates an increase in job-switching over the last decade. While there was a clear increase in 2013-2017, followed by a decrease in 2018-2019, these initial changes were neither as large in magnitude nor as drastic in their ascent. The two dotted trendlines for the pre- and post-COVID-19 period, as well as the associated equations for each document that job-switching looked distinctly different over these time periods.

*********************FIGURE 1 GOES ABOUT HERE**********************

Next, Table 1 displays the rates that (continuously employed) individuals in the wage and salary sector switched employers between two consecutive months. Statistics are broken out by demographics and by time (Pandemic+ vs. Pre-Pandemic), with additional columns included for the statistical significance of the (Pandemic+ vs. Pre-Pandemic) change and for the percentage-change ($\frac{post-pre}{pre}$) in job-changing experienced for each of the groups.

*******************TABLE 1 GOES ABOUT HERE**********************

Individuals were significantly more likely to job-switch after the onset of the COVID-19 pandemic. Changes by group correspond to 5% - 21% of baseline levels. Specifically, the individuals with the highest percentage increase in their rates of job-switching were those who were younger (18-25: 14%), Black (21%), Divorced/Widowed (14%)[10], and had less

[10] We believe that marital status may have had a selective relationship with the pandemic, since employment is more likely to change as individuals change their marital status.

than a college degree (14%-17%). Job-switching also increased more in areas with a tighter labor market (15%) and for part-time workers (14%).

We do not find significant evidence of a change in job-switching rates for those who are at potential or actual retirement age (56+), for college-educated workers, or for those with professional certification or multiple jobs. We also find similar rates of changes in job-switching for men and women, with a somewhat bigger effect for women (11% vs. 7%).

Appendix Table 1 was constructed to shed some additional light on how job-switching varies by occupation and industry, since these did not fit as easily into our Table 1 analysis. To summarize, individuals in the manufacturing, wholesale trade, retail trade, transport, healthcare, and leisure/hospitality industries experienced significant changes in job-switching. The largest of these was in transport. As for occupation, the largest changes were apparent in healthcare support and food preparation. Interestingly, job-switching decreased in the construction and extraction occupations. We regard to the non-significant industry and occupation effects, it is possible that job-switching did change, but that, for at least some of the industries and occupations, the sample size was smaller, and had more difficulty picking up significance. These changes in job-switching may be indicative of within industry/occupation trends or may reflect movements of workers across industries/occupations with different rates of job-switching.

Taken together, our results provide initial evidence in support of a general increase in job-switching after the COVID-19 pandemic began, with the largest impacts on younger workers with lower levels of education. There were also higher impacts for Black workers and those holding one position, as opposed to multiple jobs. We surmise that marital changes in job-switching may be endogenous to the nature of family structure changes during the pandemic.

We also conjecture that, for example, healthcare workers were more likely to have experienced emotional and physical trauma from their experience with the COVID-19 pandemic, that could have led to burnout and disillusionment with a particular employer/position. While our summary statistics paint a convincing story, we employ the remainder of this empirical discussion to focus on a more controlled examination of the issue.

Regression Analysis

Table 2 examines the factors related to job-switching, examining the pre- and post-pandemic periods separately and employing a Probit regression specification. All regressions further control for state of residence, month in sample, occupation, industry, and include an intercept term. In addition to regular tests of significance, we also employ Bonferroni-corrected significance levels in this table and in Tables 3A and 3B to allow for a very conservative interpretation of results.[11]

*****************TABLE 2 GOES ABOUT HERE************************

We can see from Table 2 that, other than high education and family income, the predicted probabilities associated with essentially *all* of the coefficients are positively related to differences in job-switching over time. While these difference values between the pre- and post-pandemic period may seem relatively small in magnitude, they are economically

[11] Bonferroni corrections account for the possibility that, given repeated tests of differences, sheer chance would allow some tests to show significance. There are 115 independent variables, so significance levels are adjusted accordingly.

significant, since they also represent a change of 2%-48% of initial (predicted) values of job-switching. In interpreting these results, we can say that essentially all groups—other than highly educated, high-income workers—were more likely to switch jobs after the onset of the COVID-19 pandemic. Bonferroni-corrected results display the same pattern of effects.

We next consider the possibility that the results in Table 2 represent a change in average population characteristics, rather than a change in the effect of these characteristics on job-switching. Specifically, Appendix Table 2 displays average population demographics over time. The table further stratifies on individuals either being in the full population or in the regression sample. To reiterate, while the "full population" includes the entire CPS data, the "regression sample" is limited to individuals who were employed for at least two months in a row and thus had the potential to job-switch.

Appendix Table 2 confirms that the population and the regression sub-sample did experience a demographic change of sorts. Specifically, there were fewer younger and more retirement-aged individuals after the pandemic. There was also an increase in Asian and Hispanic, and a decrease in white representation in the CPS sample. The percentage of Black individuals did not significantly change over time. The average level of education also experienced an increase, with fewer high school dropouts or people with "some college," and more individuals with at least an A.A. degree. Finally, while gender did change over time to be more representative of males, the overall shift was quite small (0.2%).[12]

Taken together, there were some shifts in demographics in the population, and, while these changes were relatively small in most cases and unlikely to fully account for changes in job-switching on their own, we do believe this question merits further consideration.

[12] See Birtz (2020) for additional information on how gender and job mismatch may play a role in switching.

Specifically, we choose to focus on one category at a time to determine how coefficients changed over time for only the group in question.

To this end, Table 3a and Table 3b each reorient Table 2 with, respectively, a further stratification on age or education. We would like to determine if changes in job-switching also obtain in these sub-categories. While not in itself definitive, finding that this is the case would help support the notion that job-switching has changed not only due to changes in demographics but also due to temporal shifts.[13]

******************TABLE 3A AND 3B GO ABOUT HERE******************

Table 3A demonstrates similar patterns of significance for the younger and working-age populations (ages 18-55). Once individuals reach early and full retirement, however, it appears that there are less significant patterns predicting job-switching. This is particularly true given the Bonferroni-corrected results. We believe this supports the notion that, in addition to changes in levels of the age variable, changes in coefficients are also important. This is particularly true for individuals aged 18-55. Table 3B shows similar results, with education up until a B.A. still showing significance of coefficients. For individuals with at least a B.A. degree, it does not appear that job-switching coefficients are particularly significant in terms of t-statistics.

Taken together, it appears that job-switching is not just a story about changing demographics, but it is also a story about temporal shifts in individual behavior. This is particularly true for those with lower levels of education and for the non-retirement age population. We also stress that the patterns of significance/non-significance accord well with

[13] Additional regressions stratify on race and gender, but these are suppressed in the interest of brevity. The general pattern of results is similar and is available upon request.

the coefficients showing significance in Table 1. Ours is a story about lower education and younger workers predominantly engaged in job-switching. This is consistent with those in the literature who have found that this younger and lower-education sector of the economy is the one who has recently been job-switching (Gilbert, 2021; Borg et al., 2021).

Our results do not, in themselves, determine whether job-switching is a good or a bad thing overall, since it could be that the increase in switching was due to a poor match during the economic downturns (COVID-19-inspired) and so individuals should switch out, or it could be that it represents a non-optimal choice that will ultimately hurt worker wages. It is also true that our analysis occurs within an historical context, and that future analyses may find that job-switching patterns have further evolved. The jury is still out on whether job-switching helps or hurts wages, but the magnitude of the switching has clearly changed, and COVID-19 has been a crucial factor driving this recent effect.

CONCLUSIONS

Our results indicate that job-switching increased after March of 2020 and the beginning of the COVID-19 pandemic. It is also apparent that these changes in job-switching were not entirely a result of changes in demographic characteristics in the population. In particular, there appears to be temporal changes in job-switching for relatively younger and less-educated workers.

We take our results as important evidence in documenting and understanding the recent increase in job-switching within the larger context of economic recession and recovery stages. We further believe that this understanding is crucial in future worker hiring, retraining, and placement efforts. Specifically, employers need to utilize new strategies in the post-COVID-19 world to keep their workers from moving away. Finally, if job-switching does indeed harm productivity, enticing certain workers to remain with their employers may be a lower-cost way to effectively increase productivity and restore national GDP to pre-COVID-19 levels.

REFERENCES

Allison, Paul D. (1999). “Comparing Logit and Probit Coefficients Across Groups.” Sociological Methods and Research. 28, 186-208.

Balasubramanian,N., Chang, J.W., Sakakibara, M., Sivadasan, J., & Starr, E. (2022). “Locked In? The Enforceability of Covenants Not to Compete and the Careers of High-Tech Workers.” The Journal of Human Resources. 57(S), S349-S396.

Baum, C.L. (2021). “Seven jobs in a lifetime? An analysis of employee tenure.” Economic Inquiry. 60(2), 543-567.

Birinci, S. & Amburgey, A. (2022). “The Great Resignation vs. The Great Reallocation: Industry-Level Evidence.” Economic Synopses. 4, 1-2.

Birtz, G. (2020). “Counting the Hours: The Influence of Gender and Occupation on Work Hour Mismatch Prevalence and Resolution in Australia.” Labor Studies Journal. 46(2), 101-133.

Borg, N., Scott-Young, C., & Naderpajouh, N. (2021). “Managing to Retain Generation Z in the Construction Industry.” Proceedings of the Australasian Universities Building Education Association Conference. 109-119.

Dreher, G. F. & Dougherty, T. W. (1980). “Turnover and competition for expected job openings: An exploratory analysis.” Academy of Management Journal. 23, 766-772

Fan, X., & DeVaro, J. (2020). “Job Hopping and Adverse Selection in the Labor Market.” The Journal of Law, Economics, and Organization. 36(1), 84-138.

Fleming, & Soborg, H. (2003). “Competition for better Human Resource Development? HR policies and internal labour markets in knowledge-intensive multinational companies.” Paper to the 13th World Congress of the International Industrial Relations Association in Berlin. 1-15.

Gilbert, E. (2021). “The Entrepreneur’s Guide to Building a Successful Business.” White Paper Report. Retrieved from: https://selfieoo.com/upload/files/2021/05/ZYWafGYQYI7nICAbtoMj_18_23f62d34203ad729b8551b0ea4d75670_file.pdf

Harrison, D., & Morath, E. (2018). “In this economy, quitters are winning.” Wall Street Journal. www.wsj. com/articles/in-this-economy-quittersare-winning-1530702001

Hobijn, B. (2022). “`Great Resignations’ Are common during fast recoveries.” FRBSF Economic Letter. 8, 1-6.

Jovanovic, B. (1979), “Job matching and the theory of turnover.” The Journal of Political Economy. 87(5), 972-990.

Levering, R., & Erb, M. (2011). "Emerging Trends in People Management." Swiss Business. January/February, 30-31.

Long, J. S., & Mustillo, S. A. (2021). "Using Predictions and Marginal Effects to Compare Groups in Regression Models for Binary Outcomes." Sociological Methods & Research, 50(3), 1284–1320.

Long, J. S. (2009). "Group Comparisons in Logit and Probit Using Predicted Probabilities." Working paper, Department of Sociology, Indiana University.

Sull, D., Sull, C., & Zweig, B. (2022). "Toxic Culture is Driving the Great Resignation." MIT Sloan Management Review. Accessed Online: https://www.acmpnorcalchapter.org/changemanagement-articles

McDonnell, S. (2022). "Is it really 'Pay up for talent, pray for retention?' Why job hopping is prevalent and retention is hard: Top Workplaces 2022." Cleveland.com. https://www.cleveland.com/business/2022/06/is-it-really-pay-up-for-talent-pray-for-retention-why-job-hopping-is-prevalent-and-retention-is-hard-top-workplaces-2022.html

Nzukuma, K.C.C., & Bussin, M. (2011). "Job-hopping amongst African Black senior management in South Africa : original research." South African Journal of Human Resource Management. 9(1).

Parker, R., & Clark, B. (2022). "UNRAVELING THE GREAT RESIGNATION: IMPACTS OF THE COVID-19 PANDEMIC ON OREGON WORKERS." University of Oregon Institute for Policy Research and Engagement White Paper.

Romanov, D., Tur-Sinai, A., & Eizman, G. (2017). "Overeducation, job mobility and earnings mobility among holders of first degrees." Applied Economics. 49(26), 2563-2578.

Royalty, A.B. (1998), "Job-to-job and job-to-nonemployment turnover by gender and education level." Journal of Labor Economics. 16(2), 392-433.

Schuster, B., Radpour, S., Conway, E., & Ghilarducci, T. (2022). "No `Great Resignation' for Older Workers—Mass Job Loss Drove the Retirement Surge." Schwartz Center for Economic Policy Analysis Working Paper, 1-6.

Sheehan, E.P. (1993), "The effects of turnover on the productivity of those who stay." The Journal of Social Psychology. 133(5), 699-706

Sousa-Poza, A. & Henneberger, F. (2004), "Analyzing job mobility with job turnover intentions: an international comparative study." Journal of Economic Issues. 38(1), 113-137

Steenackers, K., & Guerry, M.A. (2016). "Determinants of job-hopping: an empirical study in Belgium." International Journal of Manpower. 37(3), 494-510.

Sun, J., Zheng, M., Skitmore, M.,…, & Wang, X. (2019). "Industry effect of job hopping: An agent-based simulation of Chinese construction workers." Frontiers of Engineering Management. 6(2), 249-261.

Xu, J. and J.S. Long. 2005. Confidence intervals for predicted outcomes in regression models for categorical outcomes. The Stata Journal 5: 537-559.

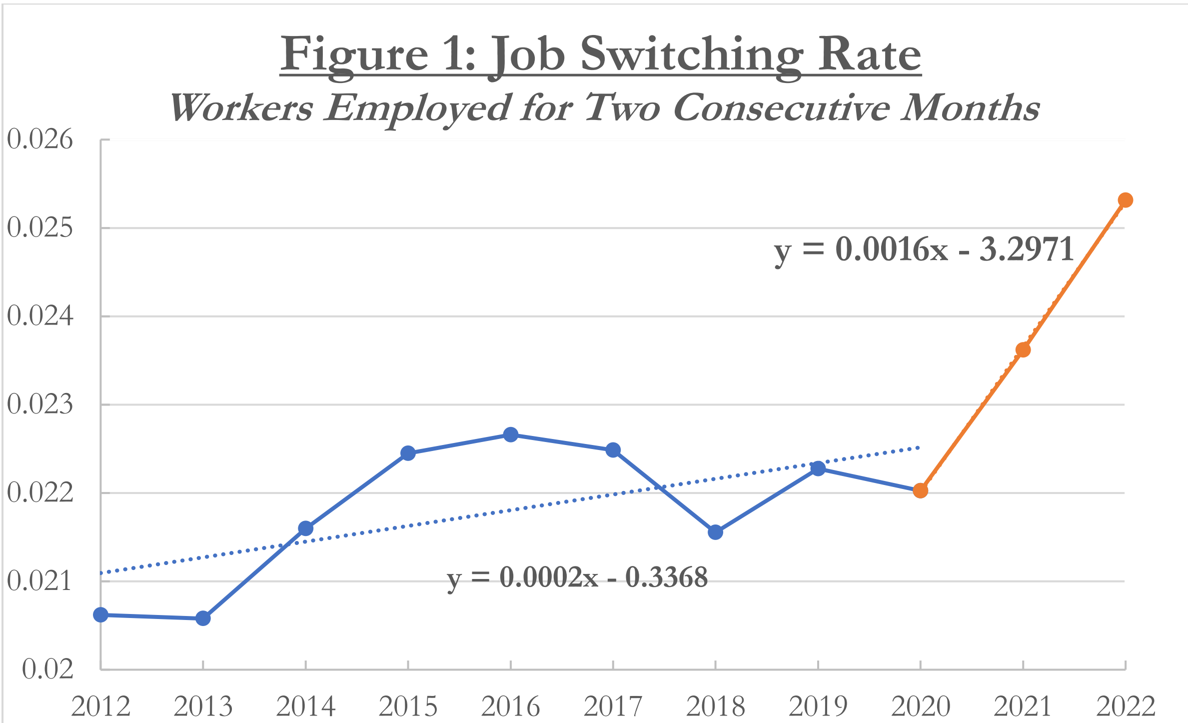

Figure 1: Job Switching Rate
Workers Employed for Two Consecutive Months
0.026
0.025
0.024
0.023
0.022
0.021
0.02
y = 0.0016x - 3.2971
y = 0.0002x - 0.3368
2012
2013
2014
2015
2016
2017
2018
2019
2020
2021
2022

TABLE 1: JOB SWITCHING RATE

		Pre-	Post-		% Change
	Total	0.022	0.024	***	9%
AGE					
	18-25	0.038	0.044	***	14%
	26-35	0.023	0.025	***	8%
	36-55	0.018	0.020	***	9%
	56-61	0.015	0.017		
	62+	0.015	0.016		
GENDER					
	Male	0.022	0.023	***	7%
	Female	0.022	0.024	***	11%
RACE					
	White	0.021	0.022	***	8%
	Black	0.024	0.029	***	21%
	Asian				
	Hispanic	0.025	0.026	***	5%
Marital					
	Married	0.018	0.019	***	7%
	Divorcee/Widow	0.021	0.023	***	14%
	Single	0.030	0.032	***	6%
Education					
	HS Dropout	0.025	0.029	***	15%
	HS Grad	0.022	0.026	***	17%
	Some College	0.025	0.029	***	14%
	AA Degree	0.020	0.023	***	14%
	BA	0.020	0.020		
	MA,PHD, Prof.	0.018	0.018		
# Jobs					
	> 1	0.050	0.052		
	(Exactly) 1	0.020	0.022	***	10%
Burnout					
	Same or Fewer Hours	0.022	0.023	***	9%
	Greater Hours	0.023	0.026	***	11%
Labor Mkt.					
	Regular	0.022	0.024	***	8%
	Tight	0.021	0.024	***	15%
FT/PT					

	PT	0.032	0.036	***	14%
	FT	0.020	0.022	***	9%
Certificate					
	No	0.023	0.024	***	7%
	Yes	0.021	0.021		

Note: The next to final column shows the significance of t-tests for differences in means pre vs. post-pandemic, ** indicates significance at the 5% level, and *** indicates significance at the 1% level. The final column displays the change in job switching rates as a % of pre-pandemic baseline rates .

Table 2: Effects of the Pandemic on Job Switching Rates (Probit)

	Pre-Pandemic		Post-Pandemic		Differences		
	Predicted prob (PP)	S.D. PP	Predicted prob (PP)	S.D. PP	% change	Sig.	BFF
Male	0.022	0.000	0.023	0.000	4%	***	
Female	0.022	0.000	0.023	0.000	7%	***	***
Age 18-25	0.040	0.000	0.044	0.001	10%	***	***
Age 26-55	0.020	0.000	0.022	0.000	6%	***	***
Age 56-61	0.016	0.000	0.016	0.000	5%	*	
Age 62+	0.015	0.000	0.016	0.000	2%		
White	0.021	0.000	0.022	0.000	5%	***	***
Black	0.025	0.000	0.028	0.001	14%	***	***
Asian	0.019	0.000	0.020	0.001	3%		
Hispanic	0.026	0.000	0.027	0.001	4%	*	
HS Dropout	0.026	0.000	0.029	0.001	15%	***	***
HS Grad	0.023	0.000	0.025	0.000	12%	***	***
Some Col. / AA	0.023	0.000	0.025	0.000	10%	***	***
BA Degree+	0.019	0.000	0.019	0.000	-3%	**	
Married	0.018	0.000	0.018	0.000	4%	***	
Divorce/W/S	0.021	0.000	0.023	0.001	11%	***	***
Never Married	0.030	0.000	0.031	0.000	3%	**	
Multiple jobs	0.049	0.001	0.050	0.001	3%		
One Job Only	0.021	0.000	0.022	0.000	6%	***	***
Hours as Reg	0.022	0.000	0.023	0.000	5%	***	***
More hours	0.023	0.000	0.025	0.000	7%	***	
Reg. L.M.	0.022	0.000	0.023	0.000	5%	***	***
Tight L.M.	0.021	0.000	0.023	0.001	11%	***	
Part time	0.032	0.000	0.035	0.001	8%	***	***
Full Time	0.020	0.000	0.021	0.000	6%	***	***
No prof cert	0.022	0.000	0.024	0.000	6%	***	***
Prof cert	0.020	0.000	0.021	0.000	4%	**	
Real Fam inc	-5.76E-08	3.28 E-09	-8.55E-08	5.64 E-09	48%	***	***
Observations	1,545,091		640,154				

Note: Predictive margins are shown for discrete variables, and average marginal effects are shown for continuous variables (family income) with significance levels to the right. * Indicates significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level. BFF displays Bonferroni corrected significance levels, considering that for each regression, there are 115 independent variables- hence 115 tests of significance. Month, State of Residence, Industry, and Occupation, and the intercept, were additionally included in a series of Booleans (Fixed Effects). A tight labor market was defined as having unemployment < 3.58% and a labor force participation rate that was under 66%.

Table 3A: Effects of the Pandemic on Job-Switching Rates (By Age)

Panel A: 18-25 year olds	Pre-Pandemic		Post-Pandemic		Differences		
	Predicted Probability (PP)	*S.D. PP*	*Predicted Probability (PP)*	*S.D. PP*	*% change*	*Sig.*	*BFF*
Male	0.039	0.001	0.043	0.001	10%	***	*
Female	0.040	0.001	0.045	0.001	11%	***	**
White	0.041	0.001	0.045	0.001	9%	***	**
Black	0.039	0.001	0.050	0.003	30%	***	***
Asian	0.032	0.002	0.031	0.003	-6%		
Hispanic	0.038	0.001	0.042	0.002	10%	**	
HS Dropout	0.038	0.002	0.049	0.003	28%	***	**
HS Grad	0.043	0.001	0.046	0.001	9%	***	
Some College / Associates Degree	0.041	0.001	0.047	0.001	14%	***	***
BA Degree or More	0.034	0.001	0.033	0.001	-2%		
Married	0.035	0.001	0.037	0.002	7%		
Divorced/Widowed/separated	0.040	0.003	0.049	0.006	24%	*	
Single - Never Married	0.041	0.000	0.045	0.001	10%	***	***
Held multiple jobs	0.089	0.003	0.104	0.005	17%	***	
Held One Job Exactly	0.037	0.000	0.041	0.001	12%	***	***
Worked Same Hours as usual	0.040	0.000	0.044	0.001	9%	***	***
Worked more hours	0.040	0.001	0.046	0.002	16%	***	
Regular labor market	0.040	0.000	0.044	0.001	10%	***	***
Tight Labor Market	0.035	0.002	0.041	0.002	20%	***	
Part time worker	0.045	0.001	0.050	0.001	12%	***	**
Full Time worker	0.038	0.001	0.041	0.001	10%	***	***
No professional certification	0.040	0.000	0.045	0.001	11%	***	***
Holds a professional certification	0.038	0.001	0.039	0.002	5%		
Mean Real Family Income		$ 64,404		$ 65,590			
Real Family income	-3.63E-08	1.11E-08	-7.62E-08	1.99E-08	110%	**	
Observations	202,560		79,325				
Pseudo R-squared	0.0187		0.0213				

Table 3A: Effects of the Pandemic on Job-Switching Rates (By Age)--CONT

Panel B: 26-55 year olds	Pre-Pandemic		Post-Pandemic		Differences		
	Predicted Probability (PP)	*S.D. PP*	*Predicted Probability (PP)*	*S.D. PP*	*% change*	*Sig.*	*BFF*
Male	0.020	0.000	0.021	0.000	6%	***	
Female	0.020	0.000	0.022	0.000	6%	***	*
White	0.019	0.000	0.021	0.000	6%	***	***
Black	0.024	0.001	0.026	0.001	11%	***	
Asian	0.019	0.001	0.019	0.001	1%		
Hispanic	0.023	0.000	0.024	0.001	4%		
HS Dropout	0.025	0.001	0.028	0.001	10%	**	
HS Grad	0.021	0.000	0.023	0.000	13%	***	***
Some College / Associates Degree	0.021	0.000	0.023	0.000	13%	***	***
BA Degree or More	0.019	0.000	0.019	0.000	-2%		
Married	0.018	0.000	0.019	0.000	6%	***	**
Divorced/Widowed/separated	0.023	0.000	0.026	0.001	13%	***	**
Single - Never Married	0.024	0.000	0.025	0.000	0%		
Held multiple jobs	0.044	0.001	0.044	0.002	1%		
Held One Job Exactly	0.019	0.000	0.020	0.000	7%	***	***
Worked Same Hours as usual	0.020	0.000	0.021	0.000	6%	***	***
Worked more hours	0.022	0.000	0.024	0.001	7%	***	
Regular labor market	0.020	0.000	0.022	0.000	6%	***	***
Tight Labor Market	0.020	0.001	0.022	0.001	9%	**	
Part time worker	0.031	0.001	0.033	0.001	5%	*	
Full Time worker	0.019	0.000	0.020	0.000	7%	***	***
No professional certification	0.021	0.000	0.022	0.000	6%	***	***
Holds a professional certification	0.020	0.000	0.021	0.000	5%	**	
Mean Real Family Income		$77,007		$ 77,486			
Real Family income	-7.22E-08	4.2E-09	-1.06E-07	7.24E-09	47%	***	***
Observations	1,019,514		418,780				
Pseudo R-squared	0.0165		0.017				

Table 3A: Effects of the Pandemic on Job-Switching Rates (By Age)--CONT

Panel C: 56-61 year olds	Pre-Pandemic		Post-Pandemic		Differences		
	Predicted Probability (PP)	*S.D. PP*	*Predicted Probability (PP)*	*S.D. PP*	*% change*	*Sig.*	*BFF*
Male	0.016	0.000	0.015	0.001	-5%		
Female	0.015	0.000	0.017	0.001	15%	***	
White	0.015	0.000	0.016	0.001	4%		
Black	0.017	0.001	0.017	0.002	-2%		
Asian	0.013	0.001	0.016	0.002	23%		
Hispanic	0.019	0.001	0.019	0.002	1%		
HS Dropout	0.016	0.001	0.019	0.002	18%		
HS Grad	0.015	0.001	0.016	0.001	12%	**	
Some College / Associates Degree	0.016	0.001	0.016	0.001	-2%		
BA Degree or More	0.016	0.001	0.016	0.001	1%		
Married	0.015	0.000	0.015	0.001	3%		
Divorced/Widowed/separated	0.017	0.001	0.019	0.001	12%	**	
Single - Never Married	0.019	0.001	0.018	0.002	-5%		
Held multiple jobs	0.033	0.002	0.039	0.004	19%	*	
Held One Job Exactly	0.015	0.000	0.015	0.000	4%		
Worked Same Hours as usual	0.015	0.000	0.016	0.001	5%	*	
Worked more hours	0.017	0.001	0.018	0.001	2%		
Regular labor market	0.016	0.000	0.016	0.000	5%	*	
Tight Labor Market	0.015	0.001	0.016	0.001	2%		
Part time worker	0.023	0.001	0.026	0.002	13%	*	
Full Time worker	0.015	0.000	0.015	0.000	4%		
No professional certification	0.015	0.000	0.016	0.001	3%		
Holds a professional certification	0.016	0.001	0.017	0.001	10%	*	
Mean Real Family Income		$ 78,820		$ 77,794			
Real Family income	-5.13E-08	8.49E-09	-6.51E-08	1.44E-08	27%		
Observations	182646		75312				
Pseudo R-squared	0.0189		0.0258				

Table 3A: Effects of the Pandemic on Job-Switching Rates (By Age)--CONT

Panel D: 62+ year olds	Pre-Pandemic		Post-Pandemic		Differences		
	Predicted Probability (PP)	*S.D. PP*	*Predicted Probability (PP)*	*S.D. PP*	*% change*	*Sig.*	*BFF*
Male	0.016	0.000	0.016	0.001	0%		
Female	0.015	0.000	0.015	0.001	5%		
White	0.015	0.000	0.015	0.001	-1%		
Black	0.016	0.001	0.023	0.002	38%	***	
Asian	0.013	0.001	0.019	0.003	50%	**	
Hispanic	0.021	0.002	0.017	0.002	-18%	*	
HS Dropout	0.017	0.001	0.018	0.002	8%		
HS Grad	0.014	0.001	0.015	0.001	11%	*	
Some College / Associates Degree	0.014	0.001	0.016	0.001	14%	**	
BA Degree or More	0.017	0.001	0.015	0.001	-11%	**	
Married	0.015	0.000	0.015	0.001	-1%		
Divorced/Widowed/separated	0.016	0.001	0.018	0.001	13%	**	
Single - Never Married	0.017	0.001	0.016	0.002	-4%		
Held multiple jobs	0.037	0.002	0.039	0.004	5%		
Held One Job Exactly	0.014	0.000	0.015	0.000	3%		
Worked Same Hours as usual	0.015	0.000	0.015	0.001	3%		
Worked more hours	0.017	0.001	0.017	0.001	2%		
Regular labor market	0.015	0.000	0.015	0.001	1%		
Tight Labor Market	0.014	0.001	0.018	0.002	23%	**	
Part time worker	0.018	0.001	0.022	0.001	20%	***	
Full Time worker	0.014	0.000	0.014	0.001	-3%		
No professional certification	0.015	0.000	0.016	0.001	9%	**	
Holds a professional certification	0.017	0.001	0.014	0.001	-14%	**	
Mean Real Family Income		$ 72,901		$ 72,292			
Real Family income	-3.06E-08	9.25E-09	-0.000000041	1.52E-08	34%		
Observations	140371		66737				
Pseudo R-squared	0.0215		0.0271				

Note: Predictive margins are shown for discrete variables, and average marginal effects are shown for continuous variables (family income) with significance levels to the right. * Indicates significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level. BFF displays Bonferroni corrected significance levels, considering that for each regression, there are 115 independent variables- hence 115 tests of significance. Month, State of Residence, Industry, and Occupation, and the intercept, were additionally included in a series of Booleans (Fixed Effects). A tight labor market was defined as having unemployment < 3.58% and a labor force participation rate that was under 66%.

Table 3A: Effects of the Pandemic on Job-Switching Rates (By Education)

Panel A: HS Dropout	Pre-Pandemic		Post-Pandemic		Differences		
	Predicted Probability (PP)	*S.D. PP*	*Predicted Probability (PP)*	*S.D. PP*	*% change*	*Sig.*	*BFF*
Male	0.026	0.001	0.028	0.001	8%	*	
Female	0.025	0.001	0.032	0.001	28%	***	***
18-25	0.038	0.002	0.049	0.003	28%	***	**
26-55	0.025	0.001	0.028	0.001	11%	**	
56-61	0.016	0.001	0.019	0.002	17%		
62+	0.017	0.001	0.018	0.002	7%		
White	0.026	0.001	0.033	0.002	28%	***	***
Black	0.024	0.002	0.029	0.003	18%	*	
Asian	0.022	0.002	0.026	0.004	16%		
Hispanic	0.026	0.001	0.027	0.001	4%		
Married	0.022	0.001	0.024	0.001	11%	**	
Divorced/Widowed/separated	0.025	0.001	0.028	0.002	13%	*	
Single - Never Married	0.032	0.001	0.038	0.002	17%	***	
Held multiple jobs	0.059	0.005	0.068	0.008	15%		
Held One Job Exactly	0.025	0.000	0.029	0.001	15%	***	**
Worked Same Hours as usual	0.025	0.001	0.029	0.001	16%	***	**
Worked more hours	0.028	0.001	0.031	0.002	11%		
Regular labor market	0.026	0.001	0.030	0.001	16%	***	***
Tight Labor Market	0.021	0.002	0.025	0.003	19%	*	
Part time worker	0.033	0.001	0.039	0.002	19%	***	
Full Time worker	0.024	0.001	0.027	0.001	13%	***	
No professional certification	0.026	0.001	0.029	0.001	15%	***	**
Holds a professional certification	0.027	0.002	0.031	0.004	18%		
Mean Real Family Income		$ 45,920		$ 48,202			
Real Family income	-1.36E-07	1.59E-08	-1.03E-07	2.81E-08	-24%		
Observations	106,132		36,983				
Pseudo R-squared	0.0226		0.0283				

Table 3A: Effects of the Pandemic on Job-Switching Rates (By Education)--CONT

Panel B: HS Graduate	Pre-Pandemic		Post-Pandemic		Differences		
	Predicted Probability (PP)	*S.D. PP*	*Predicted Probability (PP)*	*S.D. PP*	*% change*	*Sig.*	*BFF*
Male	0.023	0.000	0.025	0.001	9%	***	**
Female	0.022	0.000	0.025	0.001	16%	***	***
18-25	0.043	0.001	0.046	0.001	9%	***	
26-55	0.021	0.000	0.023	0.000	13%	***	***
56-61	0.015	0.001	0.016	0.001	12%	**	
62+	0.014	0.001	0.015	0.001	10%	*	
White	0.022	0.000	0.024	0.000	13%	***	***
Black	0.025	0.001	0.028	0.001	11%	**	
Asian	0.022	0.001	0.024	0.002	8%		
Hispanic	0.026	0.001	0.029	0.001	9%	**	
Married	0.018	0.000	0.019	0.000	10%	***	
Divorced/Widowed/separated	0.020	0.001	0.024	0.001	20%	***	***
Single - Never Married	0.033	0.000	0.034	0.001	6%	**	
Held multiple jobs	0.052	0.002	0.057	0.003	9%	*	
Held One Job Exactly	0.022	0.000	0.024	0.000	13%	***	***
Worked Same Hours as usual	0.022	0.000	0.025	0.000	11%	***	***
Worked more hours	0.024	0.001	0.028	0.001	16%	***	**
Regular labor market	0.023	0.000	0.025	0.000	11%	***	***
Tight Labor Market	0.022	0.001	0.027	0.001	21%	***	*
Part time worker	0.033	0.001	0.036	0.001	10%	***	
Full Time worker	0.021	0.000	0.024	0.000	13%	***	***
No professional certification	0.023	0.000	0.026	0.000	12%	***	***
Holds a professional certification	0.023	0.001	0.025	0.001	10%	**	
Mean Real Family Income		$ 60,926		$ 61,001			
Real Family income	-4.98E-08	6.62E-09	-1.04E-07	1.16E-08	109%	***	***
Observations	428,729		172,609				
Pseudo R-squared	0.0289		0.0282				

Table 3A: Effects of the Pandemic on Job-Switching Rates (By Education)--CONT

Panel C: Some College/AA Degree	Pre-Pandemic		Post-Pandemic		Differences		
	Predicted Probability (PP)	*S.D. PP*	*Predicted Probability (PP)*	*S.D. PP*	*% change*	*Sig.*	*BFF*
Male	0.023	0.000	0.025	0.001	8%	***	
Female	0.024	0.000	0.026	0.001	11%	***	***
18-25	0.041	0.001	0.047	0.001	14%	***	***
26-55	0.021	0.000	0.023	0.000	13%	***	***
56-61	0.016	0.001	0.016	0.001	-2%		
62+	0.014	0.001	0.016	0.001	14%	**	
White	0.023	0.000	0.025	0.000	9%	***	***
Black	0.025	0.001	0.031	0.001	23%	***	***
Asian	0.021	0.001	0.023	0.002	6%		
Hispanic	0.026	0.001	0.028	0.001	5%		
Married	0.018	0.000	0.019	0.000	9%	***	
Divorced/Widowed/separated	0.022	0.001	0.024	0.001	11%	***	
Single - Never Married	0.033	0.000	0.035	0.001	8%	***	
Held multiple jobs	0.055	0.001	0.054	0.002	-1%		
Held One Job Exactly	0.021	0.000	0.024	0.000	13%	***	***
Worked Same Hours as usual	0.023	0.000	0.025	0.000	10%	***	***
Worked more hours	0.025	0.001	0.027	0.001	9%	**	
Regular labor market	0.023	0.000	0.026	0.000	11%	***	***
Tight Labor Market	0.022	0.001	0.023	0.001	3%		
Part time worker	0.034	0.001	0.038	0.001	13%	***	**
Full Time worker	0.021	0.000	0.023	0.000	10%	***	***
No professional certification	0.024	0.000	0.026	0.000	10%	***	***
Holds a professional certification	0.022	0.000	0.024	0.001	9%	***	
Mean Real Family Income		$ 70,249		$ 70,065			
Real Family income	-5.49E-08	5.95E-09	-9.87E-08	1.09E-08	80%	***	**
Observations	468,127		178,886				
Pseudo R-squared	0.0304		0.0315				

Table 3A: Effects of the Pandemic on Job-Switching Rates (By Education)--CONT

Panel D: BA Degree or more	Pre-Pandemic		Post-Pandemic		Differences		
	Predicted Probability (PP)	*S.D. PP*	*Predicted Probability (PP)*	*S.D. PP*	*% change*	*Sig.*	*BFF*
Male	0.019	0.000	0.018	0.000	-2%		
Female	0.020	0.000	0.019	0.000	-3%	*	
18-25	0.033	0.001	0.033	0.001	-2%		
26-55	0.019	0.000	0.019	0.000	-2%		
56-61	0.016	0.001	0.016	0.001	1%		
62+	0.017	0.001	0.015	0.001	-11%	**	
White	0.019	0.000	0.018	0.000	-4%	**	
Black	0.024	0.001	0.025	0.001	6%		
Asian	0.018	0.001	0.018	0.001	2%		
Hispanic	0.022	0.001	0.021	0.001	-4%		
Married	0.017	0.000	0.017	0.000	-1%		
Divorced/Widowed/separated	0.021	0.001	0.021	0.001	2%		
Single - Never Married	0.025	0.000	0.023	0.001	-8%	***	
Held multiple jobs	0.041	0.001	0.043	0.002	6%		
Held One Job Exactly	0.018	0.000	0.017	0.000	-3%	**	
Worked Same Hours as usual	0.019	0.000	0.019	0.000	-3%	*	
Worked more hours	0.020	0.000	0.020	0.001	-2%		
Regular labor market	0.019	0.000	0.019	0.000	-4%	**	
Tight Labor Market	0.018	0.001	0.020	0.001	9%	*	
Part time worker	0.029	0.001	0.029	0.001	-2%		
Full Time worker	0.018	0.000	0.018	0.000	-2%		
No professional certification	0.020	0.000	0.019	0.000	-3%	**	
Holds a professional certification	0.018	0.000	0.018	0.000	-1%		
Mean Real Family Income		$ 96,512		$ 93,344			
Real Family income	-5.66E-08	5.13E-09	-6.34E-08	8.39E-09	12%		
Observations	541,761		251,566				
Pseudo R-squared	0.0193		0.0223				

Note: Predictive margins are shown for discrete variables, and average marginal effects are shown for continuous variables (family income) with significance levels to the right. * Indicates significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level. BFF displays Bonferroni corrected significance levels, considering that for each regression, there are 115 independent variables- hence 115 tests of significance. Month, State of Residence, Industry, and Occupation, and the intercept, were additionally included in a series of Booleans (Fixed Effects). A tight labor market was defined as having unemployment < 3.58% and a labor force participation rate that was under 66%.

Appendix Table 1: SAME EMPLOYER RATE
(Ind. & Occup.)

	PRE-PANDEMIC	POST-PANDEMIC	SIG.
INDUSTRY			
Agriculture, Forestry, Fish	0.973	0.972	
Construction and extraction	0.973	0.974	*
Mining	0.978	0.980	
Manufacturing	0.983	0.981	***
Wholesale trade	0.981	0.979	**
Retail trade	0.979	0.975	***
Transport and utilities	0.978	0.972	***
Information	0.981	0.979	
Finance, Insurance and Real Estate	0.982	0.981	
Professional and business services	0.975	0.975	
Education	0.979	0.979	
Healthcare	0.981	0.978	***
Social assistance	0.977	0.973	
Leisure and hospitality	0.971	0.968	***
Other services	0.975	0.976	
OCCUPATION			
Managers, administrators	0.984	0.982	***
Business and financial operations	0.980	0.982	
Computers and mathematical	0.982	0.982	
Architecture and engineering	0.984	0.985	
Life, physical and social sciences	0.982	0.979	
Community and social services	0.981	0.977	*
Legal	0.981	0.982	
Education, instruction, and library	0.977	0.976	
Arts, design, entertainment, sports, media	0.973	0.971	
Healthcare practitioners	0.983	0.981	**
Healthcare support	0.976	0.970	***
Protective services	0.974	0.971	
Food prep and serving	0.969	0.965	***
Grounds cleaning and maintenance	0.972	0.971	
Personal care and service	0.970	0.967	**
Sales	0.979	0.976	***
Office and admin support	0.979	0.975	***
Forestry, fishing, farming	0.969	0.970	
Construction and extraction	0.971	0.974	**

Installation, maintenance and repair	0.981	0.977	***
Production	0.980	0.978	***
Transport and materials moving	0.973	0.970	***

* indicates significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

Appendix Table 2: Demographics Over Time (in Percentages)

	Full Population				*Regression Sub-Sample*			
	Pre	**Post**	**Difference**	**Sig.**	**Pre**	**Post**	**Difference**	**Sig.**
18-25	13.22	12.16	-1.06	***	11.08	10.37	-0.71	***
26-35	17.84	17.43	-0.41	***	21	21.21	0.21	***
36-55	36.95	34.8	-2.15	***	45.23	43.9	-1.33	***
56-61	11.86	11.55	-0.31	***	12.64	12.54	-0.1	***
62+	20.13	24.06	3.93	***	10.04	11.99	1.95	***
White	71.65	70.04	-1.61	***	74.04	72.06	-1.98	***
Black	10.01	10.03	0.02		8.4	8.55	0.15	***
Asian	5.54	6.16	0.62	***	5.4	6.18	0.78	***
Hispanic	12.81	13.77	0.96	***	12.16	13.22	1.06	***
H.S. Dropout	9.83	8.1	-1.73	***	6.15	5.1	-1.05	***
H.S. Degree	28.96	28.49	-0.47	***	26.1	24.99	-1.11	***
Some College	18.99	17.13	-1.86	***	18.15	15.82	-2.33	***
A.A. Degree	10.27	10.6	0.33	***	11.47	11.42	-0.05	
B.S. Degree	20.47	22.51	2.04	***	24.07	26.26	2.19	***
Prof. Degree	11.47	13.17	1.7	***	14.07	16.42	2.35	***
Male	48.29	48.5	0.21	***	52.03	52.43	0.4	***
Female	51.71	51.5	-0.21	***	47.97	47.57	-0.4	***